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The use of multi-criteria decision-making methods in the integrated assessment of climate change: implications for IA practitioners

Michelle L. Bell*, Benjamin F. Hobbs, Hugh Ellis

Department of Geography and Environmental Engineering, The Johns Hopkins University, Baltimore, MD 21218, USA

Abstract

Integrated assessment (IA) considers interactions of physical, biological, and human systems in order to assess long-term consequences of environmental and energy policies such as limits on greenhouse gas emissions, and other strategies to negate climate change. Users of IA face the daunting task of interpreting large amounts of data and uncertainties. Multi-criteria decision-making (MCDM) methods can help users process IA data, understand policy tradeoffs, and learn how their value judgments affect decisions. We held a workshop during which climate change experts tested several MCDM methods for using IA outputs to rank hypothetical policies for abating greenhouse gas emissions. Participants also evaluated several methods for visualizing tradeoffs under both certainty and uncertainty cases. This paper explores potential roles for MCDM in IA identified during the workshop, along with implications for IA design and implementation. We summarize the workshops' results regarding intertemporal discounting (a type of MCDM weighting judgment), visualization of impacts, how MCDM methods can help users to incorporate their background knowledge, and how MCDM can improve understanding of tradeoffs and the importance of value judgments. A key result is that the interest rates IA experts recommend for discounting future impacts depend strongly on what type of impact is being discounted, as well as upon the exact phrasing of questions used to elicit rates from the experts.

Keywords: Policy analysis, climate change, multi-criteria decision-making, decision analysis, integrated assessment, discounting, visualization

*Corresponding author. Tel.: +1-410-516-6173; fax: +1-410-516-8996.
E-mail address: chelbell@jhu.edu (M.L. Bell).

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1. Introduction

Integrated assessment (IA) integrates, interprets, and communicates knowledge from several scientific disciplines in order to understand cause-and-effect relationships between human behavior and environmental and economic outcomes [1]. IA involves both the modeling and description of impacts and evaluation of policy alternatives (Table 1). The aim of IA is to help users, such as policy makers and stakeholders, make better decisions by improving their understanding of the consequences of assumptions and policy choices. IA has been used to: (1) explore future scenarios for human and natural systems; (2) describe policy impacts; and (3) prioritize research needs [2]. Greenhouse gas policy is the most prominent application [3]. In such applications, IA is used to estimate the impacts, such as global temperature change and cost, from various policy alternatives, such as use of alternative fuels.

Effective use of IA requires that users understand its many outputs, including complex tradeoffs among environmental, economic, and social criteria. Numerous criteria must be considered because there are multiple stakeholders and a wide range of impacts. Research results need to be accessible to policy makers and compatible with the policy process (e.g., expressed in terms easily understood) [4]. Multi-criteria decision-making (MCDM) methods are formal approaches to structuring information and decision evaluation in problems with multiple, conflicting goals. MCDM can help users understand IA results, including tradeoffs among policy objectives, and use those results in a systematic, defensible way to develop policy recommendations. The purpose of MCDM in this context is not to calculate the "right" decision, but to help improve understanding for decisions involving risks, multiple criteria, and multiple interests. MCDM attempts this in three ways:

- By *displaying tradeoffs* among policy evaluation criteria (e.g., global temperature increase, control cost) along with their uncertainties so that users can interpret the relative advantages and disadvantages of alternative policies (e.g., CO_2 taxes, promotion of nuclear power).
- By moving the discussion away from policy alternatives and towards *fundamental objectives*. This facilitates negotiation by encouraging people to think about common interests while avoiding the defensive discussions that may result from anchoring on a preferred alternative [5–9]. A focus on fundamental objectives can also help define new options that better satisfy group goals [10,11].
- By helping people to systematically consider, articulate, and apply *value judgments*, resulting in logical and documented recommendations concerning which alternatives are most preferred.

Thus, MCDM can help with both the impact modeling/description and decision evaluation functions of IA. While decision-making methods can benefit a variety of environmental decisions, this research explores the use of MCDM in the IA of climate policy.

Table 1 shows the tasks required for an IA system to successfully execute its modeling and decision evaluation functions. These functions are shown as columns, with the tasks (ranging from formulation to documentation) arranged in rows. The decision evaluation function is divided into the sub-functions of evaluating tradeoffs and risks. Research is needed to enhance our ability to perform each of the tasks described in Table 1. Several observers stress the need to: recognize a variety of perspectives and objectives; explicitly acknowledge and deal with ubiquitous uncertainties; and foster greater communication among users and developers of IAs [3,12,13]. The workshop described in this paper addressed some of these research needs by exploring how MCDM can be used most effectively together with IA for policy-making, and how decision-making concerns should be addressed in IA design and implementation.

In this paper, we first discuss links between IA and policy evaluation, and ways in which IA design can affect decision-making. Then, we consider potential roles of MCDM in IA and possible reasons why MCDM has not been widely used in this context. We then review the results of a workshop that explored the use of MCDM in IA. Conclusions from the workshop have implications for the design of IAs and for the integration of MCDM into IA.

In the workshop, climate change and policy experts applied several MCDM methods to a hypothetical policy decision to mitigate greenhouse gas emissions. The experts reviewed the MCDM results, and evaluated the methods. Participants also compared several tradeoff visualization methods and explored methods for choosing discount rates for climate change impacts. The results of their application of the various MCDM methods are quantitatively compared elsewhere [14]; this paper focuses instead upon the implications of the workshop's results for IA practice.

2. Links between IA and decision-making

2.1. Decision evaluation tools can be incorporated into IA models

IAs are more useful to decision-makers if they are explicitly linked to policy-making [15,16]. This connection can be achieved in several ways. One is through *decision-focused models,* which build formal decision analytic capabilities, such as tradeoff displays, directly into IA models. Another is *policy-oriented impact assessment*, designed to provide impact information that can be used outside of the IA system [17].

An advantage of incorporating decision evaluation within an IA system is that users can insert value judgments, such as discount rates or criteria weights, and receive immediate feedback on their implications for policy evaluation. Such feedback can enhance user confidence in the results [18], consistent with general findings in the decision support system literature on the importance of feedback [19,20]. In general, decision support systems that explicitly include decision evaluation increase user satisfaction and better facilitate group discussion and compromise (e.g. [21,22]). We perceive an increasing need for IA systems that include both modeling and decision evaluation functions.

Examples of decision-focused systems are: (1) the RAINS model [23], developed to support the European Sulfur and Nitrogen Protocols; (2) USEPA's Tool for Environmental Assessment and Management (TEAM), a multi-criteria system that displays tradeoffs among adaptation strategies for the coastal zone, water resources, and agriculture [24]; and (3) a system for determining "optimal" levels of SO_2 reduction at large Canadian point sources so that prescribed wet sulfate deposition levels would be achieved at selected receptors [25]. There is thus a need for decision-focussed IA systems for greenhouse gas and other environmental policy analysis.

Table 1
Tasks and desirable features in decision-focused integrated assessment models

Task	Desirable features in system modeling function	Desirable features in decision evaluation function	
		Concerning objectives: What are the criteria? What tradeoffs are acceptable?	*Concerning risk:* What are the risk dimensions of concern? What risks are acceptable?
Formulation	Choices of system components; Linking of components; Scale (spatial and temporal); accommodation of alternative judgments about system structure	Alternative formulation of objectives; Forms of value functions/preference statements. (If benefit–cost analysis is used, as is often the case in climate change assessments, then emphasis will not be on tradeoffs in the below tasks, but rather the economic evaluation of different categories)	Dimensions of risk of interest to user (acceptable risk thresholds, utility functions)
Initial parameter estimation	Empirically based and subjective estimates; characterizations of their uncertainty	Initial characterization of multi-criteria utility functions (should be based on transparent, easy to use methods and likely to yield parameters (e.g., criteria weights) that are valid representations of preferences). Alternatively, can capture initial, partial statement of preferences	Initial characterization of risk preferences (e.g., risk aversion or risk neutrality)
Computation and screening of alternatives	Efficient simulation methods (e.g., use of variance reduction methods in uncertainty propagation)	Rapid generation of non-dominated solutions; Ability to generate links between value judgments, solutions in objective space, and solutions in decision space	Rapid generation of efficient solutions in terms of risk (e.g., stochastic non-dominance)
Information presentation	Presentation of structure and parameters of model (graphical/object orientation)	Non-inferior or subsets of options; Use of more than one way to portray tradeoffs (e.g., Cartesian plots, value path plots, and tabulations)	Stochastically non-dominated solutions; Use of multiple ways to portray risks, including probability distributions, moments, conditional expectations, ranges (e.g., tornado diagrams), regret,

Table 1 (*continued*)

Task	Desirable features in system modeling function	Desirable features in decision evaluation function	
		Concerning objectives: What are the criteria? What tradeoffs are acceptable?	*Concerning risk:* What are the risk dimensions of concern? What risks are acceptable?
			decision trees, influence diagrams, and correlations between uncertain parameters and outputs
System–user interactions	Exploratory modeling (should have systems in which users are able to explore and alter system parameters and even structure to explore implications of alternative assumptions)	User-directed sensitivity analyses of effect of different multi-criteria value judgments. Multiple interactive approaches available (including some based on partial information on preferences), so that users can choose method most appropriate for their decision-making style and view the problem from different perspectives	User-directed sensitivity analyses of effect of different risk attitudes upon decisions; Variety of interactive approaches available
Communication among stakeholders	Presentation of individual model components and their assumptions and implications (should be easily available)	Group processes for eliciting and discussing judgments on criteria's definitions and priorities; Exchange of views on priorities, acceptable tradeoffs, thresholds, focusing on implications	Group processes for eliciting and discussing judgments on risk definitions and attitudes; Exchange of views on risk attitudes, etc., focusing on implications
Justification and documentation of decisions	Documentation of system structure and parameters (should be easily generated)	Precise judgments (e.g., quantitative weights) as basis of recommendation, or imprecise justifications can be used based on robustness of decision	Precise judgments (e.g., risk attitudes); Imprecise justifications based on robustness of decision

2.2. Assumptions and presentation of impacts affect policy evaluation

In general, IAs differ widely in modeling choices, assumptions, and how they present results. For instance, divergent representations of climate change impacts may be a weak point in current IAs [26]. Many models are not transparent or user-friendly [27]. Assumptions, such as discounting, can propagate through IA models and bias final outputs in ways that are hidden to users [28].

The needs of policy-makers should be considered in all stages of IA design and implementation. Decision evaluation is affected by a number of modeling choices and assumptions, including:[1]

- what impacts and decision criteria are considered;
- level of disaggregation of impacts (e.g., economic impacts upon different societal groups);
- spatial scale in terms of grid size and grouping of regions or countries;
- temporal scale in terms of time steps and horizons;
- choice of physical and socio-economic models and related assumptions;
- assumptions underlying calculation of impacts (e.g., sea-level rise as a linear function of temperature change, or assumed monetary values for damages);
- treatment of uncertainty;
- presentation of outputs (e.g., visualization methods, data format);
- presentation of assumptions and models used;
- treatment of adaptation and technological change; and
- policy alternatives considered.

The first of these modeling choices is crucial. Inclusion of all the important impacts is challenging in the realm of climate change, as stakeholders' fundamental objectives are often unarticulated or vague. The impacts modeled should be those of interest to potential users. If key impacts are omitted, people may be forced to make inferences about them based on intuition or background knowledge about the relationship of modeled impacts to their real concerns. For example, presented results may omit key information on the geographic distribution of impacts.

Importantly, missing information on impacts can be viewed as a type of uncertainty, wherein a user's subjective application of background knowledge can help reduce that uncertainty [29]. But users' interpretations of the same model output will likely diverge for reasons that are difficult to document, including unstated assumptions.

If numerous impacts/criteria are considered, users may have difficulty digesting the resulting wealth of data. IAs must thus simultaneously provide this data without overwhelming users to the point that the information becomes confusing and key tradeoffs are obscured. MCDM can help make sense of large amounts of information by providing a framework for screening alternatives, and systematically processing large amounts of information on their performance.

[1] Drawn from discussions amongst the authors.

3. Purpose and roles of multi-criteria decision-making in the context of IA

3.1. What can MCDM contribute?

MCDMs purpose is to help users understand and evaluate the kind of criteria tradeoffs that are commonly encountered in IA. Climate change policy, for example, must consider numerous criteria such as prevention and adaptation costs, temperature increase, ecosystem damage, and sea-level rise. Climate policy deals with broader temporal, spatial, and socio-political scales than most conventional policy analysis [30]. Further, climate policy-making is complicated by multiple decision-makers, long time-horizons, uncertainty, irreversible impacts, and global cooperation [31], all of which contribute to the proliferation of evaluation criteria.

However, MCDM is not the most frequently used approach to dealing with multiple criteria in climate change IAs; rather, it is more common to aggregate the many performance indices into a single economic metric. This metric can be net economic benefits, combining mitigation, adaptation, and/or damage costs. Alternatively, a cost-effectiveness approach can be taken, where the expense of achieving a specified atmospheric concentration of CO_2 or temperature increase is minimized [32]. One drawback to using just a monetary metric to evaluate policies is that fundamental value judgments concerning, for instance, the worth of human life at different times and places, are made by analysts and may be buried in the calculations [18]. Uncertainties and disagreements about values in climate policy are important, and can have even more effect on policy choices than scientific uncertainties [33]. Another drawback of monetization is that the utilitarian assumptions of welfare economics are not universally accepted—for example, that non-human creatures and ecosystems have no inherent rights [18,34].

In contrast, the goal of MCDM analysis is to make such value judgments the focus of policy deliberation. Explicit consideration of multiple criteria is key to engaging policy-makers because disagreements often stem from differing priorities among objectives. Therefore, analysis of tradeoffs is essential if IA is to effectively promote discussion among interested parties [9]. Gardiner and Ford argued that early systems dynamics models, such as the "Limits to Growth" model of global dynamics, failed to focus on objectives and tradeoffs, and thus diminished their effectiveness [35]. The increasing involvement of diverse stakeholders in IA (e.g. [36]) will increase the need for explicit consideration of multiple criteria.

The fundamental nature of multi-criteria problems is that no single alternative will optimize all criteria at once, as improving performance for one criterion generally comes at a cost of deterioration in others. MCDM analysis starts by focusing on policies that are not clearly dominated by any other alternative, or by the tradeoffs implied by picking one such "non-dominated" option over another. For instance, a "business as usual" greenhouse gas policy may be relatively attractive in terms of control cost but perform poorly with regards to temperature increase. MCDM methods can help users make tradeoffs among multiple conflicting criteria by providing a systematic framework for them to consider the implications of different value judgments for decisions (i.e., whether altered weightings on criteria will change decisions).

In particular, Stewart [37] proposes three distinct ways that MCDM can help analyze tradeoffs in public sector decision-making: (1) initial impact assessment and screening of alternatives by analysts; (2) "within interest" structuring and evaluation, to help each group determine their priorities; and (3) "between interest" negotiation and decision-making, to help identify areas of agreement, disagreement, and possible compromise. Each of these roles is directly relevant to climate policy.

Applications of MCDM in IA, as in any decision process, should have the following characteristics:

- *Clarity:* "Black-box" MCDM methods and unnecessary complexity should be avoided.
- *Feedback:* Users should be able to conveniently examine how changes in value judgments affect policy choices.
- *User control:* Methods should support users' thinking, not replace it.
- *Efficient communication among users:* Judgments (e.g., criteria weights) should be discussed in a structured group setting that allows participants to share insights and raise issues. In several applications, we have found the Nominal Group technique [38] can effectively accomplish these goals [39,40].
- *Patience:* Time and patience are needed to ensure that users understand and have confidence in the process.
- *Multiple approaches:* Ample empirical evidence shows that different multi-criteria valuation methods are most appropriate for different individuals and that various methods can yield different recommendations [41]. Users gain insight, satisfaction, and confidence by looking at the problem in more than one way using more than one MCDM method and then resolving inconsistencies among the results [18,42–44].

3.2. Why are applications of MCDM in IA rare?

This paper is not the first one to call for greater use of MCDM and risk-based decision analysis in IA. For instance, the Intergovernmental Panel on Climate Change (IPCC) devotes a chapter of *Climate Change 2001: Mitigation* to decision-making frameworks [2]. The authors note that:

- formal decision analysis methods can help keep the amount of information manageable for users by adding structure;
- users have different values, which must be explicitly considered in any decision process; and
- decision analysis should not be used to identify a globally optimal alternative, but can help frame the problem, identify its critical features, evaluate alternatives, and offer insights.

As examples of applications, Ridgley [45] and Ringius et al. [46] recommend MCDM for designing fair allocations of burdens for reductions of greenhouse gas emissions among nations and regions. Ridgley proposes a three step approach: (1) determination of the desired global reductions of greenhouse gases; (2) computation of equity indicators based on fairness measures that any party wishes to have considered; and (3) determination of a fair compromise. Ramanathan [47] shows how a modified analytic hierarchy process (AHP) could be used to select greenhouse gas mitigation options. Meier and Munasinghe [48] use tradeoff analysis to evaluate greenhouse gas reduction strategies for Sri Lanka. Others recommend MCDM to help decision-makers better understand how policies affect the performance of multiple sustainability indicators [49].

However, risk-based decision analyses have been more common in IA than MCDM studies. For instance, risk analyses estimate the value of better information concerning IA model parameters [50,51]. Loulou and Kanudia [52] explore a "minmax" regret strategy to determine the "safest" policy option for global warming using the MARKAL model. Lave and Dowlatabadi [53] illustrate the use of minmax regret and minimal expected regret approaches in the context of global climate change abatement policies under uncertainty, and in ways that incorporate risk attitudes and values for multiple criteria. Manne and Richels [54] use expected cost criteria to examine climate change decision-making under uncertainty. Hammitt et al. [55] and Valverde et al. [56] explore sequential climate change abatement strategies that take advantage of information gained over time.

Given the apparent natural fit between IA and MCDM, it is surprising how infrequently formal multi-criteria methods have been used in this context. The examples we cite involving the use of MCDM with IA have been largely academic studies. The objective of this paper is to aid the integration of MCDM and IA in a way that will increase the usefulness of IAs to policy makers.

We propose several reasons for this apparent lack of use of MCDM in actual IAs:

- *Complex tradeoffs:* IAs may involve dozens of performance criteria. The difficulty of portraying tradeoffs in numerous dimensions hinders use of MCDM with IAs. Further, users may have difficulty imagining highly uncertain consequences that occur far in the future. Climate policy differs from most traditional decisions in the breadth of its temporal, spatial, and socio-political scales [30].[2] However, it is precisely because of this complexity that methods are needed to help assimilate IA information.
- *Use of a single approach and failure to recognize the fluidity of value formation:* The use of MCDM with IA is further hindered by the implicit assumption in many MCDM applications that user preferences are completely formed, coherent, readily expressed in quantitative terms, and consistent over time. In reality, users do not have fully formed "value functions" [58], especially for decisions involving important consequences in unfamiliar circumstances. Further, some MCDM practitioners adopt a "one-size-fits-all" approach even though different methods work better for some people and situations than for others. Some users may react negatively to the chosen approach, lessening acceptance of the process. Different methods can yield different results. Such inconsistencies are an opportunity to reflect on results from different framings of the decision; that opportunity is lost when a single method is used.
- *Insufficient explanation of methods to users:* Users can be frustrated by the seeming arbitrariness and lack of control of a "black box" method that translates value judgments, such as weights, into ranks of alternatives. As a result, MCDM methods often are used inappropriately—to supplant rather than support difficult thinking, insight, and careful articulation of rationales

[2] Keeney and McDaniels [57] argue that because of the huge uncertainties in impacts on a multi-century scale, and the fact that climate policy decisions will be revisited frequently before their impacts will be completely felt, policy makers should not even attempt to evaluate long-term impacts in terms of fundamental social, economic, and environmental objectives. Instead, a more practical approach is to use surrogate goals for near-term decision making that, if accomplished, will be leave society better able to manage the causes and effects of long-term climate change. Such criteria would measure, for example, progress in society's ability to address long-term climate change and its progress in limiting the magnitude of such change by some close-in date (e.g., 2020).

for a decision [59]. If users are frustrated and confused by how a method is applied, they are unlikely to have faith in the results.
- *Insufficient demonstration of MCDM methods in realistic settings:* There has been a lack of careful evaluation by real decision-makers of which methods work in practice and why. Convincing comparisons of methods in actual problem settings, including IA, are relatively few in number (see surveys of experimental evaluations in [41,60,61]). Consequently, there is a gap between a theoretical literature full of elegant but untested multi-criteria methods, each with their own advocates, and potential users who must sort out the conflicting claims. The workshop we discuss in this paper was aimed at addressing this concern by exploring the use of MCDM with IA with actual IA practitioners and policy-makers.

The above problems have several undesirable results. One is an MCDM research community that often seems out of touch with the needs of potential users. Another includes MCDM applications that obscure rather than illuminate tradeoffs and that distort preferences by quantifying them in inappropriate ways. Consequently, possible users of multi-criteria methods may be wary of them. Thus, the potential of the multi-criteria approach to promote dialogue among stakeholders and a deeper understanding of the problem may well go unrealized.

4. Description of MCDM approaches used in the workshop

Common functions of MCDM include tradeoff display or visualization, value scaling of individual criteria, weighting of the criteria, and combination—or "amalgamation"—of weighted criteria, yielding a ranking or screening of alternatives. There are many available MCDM approaches for performing these functions, each with advantages and disadvantages [18,41,62–64]. However, no single method can elicit definitive rankings or estimates of user preferences, and, as noted, different methods often yield unlike results.

In this section, we define each of these functions and then briefly describe the methods we tested. The first function, visualization (i.e., pictorial representations of criteria values and tradeoffs), can help communicate what is at stake, especially in decisions involving large amounts of data. This important function is further explored in Section 5.6. The second function, value scaling, converts criteria measured in physical or socio-economic units into a normalized value scale (usually 0–1). Scaling can account for thresholds, diminishing or increasing marginal value, and willingness to accept risks.

Criteria weighting, the third function, involves another type of value judgment, the relative importance of different criteria. For instance, which is of more concern: sea-level rise or altered drought frequency? How much more important is one than the other? Amalgamation methods use such judgments to combine criteria and rank policy alternatives. Weighting judgments for the criteria must consider the range of possible outcomes, rather than other notions of importance (e.g., the idea that "environment and economy should receive equal consideration" does not imply that equal numerical weights should be assigned to them). There are many distinct types of weighting methods with different philosophies (e.g., the AHP vs. inference of weights from stated willingness to accept tradeoffs among attributes).

The last function, amalgamation, can produce a rank ordering of alternatives or eliminate the least attractive ones. There are two types of amalgamation methods, deterministic and risk-based, both of which have advantages. Experts' opinions and IA results can disagree on the nature, distribution, and timeframe of impacts [65]. Thus, methods that incorporate uncertainties better represent our understanding of policy-decision outcomes, such as climate policy impacts, than do MCDM methods that assume that all consequences are known with certainty. However, deterministic approaches are simpler and more transparent.

Explicit consideration of uncertainty, like consideration of multiple criteria, should be a powerful means of engaging decision-makers and enhancing the policy relevance of IA, but it often is not. Rather than enhance realism, uncertainty can unfortunately sometimes alienate users who want "bottom-line" answers and justifications for policies. For example, in workshops held to evaluate the effect of climate change upon Great Lakes management, US and Canadian water resource managers preferred methods that use deterministic scenarios. Although they recognized the need to explicitly consider uncertainty, they were distinctly uncomfortable with the use of subjective probabilities [66]. In general, the concept of uncertainty can be very confusing, even to technically literate people. Thus, there is a need to enhance the communicability of uncertainty-based approaches in IA.

MCDM methods tested in the workshop combine several of the above functions. Several of these methods have been applied in the IA literature noted in Section 3. As an example, value function methods weight and then amalgamate "single criterion value functions," each of which represents the relative desirability of different levels of a criterion. The alternatives are then ranked by their relative weighted sum of criteria. These methods assume that the outcomes of each policy alternative for each criterion are known with certainty or that the users are risk neutral.

In contrast, utility function methods attempt to capture the user's willingness to accept risks. These methods may be more appropriate for evaluating IA output described by uncertainty ranges or distributions if users have well-defined risk attitudes and can communicate them. Application of utility functions often requires subjective judgment by experts as to the probability distribution of IA inputs or criteria values. While our focus is upon value judgments, not subjective probabilities, the crucial role of probability judgments should not be overlooked, as experts often disagree on the likelihoods of climate change and its impact [65].

Another MCDM approach involves pair-wise comparisons, like those used in ELECTRE [63]. This approach compares two alternatives at a time and selects one over the other if the first is better in most criteria and not unacceptably worse in the remaining criteria. Yet another approach, goal programming, focuses instead on how close different alternatives come to numerically defined goals. Several other philosophies of deterministic MCDM have been proposed and applied to a variety of environmental problems [e.g., 18,63,64].

Utility functions are not the only MCDM approach to decision-making under uncertainty. Regret-based methods, for example, choose alternatives whose worst performance (across scenarios, relative to other alternatives) is better than the worst performance of other alternatives. For each scenario, or "state of nature", "regret" is defined as the difference between how well a policy performed under the given scenario and the best performance among all policy alternatives under that same scenario. Another approach, stochastic dominance, does not necessarily produce complete policy rankings [67–69]. It only eliminates options that could never be selected over other options, regardless of the users' willingness to accept risks. Which of the surviving alternatives is preferred depends on the user's risk attitude.

5. Workshop to explore the use of MCDM with IA

5.1. Workshop description

To explore the potential value of MCDM to IA, we held a two-day workshop in which climate change experts and policy makers applied a range of multi-criteria methods in the context of a hypothetical policy decision. One purpose of the workshop was to expose participants to MCDM methods in the context of IA. Another was to evaluate the use of MCDM approaches in IA and to allow practitioners to give feedback on the relative merits of approaches for valuation, risk analysis, and visualization in IA. Workshop results provide guidance for the use of MCDM with IA, and for IA development and implementation. Results also have implications for the visualization of model outputs and the use of discounting.

The participants applied the methods mentioned in the preceding section, along with several others, to quantify the relative importance of criteria (via weighting) and to rank the predefined policies. The weighting methods used were point allocation, hierarchical point allocation, a hybrid of swing weighting and the AHP, tradeoff weighting, and a final review and revision of weights. The deterministic ranking methods included an initial holistic assessment, additive linear and non-linear value functions, goal programming, ELECTRE I, fuzzy sets, and final holistic assessment. (Holistic assessment asks the user to rank policies, without the aid of a formal MCDM method.)

The risk-based methods applied by the participants were an initial holistic assessment, linear and non-linear utility functions, minmax regret, stochastic dominance, and a final holistic assessment. Also, several visualization methods (bar graphs, Cartesian plots, value path plots, and box plots) were used to portray tradeoffs and uncertainties (see Section 5.6). Participants evaluated MCDM methods in terms of their appropriateness, ease of use, and validity (faithfulness to preferences). Analysis of method results provided evidence on whether choice of approach can significantly affect policy ranks. Visualization methods were assessed in terms of effectiveness and user comfort. Our conclusions about the performance of different MCDM and visualization methods are based both on self-reports through questionnaires and group discussions, and objective data (e.g., differences in policy rankings).

The workshop was held in June 1998 at the Johns Hopkins University. Organizations represented were: Argonne and Battelle Pacific Northwest National Laboratories; American University; Carnegie Mellon University; Case Western Reserve University; Johns Hopkins University; Charles River Associates; Lumina Decision Systems; Margaree Consultants, Inc.; The RAND Corporation; Resources for the Future; The H. John Heinz III Center; US Environmental Protection Agency; US General Accounting Office; and the US Global Change Research Program.

The 20 workshop participants used the MCDM methods to compare the following policy options for limiting climate change due to greenhouse gas emissions: base case (no special controls); globally applied taxes of \$75, \$150, or \$300 per ton of CO_2 emitted; relaxed sulfur dioxide (SO_2) emission standards; promotion of nuclear power through subsidies for nuclear fuel;

and promotion of biomass energy. Policies were compared with respect to six criteria: temperature increase from 1990 to 2050; ecosystem stress in 2050; sea-level rise from 1990 to 2050; annualized SO_2 emissions from 1990 to 2050; annualized nuclear waste generation from 1990 to 2050; and annualized cost in 2050. The Holmes/Ellis IA Model [70,71] was used to obtain global aggregate estimates for each criterion under each policy alternative. Uncertainty was quantified using Monte Carlo simulation based upon subjective probabilistic inputs for climate sensitivity, SO_2 cooling effect, energy efficiency, labor productivity, natural gas reserves, and population growth. Our simplified IA analysis was used solely to generate values for the workshop and does not constitute a thorough IA study. The emphasis of the workshop was on evaluation of the MCDM valuation and visualization techniques in the context of IA, not the integrated model itself or its predictions of climate impacts.

This type of experiment cannot provide conclusive comparisons of the methods, as our sample sizes are small and we could not control for all alternative hypotheses that might explain differences among methods (such as the hypothesis that rankings from the first method applied differ systematically from those applied later solely because of order effects). However, the participation of IA and climate change experts enabled us to simulate a more realistic policy-making setting than better controlled experiments involving less experienced subjects [43,72,73]. Because the participants are active in the IA community, their insights into the potential uses of MCDM in IA are particularly helpful.

5.2. *Results from quantitative analysis of the use of MCDM methods with IA*

A quantitative analysis of the MCDM results is summarized briefly here (see [14] for details). These results address the following issues: Do different methods yield different weights and policy ranks? Can users provide ranges representing their uncertainty about the relative importance of criteria, and can these ranges be used to eliminate some policies? Are IA experts subject to classic biases in multi-criteria valuation? Could use of more than one MCDM method and resolution of their results provide worthwhile insights?

Quantitative analysis of the results of the MCDM valuation methods demonstrated that policy rankings differ both by the method used (i.e., various methods produced conflicting results), and person (i.e., people had unlike alternative rankings for a given method). In addition, weighting methods produced markedly dissimilar weights. The methods also had significantly different predictive validity, which refers to a method's ability to reflect the holistic policy ranks chosen at the end of the workshop (and which are, presumably, better informed). Divergent results from MCDM methods for a given user have been observed in other field studies and are a major criticism of MCDM [74]. However, we believe that inconsistencies in results actually present an opportunity for reflection and insight in that each method frames the problem differently.

Some workshop exercises asked participants to provide a range, rather than a point estimate, for their answer to MCDM questions (e.g., "Criterion A is two to three times as important as Criterion B"). Such ranges generally prevent a complete ranking of alternatives, yet it is often still possible to find some alternatives that outrank others. Thus, within the ranges provided by the participant, some alternatives were never better and sometimes worse than at least one other alternative. This approach eliminates some alternatives and allows users to express confidence in their answers to MCDM questions; this may therefore better represent their preferences and increase their comfort with the process.

Previous experiments have shown that inexperienced subjects (e.g., students) are subject to the classic "splitting bias," in which less weight is assigned to a general category of impacts (e.g., "environment") than if its component criteria are weighted separately (e.g., "SO_2 emissions," "nuclear waste," and "climate") [18,41,73,75,76]. We administered an experiment designed to determine if our experts would also be subject to this bias when selecting weights. In fact, it was exhibited to a statistically significant degree, which demonstrates that greater knowledge and experience does not necessarily immunize experts from method-caused biases.

Finally, the workshop results support the use of multiple MCDM methods. This is evidenced by the varying predictive validities (with some methods doing better for some people, and other methods performing better for others); the often large divergences in the policy rankings given by different methods; and the fact that different people prefer using different approaches. Moreover, participants explicitly stated that they support the use of multiple methods in actual policy-making. In particular, the weighting method they most recommended for actual decision-making was reconciliation of weights from more than one method. However, participants also preferred holistic assessment to *any* MCDM method for both deterministic and uncertain problems, indicating that MCDM methods should assist subjective comparisons of policies, not supplant them.

Details on these MCDM method comparisons are discussed elsewhere [14]. Below, we discuss four other categories of general conclusions concerning IA practice that can be drawn from the workshop. In particular, we consider the incorporation of expert knowledge through use of MCDM methods, the use of MCDM to better understand decision and users' value judgments, the discounting of impacts, and the portrayal of IA output by visualization methods.

5.3. Incorporation of user preferences and knowledge

Parson [77] encourages the development of alternative IA methods, such as role-playing, to address needs not met by traditional assessment methods, such as formal models or expert panels. Because such alternative methods directly involve individuals, they can directly incorporate user preferences (e.g., the relative importance of different criteria) or personal judgment (e.g., understanding of the implications of a given impact estimate).

MCDM methods are one particular way for helping users to include background knowledge and preferences in IAs. Experts, for example, might introduce background knowledge because model results omit information relevant to the their concerns. For instance, a model might report temperature changes but not sea-level rise, which would be of major concern to a coastal manager. Such background knowledge, which may be quantitative or qualitative, can be used to infer values for omitted variables by considering their expected covariation with model outputs or from general understanding of the variable's behavior [29].

Background knowledge can also be included when making value judgments, such as weight selection. For example, the weight for sea-level rise should undoubtedly be based on the assessor's knowledge of what damages such a rise would cause, in addition to what value she or he places on avoiding those damages. Thus, MCDM weights are not just dependent on priorities, but also on perception and knowledge.

Most participants reported that they relied heavily on their own background knowledge in addition to IA model results when applying the MCDM methods and ranking policies. For example, one participant was very knowledgeable about the human health effects of SO_2 emissions, which affected his preferences concerning the SO_2 criteria. Another participant assigned geographical and socio-economic distributions to the presented values for nuclear waste. This background knowledge was incorporated into the MCDM process through their choice of weights, and was shared with other participants through structured (nominal group) discussions [38]. While no participant ignored the Holmes/Ellis model outputs and relied exclusively on background knowledge, 21% of the participants stated that they used such knowledge *more* than the model outputs.

5.4. Improving user understanding of how preferences affect the choice of policy

The use of MCDM can help users better understand how their preferences affect policy choices. This benefit of MCDM was evident in the workshop in several ways. Many participants felt that the MCDM exercises helped them better understand how they think about the decision holistically, and how their background knowledge and values affect the decision. One participant, for example, chose costly alternatives during the unaided holistic exercise, but placed a high weight on cost during the formal MCDM methods. After he noticed this contradiction, he reconsidered the relative importance of cost.

MCDM can also help people better understand the priorities underlying others' recommendations. For example, our analysis revealed that disagreements between two particular participants' initial policy rankings largely stemmed from different weights for SO_2 emissions. When the participants formally discussed the MDCM results, one of those two participants explained his judgments by describing the consequences of SO_2 emissions. Afterwards, the other participant revised his weight for the SO_2 emissions criterion, citing "new information" as the reason for the change. This change caused the two users' policy ranks to converge. Thus, the MCDM process helped the participants understand why their views initially differed, first by identifying differences in value judgments, and secondly by encouraging discussion focused on priorities among objectives (rather than policy alternatives), which revealed the reasons for their disagreement.

The impact of MCDM on policy recommendations was also apparent when we compared participants' holistic rankings before and after the formal MCDM exercises. Policy rankings of the seven alternatives changed for most participants, especially for the deterministic ranking task. All but one of the participants changed their ranks for at least some alternatives in the deterministic case; the average correlation between the initial and final holistic assessments was 0.5. Based on our observations, we conclude that many of these changes are due to the rethinking of judgments in response to group discussions of MCDM results.

5.5. Discounting of climate change impacts

5.5.1. Advantages and disadvantages of discounting climate change impacts

Discounting is also a value judgment; it weights impacts according to when they occur, thereby allowing impacts in the far future to receive less (or more) weight than impacts in the near future.[3] With a positive discount rate, consequences in the distant future are less important than those in the near future. A negative discount rate gives more weight to future impacts, while a neutral discount rate (0) treats all impacts equally, regardless of when they occur. Thus, discounting can be viewed as a form of multi-criteria weighting that depends on how the user values present-day impacts relative to future impacts [30].[4]

Advantages of applying a discount rate include the following [78,79]:

- positive discounting is generally used in cost/benefit analysis and reflects the judgment of capital markets that future economic benefits are valued less than present ones;
- discounting allows users to incorporate their own time preferences;
- positive discounting addresses uncertainty in that impacts further in the future are generally more uncertain and, arguably, should therefore receive less weight; and
- discounting can account for advances in technology that may make future consequences easier and cheaper to address.
- counter-arguments include [78,79]:
- discounting can significantly alter, and thereby possibly distort, the impact values presented wherein such values greatly depend on which discount rate is used;
- discounting is an inappropriate means to address uncertainty about future impacts, and, in fact, creates an additional uncertainty concerning the choice of an appropriate discount rate; and
- discount rates that rely on future technological developments introduce additional uncertainty since those developments may or may not materialize.

In sum, the criticisms argue that discounting introduces additional assumptions than can obscure the results, and that it is better to explicitly model uncertainty and technological change rather than bury assumptions about them in a discount rate. In rebuttal, supporters of discounting point out that not discounting at all implicitly assigns an interest rate of zero, which is itself a very strong assumption, and that capital markets indeed assign higher interest rates to riskier prospects.

As might be expected from the above debate, there is no clear consensus on what discount rate should be used for policy analysis, such as those involving climate change. Economists generally support the use of discounting for climate change policy but disagree on the rate to be used and the method for determining it [80]. Indeed, because many of climate change's effects may only be felt many decades in the future, the emergence of climate as a policy issue has apparently shattered the consensus that emerged in the 1970s about the appropriate economic basis for discounting policy impacts [78]. The economic principles that had been accepted were: the desirability of converting future benefits and costs converted into equivalent changes in consumption by the people affected; the need to adjust for marginal productivity of capital if capital formation is affected; and the use of a social rate of time preference. In the 1990s, debates emerged between

[3] Using a discount rate of r per year, the present worth value, P, of a future impact, F, is defined as $P = (1 + r)^{-n}F$, where n is the number of years.

[4] The discount rate can greatly affect the calculated criteria values, especially when long time frames are involved, as in climate change studies. For example, consider a yearly control cost of $\$300 \times 10^9$ each year from 1990 to 2050. This has a "present" value of $\$8302 \times 10^9$ in 1990 using an annual discount rate of 3% (assuming end of period cash flows). In contrast, rates of 0% and 10% give costs of $\$18{,}000 \times 10^9$ and 2990×10^9, respectively.

advocates of an ethical basis for discounting and those who argued for basing rates on observed capital productivity; whether or not capital growth will compensate future generations for environmental damage; and whether different interest rates should be used for different time horizons. For further discussion of the discounting of climate change impacts, including advantages and disadvantages, see [78,79].

5.5.2. Results from discounting exercises

Our workshop instead focussed on the issue of the unreliability of discount rates when they are elicited directly from experts, irrespective of the economic basis of their reasoning. As with all weighting judgments, how discount rates are elicited often affects the values obtained. Because people are unsure of their precise priorities, the values they articulate are more likely to be subject to bias or random errors resulting from theoretically irrelevant aspects of the method [58].

Two discounting exercises were conducted at the workshop to assess how discount rates can depend on the way they were obtained. The first directly asked participants, "What discount rate should be used to compare criteria values for different years ranging from 1998 to 2100?" for global temperature increase, global SO_2 emissions, nuclear waste, and control cost. The second discounting question asked, "What value of an impact in the year 2075 is equivalent to a unit impact in the year 2025?" for each of these four criteria. Answers to the second set of questions were used to calculate the implied discount rates. Table 2 summarizes the results.

Immediately apparent in the table is that a wide range of discount rates has been given for each criterion, indicating that people disagree on what rates are appropriate. Discount rates also differ by criteria, meaning that most participants feel that use of a single discount rate for all impacts may be inappropriate. The rates chosen differ by criteria for 79% of the participants for the first (direct) question and 81% for the second (indirect) question. SO_2 emissions are discounted significantly more than temperature increase and nuclear waste for the direct question (Wilcoxon signed-rank test p-values of 0.01 and 0.02, respectively). For both questions, rates for control cost are higher than rates for all other criteria, and significantly so for the indirect question (p-values <0.05). The positive difference of approximately 3% between the rate for control cost and that for other variables means that $1 in 2050 receives only 23% as much weight, relative to other

Table 2
Discount rates given by workshop participants (%/yr)

Criteria:	Temperature increase	SO_2 emissions	Nuclear waste	Control cost
Question 1: Discount rates asked directly				
Minimum	–5.00	–3.00	–5.00	1.00
Maximum	10.00	10.00	10.00	8.51
Average	1.98	3.28	1.67	4.05
Question 2: Discount rates implied				
Minimum	–2.38	–2.73	–4.50	–4.50
Maximum	2.22	2.81	4.71	10.00
Average	–0.25	–0.21	–0.16	2.71

impacts, as $1 spent in 2000. This differential weighting will favor strategies that involve less up-front costs.

For the directly assessed discount rates, several participants specified negative rates, indicating that impacts in the distant future are more important than impacts closer in time. Negative discount rates were provided for 17% of the temperature increase answers, 5% of SO_2 emissions responses, 11% of nuclear waste answers, and none of the control cost discount rates. There are several possible justifications for a negative discount rate. One could be that the environmental cost of a ton of waste or a degree temperature change will be more keenly felt in the future (e.g., due to larger environmental problems and larger populations). Another is that the discount rate could be viewed as an accountability factor giving more weight to impacts upon people who did not contribute to these impacts (i.e., future generations). Alternatively, the negative discount may represent some misunderstanding of the discounting process; however, if this hypothesis is true, then we would expect that about the same number of negative rates would be provided for all criteria, which was not the case.

The implicit discount rates derived from the implicit question differ strikingly from those directly provided. On average, implicit discount rates were 2.2% lower than direct rates. They were significantly lower for temperature increase, SO_2 emissions, and nuclear waste (p-values 0.03, 0.003, and 0.003, respectively). Most participants kept the same sign (positive, negative, or neutral) for discount rates in both questions (67% of responses for temperature increase, 53% for SO_2 emissions, and 73% for nuclear waste and control cost). However, several participants gave positive direct rates but negative implied rates (27% for temperature increase, SO_2 emissions, and nuclear waste, and 20% for control cost). This may reflect confusion regarding discounting. The remaining discount rates were positive when asked for directly, and zero when derived from the implicit question (7% of the participants for temperature increase and control cost, 20% for SO_2 emissions, and 0% for nuclear waste). The implied rates were negative for 40% of responses for temperature increase, 33% for SO_2 emissions and nuclear waste, and 19% for control cost. In sum, comparison of discount rates for the two types of questions implies that discount rates differ based on the method used to solicit them. This is consistent with the generally accepted principle in decision analysis that how values are elicited can affect the results.

The disagreement over discount rates reflected in Table 2 is surprising, given the absence of objections to our use of them to describe the impacts of the policies. For the MCDM exercises at the workshop, the IAs model estimates of SO_2 emissions, nuclear waste, and control cost for the years 1990–2050 were converted to an annualized average that accounts for discounting.[5] A discount rate of 3% was used. Meanwhile, global temperature increases were not discounted. We explained our discounting procedure to the participants, but they did not discuss or question our decision to discount criteria values or the discount rate used. Participants' concerns and questions focused on issues other than discounting, even though their discounting preferences generally disagreed with the rates we used and discounting drastically affects calculated criteria values.

To summarize, results from the discounting questions indicate that discount rate preferences differ by person, criteria, and the method used to solicit the rate. Large differences between directly assessed and implied discount rates, including frequent changes in sign, highlight the difficulty in choosing an appropriate discount rate. This suggests that discounting can be highly

[5] Annualization factor $= r(1+r)^n/(1+r)-1$, where r is the annual discount rate and n the number of years.

confusing, even to technical experts. It is reasonable to assume that other IA users face similar problems with discounting. Therefore, IA practitioners must be very cautious when deciding whether to discount and what rate to use, making all assumptions clear. Presentation of IA results for several discount rates may help by alerting decision-makers to discounting's potentially dramatic effects.

5.6. Visualization methods for displaying IA information

5.6.1. Benefits of visualization methods

Effective presentation of information on tradeoffs and risks is vital to improving stakeholder understanding of IA outputs. Because of the large number of criteria and uncertainties in IA, the basic challenge is to portray highly dimensional data sets in such a way that users can grasp general trends and be stimulated to explore results further. Given that different people find different modes of presentation more effective, several approaches for presenting tradeoffs and risks may be needed.

Visualization of data helps people process information that would otherwise be difficult to comprehend. The use of abstract visual metaphors to show data began in the late 18th century with the work of Crome and Playfair. Playfair developed the bar chart in *Commercial and Political Axis* (1786) and the pie chart and circle graph in *The Statistical Breviary* (1801). Subsequent developments involved such famous names as Bessel (the graphic table) and Fourier, who introduced the cumulative distribution curve [81]. Modern day visualizations allow the viewer to analyze and compare multivariate data, to recognize both the local and global properties of data, and to study the relationship with time. Structure in data that would otherwise be beyond our processing abilities can be revealed. Defanti et al. [82] contend that "(t)he information undergoes a qualitative change because it brings the eye-brain system, with its great pattern-recognition capabilities, into play in a way that is impossible with purely numeric data." Goettl et al. [83] and Carswell and Wickens [84] argue that displays with multiple variables can help decision-makers in judgments that require multi-criteria tradeoffs.

An important rationale for visualization methods is that many errors in decision-making under multiple criteria can be attributed to difficulties in processing multi-dimensional data. Experimental investigations have uncovered systematic errors of several sorts. First, unaided users generally focus on one or a few criteria and pay inconsistent attention to them [85]. They also may not consider alternatives that fail to reach some thresholds set on one or more particular criteria, even if those options have advantages that, on the whole, would render them attractive [86]. Users tend to limit their searches to those regions in criteria space that initially attracted their attention, and overlook other, very different alternatives. This type of behavior is referred to as anchoring [87]. Therefore, an effective visual presentation should ideally include all the alternatives (or, at least a representative set [88]), and all criteria.

At least one comparison has been made previously of methods for visualizing impacts of climate change. Lane et al. [89] evaluated different graphical presentations of global warming impacts on regional water resources. They compared the star diagram, stacked bar chart, and a mapping technique using pie charts and found the star diagram to be the most effective.

5.6.2. Results of participants' evaluation of visualization methods

Our workshop also evaluated several visualization techniques for conveying multi-criteria tradeoffs and risks, using the hypothetical greenhouse gas policy problem described in Section 5.1. Tables of criteria values also were presented to the participants for purpose of comparison. All the methods present the same data set within a group (deterministic or uncertain), but in different ways. The methods evaluated are listed in Table 3.

Figs. 1–4 provide several examples of the visualization methods that were evaluated. Figs. 1 and 2 are deterministic methods. An example bar graph of policy performance for the annualized cost

Table 3
Summary of visualization methods and summary tables evaluated

Deterministic case	Uncertain case
Data table	
Table of criteria values for each policy	Table of criteria distributions (mean, standard deviation, minimum, maximum) for each policy Table of regret values
Visualization aid	
Bar graphs of criteria values for each alternative (e.g., Fig. 1)	Cartesian (x, y) plots showing how each policy performed for K simulations on two criteria at a time (e.g., Fig. 3)
Cartesian (x, y) plots showing how each policy performed on two criteria at a time	Box plots, which represents the distribution of each criterion for each policy (e.g., Fig. 4)
Value path plots showing the relative performance of each policy for a given criterion (e.g., Fig. 2)	

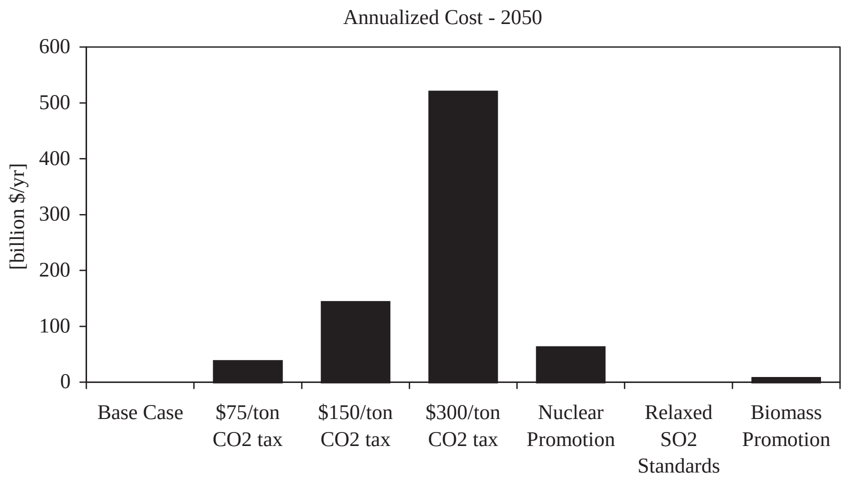

Fig. 1. Example bar graph of performance of policies on one criterion.

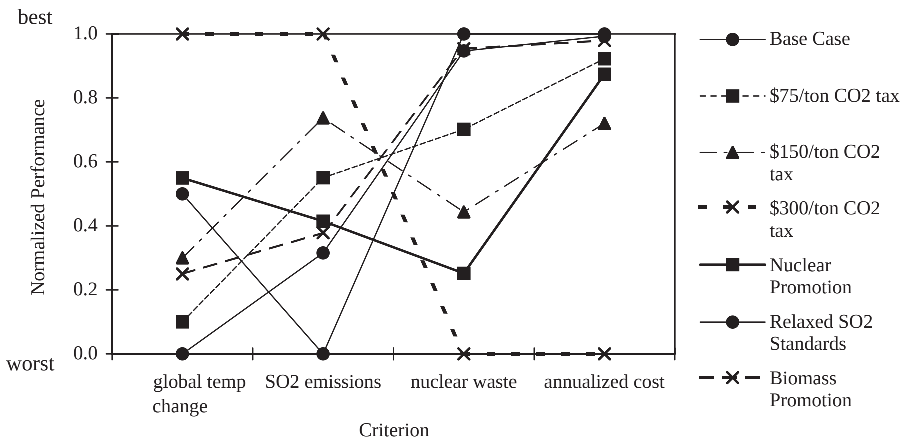

Fig. 2. Example value path plot for seven policies.

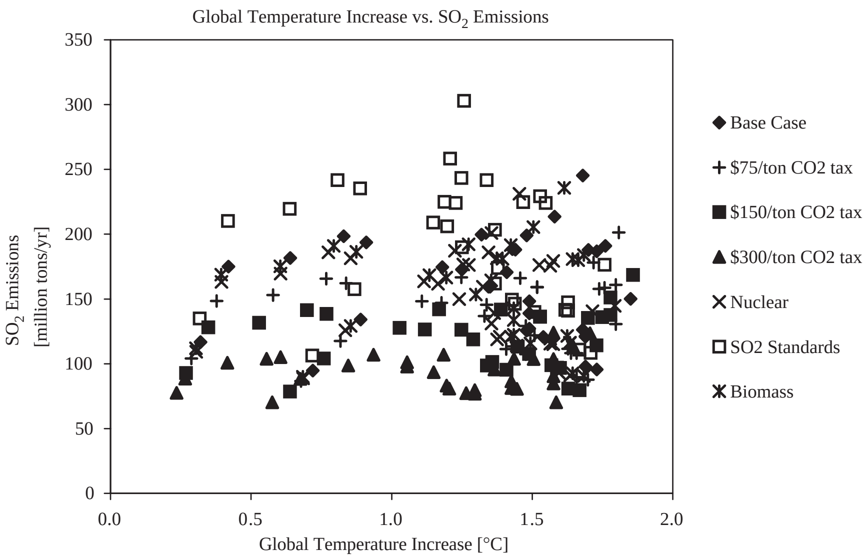

Fig. 3. Example Cartesian plot for uncertain case for seven policies.

criterion is shown in Fig. 1. Similar bar graphs for other criteria were provided to workshop participants. From the graph, one can assess the performance of each policy for the specified criteria. In this case, the $300/ton CO_2 tax alternative is far more costly than all others.

Fig. 2 shows an example value path plot. This graph depicts the relative performance of each policy for each criterion. A value of 1 represents the best value for a given criterion, whereas 0 represents the worst value. Other values are normalized between 0 and 1 accordingly. In this hypothetical policy decision, the $300/ton CO_2 tax alternative has the best performance for global temperature change and SO_2 emissions, but the worst performance for nuclear waste and annualized cost.

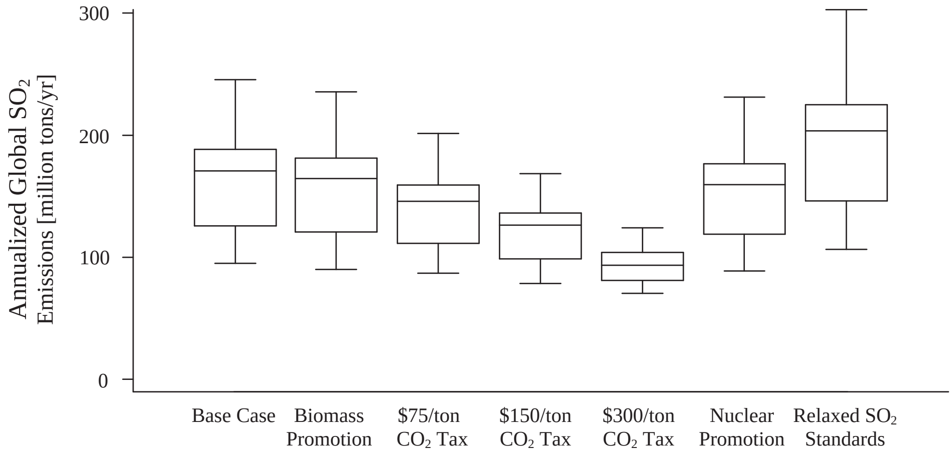

Fig. 4. Example of box plot of performance of one criterion for seven policies.

Table 4
Number of participants who ranked each visualization method as the best, by method evaluation criterion

	Easiest to understand	Relied upon most for workshop exercises	Recommended most for actual policy-making
Deterministic case:			
Table of criteria values	9	11	5
Bar graphs	4	6	10
Value path plots	5	6	10
X, Y plots	3	2	3
Uncertain case:			
(using distributions)			
Table of criteria averages	4	11	10
Table of regret averages	8	2	6
X, Y plots	13	4	4
Box plots	2	8	11

Note: This data exclude evaluations in which all methods were evaluated equally.

Figs. 3 and 4 are example visualizations that incorporate uncertainty. Cartesian plots were used to compare each policy's potential outcome for all policies and two specified criteria. Fig. 3 is an example of such a plot using the criteria of SO_2 emissions and global temperature increase. Similar plots were generated for each pair of criteria. This graph allows users to compare the uncertainty of two criteria for all policies. For example, from this plot an observer could determine that a range of global temperature increase values are possible for each alternative, and that SO_2 emissions are more uncertain for some policies than others.

Fig. 4 is a boxplot depicting the expected outcome and associated uncertainty for global SO_2 emissions for each policy. In the workshop, participants were provided with similar graphs for the other criteria. Each box represents potential outcomes for a given policy. The box extends from the 25th percentile ("lower hinge") to the 75th percentile ("upper hinge"), with a horizontal line at the median. Vertical lines extend from the box to the "lower fence" [smallest value$\geqslant$lower hinge$-1.5\cdot$(upper hinge$-$lower hinge)] and the "upper fence" [largest value$\leqslant$upper hinge$+1.5\cdot$(upper hinge$-$lower hinge)]. This graph shows that the \$300/CO_2 tax has the best performance and lowest uncertainty for SO_2 emissions.

Workshop participants evaluated the visualization approaches on a scale of 1 (worst) to 5 (best) for several criteria including ease of use, whether they used the method in the MCDM policy ranking exercises, and whether they would recommend the method for climate change decision-making.

Visualization approaches should succinctly present the information without unnecessary complexity that could cause confusion, and without bias or misrepresentation that could direct the user towards a particular set of alternatives. In this sense, it may seem appropriate to use the simplest, easiest to understand method so that the information could be processed as quickly as possible with the least potential for confusion.

Yet, the participants' answers support another hypothesis. On average, participants found the numerical tables to be the easiest of all the deterministic displays to understand, with bar charts, value path plots, and Cartesian (x, y) plots equally difficult to understand. However, the bar graphs and value path plots were more highly recommended for actual climate change decision-making. In the case of methods for presenting uncertain impacts, participants also recommended the two methods that were most difficult to understand (table of criteria averages, box plots) as opposed to those that they found easier to digest (table of regret values, Cartesian plots). We suggest that users believe more difficult approaches are necessary to convey the complex information provided by IAs, and that users are willing to work through complex presentations of data in order to understand tradeoffs.

It is also important to note that for the uncertain case, the table of criteria values was recommended for actual use even though it does not present the data visually. This suggests that for more complicated information representing uncertainty, participants were not satisfied with the visualization methods presented; such methods should thus not supplant tabular presentation of numerical data. However, for the deterministic case, participants recommended all three visualization approaches as opposed to the tabulated values for use in climate policy evaluation. Overall, approaches that performed well included value path plots for the deterministic case (second most relied upon by participants in the MCDM exercises, most highly recommended for actual climate change decision-making), table of criteria averages for the uncertain case (most used in exercises, most highly recommended), and box plots for the uncertain case (second most used in exercises, second most highly recommended). In contrast, participants disliked the Cartesian plots, perhaps because only two criteria are presented in each plot. This method was the least used in MCDM exercises and least recommended for real decision-making, for both the deterministic and uncertain cases.

Not surprisingly, different participants preferred different visualization methods. Table 4 provides the number of participants who thought each method was the easiest to understand, which method they relied on most during the workshop exercises, and which they would recommend for actual policy-making. Each method was found by at least two participants to be the easiest to understand and the most recommended for actual use, while being the most used by at least two persons to complete MCDM exercises. Thus, different methods work better for different people. This suggests that data in IAs should be displayed in more than one format.

6. Discussion

The ultimate aim of IA is to provide users with a representation of economic and environmental systems that gives insight into the consequences of different policies and assumptions. While IA designers and practitioners may attempt to be as objective as possible in modeling these systems, decisions made at each stage of design and implementation can greatly impact an IAs conclusions. Choices and assumptions, such as how different types of impacts are aggregated, are propagated through the IA and may bias policy decisions. Nevertheless, aggregation is essential because IAs must balance the need to present huge quantities of data with the limited ability of users to process information. MCDM methods can help IA users manage large amounts of information by providing a systematic way to aggregate impacts in a manner consistent with a user's values; this, while giving a framework for screening alternatives, gaining insights into tradeoffs among alternative policies, and attaining a better understanding of how their own and other users' value judgments affect policy recommendations.

In a workshop held to explore the use of MCDM with IA, climate change experts and policy-makers applied and evaluated several MCDM methods in the context of a hypothetical greenhouse gas policy decision. This research differs from earlier comparisons of MCDM methods in that the participants were potential users of IA, as opposed to students or other naive subjects. Quantitative comparison of policy rankings showed that MCDM methods produced different results and had dissimilar predictive validities. Results also differed by participant. These findings indicate that both *who* applies a method and *which* method is used can significantly impact policy recommendations. This supports the use of multiple MCDM approaches within IA. Also, although workshop participants were experts in climate change and IA, they were, nonetheless, just as subject to the "splitting bias" in weight assessment as more inexperienced users.

Results of the workshop indicate that MCDM methods can combine formal modeling (e.g., impact estimates) with information that traditional models may omit, such as users' background knowledge (e.g., understanding of impacts not represented by the IA, or a full appreciation of the consequences of a particular impact), and preferences (e.g., the relative importance of one criterion over another). When ranking policies, many participants relied on their own understanding of the issues more than IA model results. This provides insight into how IA output may be used in an actual decision-making process. Our research indicates that MCDM could be used in conjunction with IA to incorporate the users' own background knowledge and preferences with model output. The danger is that these subjective inputs will affect policy rankings in ways that are difficult to document, justify and communicate.

Many participants felt that the MCDM exercises helped them better understand how they think about policy decisions. Participants reported that MCDM exercises gave them insight into how their own, and others', value judgments affected policy choices.

The discounting exercises suggest that the discount rate differs by person, criteria, and the method used to elicit the rate. However, in their discussions and written evaluations, the participants did not focus on discount rates even though rates can greatly influence the conclusions of an IA, suggesting that more attention should be paid to this issue.

The workshop participants' evaluation of methods for displaying tradeoffs found that while some approaches were, on average, more useful than others, different people preferred different methods, supporting the use of multiple visualization methods. More complex and difficult to understand methods were most often recommended for actual decision-making, suggesting that complicated visualizations are necessary to communicate IA information.

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