Coping with Uncertainties

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"The expansion of economic, technological, and ecological interdependence has stimulated a growing volume of research on its implications and consequences. The International Institute for Applied Systems Analysis (IIASA) itself is one institutional manifestation of this expansion. Much of the work to date has been based, implicitly or explicitly, on an evolutionary paradigm – the gradual, incremental unfolding of the world system in a manner that can be described by surprise-free models, with parameters derived from a combination of time series and cross-sectional analyses of the existing system....The focus on surprise-free models and projections is not the results of ignorance or reductionism so much as of the lack of practically usable methodologies to deal with discontinuities and random events."
Harvey Brooks, The Typology of Surprises in Technology, Institutions, and Development, in: W.C. Clark and T.E. Munn (eds.), *Sustainable Development of the Biosphere*, Cambridge University Press, 1986.[2]

Abstract:
Uncertainty is a pervasive characteristic of all research addressed at IIASA. The role of science in better coping with uncertainty is twofold: First, to describe uncertainties as comprehensive and well as possible, both quantitatively and qualitatively. Second, the role of science is to develop methods that can lead to improved decision making under uncertainty. Here increasingly the concept of "optimal" is replaced by one of "robust" decisions, i.e. decisions that make sense *vis à vis* multiple uncertainties. The paper and presentation illustrate selective examples from IIASA research that contribute to the twin objectives of better description of uncertainty and improved decision making under uncertainty drawing from research in the fields of technology dynamics, climate change policy, as well as catastrophic risk management and portfolio analysis. The conclusions emphasize the need for basic research strategy aimed at elucidating uncertainties in both parameters as well as in alternative model representations and in developing improved models for robust decision making that emphasize risk hedging and spreading both spatially as well as well as through a portfolio of a wide range of policies.

[1] Contributions from Tanja Ermolieva, Alexey Smirnov, Marek Makovski, and Tony Patt are gratefully acknowledged.

[2] We dedicate this paper to the memory of the late Harvey Brooks, stimulating colleague and friend of IIASA.

Introduction

Uncertainty is a pervasive characteristic of all research addressed at IIASA. The role of science in better coping with uncertainty is twofold: First, to describe uncertainties as comprehensive and well as possible, both quantitatively as well as qualitatively. A hallmark of IIASA's research is certainly a keen interest in methods and empirical analysis of "long-tailed" distributions and extreme event analysis and in the development of scenarios that probe into an uncertainty space that often is beyond reach of deterministic projections and surprise-free model representations.

Second, the role of science is to develop methods that can lead to improved decision making under uncertainty. Celebrating IIASA's 35th birthday, let us recall that the intellectual/scientific traditions that led to the creation of the Institute were strongly influenced by perceptions on the possibilities of forecasting and new methods of operations research developed for optimal planning and decision making after WWII. In both it's methodological (e.g. the gradual extension of linear programming to stochastic optimization approaches) as well as in it's applied research (extending over ever longer time horizons, and evolving to the study of ever larger complex, interrelated phenomena such as Global Change) IIASA's science itself reflects an increasing awareness about the need to complement traditional decision paradigms such as "rationality" or "optimality" with new concepts such as "robust" decision making[3], i.e. decisions that make sense *vis à vis* multiple (type of) uncertainties.

Types of Uncertainties

Uncertainties can take many incarnations and spreads. They range from "parametric" uncertainty, e.g. uncertain parameters and thresholds of otherwise well established dose-response relationships, abundant especially in the environmental field, to "functional" uncertainties, i.e. where a relationship between two variables is ascertained, but not only parameters, but also sign of influence remain uncertain (e.g. does the availability of new communication technologies and telecommuting lead to less or more travel?), to straightforward ignorance: There are *"unknown unknowns --* [things] *we don't know we don't know"* (© Donald Rumsfeld).[4] Despite being known to science ever since the

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[3] See e.g. Yuri Ermoliev and Leen Hordijk, *Global Changes: Facets of Robust Decisions*, IR-06-001, IIASA, Laxenburg, Austria (January 2006).

[4] *"Reports that say something hasn't happened are interesting to me, because as we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns — the ones we don't know we don't know."*
Quite ironically, Donald Rumsfeld seems to have paraphrased an old anonymous Arab proverb:
He who knows not and knows not that he knows not is a fool. Shun him.
He who knows not and knows that he knows not is simple. Teach him.
He who knows and knows not that he knows is asleep. Wake him.
He who knows and knows that he knows is wise. Follow him.
http://www.chara.gsu.edu/~gudehus/Quotations/

end of the 19th century, climate change might in fact be a good illustration of an "unknown unknown" to the policy realm. What Harvey Brooks calls "sudden emergence into political consciousness" constituted a genuine surprise to policy makers, when climate change was first proposed for deliberations at a (now) G-8 summit in back in 1978.[5]

It is beyond the scope of this paper to propose a comprehensive taxonomy of uncertainties.[6] For the subsequent discussion, we differentiate between three main classes of uncertainty including *epistemic* (e.g. uncertain data and/or models), *linguistic* (e.g. vagueness and/or failure to precise context specificity), and finally *contingency/agency* (uncertainties arising from human intentionality, i.e. the very policy decisions, a particular study aims to contribute to).

The domain of *epistemic* uncertainty comprises uncertainties in both data and models. While well known to science it continues to be a major stumbling block in communicating science to policy and the public at large, frequently being subject to *linguistic* uncertainty (discussed below). Data and model uncertainties interact in important ways for all those phenomena that are not directly observable/measurable (and thus not lending themselves to the traditional statistical tools of handling measurement errors [imperfect observations] or systematic errors [bias in sampling or in measurement devices]) and their ensuing communication via empirical distribution functions (the ominous "PDF's", or probability density functions). Consider as example the issue of detection of historical climate change (subject to measurement and systematic errors) vs. the issue of describing uncertainty of future, <u>projected</u> climate change (involving in addition also substantial modeling uncertainties) in which the ensuing probability density functions become themselves *conditional* on the particular model used or to *subjective* model interpretations, reflecting different "degrees of belief" of expert opinions. Dependence on a single model (or on a too restricted group of experts polled) will lead to an undesirable compression of uncertainty (overconfidence).

Recent developments (with important contributions from IIASA, particularly in the field of technology studies) that complement traditional techniques for describing uncertainty such as expert opinion polling, or Monte Carlo simulation techniques based on a single model include: the comparative use of model ensembles and the use of massive computation techniques either via parallel processing or agent-based simulations. Common to them all is the aim to generate distributions of to date unobserved states of a system that combine both data as well as modeling uncertainties (as discussed in the super-computer simulations of technological uncertainty by Gritsevskyi and Nakicenovic below). These new

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[5] For a vivid account see Tom Schelling, Research by Accident, *Technological Forecasting and Social Change* 53(1996):15-20. Schelling also highlights that back in *1978 "only at IIASA the topic* [of climate change*] seems to have organized itself...*[resulting*] in integrated work on the subject".*

[6] For a good introduction see e.g. H.M. Regen, M. Colyvan, and M.A. Burgman, A taxonomy and treatment of uncertainty for ecology and conservation biology. *Ecological Applications* 12(2)(2002):618-628.

approaches often reveal "badly behaved" distributions (e.g. characterized by long tails and multiple peaks) that too often cannot be represented by traditional methods of describing the outcomes of epistemic uncertainty.

Linguistic uncertainty refers to vagueness, ambiguity, or underspecificity in defining the nature and boundary conditions of a particular decision problem at hand (e.g. what constitutes *"dangerous interference with the climate system"* to quote the UNFCC [United Nations Framework Convention on Climate Change]), or in failing to reveal appropriate *context*. For instance, based on a priori assumed “reasonable” bounds on uncertainty, there is a vast body of literature, considering climate change as an economic cost-benefit optimization problem. Conversely, considering "deep" uncertainty, the problem at hand will rather be a (catastrophic) risk management issue, evoking the need of policy makers to reveal explicit preferences/criteria for risk aversion (e.g. "pre-cautionary" principles), framing an entirely different context for decision making and policy modeling (as illustrated in the attainability domain analysis of the DICE climate change policy model below).

With respect to *linguistic* uncertainty, it is especially important to acknowledge profound differences between the natural and social sciences. "Observations" mean very different things to these two disciplines. In the social sciences any observations are subject to interpretation, or are straightforward "synthetic", in terms that they are generated by polling "experts" (or the lay public) with well known manifestations of inherent biases *("heavier than air flying machines are impossible,* ©Lord Kelvin, 1895) or methodologically induced "compression of uncertainty" (loss of the "minority view"), e.g. in two staged Delphi polls. This is in stark contrast to the natural sciences with its emphasis on *"sine ira et studio"* empiricism, although important feedbacks exist between the social and natural science realms (e.g. the initially persistent filtering [dismissal] of data on the emerging ozone hole that where inconsistent with prevailing natural science theories and models as described by IIASA Scholar Paul Crutzen in his personal history on the discovery of the "ozone hole".[7]

An important implication of linguistic uncertainty is the need for a careful communication strategy that clearly specifies the limits and conditionality in both the decision making context as well as in formal representations (e.g. subjective probabilities) of uncertainty a particular study entails and that are subject to dramatic revisions once new data or improved model representations become available.

C*ontingency/agency* uncertainty prevails in all those cases where the probability of a (future) event cannot be determined *ex ante* as determined by human intentionality, e.g. as influenced by the very societal/policy decisions that are

[7] Brian C O'Neill, Paul Crutzen, Arnulf Grübler, et al., Learning and climate change. *Climate Policy* 6(2006):585–589.

subject to our scientific enquiry. There is strong and weak *contingency* defining uncertainty.

A strong contingency prevails in a case where intervening decisions determine the outcome, but the ultimate equilibrium outcome remains indetermined. A classical case, and one of the stellar contributions of IIASA research to the understanding of technological dynamics is the case of "lock-in" investigated by Brian Arthur and colleagues through an Urn-scheme model. They showed that through a random accumulation of "small events" (of atomistic individual decisions) a choice between two alternative technological innovations introduced on the market will ultimately lead (deterministically) to a complete adoption of either technology "A" or "B", but that the ultimate outcome (whether "A" or "B" become the dominant technology) cannot be determined *ex ante.* (This finding is first of all result of a phenomenon of "increasing returns" (to adoption)[8] underlying the model, but as recent research [*inter alia* at IIASA] has shown, this is a prominent feature of almost all large technological systems and infrastructures.) Parenthetically, we might also note here (as information to IIASA sponsors), the substantial time lags involved between the creation of path-breaking research, and its wider recognition, which can take well in excess of a decade.[9]

A weak contingency prevails in the case where intervening decisions might influence the ultimate outcome, but the extent of leverage of these intervening policy actions remain undetermined. Consider the case of public sector R&D in low and zero-carbon technologies. First, extent of these public sector investments remain uncertain (both in terms of amounts as well as [more importantly] in terms of consistency and perseverance of these investments). Second, the outcome of these R&D investments remains highly uncertain: can they "deliver" the desired technologies or not (after all, despite continued, perseverant investments in nuclear fusion R&D, we still do not have a functioning fusion reactor prototype). In the parlance of technology innovation studies that

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[8] Under increasing returns, the benefits of using a particular technology (or sharing a technological infrastructure) increase non-linearly with the number of adopters (as opposed to the standard assumption of decreasing returns in neo-classical economics), ultimately leading to the preference for singular, technology standards, or technology "lock-in" (think about mobile telecommunication standards such as GSM). Mathematically, resulting models involve non-convexity, which explains the relative paucity of decision models incorporating phenomena of increasing returns. See e.g.:
W. B. Arthur, 1983, *On Competing Technologies and Historical Small Events: The Dynamics of Choice under Increasing Returns*. IIASA WP-83-090.
Y. Ermoliev, W.B. Arthur , and Y.M. Kaniovski, 1987, Path-dependent processes and the emergence of macro-structure. *European Journal of Operational Research*, 30(3):294-303.
W.B. Arthur, 1989, Competing technologies, increasing returns, and lock-in by historical events, *The Economic Journal* 99(394):116-131.

[9] It is interesting to note the long diffusion and recognition times of this important field of research. 6 years elapsed between the first paper published at IIASA in 1983 and a first publication in a disciplinary economic journal in 1989 (characterized by an agonizing review process and final acceptance only after an appeal to the journal by a group of distinguished economists including Nobel Laureates). And it took another 10 years before that very paper saw the crest of it's citation impact as documented in the *Institute for Scientific Information* (ISI) citation data base.

quote the Bible: *"many* [innovations] *are called, but few are* [ultimately] *chosen.* Innovation payoffs are actually among the empirically best documented cases of extreme tailed distributions.[10] Finally, third, there is profound uncertainty in the adoption environment: Even given innovation success, market adoption (and corresponding impacts on lowered environmental burdens) remains uncertain as depending both on (uncertain) public sector policy signals (e.g. carbon taxes) as well as (uncertain) private sector responses to these policy signals.

Given these compounding uncertainties that resist traditional probabilistic treatments, the complexity of "chained events" that entail contingency/agency is best described by alternative scenarios, a technique that has a long and distinguished tradition at IIASA in the domains of long-term energy and climate change developments (see especially Nebojsa Nakicenovic' contribution to this Conference). Uncertainties that either characterized by poor observability (high epistemic and linguistic uncertainty) or weak contingency, or worse: by both, are the ones most at odds with traditional decision making paradigms, e.g. entailing "best guess" projections or optimization of single variable objective functions. Instead, comprehensive description of uncertainties and concepts of adaptive, and "robust" decisions, e.g. drawing from portfolio management and risk hedging theories, are called for. It is certainly also not coincidental that in its own intellectual history, IIASA has placed increasing research emphasis in this "difficult" quadrant of the uncertainty cosmos, and more importantly has achieved important results, helping to improve decision making under uncertainty. As we will argue below, climate change is perhaps the prototypic policy question in this realm of above discussed "badly behaved" uncertainty space (of poor obsvervability and weak contingency), being the reason to focus on it in this paper when presenting a selective review of IIASA research accomplishments.

Describing Uncertainties

Let us begin our review of descriptive models of uncertainty with a somewhat atypical example, by reviewing a deterministic model of optimal climate change cost-benefit calculus based on the widely cited and used DICE model developed by Bill Nordhaus at Yale University.[11] This example is chosen for three reasons: First, it honors the important scientific contribution of an IIASA alumnus, who has pioneered the field of climate change policy modeling work while resident at IIASA in the mid 1970s. Second, it illustrates the continued important contributions of participants of IIASA's Young Summer Scientists Program (YSSP) to the Institute's ever evolving research agenda, as illustrated below by the attainability domain analysis of the DICE model performed by Alexey

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[10] F.M. Scherer and D. Harhoff, 2000. Technology Policy in a world of skew-distribution outcomes. *Research Policy* 29(2000):559-566.

[11] W.D. Nordhaus, Managing the Global Commons. The Economics of Climate Change, MIT Press, 1994.
W.D. Nordhaus and J. Boyer, Warming the World — Economic Models of Global Warming, MIT Press, 2001.

Smirnov.[12] Finally, the analysis helps us to frame linguistic uncertainty in the case of climate change policy analysis, pointing to the need for comprehensive modeling descriptions of epistemic uncertainty that comprise both data and modeling uncertainties, as well as a recasting of the decision making paradigm away from "optimality" in direction of hedging strategies and "robust" decision making.

The power of simple, reduced form models has always been that they allow insights arising from parsimony rather than complexity. The DICE model of climate change policy analysis has gained prominence not at least because its elegance and simplicity in model formulation. Using a cost-benefit optimization framework and drawing on a neo-classical economic growth model with exogenous total factor productivity growth as well as exogenous climate-relevant technology change, the model assumed a pioneering role in a research field, now known as *integrated assessment*. Starting from a "best guess" model calibration of economic growth and associated greenhouse gas (GHGs) emissions, DICE translates emissions into atmospheric concentrations, and resulting changes in radiative forcing and ensuing global warming. Drawing on calibrated "dose-response" relationships, the "damage function" from climate change is contrasted with the corresponding GHG "abatement cost function" enabling the formulation of the climate change policy challenge within an economic cost-benefit framework.

Using concepts and methods developed for optimal control theory that has a long distinguished tradition at IIASA, attainability analysis allows the analytical derivation of the entirety of the solution space of a model, thus allowing for an <u>analytical</u> description to the entire uncertainty domain of a particular model, complementing traditional methods of massive Monte-Carlo simulation. (It should be noted that the applicability of this method is restricted to simple linear models [requiring even a simplifications of the original DICE model]). Attainability analysis deals with a systems' *attainability domains*. Given a *target date* in the future, a system's attainability domain is by definition the set of all the states the system is principally able to reach at that target date. Thus, each state belonging to the system's attainability domain is reachable by the set of control variables of a system under consideration. Conversely, the control variables under consideration can not bring the system to any state located <u>outside</u> its attainability domain. In the case of the DICE model these two control variables are investments (yielding GDP growth) and the level of abatement (reducing the emissions from the unabated levels resulting from GDP growth). Rather than looking at annual flows Figure 1 below shows these two decision variables as stock variables, i.e. the capital stock of the economy, and the carbon content of the atmosphere (compared to pre-industrial time), which (when multiplied by the so-called *climate sensitivity*) is a proxy for climate change.

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[12] A. Smirnov, 2005. Attainability Analysis of the DICE Model. IR-05-049. International Institute for Applied Systems Analysis, Laxenburg, Austria.

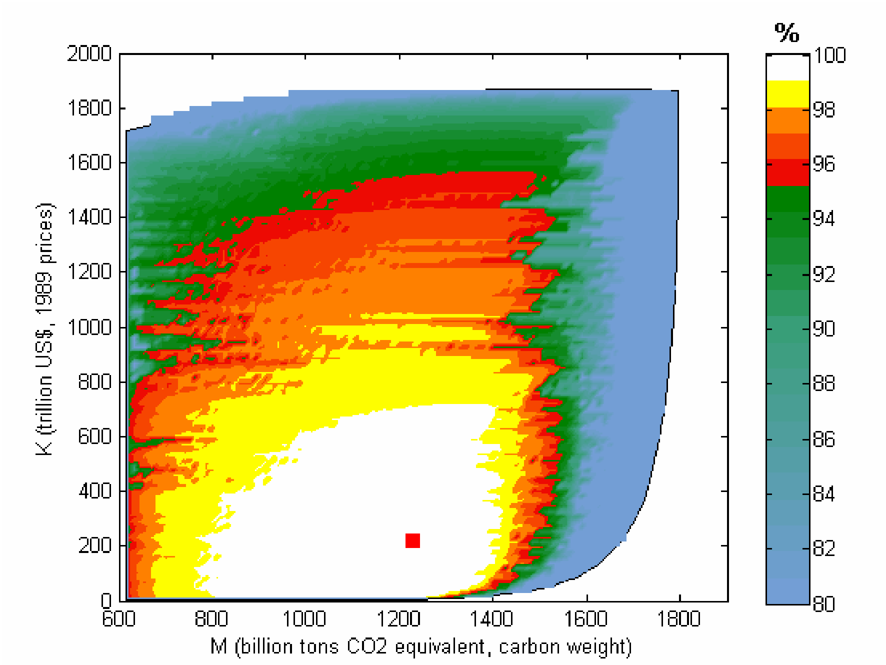

Figure 1. *Attainability Domain analysis of the Nordhaus' DICE model of global warming, showing the entirety of the model solution space as a function of the models two control variables: investment (i.e. the resulting capital stock of the economy, trillion $) and carbon content in the atmosphere (result of annual emissions minus abatement levels, combined with a simplified carbon cycle model, in billion tons C-equivalent) for the year 2100. Superimposed are isolines of equal values of the model's objective function (percent of maximum). The optimum of the original DICE solution is denoted by a red dot. Source: Illustration courtesy of Alexey Smirnov, IIASA.*

In a first step of the analysis, the attainability domains can be studied in their evolution over time. It is particularly instructive to note the almost quadratic shape of the model's attainability domain: For any given levels of investment and hence GDP there is a wide range of corresponding carbon emissions; conversely, for any given level of emissions, there is also a wide range of possible investment and GDP levels associated with it, suggesting a comparatively weak link between income and resulting emissions when compared to other (exogenous) influencing variables. More instructive even is to project onto the attainability domain the corresponding values of the model's objective function (the discounted utility of consumption, after subtracting climate change damages). It is interesting to note in particular the "flatness" of this objective function and the resulting large "indifference space" with less than one percent difference (white shaded area in Figure 1). In other words, framing the decision problem at hand as an optimization problem that balances climate change damages vs. abatement costs is akin to deciding to jump over a stone on the top of a mountain (or not), while externalizing the question whether to climb the mountain in the first place, or which mountain to climb. Explicitly addressing the relative uncertainties of climate damage vs. emission abatement costs will not change the linguistic ambiguity of this particular example, as the uncertainties affecting the models objective function beyond climate costs (emission reductions) and benefits (avoided damage as result of emission reductions) remain exogenous. (It is noteworthy to note that the two out of three of most important uncertainties affecting the model results have a technology dimension: total factor productivity growth [that leads to GDP growth even in absence of the models decision variable investment], as well as the abatement cost function [both affected by technological change uncertainty as discussed below]).

In a subsequent analysis conducted under the auspices of IIASA's Greenhouse Gas Initiative (GGI) Smirnov combined his DICE attainability analysis with a probabilistic approach for catastrophic risks, using the example of a possible shutdown of the thermohaline circulation (the Gulf Stream) as a result of climate change. Drawing on the work of Keller et al.[13] it was possible to calculate "risk exposure" surfaces for a range of climate sensitivities for the entirely of the solution space (attainability domains) of the original DICE model. The most important conclusion from this exercise was to illustrate that under a plausible range of climate sensitivities (4 degrees equilibrium warming for a doubling of pre-industrial CO_2 concentration, i.e. the atmospheric carbon stock variable in Figure 1), the zone of a 10 percent probability of a thermohaline collapse encompasses all of the "indifference zone" of the objective function of +/- 1%, beyond 1300 GtC-equiv., bordering in addition to the "optimal" cost-benefit solution of the original DICE model that excluded uncertainty as well as the risk of catastrophic changes. These results caution against the postulation of the climate change problematique as a purely economic cost-benefit optimization problem without due regard to uncertainties and especially to the possibility of "surprise", i.e. large-scale, non-linear (catastrophic) environmental change.

Revealing linguistic uncertainty and context specificity of policy approaches and models remain therefore a continued challenge where IIASA has and continues to make important contributions.

In above discussion, we have eluded to the central role of technological uncertainty in both determining the magnitude of the climate problem, as well as in the feasibility and costs of emission reductions and hence in avoiding further large-scale climate change. Important illustrations of the magnitude and importance of technological uncertainties have been achieved both through Delphi-type expert opinion polls, scenario studies (as discussed in Nebojsa Nakicenovic' contribution to this conference) as well as through structured modelling comparisons, e.g. those performed under the auspices of the *Energy Modelling Forum* (EMF).

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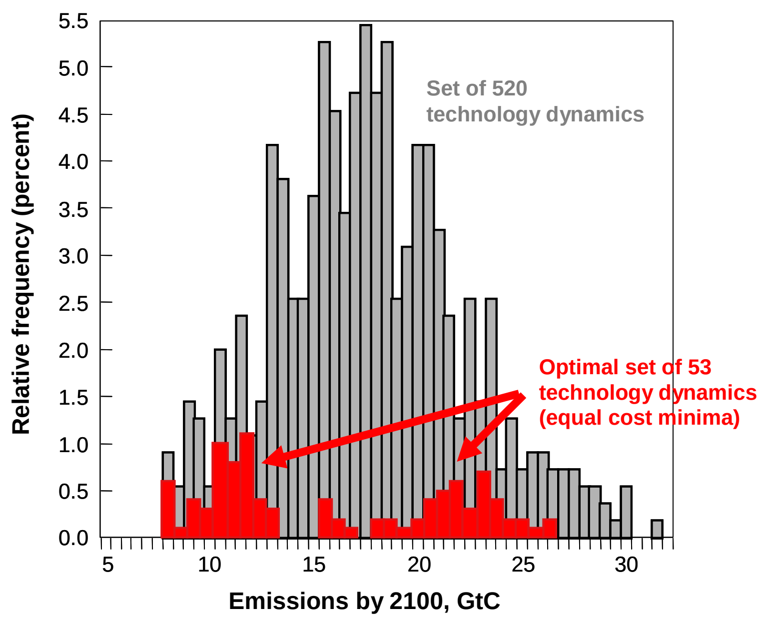
[13] Keller K., Tan K., Morel F., Bradford D., Preserving the ocean circulation: implications for climate policy, *Climatic Change*, 47(2000):17-43.

The most exhaustive examination of the influence of technological uncertainty performed to date is the modelling study conducted at IIASA by Andrii Gritsevskyi and Nebojsa Nakicenovic.[14] That study constituted a landmark in technological uncertainty modelling as extending traditional approaches that have focused on data uncertainty by also including modelling uncertainty of the main range of drivers of technological change. Through the use of massive computation on a CRAY supercomputer (the access to which was facilitated by the late Gordon MacDonald), a full range of technological uncertainties incl. future costs, increasing returns to adoption (with resulting non-convex optimization), as well as technological interdependence (e.g. hydrogen fuel cell vehicles requiring a corresponding hydrogen production, transport and distribution infrastructure) as well as technology spillover effects were examined for a given energy demand scenario and assuming no climate policies. Altogether the model simulations generated some 130,000 scenarios regrouped into 520 sets of technology dynamics that span a carbon emission range of between 6 to 33 GtC by 2100 (Figure 2).



. Note in particular the bi-modal distribution of emissions for the subset of scenarios sharing the same least-cost criterion for objective function. Source: Gritsevskyi and Nakicenovic, 2000.

In other words, a systematic exploration of all contingent uncertainties of long-term technological change spans a comparable range of future emissions as almost the entirety of the no-climate policy emissions scenario literature, illustrating overconfidence in previous uncertainty studies. Limitations in available

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[14] A. Gritsevskyi and N. Nakicenovic, Modeling uncertainty of induced technological change, *Energy Policy* 28(13)(2000):907-922. It should be noted that also for this seminal paper, six years elapsed before it became widely accepted in the scientific community as an important contribution (as reflected in ISI citation statistics).

computation time, did not allow to further extend the uncertainty analysis by also including demand as well as climate policy (contingency/agency) uncertainties. However, the study furthered progress in parallel computing and solution search algorithms that have made it possible to deal with similar problems of non-convex, stochastic optimization even in the more modest computing environment available at IIASA (cf. the discussion on stochastic optimization below).

Another finding from that study is particularly instructive for policy. The study identified some 13,000 scenarios regrouped into a set of 53 technology dynamics among the entire scenario set generated, which are all "optimal" in the sense that they satisfy the same cost minimum in the objective function (akin to the objective function indifference space discussed above in the attainability domain analysis example). In terms of emissions outcomes, however the uncertainty distribution is bimodal, defying traditional uncertainty descriptions by “well behaved” distribution functions. In other words, considering full endogenous technological uncertainty produces a pattern of "technological lock-in" into alternatively low, or high emissions futures that are equal in terms of their energy systems costs. As such, the study constitutes an important extension from the original Arthur model of technological lock-in under presence of increasing returns to adoption, while confirming the dynamic behaviour and policy conclusions of the original model. Under increasing returns, the ultimate outcomes of alternative technology lock-ins are indistinguishable in economic terms (even if producing vastly different environmental impacts), illustrating the ambiguity of associating cleaner environmental performance invariable with “high” costs, and environmentally “dirty” with low costs in the long-term (as characteristic for climate change policy analysis).

The study’s results also cast doubts on the plausibility of central tendency technology and “best guess” emissions scenario projections. More importantly, the results confirm the value of technology policy as a hedging strategy aiming at lowering future carbon emissions even in absence of directed climate policies as costs of reducing emissions even further from a given baseline are *ceteris paribus* proportionally lower with lower baseline emissions.[15]

Improved Decisions under Uncertainty

Given above conclusions about the importance of uncertainty, the natural question arises: what should we do instead? We have argued above for the need of what almost corresponds to a paradigm shift in many traditional fields of systems and decision science: moving from deterministic modeling (with –

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[15] Modeling studies at IIASA in the ENE Program and within GGI have played a central role in quantifying this insight. See in particular:
R.A. Roehrl and K. Riahi, Technology dynamics and greenhouse gas emissions mitigation: A cost assessment. *Technological Forecasting & Social Change* 63(2-3)(2000):231-261.
K. Riahi, A. Grubler, and N. Nakicenovic, Scenarios of long-term socio-economic and environmental development under climate stabilization, *Technological Forecasting & Social Change* 74(7)(2007):887-935.

hopefully extended sensitivity analyses) and its (futile) quest for “optimality” to the concept of “robust” decision making that takes uncertainties explicitly into account, transforming optimality conditions from singular decision variables/criteria to whole ensembles, or portfolios of response options, that in their combination constitute optimal hedging strategies *vis à vis* uncertainties.

Space limitations do not allow discussing the multitude of approaches towards decision making under uncertainty that have been developed and applied at IIASA.[16] Instead we focus below on two illustrative examples of applications of variants of stochastic optimization methods[17] developed at IIASA: technology portfolio analysis modeling as well as catastrophic risk management.

Technology Portfolios in Response to Technological and Climate Risks

Investments into new technologies entail two fundamental risks: First, any investment decision is long-lived, extending in many cases (such as power plants or transport infrastructures) several decades into the future, being thus subject to changing boundary conditions (e.g. new environmental policy). Second, the range of investment options include both existing, well tried technologies, as well as emerging new ones. These potentially offer significant improvements in performance, costs, or environmental compatibility, but require upfront investments (e.g. into R&D and niche market testing) in order to reveal their full potential. Shying away from these investments would actually correspond to stalling technological change, or relegating it to a "manna from heaven" externality, unfortunately still embraced in a number of climate change policy models. But even if recognizing the need for investments into a range of technology options, we still need to answer the question: How *much* investment into *which* technologies? Here the concept of *portfolios*, long established in financial investments can be usefully applied to the climate change issue.

A new model under development at IIASA by Keywan Riahi and Volker Krey provides a good illustration of methods for improved investment decisions into technologies in a climate constrained world. In their model the two most salient uncertainties framing investment risks are included: feasibility/availability and

[16] Here we refer in particular to important work in multi-criteria optimization, decision support systems, (structured) policy exercises, and adaptive environmental management, where IIASA scientists have made important contributions to both theory and practice.
[17] Yet another reason to choose this example, is to highlight the importance of a consistent, patient, long-term basic research strategy. By establishing a Committee on Stochastic Programming of the Mathematical Programming Society at IIASA in the early 1980s it was possible to bring together scientists, synthesizing and cross-fertilizing their research. The resulting research outcome was documented in Y. Ermoliev and R. Wets (eds), 1988. *Numerical Techniques for Stochastic Optimization*. Springer Verlag, Berlin, 571 pp, and provided a basis for further development of the methodology and novel applications over the last 7 years. The comparative advantages of IIASA as convener of methodological research is also illustrated in the continued conference series on “Coping with Uncertainty” jointly organized by IIASA, IFIP (the International Federation of Information Processing) and GAMM (the International Association of Applied Mathematics and Mechanics) that provided the title for this paper.

costs of technologies as well as potential climate constraints (modeled via an uncertain carbon tax). The novel feature of this stochastic programming approach is the explicit and transparent modeling of risk, that becomes an endogenous decision variable. Given different degrees of risk aversion, revealed by decision makers in their "willingness to pay" a risk premium above economic cost minima "indifference surfaces" (recall here above discussion of the modeling work of Smirnov and Gritsevskyi/Nakicenovic), alternative "optimal" technology diversification portfolios can be generated using a simplified bottom-up model of the global energy system.

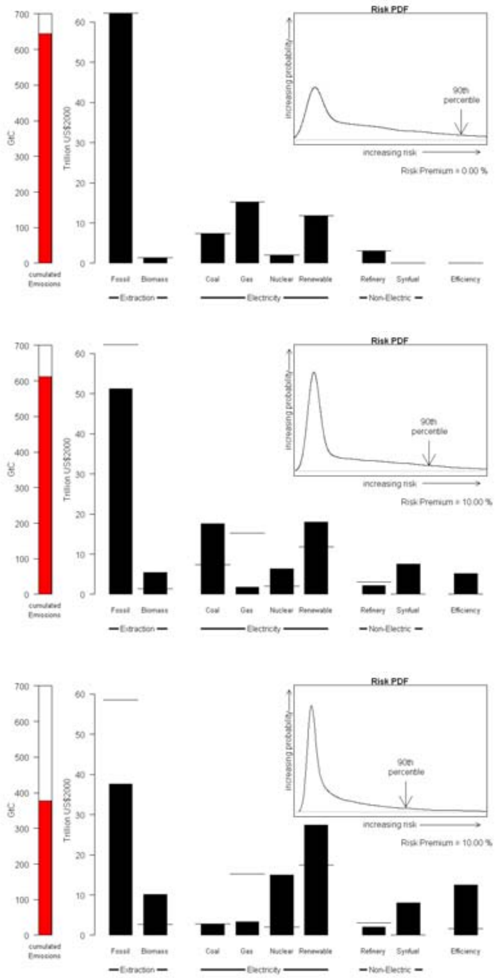

Figure 3. *Technology investment portfolios investments (trillion US$) into a range of energy technologies and resulting risk PDF (insert) for a deterministic case without diversification (top panel), under consideration of technological (cost) uncertainty (middle panel) and in considering in addition climate constraints uncertainty (modeled via an uncertain carbon tax) (bottom panel). The "risk premium" corresponds to the willingness to pay in terms of exceedence of the cost minimal deterministic solution (0% in the top panel versus 10% in the illustrative diversification solutions shown in the middle and bottom panel). For comparison, the carbon emission implications of the three solutions in terms of cumulative carbon emissions over the period 2000-2100, in GtC) is also shown (most-left red bars on panels). Source: Illustrations courtesy of Keywan Riahi and Volker Krey.*

For instance, compared to a deterministic cost minimal solution that exhibits the highest risk exposure (top panel of Figure 3), adding a technological risk (cost uncertainty) response (middle panel in Figure 3) drastically changes the technology portfolio mix, while at the same time also reducing the risk distribution function (mean and variance of the PDF). Adding in addition the risk of an uncertain carbon tax (bottom panel of Figure 3) not only changes the technology portfolio further, but more importantly reduces the risk PDF rather than increasing it. This is simply the result of a *contingency/agency uncertainty* response by a further diversification of the technology portfolio (that would not have been justified by ignoring the additional climate constraint uncertainty in the first place). Evidently, this risk reduction comes at a price (the "risk premium" in Figure 3), in terms of the acceptable additional systems costs associated with risk hedging (a rather extreme value of 10 percent is shown in the simulations in the middle and bottom panels of Figure 3, generally substantial risk reductions are achievable at risk premiums of a fraction of one percent of total systems costs).

Even more important than these insights into the technology portfolio, investments, and risk reduction implications of diversification, is to recognize the potential of this novel approach to make the representation of uncertainty much more transparent to decision makers than was possible with traditional approaches. From that perspective, considering and explicit treatment of uncertainty makes the life of the modeler easier, as no longer in need of justifying ("best judgment" or even arbitrary) model parameter choices. Work is in progress to extend the model framework into a versatile modeling platform that both makes the description of uncertainty fully transparent to the user, as well as endogenizes risks, the treatment of which becomes a decision variable, rather than pre-specifying them (and thus being often shrouded in mystery). As such this research illustrates nobly the twin missions of systems science (and of IIASA): helping not only to cope with uncertainty, but making it also more transparent and easier for the policy maker to understand and to steer.

Catastrophic Risk Management: The Example of Earthquake Insurance

Our last example for improved methods of decision making under uncertainty comes from a seemingly unrelated field to climate change: insurance against catastrophic risks (earthquakes in Italy). However there are more commonalities (and thus potential fruitful transfer of methods) in these two fields than meets the eye at first sight. First, it is increasingly recognized, that the main risks associated with climate change will lie less in the gradual unfolding of projected global average trends, but rather in increased frequency and severity of extreme events that (like other natural disasters like floods or earthquakes) will have spatially extremely heterogeneous effects, not at least because of decisive differences in social vulnerability and possibilities for adaptation (as eluded to in Tony Patt’s contribution to this Conference). Secondly, again much alike in responding to risks in natural disasters, *insurance* is increasingly studied as a response strategy in managing climate impact risks (for instance in IIASA's Risk and Vulnerability [RAV] Program), not at least because some climate change is already committed to unfold as a legacy of past emissions and because of the twin inertias of the climate system and of our technological infrastructures, which need drastic changes for significant emission reductions.

In a case study for the Tuscany region in Italy Tanja Ermolieva and colleagues[18] have performed a number of modeling studies to help to improve the diversification of local insurers against earth quake risks. (A distinguishing feature of the region is that insurers operate locally concentrated [with no spatially diversified portfolios; see Figure 4] which implies a major financial insolvency risks for both insurers and their clients.) In collaboration with local geological experts first a probabilistic and spatially explicit earth quake simulator software was developed to generate scenarios of risk exposure given the current distribution of insured properties from two insurers. In a subsequent step, stochastic optimization techniques were used for optimally diversifying the spatial spread of the insurers portfolios in order to avoid potential insolvencies (Figure 5). Thus, not unlike in the case of technological responses to climate change risks, the key to success lies in *portfolio diversification*, but this time in a spatial context, a concept that might be ultimately also required for climate risk insurance schemes (albeit likely encompassing a daunting global level).

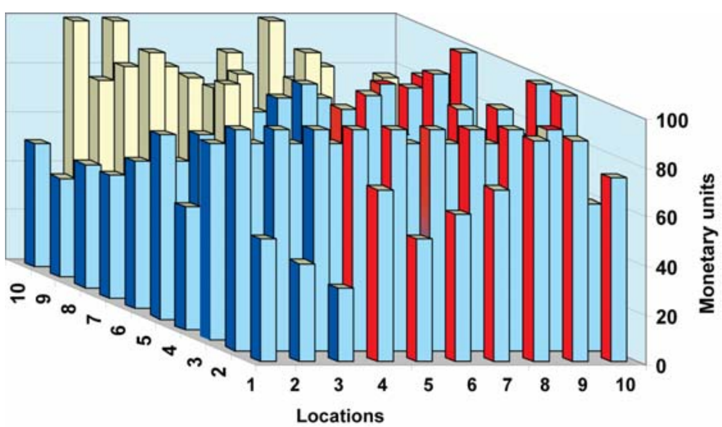

Figure 4. *Insured property values in the Tuscany Region of Italy, vulnerable to earthquake risks. The initial spatial distribution is characterized by a spatial concentration of the respective insurers (red and blue bars) in subregions, posing insolvency risks in case an earthquake would hit their subregion. Source: Illustration courtesy of Tanja Ermolieva.*

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[18] Y. Ermoliev, T. Ermolieva, G. MacDonald, and V. Norkin, Stochastic optimization of insurance portfolios for managing exposure to catastrophic risks. *Annals of Operations Research* 99(2000):207-225.

Ermolieva, T., Ermoliev, Y., Fischer, G., Galambos, I., The Role of financial instruments in integrated flood management. *Multinational Finance Journal* 7(3-4)(2003):207-230.

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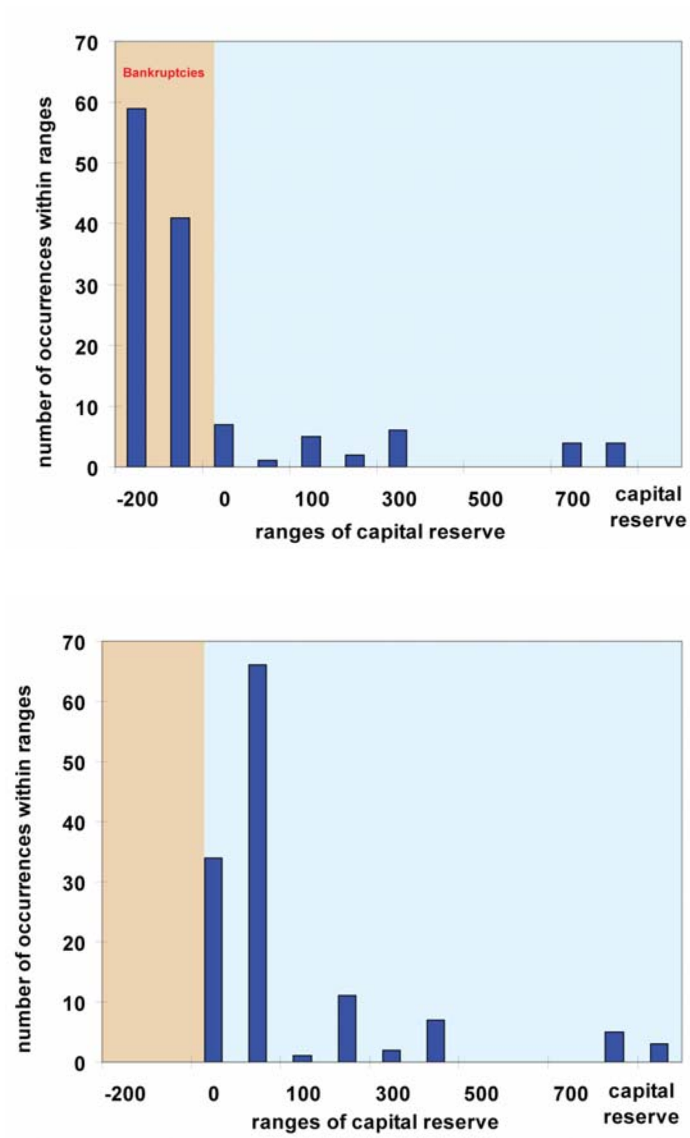

Figure 5*. Frequency of risk exposure (in terms of insurer's capital reserve) for initial distribution (top panel) over an ensemble of earthquake impact scenarios generated versus optimized, spatially diversified portfolio (bottom panel) illustrating elimination of bankruptcy risks. Source: Illustration courtesy of Tanja Ermolieva.*

Conclusions

The take-home "message" from this selective and synoptic overview of uncertainty related research at IIASA is that improved system science methods and models can help to better cope with decisions under uncertainty in both better describing the cosmos of uncertainty as well as to help to improve decision making under uncertainty.

Methodologies are now available to display uncertainties to decision makers without relying on expert filtering or uncertainty distribution tail-cutting, as well as to offer an alternative decision making paradigm to traditional utility maximization "learn-then-act" or worst case (pre-cautionary principle) decision making.

"Robust" decisions are those that: a) increase adaptive capacity to change course as new information becomes available (e.g. via diversified technology portfolios), and b) provide insurance against extreme, undesirable outcomes while respecting resource constraints (i.e. provide flexibility and insurance at comparable costs to traditional optimal cost-benefit calculations but at drastically lower costs than worst-case scenario approaches).

The task of further improving science tools as well as to openly address linguistic uncertainty in framing the appropriate contexts for decision making rests as always with the scientific and policy communities involved. A 35 year legacy of important IIASA contributions is both motivation and responsibility to contribute towards the noble goal of better coping with uncertainties.