ARCHIVES OF ENVIRONMENTAL PROTECTION

vol. 36 no. 1 pp. 129 - 143 2010

PL ISSN 0324-8461

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ADVANCES IN MODELING METHODOLOGY FOR SUPPORTING ENVIRONMENTAL POLICY-MAKING

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Keywords: Environmental policy-making, decision-making support, mathematical modeling, structured modeling, knowledge management, uncertainty, integrated risk management, natural catastrophes.

Abstract: The paper deals with recent developments in the fields of applied mathematics and operational research triggered by the needs of effective support of environmental policy-making processes that require interdisciplinary science-based advice. Mathematical models developed for this purpose demand new modeling paradigms for an adequate integration of pertinent knowledge, and creation of knowledge needed for rational decision-making. The article first summarizes the model-based support for problem solving from the point of view of actual decision-makers. Next, it discusses the model representation of the knowledge pertinent to a given decision-making problem, and the recently developed modeling technology supporting the whole process of modeling complex problems. The last part deals with novel methods and tools for integrated management of risks related to natural catastrophes. The presented methodology is illustrated by its application to actual environmental policy-making support.

INTRODUCTION

Rational policy making is becoming more and more difficult because the corresponding decisions cannot be adequately represented by well-structured problems that are easy to solve by intuition or experience supported by relatively simple calculations. Even the same type of problems that used to be easy to define and solve, are now much more complex because of the globalization of the economy, and a much greater awareness of its linkages with various environmental, social, and political issues. One of the dominant driving forces is efficiency, which has led to globalization, increased dependency among more diversified systems, a reduction in many safeties (both technological and social) margins, and other factors which contribute to increased vulnerability. Traditional societies developed slower but in a more robust way, i.e., the consequences of wrong decisions or natural catastrophes were rather limited. Nowadays, the consequences of wrong decisions may be wider (even global and long-term) and more serious (in terms of economical, social and environmental impact).

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Rational support for policy making should be based on a comprehensive analysis of the underlying problem aimed at finding a possibly best portfolio of decisions. One should stress that *possibly best* does not mean an optimal solution in the traditional sense of mathematical programming. Comprehensive analysis implies exploitation of pertinent science (i.e. organized knowledge relevant to the decision problem) to analyze the consequences (outcomes) of various decisions, and to help to identify a portfolio of decisions that correspond best to the preferred trade-offs in the outcome space. Thus, science-based support for policy-making means (1) integration (for properly representing relations between decisions and their consequences) and (2) creation (for analysis of attainable trade-offs between the consequences) of knowledge, both aimed at providing a basis for rational decision-making. This sounds to be an obvious conclusion. However, its proper application to the modeling process requires more attention to the modeling technology than is commonly recognized.

The key features of policy-making are commonly known. Decisions:

- are rarely based on complete and precise information about the relations between decisions and all consequences of their implementations,
- have impacts on diversified stakeholders, typically having different, often conflicting, interests and goals,
- often have consequences on various spatial and temporal scales,
- are done for the future, which always is uncertain.

It is not possible to analyze all these elements for any actual decision problem. Yet, decisions have to be made, either with or without science-based support. Policy-making can be greatly either supported or misled by science. The unquestionable successes of operational research show opportunities of using mathematical models and their analysis for substantially contributing to solving problems in a better way than it would be possible without using models. Despite the countless number of successful applications, there is also well-justified criticism of various critical aspects of modeling, e.g., in [1, 2, 5, 19, 33]. The role of models in modern decision-making, a view shared by the author of this paper, is discussed in detail in [35], which also presents methodology and tools for model-based decision-making support, and illustrates them with several applications to complex environmental policy-making problems. A more focused discussion of selected elements of modeling for decision support is provided in [25], which also includes an updated bibliography on modeling for decision support.

This article discusses selected recent methodological developments triggered by actual applications of system analysis to supporting environmental policy-making. Although developed for addressing specific practical environmental policy-making problems, the methods and tools have also been applied to other problems; therefore they may also be interesting to both researchers and practitioners working in the field of environmental protection.

The remaining part of this paper is composed of three parts. The first one summarizes the model-based support for problem solving from the point of view of actual decision-makers. In the next part we discuss the model representation of knowledge pertinent to a given decision problem, and the recently developed modeling technology supporting the whole process of modeling complex problems. The last part deals with novel methods and tools for integrated management of risks related to natural catastrophes. The presented methodology is illustrated by applications to actual environmental policy-making support.

MODEL-BASED PROBLEM SOLVING SUPPORT

A mathematical modeling process for supporting problem solving is actually a network of carefully designed activities driven by the requirement analysis. The role of the requirement analysis is often underestimated although it is commonly known that a properly done analysis is a key condition for any successful modeling process. This topic is far beyond the scope of this paper, therefore we mention here only those key elements of the requirement analysis which are directly related to the process of knowledge integration and creation aimed at supporting analysis and solving of a given problem:

- What decisions are to be made?
- How the consequences of decisions are measured?
- What relations between the consequences and the decisions should be considered?
- What data is available?
- How the decision-maker(s) and/or stakeholders' preferences (for different decisions and the corresponding consequences) can be represented and analyzed?

However, we emphasize that the requirement analysis (and the corresponding modeling process) should be specific to a given decision-making situation.

Mathematical models are probably the best way to manage (integrate and create) knowledge for problem solving whenever it involves analysis of large amounts of data and/or non-trivial relations. In such cases the elements of the requirement analysis correspond to the basic elements of a typical structure (illustrated in Fig. 1) when using a mathematical model for problem solving.

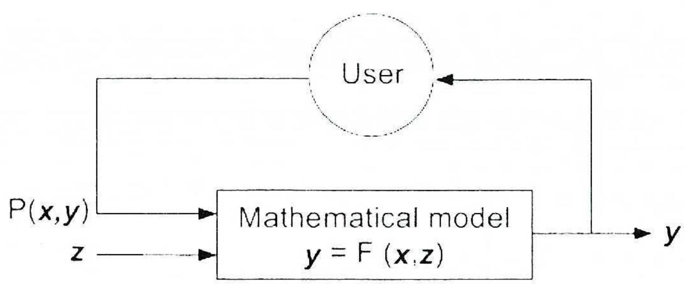

Fig. 1. A typical structure when using a mathematical model for problem solving

A mathematical model describes the modeled problem by means of variables, which are abstract representations of these elements of the problem that should be considered for evaluation of the consequences of implementing a decision (typically represented by a vector composed of many variables). We present here a view on mathematical models from the perspective of actual users (who are rarely familiar with operational research) that differs from typical formulations of the corresponding mathematical programming problems. The term *user* denotes a person (or a group of persons) who make decisions, advise actual decision-makers, or use the model for analyzing the underlying problem. From a user (or decision-making) perspective, a model is developed using the following concepts:

- Decision (control, input) variables x, which are controlled by the user.
- External decisions (inputs) z, which are not controlled by the user.

- Outcome (criteria, indicator, metric, output) variables y, used for measuring the consequences of implementation of the decisions.
- Auxiliary (other) variables defined and used in order to make the model easier to develop and analyze. A large model may have several millions of variables and constraints, even when the number of decision and outcome variables is much smaller (say several thousands). However, auxiliary variables are usually not interesting for the users; therefore for the sake of brevity we do not consider such variables here.
- Relations between decisions x and z, and outcomes y, such relations are typically presented in the form:

$$y = F(x, z, A), \tag{1}$$

where $F(\cdot)$ is a vector of functions having parameters denoted by matrix A. In mathematical programming the relations are conventionally called constraints, and typically defined as:

$$y - F(x, z, A) = 0$$

- A representation of a preferential structure $P(x, y)$ of the user, used for selecting (out of typically an infinite number of solutions) a manageable subset of solutions corresponding best to user's preferences.

The compact form of equation (1) may be misleading for those who are not familiar with the complexity of the underlying knowledge representation. The latter is critically important for the model quality, therefore we discuss below the key aspects of modeling methodology.

A common form of knowledge is a collection of facts and rules about a subject. Let us therefore consider mathematical models as composed of entities of three types:

- parameters, values of which represent facts (data),
- variables, values of which are assigned during the model analysis,
- relations (1) that represent knowledge about the relationships among parameters and variables.

Thus, by a proper definition of decision and outcome variables a model can indeed represent knowledge pertinent to analyzing consequences of various decisions aiming at finding the trade-offs between the consequences that best fit the preferences of decision-maker(s) and/or stakeholders. This simple methodological recipe is however difficult to implement, even for problems that appear to be easy to analyze. To justify this statement we will now discuss key elements of the knowledge integration process, and illustrate it by a practical problem.

KNOWLEDGE INTEGRATION

Complex problems are typically composed of heterogeneous subjects, and often complexity of the knowledge represented by the corresponding model is difficult to be judged from articles focusing on a model application, such as [7] summarizing the results of the RAINS/GAINS model. Actually, the structure of this model illustrated in Fig. 2 is pretty complex; it is composed of the following subjects: several sectors of economy (industry, transportation, agriculture, etc), the corresponding technologies, atmospheric chemistry, ecology, environmental and health impacts, and environmental targets. Moreover, for developing and maintaining this family of models also deep knowledge of negotiations,

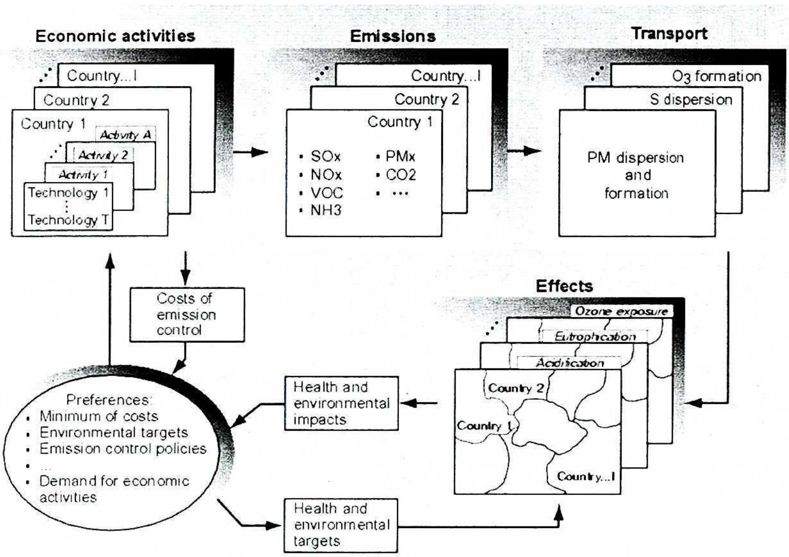

Fig. 2. RAINS/GAINS model structure

policy making, and operational research is necessary. Each of these subjects is rather complex, and for each there exists a huge amount of knowledge accumulated in various fields of science and practice. Thus one of the challenges is to select a tiny subset of the (globally) available knowledge that is relevant to the modeled problem. Although heterogeneity of subjects represented by the RAINS/GAINS model is far beyond a typical model, selection of appropriate (for the problem at hand) elements of knowledge remains a challenge also for rather homogeneous (in terms of the science disciplines) problems.

In many situations symbolic model specification can be based on commonly known rules of science. However, in other situations knowledge pertinent to a particular relation is so diversified that a definition of a single relation requires a dedicated study. To illustrate this problem let us recall that the relation between trophosperic ozone and its two precursors (nitrogen oxides and volatile organic compound) can be defined in very different ways, each having the corresponding diversified advantages and disadvantages depending on the content in which the relation is applied, see e.g., [19]. Relations for each subject (in large scale models represented by a submodel) are defined in a close cooperation between specialists in the corresponding area and a team of modelers capable to:

- assess the consequences of the considered relation types on numerical complexity of the resulting computational tasks, and
- assure consistency of the whole model to which the relation will be included.

A model integrates knowledge pertinent to analyzing a particular problem on two levels:

- symbolic model specification,
- model instance (also called *substantive model* or *core model*) composed of model specification and a selected set of data used for instantiation of relations (through assigning values to parameters of the relations).

Models are generated (except of tiny models composed of a small number of variables) from symbolic model specifications defined with help of compound entities (parameters, variables, and relations) and sets of indices, the latter used for generating the corresponding sets of entities. Thus, a compound entity is actually a multidimensional vector composed of the corresponding primitive entities defined by a generic entity and all admissible combinations of indices declared for it. To illustrate this point let us consider a simple definition of an auxiliary variable in the GAINS model:

$$xs_{sipa} = \sum_{t \in T_{pa}} w_{iat} \ x_{iat}, \quad i \in I, \ p \in P, \quad a \in AIP_{ip} \tag{2}$$

where $\boldsymbol{xs}$ and $\boldsymbol{x}$ are compound variables, $\boldsymbol{w}$ is a compound parameter, and indices i, p, a, t denote a country, pollution type, economic activity, and technology, respectively. For a typical instance of the GAINS/RAINS model there are about 200 subsets $\boldsymbol{AIP}_{ip}$ of the activity set $\boldsymbol{A}$; the equation (2) is therefore represented in the corresponding optimization problem by about 40 000 constraints (and the same number of corresponding primitive variables $\boldsymbol{xs}_{ipa}$) with about 200 000 corresponding non-zero elements of the Jacobian.

The complexity of this relation is caused by the fact that indices t and a are members of sets which are indexed by other indices. Moreover, the actual model is defined by dozens of compound relations; most of them are much more complex than one of the simplest relations represented by equation (2). Therefore, even if the size of each set is not large, the structure of the corresponding indexed subsets is pretty complex and requires effective management. Such a management includes:

- efficient handling of the underlying data structures that in turn requires advanced use of DBMS (Database Management System), which is inevitable for an effective modeling process of large scale models;
- analysis of semantic correctness of indexing structures.

Moreover, the modeling processes supporting policy making have to meet the strong requirements of: credibility, transparency, replicability of results, integrated model analysis, controllability (modification of model specification and data, and various views on, and interactive analysis of, results), quality assurance, documentation, controllable sharing of modeling resources through the Internet, and efficient use of resources on computational Grids. These requirements also demand novel modeling technology. We comment here on only two related problems:

- Assuring semantic consistency of model specification requires verification of measurement units of all model entities. The fact that this functionality is not provided by the general purpose modeling environments illustrates the underlying challenges. Recent achievements in this area are reported in [29].
- Data for large models comes from different sources (also as results from analysis of various models), and larger subsets of data are maintained by teams. Persons working with well-defined subsets of data are experienced in collecting, cleansing, verifying, and maintaining the data they are responsible for. Therefore the "only" problem is how to structure the process of aggregating the subsets of data maintained by various teams (typically also using different hardware and software) into a data collection that can be used for model instantiation and analysis. To achieve this, a structured approach (such as the SMT described below) based on DBMSs and an automatically generated data warehouse is a must.

STRUCTURED MODELING TECHNOLOGY (SMT)

The Structured Modeling Technology (SMT) has been developed in response to the modeling needs of the RAINS/GAINS family of models, which could not be met by the available modeling tools. Although SMT exploits a great deal of modeling legacy, a number of challenging problems had to be solved to provide the needed functionality. This includes the SMT features summarized below. Finally, one has to stress that although the design and development of SMT was directed by the characteristics of the RAINS family of models this does not restrict applicability of SMT because the features of the RAINS models are typical for a wide range of complex models.

The complexity of problems, and the corresponding modeling process involving inter-disciplinary teams are the two main factors that determine the requirements for modeling technology; such requirements are not met by the technologies successfully applied to modeling well-structured and relatively simple problems. In most publications that deal with modeling, small problems are used as an illustration of the presented modeling methods and tools. Often, they can also be applied to large problems. However, as discussed above, the complexity is characterized not primarily by the size, but rather by the requirements of integrating heterogeneous knowledge, by the structure of the problem, and by the requirements for the corresponding modeling process. Moreover, efficient solving of complex problems requires the use of a variety of models and modeling tools; this in turn will require even more reliable, re-usable, and shareable modeling resources (models, data, modeling tools). The complexity, size, model development process, and the requirements for integrated model analysis form the main arguments that justify the needs for the new modeling methodology.

SMT has been developed for meeting such requirements. It supports distributed modeling activities for models with a complex structure using large amounts of diversified data, possibly from different sources. A description of SMT is beyond the scope of this paper, therefore we only summarize its main features here:

- SMT is Web-based, thus it supports *any-where*, *any-time* collaborative modeling.
- It follows the principles of Structured Modeling proposed by Geoffrion, see e.g., [15]; thus it has a modular structure which supports the development of various elements of the modeling process (model specification, processing (subsets of) data, integrated model analysis) by different teams.
- It provides automatic documentation of all modeling activities.
- It uses a DBMS for all persistent elements of the modeling process, which results in efficiency and robustness; moreover, the capabilities of DBMSs allow for the efficient handling of huge amounts of data.
- It ensures the consistency of: model specification, meta-data, data, model instances, computational tasks, and the results of model analysis.
- It automatically generates a Data Warehouse with an efficient (also for large amounts of data) structure for:
  - data, and the tree-structure of data updates,
  - definitions of instances,
  - definitions of preferences for diversified methods of model analysis,
  - results of model results,
  - logs of all operations during the modeling process.

This conforms to the requirement for the persistency of all elements of the modeling process:

- It exploits computational grids for large amounts of calculations.
- It also provides users with easy and context-sensitive problem reporting.
- The methodological background of structured modeling (including an overview of diversified modeling paradigms and the standard modeling methods and tools) as well as a detailed SMT description is available in [22].

COPING WITH UNCERTAINTY

Out of the huge scientific area of uncertainty we are dealing here only with recent developments in integrated management of risks related to natural catastrophes. Policy options for such risk management include various ex-ante measures (such as mitigation, different arrangements for risk spreading) and ex-post measures aimed at reducing and sharing losses. The outcomes of implementing a given set of policy measures are typically measured by various indicators such as ex-ante and ex-post costs, benefits from mitigation measures, welfare, quality of the environment, and indicators of risk exposure (value at risk, insolvency).

Novel methods for effective risk management had to be developed because the traditional approaches that rely on real observations and experiments are not applicable to rare events such as natural catastrophes. The first main issue is the lack of historical data on extreme events characterized by abrupt irreversible changes. The second key problem is that extreme events having such a big impact on societies are typically evaluated as improbable events during a human lifetime although a 1000-year (an extreme event that occurs on average once in 1000 years) earthquake may occur even tomorrow; e.g., the Chernobyl disaster of 1986 was quantified as 1 000 000-year event, and it occurred 9 years after the power plant was commissioned. The third important issue is the evaluation: actually, it is not rational to evaluate consequences of catastrophic events using traditional approaches. The traditional models in economics, insurance, risk-management, and extreme value theory are based on exact predictions and evaluations. Standard insurance theory essentially relies on the assumption of independent, frequent, low-consequence (conventional) risks, such as car accidents, for which decisions on premiums, claims estimates and the likelihood of insolvency can be calculated from rich historical data. Also the established extremal value theory deals primarily with independent events and assumes that these events are quantifiable by a single number [9]. However, catastrophes should not be quantified in this way because they have significant spatial and temporal patterns that induce heterogeneity of losses and gains. Moreover, random variables characterizing catastrophes have probability distributions with heavy tail; often the distributions are multimodal with expected values that correspond to events that never occur.

The most important scientific challenge in addressing the problems summarized above is to develop proper methods for comparative analysis of feasible decisions and to design robust policies with respect to the uncertainties and risks involved. Although exact evaluations are impossible, the preference structure among decisions can be a stable basis for a relative ranking of alternatives. This issue is discussed in more detail in [16] along with other open research problems related to proper treatment of irreducible uncertainty, catastrophic risks, spatial and temporal heterogeneity, downscaling, and discounting.

Designing robust policies for integrated catastrophic risk management is a complex interdisciplinary problem requiring knowledge of environmental, natural, financial, and social systems. Consequences of catastrophes are unevenly distributed; therefore a corresponding decision-making process requires participation of various agents and stakeholders such as governments, individuals, producers, consumers, insurers, investors. The perception of catastrophes by all these actors, and their goals and constraints with respect to these rare but high-consequence events is very diversified. A rational policy-making should therefore take into account all these elements which is hardly possible without support provided by a dedicated interdisciplinary modeling effort.

Below, we outline the system of models developed for supporting actual policy-making processes related to integrated management of natural catastrophe risks. These models support analysis of spatial and temporal heterogeneity of various agents (stakeholders) induced by mutually dependent losses from extreme events. The implemented approach addresses the specifics of catastrophic risks: diversified interdisciplinary knowledge about the catastrophes, limited data available for each specific case, the need for long term perspectives and geographically explicit models, and a multi-agent decision-making structure. Therefore, the corresponding models combine the available data representing the geographically explicit distribution of capital stocks and economic values of the regional infrastructure and agriculture with a stochastic model that generates occurrences, magnitudes, and locations of catastrophes. Using advanced stochastic optimization techniques, the model supports the search for, and the analysis of, robust optimal portfolios of ex-ante (land use, structural mitigation, insurance) and ex-post (adaptation, rehabilitation, contingent credits, redirecting of funds) measures for decreasing the vulnerability measured in terms of economic, financial, and human losses as well as in terms of selected welfare growth indicators.

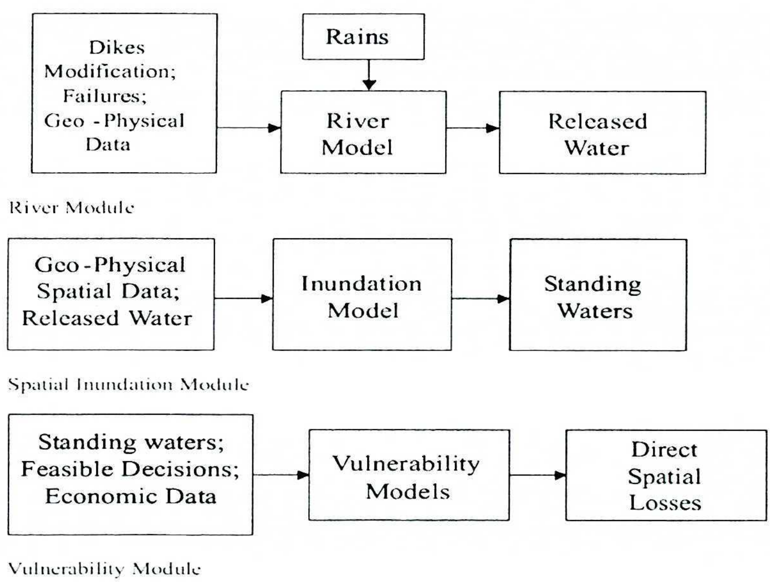

Fig. 3. River, inundation, and vulnerability modules of the system of models for supporting integrated management of risks related to catastrophic floods

The system of models has a modular structure illustrated in Figures 3 and 4 consisting of the following modules:

– A catastrophe module simulates a natural phenomenon. It is based on the knowledge of the corresponding type of event represented by a set of variables and relations between them, and uses the spatial data for a given location. Different versions of this module are implemented for different types of natural catastrophes. For example, a flood simulator (illustrated by the first two modules shown in Fig. 3) is composed of precipitation curves, water discharge, river characteristics, and spatial inundation models. For a hurricane simulator, the variables include the radius of the maximum winds, or the forward speed of the storm. An earthquake module simulates shaking of the ground using epicenter locations, magnitudes of earthquakes, Gütenberg-Richter laws, and attenuation characteristics. A catastrophe module therefore compensates the lack of historical data on the occurrence of catastrophes in locations where the effects of catastrophes may have never been experienced in the past. The catastrophe models used in various IIASA's case studies are based on the Monte Carlo dynamic simulations of geographically explicit catastrophe patterns in selected regions. Discussion of these models is beyond the scope of this paper but can be found, e.g., in [3, 6, 10, 14, 34].
– A vulnerability module, which provides estimations of damages caused by a specific (generated by the catastrophe module) catastrophe. Physical indicators (like shaking intensities, duration of standing water, water discharge speed or wind speeds) generated by the corresponding catastrophe module are used for calculating the corresponding damages. The vulnerability module uses vulnerability curves and infrastructure data (such as the age of buildings, the number of stores) for estimating damages induced by the simulated disaster. This module, therefore, provides spatial distributions of direct losses.

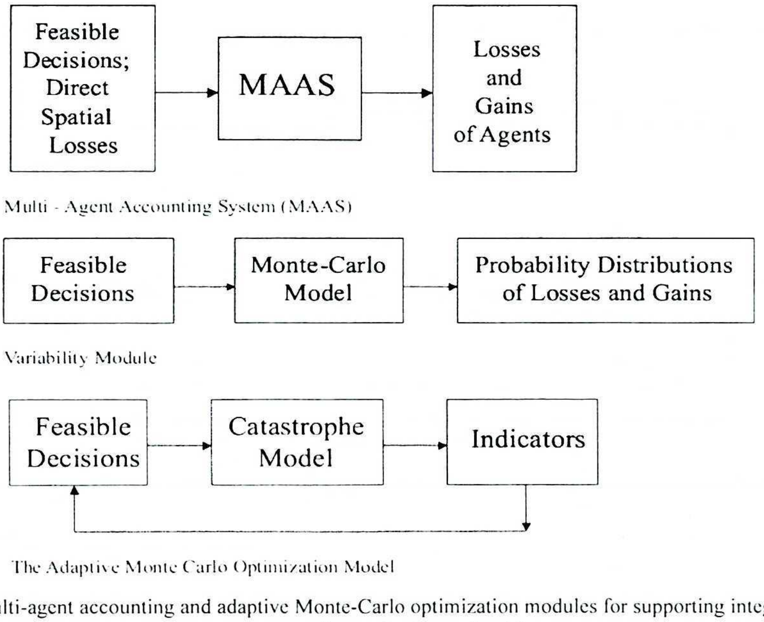

Fig. 4. Multi-agent accounting and adaptive Monte-Carlo optimization modules for supporting integrated management of natural catastrophe risks

- The economic multi-agent accounting system (MAAS, see Fig. 4) is a stochastic dynamic welfare growth model (see, e.g., [11, 12]) that maps spatial losses (which depend on selected loss mitigating and sharing policy options) into gains and losses of agents (stakeholders) involved in the policy-making, e.g., central and local governments, a (mandatory) catastrophe insurer, investors (e.g., interested in providing structural measures mitigating the consequences of a catastrophe), and individuals exposed to the catastrophe risks.
- The adaptive Monte-Carlo optimization is used together with the variability module for designing "robust" optimal decisions. The design is done by incorporating stochastic spatial adaptive Monte-Carlo optimization techniques into catastrophic modeling that enables the design of desirable robust solutions without evaluating all possible alternatives. Discussion of the methodological background of the applied approach (presented in [12]) is beyond the scope of this paper. Here we only mention that different catastrophic scenarios lead to different decision strategies, and the number of alternative decisions is typically huge; therefore a straightforward *if-then* evaluation of all alternatives is not practicable. The novelty of the implemented approach is that it effectively supports finding a combination of decisions that forms a "best" strategy against almost all possible scenarios. This strategy takes into account the goals and constraints agreed with all stakeholders.

The modular structure not only conforms to good software engineering practice but also allows for reuse of modules for case studies involving different types of natural catastrophes.

The above summarized methodology for the system of models developed for integrated management of risks related to natural catastrophes is an example of application of novel methods and tools for effective coping with uncertainties. Descriptions of other methods and applications can be found in [21]; a broader scope of recent developments in coping with uncertainty is presented in [26–28]. Here we only mention the recently developed fundamentally new concept of endogenous spatio-temporal discounting, so-called stopping time discounting [13]. This method is based on undiscounted stopping-time criterion which is equivalent to the standard discounted criterion in the case of market-related discount factors. It enables a complementary (to the approach summarized above) evaluation of long-term spatially explicit robust risk management strategies against potentially extreme catastrophic events.

CONCLUSIONS

This paper presents selected recent developments in modeling methodology and illustrates their applicability to supporting actual environmental policy-making. We close the presentation with more general comments that are based on the lessons from many real-life applications.

Most new modeling practitioners dealing with complex problems are surprised by the amount of work and the length of time required to obtain results truly useful for policy-making support. Complex problems are modeled by interdisciplinary teams that first have to find a common language, and then for a selected modeling paradigm must find a way of avoiding too much detail while preserving the essential features of the considered problem. Although many well-developed modeling paradigms exist (an overview can be found in [31], more specific approaches in, e.g., [4, 17, 18, 22, 25, 35, 36]), it is not easy to select and implement the one that best serves the problem at hand. Moreover, sometimes a simple modification of a model specification results in a dramatic decrease of the computing resources needed to solve the underlying computational task, or in providing solutions having more desired properties. Several examples illustrating this point can be found in [20, 30].

We also recommend the old (but still very relevant) guidelines formulated by Dantzig, who summarized in [8] the opportunities and limitations of using large-scale models for policy making. Dantzig also coined the term *Laboratory World* that today can be interpreted as modeling environment in which various models are developed and used to learn about the modeled problem in a comprehensive way. Thanks to the development of algorithms and computing power today's large-scale models are at least 1000-times larger; thus, large-scale models of the 1970s are classified as rather small today. This, however, makes Dantzig's message relevant to practically all models used today, not only for policy-making but also in science and management. Today's models are not only much larger. The modeled problems are more complex (e.g., by including representation of knowledge coming from various fields of science and technology), and many models are developed by interdisciplinary teams. The complexity, size, model development process, and requirements for integrated model analysis form the main arguments justifying the needs for the new modeling methodology. More detailed arguments (including overview of the standard modeling methods and tools) supporting this statement are available in [22].

One should also point out tacit advantages from modeling complex problems: the modeling process (especially the specification and verification of various versions of the model) typically facilitates learning about many characteristics of the modeled problem that had not been recognized even by experienced "problem-owners" before the modeling process started. To illustrate this issue let us note that even a simple (from decision-making point of view) problem of selecting a solution from a set of discrete alternatives poses methodological challenges and pitfalls, see e.g., [23]. Thus learning about the decision problem during the modeling process is typically at least equally important as a model-based support for finding a solution that the user considers fitting best her/his preferences. Note that the classical (and still most popular) approach is based on looking for an "optimal" solution, although actually any feasible solution can be proven to be (in a sense) optimal. This observation shows how important it is to properly use the power of optimization for solving actual problems, see e.g., [23, 25].

The truth is that there are no simple solutions for complex problems. Modeling a non-trivial problem, especially aimed at supporting policy-making, requires not only interdisciplinary team-work and appropriate modeling tools, but also a combination of explicit and tacit knowledge, experience, intuition, and taste. Aggregation of diversified modeling skills is rather difficult; therefore modeling remains and will remain an art. In other words, modeling is in a sense similar to cooking: recipes, ingredients, experience, and tools are necessary, but actually neither cooking nor modeling can be mastered from books.

Acknowledgments

Many colleagues and friends have helped in various ways to understand different elements of key modeling and knowledge paradigms, and to develop ideas, concepts, and tools. There is no way to adequately characterize individual contributions. Therefore the author thanks here only colleagues whose impact on the research outlined in this paper has been most significant. T. Ermolieva and Y. Ermoliev of IIASA have made most of the key contributions reported in the Coping with uncertainty part. Colleagues from the IIASA APD Program have been collaborating with the author in developing and analyzing various models for over 20 years; this has provided incentives to develop several modeling methods and tools. Many ideas exploited in SMT have resulted from countless discussions and joint activities of the author with J. Granat and A.P. Wierzbicki. A. Geoffrion has provided a basis for SMT by formulating the structured modeling methodology and organizing various activities supporting dissemination of this fundamental concept. Finally, M. Sądelski (of the Institute of Environmental Engineering of the Polish Academy of Sciences, Zabrze, Poland) introduced the author (then focusing on rather theoretical aspects of mathematical modeling and optimization) into the challenging world of actual support of environmental policy-making [32].

The author gratefully acknowledges all these contributions, but he assumes the sole responsibility for the content of this paper.

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Received: December 8, 2008; accepted: June 2, 2009.

POSTĘPY W METODOLOGII MODELOWANIA MATEMATYCZNEGO DLA WSPOMAGANIA PROCESÓW DECYZYJNYCH DOTYCZĄCYCH ŚRODOWISKA NATURALNEGO

W artykule przedstawiono nowe osiągnięcia w dziedzinach matematyki stosowanej i badań operacyjnych, które są wynikiem badań motywowanych potrzebami efektywnego wspomagania procesów decyzyjnych związanych z problemami środowiska naturalnego. Takie wspomaganie wymaga współpracy naukowców z różnych dziedzin w celu budowania modeli matematycznych, które nie tylko reprezentują zintegrowaną wiedzę dostępną w różnych dziedzinach nauki, ale także wspomagają tworzenie wiedzy użytecznej dla podejmowania racjonalnych decyzji. W artykule scharakteryzowano rolę modeli matematycznych w procesach wspomagania decyzji z punktu widzenia decydentów i ekspertów używających tych modeli. Następnie przedstawiono zagadnienia matematycznej reprezentacji interdyscyplinarnej wiedzy użytecznej dla danego problemu decyzyjnego; w szczególności opisano nową technologię modelowania strukturalnego, która wspomaga cały proces modelowania. Ostatnia część artykułu poświęcona jest nowej metodologii zintegrowanej analizy ryzyka związanego z naturalnymi katastrofami; analiza służy znajdowaniu rozwiązań racjonalnych dla instytucji i społeczeństwa, które mają różne cele i ograniczenia. Wszystkie prezentowane metodologie są ilustrowane praktycznymi zastosowaniami we wspomaganiu procesów decyzyjnych dotyczących środowiska naturalnego.