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REVIEWS

"Biases" in Adaptive Natural Resource Management

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Abstract

Uncertainties about the consequences of natural resource management mean that managers are required to make difficult judgments. However, research in behavioral economics, psychology, and behavioral decision theory has shown that people, including managers, are subject to a range of biases in their perceptions and judgments. Based on an interpretative survey of these literatures, we identify particular biases that are likely to impinge on the operation and success of natural resource management. We discuss these in the particular context of adaptive management, an approach that emphasizes learning from practical experience to reduce uncertainties. The biases discussed include action bias, the planning fallacy, reliance on limited information, limited reliance on systematic learning, framing effects, and reference-point bias. Agencies should be aware of the influence of biases when adaptive management decisions are undertaken. We propose several ways to reduce these biases.

Introduction

Natural resource management is often a complex and uncertain process. The underlying environmental and physical processes are sometimes not well understood. Even when they are understood, there are likely to be uncertainties about the quantitative outcomes of management. The current actual status of the resource may be difficult to determine. Managers cannot always fully control which on-ground actions are undertaken due to lack of resources, legal powers, or capacities (Williams & Brown 2014).

These complexities and uncertainties mean that managers are required to make judgments. However, it has been shown that, in making judgments of these types, decision makers do not always undertake decisions "rationally." Simple rational decision-making models assume that agents always take decisions to maximize the achievement of their objectives, based on accurate knowledge of the outcomes, costs, and constraints. In reality, however, people have limited information, limited time, and limited cognitive capacity. As a consequence, they are restricted in formulating and solving complex problems, and they are susceptible to different types of biases (Arnott 2006; Tasic 2011)—beliefs that are inconsistent with reality (Chira *et al.* 2011) or behaviors that compromise the achievement of objectives. For example, Guthrie *et al.* (2000) found that some of the biases listed in Box 1 affect judges when they are making judicial decisions. Similarly, Hirshleifer (2008) found that financial regulators are subject to a different set of biases that influence their decisions, plans, and polices. The impacts of such biases can be substantial. For example, Kahneman (2012) reports on a 2005 study of rail projects worldwide undertaken between 1969 and 1998. Passenger usage of the rail system was overpredicted in 90% of cases. On average, planners overestimated passenger usage of new train lines by over 100%, reflecting a common bias known as the "planning fallacy."

Box 1: Selected behavioral biases with potential impact on adaptive management

- Action bias: Tendency to take actions even when it is better to delay action
- Framing effect: Tendency to respond differently to alternatively worded but objectively equivalent descriptions of the same item
- Reference-point bias: Tendency to overemphasize a predetermined benchmark for a variable when estimating the level of that variable
- Availability heuristic: Tendency to give more weights to events that can be recalled more easily
- Planning fallacy: Making judgments about a planned activity that are systematically over-optimistic, including underestimating project completion time, underestimating costs, or overestimating benefits
- "Satisficing rule": Tendency to stop searching for a better decision once a decision that seems sufficiently good is identified
- Loss aversion: Tendency to value losses more highly than similar gains
- Reliance on limited information: Tendency to use a subset of information even when full set of information is available
- Limited reliance on systematic learning: Tendency to use information from past successful efforts rather than using information from both successful and failed efforts

For a general list of behavioral biases, see Arnott (2006) and Gino & Pisano (2008).

Managers of natural resources and the environment are likely to be just as susceptible to these biases as are other professionals who must make complex judgments, such as judges and financial regulators (Carlsson & Johansson-Stenman 2012). However, these issues have received little attention in the conservation literature. Our aim in this article is to draw from psychology, behavioral economics, and behavioral decision theory research literatures to identify key insights about biases that are relevant to conservation, and to understand their implications for managers responsible for management of environmental projects or programs.

In doing so, we focus to some extent on Adaptive Management (AM), since this is a process that has been promoted or used to manage complex and uncertain natural resource issues. AM is a process of "learning by doing" (Walters & Holling 1990) where learning from experience is combined with the need for immediate action (Westgate *et al.* 2013). Under AM, management policies are formulated as experiments that investigate ecosystems' responses to changes in people's behavior or management actions (Lee 1999). Conceptually, a set of potential models representing relationships between human actions and ecological outcomes are developed and tested. Viewing the learning process through a Bayesian lens, each model is assigned a probability of being the true model. In each time step, a management decision is made based on the current model probabilities, the current system state, and predicted future states. Model probabilities are updated after each time step based on each model's success in predicting outcomes (Conroy & Peterson 2012), and management may subsequently be modified.

Traditionally, AM has focused on learning from experimental trials or pilots of management approaches for biological and ecological systems (Wilhere 2002; McCarthy & Possingham 2007). It has been assumed that the decision makers will interpret the information collected and make their choices or decisions rationally and without bias. We will explore the extent to which research on human behavior and decision making casts doubt on this assumption. Broader implications for management of natural resources and the environment will also be discussed.

AM: Definition and Stages of Learning

AM has been defined by Williams *et al.* (2009) as "a systematic approach for improving resource management by learning from management outcomes" (p. 1). In active AM, the learning process is supported by purposefully collected information (Walters & Holling 1990), rather from observation of management actions chosen without regard to their ability to provide useful information for future decisions. In active AM, learning is often represented through single- and double-loop processes (Figure 1). Under a single-loop learning cycle, the key steps involved are: (1) define management goals with stakeholders involvement (step 1); (2) develop alternative management options, including an option to maintain the "status quo" (step 2); (3) develop models or statistical processes to trace system responses to management actions (step 2); and (4) implement management options (step 3; Westgate *et al.* 2013). Steps 4 and 5 involve monitoring and assessment of the outcomes, respectively. In a single-loop learning cycle, it is often assumed that project objectives, societal needs, and policy structures are fixed (Allen & Gunderson 2011).

In double-loop learning, on the other hand, it is assumed that policy objectives and structure could change. For example, in long-term projects, societal values and

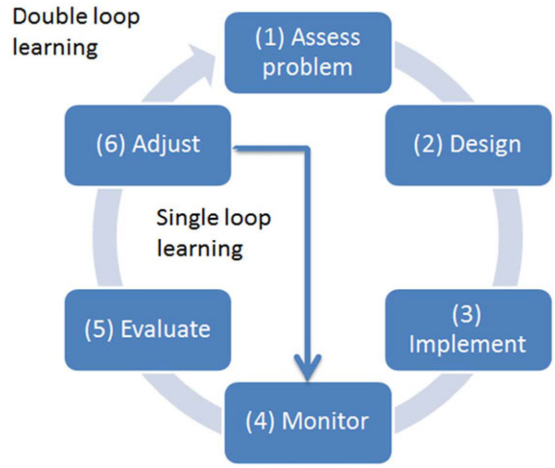

Figure 1 Different steps in active AM cycle with single- and double-loop learning (based on Williams & Brown 2014).

needs could change as time progresses and new management actions are introduced. The resource or the system under experimentation could also change to make the original project objectives unsuitable or unattainable. Therefore, the objectives, management options, or institutional arrangements might need to be changed. Under double-loop learning, original project objectives and management options are revisited after certain steps (step 6). New information from experimentation and model predictions are taken into account as well as changed policy and societal landscapes (Williams & Brown 2014).

In an AM regime, decision makers are responsible for defining management goals, identifying alternative management options, developing models, and implementing programs (Westgate *et al.* 2013). It is common to assume that in each step the resource managers would make "rational" decisions based on the information obtained from biological, physical, and social experiments. However, numerous studies inform us that people have cognitive limitation and bounded rationality, and are influenced by different types of biases. We expand on these issues in the following section.

Key Behavioral Biases

Both psychology and economics have rich literatures on the influences of different types of bias on behavior. Experimental economics serves three main purposes: testing theories, building new theories from observing experimental outcomes, and testing policy and management options. Behavioral economics also integrates insights from psychology to explain economic decision making. It studies the effect of psychological factors such as emotional, social, and cognitive factors on many decisions and economic processes (Camerer 1999). A related field is behavioral decision theory, which studies how people make decisions as well as how they should make decisions (Moore & Flynn 2008). The key biases identified in these research efforts that are relevant to AM are outlined below.

Action bias

"Action bias" occurs when the decision makers choose to take actions even when a "rational" decision maker would prefer to delay actions to allow further information collection, or to take no action. Possible reasons for action bias include that decision makers give higher weight to things that are readily observable and attributable (i.e., the management actions themselves), rather than to things that are delayed, indirect, or unobservable (i.e., potentially the outcomes from those actions; Patt & Zeckhauser 2000). For example, a study of elite soccer goalkeepers showed that they tend to jump to try to save goals even when the optimal strategy is to stay in place (Bar-Eli *et al.* 2007). In this case, taking action is valued in its own right, in addition to the value attributed to the outcome achieved. Similarly, environmental managers may feel that they will earn credit from their superiors, the general public, and the media if they take action even when it is not justified or should be of relatively low priority (Tasic 2011).

Action bias could be increased by uncertainty (Tan *et al.* 2012). In most environmental projects, knowledge of the effectiveness of interventions that will be taken on the ground is rather weak (Ferraro & Pattanayak 2006). As a result, taking action may be evaluated more positively than collecting additional information, partly because of a lack of evidence that actions would be ineffective.

The implication of "action bias" for AM is that it may be difficult to convince managers that an investment in information collection (i.e., AM) is worthwhile. They will tend to prefer to allocate the resources to additional on-ground management actions. Proponents of AM may enhance their persuasiveness by arguing that AM does not require actions to be delayed, and allows more effective or less costly actions to be taken in future. If AM is implemented, it should help to reduce action bias over time by providing additional information about whether the actions being undertaken are effective.

The planning fallacy

The "planning fallacy" is the tendency of project planners to be excessively optimistic about the performance of a project that they are developing (Kahneman & Tversky 1977; Kahneman & Lovallo 1993). For example, many investments in abatement of dryland salinity under Australia's National Action Plan for Salinity and Water Quality program were too small to make a notable difference to salinity outcomes (Auditor General 2008; Pannell & Roberts 2010). Apparently, managers choosing these investments greatly overestimated the effectiveness of the actions being funded, despite ample scientific evidence being available (Prosser *et al.* 2001; Dawes *et al.* 2002). The extent of bias due to the planning fallacy can be substantial. According to Griffin & Buehler (1999), only 1% of the U.S. military high-technology equipment purchases were delivered on time and on budget.

There are various factors that contribute to the planning fallacy. Buehler *et al.* (1994) observed that people estimate a project's expected completion time by constructing mental scenarios of how the project may develop. However, due to cognitive limitations, they generate a smaller range of scenarios than is realistically possible, overlooking many barriers and risks. The scenarios generated tend to reflect their hopes and preferences (Newby-Clark *et al.* 2000) and to neglect their own previous negative experiences with similar projects (Koole & van't Spijker 2000). To some extent, overoptimism is likely to reflect strategic biases adopted to increase the competitiveness of projects when funding is being allocated (Flyvbjerg 2007), but overoptimism is often present even when planners are attempting to be realistic (Kahneman 2012).

A strategy to reduce the planning fallacy is to ask managers to forecast the completion time, cost, or benefits for a range of comparable projects rather than a single project. This strategy, known as Reference Class Forecasting (Kahneman & Tversky 1977), has been effective in reducing time and cost overruns of large infrastructure projects (Buehler *et al.* 2010).

Where the planning fallacy is in evidence, AM may help to reduce its adverse consequences. AM, involving information collection and refinement of project design, helps in correcting decisions that were initially made on an excessively confident or optimistic basis. If necessary, targets can be modified or the project can be terminated following the collection of improved information (Dvir & Lechler 2004).

Reliance on limited information

Decision makers sometimes use only a subset of information even when the full-set information is available. In a series of experiments with common-pool resources, Apesteguia (2006) studied the impact of additional information on individual behavior and payoffs. The individual payoff depended on player's own investment as well as investments made by others. In one treatment, participants had complete information about the expected payoffs from their choices, while in another they had no relevant information. The experimenter observed that the aggregate outcomes (in terms of investment decisions and actual payoffs from the decisions made) were not significantly different between these two treatments (Apesteguia 2006). More-or-less similar observations have been made in other studies (Mookherjee & Sopher 1994; Oechssler & Schipper 2003; Van Huyck *et al.* 2007). One hypothesis to explain this phenomenon is that decision makers follow a "satisficing rule" to limit the cognitive costs of decision making (Hertwig & Pleskac 2010). Under such a rule, the decision maker stops searching for a better decision once he or she identifies a decision that seems sufficiently good.

Another version of this bias is "availability bias" in which people give more weights to certain types of events that can be recalled more easily (Tversky & Kahneman 1974). For example, a manager may assess the risk of bushfire higher than the risk of plant disease spread if bushfires have been more common or more salient in recent times. Underutilization of information is often observed in environmental planning. For example, it has been observed that many existing environmental planning systems fail to account for project costs (Mazor *et al.* 2013), for the effectiveness of management actions (Maron *et al.* 2013), or for behavior change (Pannell & Roberts 2010).

AM potentially provides a mechanism to counter this tendency of decision makers to ignore relevant information. It has been shown in many studies that use of systematic learning through use of data and models could outperform heuristic decision making and predictions by experts (Camerer 1981). It has also been shown that decision makers may employ information more comprehensively if they are asked to make a decision several times sequentially (with time delays) and to explain their decisions to third parties (Vul & Pashler 2008; Herzog & Hertwig 2014). By emphasizing the importance of using accurate information and encouraging use of a structured approach for doing so, AM may prompt a general strengthening of the evidence base for environmental decision making. There can also be a social aspect to AM, with different people contributing to decisions about how management should be adapted in response to new information. This socialization of the process may reduce the tendency of any individual to ignore information.

Limited reliance on systematic learning

Active AM involves systematic experimentation and learning from the outcomes. However, experimental studies on learning reveal that humans are not good at systematic learning. Instead, learning is often messy, noisy, and based on trial-and-error (Hertwig & Pleskac 2010). In practice, people hardly use systematic learning models where they compute and compare expected outcomes from every option before making a decision. Rather, they use heuristics and repeat their past successful choices without fully considering other potentially superior alternatives (Erev & Haruvy 2009).

One implication of limited reliance on systematic learning is that managers will try to learn only from their past “successful” project rather than learning from both “successful” and “failed” projects. In doing so, risk-averse managers are more likely to repeat their past successful choices instead of trying new management interventions (Denrell & March 2001). They are less likely (relative to risk-neutral managers) to invest resources to collect more information about the past unsuccessful strategy (Erev & Haruvy 2009). By contrast, a systematic AM approach would seek to learn from previous mistakes to avoid repeating them, and to enhance the resilience of the management system. AM encourages a systematic approach to learning, and to the use of new information for decision making. It makes explicit the importance of obtaining and using new information, at least partially countering tendencies not to do so.

An institutional barrier to systematic learning is staff turnover, which can be high in the environmental sector, sometimes due to the short duration of funding programs (Grafton 2005). Unless new staff commence before the departures of experienced staff, they must rely on written or verbal communication to learn about the existing or past project (Shogren & Taylor 2008). If the logic behind past decisions is not well-documented, new staff cannot integrate the successes or failures of past decision-making processes into their decision making. There are also differences in the way a new and an experienced manager would approach a problem. A new manager would use facts in a context-free manner whereas, for an experienced manager, problem recognition and action selection would be more intuitive (Hayes 2013).

One potential way to promote systematic learning is through the use of decision support systems (DSSs) that enable the storing of such information. There can be synergies between the use of DSSs and AM. Depending on the type of DSS, it may increase the transparency and evidence base of the initial decision to support a project. This transparent information can be updated as the AM process proceeds, allowing the DSS to inform decisions about modifications to the project (Dicks *et al.* 2014).

Framing effect and reference-point bias

The “framing effect” refers to a situation when people respond differently to statements that are worded differently but are objectively equivalent. Among the many ways of framing an environmental management issue, we mention three that are commonly discussed in the literature: (1) risky choice framing, where the expected outcomes of a risky option are described in different ways; (2) attribute framing, where some characteristics of an object or event are highlighted or focused on; and (3) goal framing, where different potential objectives of the program or activity are emphasized (Levin *et al.* 1998). In a risky choice, framing the outcomes from a lottery could be presented as a loss (say 50% chance of losing) or as a gain (50% chance of winning). In attribute framing, we might focus on only one or a few features of a project (say number of days required to complete a project) rather than all relevant features. For example, we could say that the project is successful if it is completed within a certain number of days (and ignore other features such as the achievement or nonachievement of environmental outcomes). In goal framing, we could focus on gain from undertaking a project (such as “Native animal population will increase if fox control bait is used”) or loss from not undertaking the project (such as “Native animal population will continue to decline if fox control bait is not used”; Krishnamurthy *et al.* 2001).

Reference-point bias may cause managers to respond differently to a program or activity depending on the level of a predetermined reference point or benchmark. For example, the same level of environmental improvement could be seen as a success if it is well above a benchmark level of improvement or a failure if it is less than a benchmark, even if the benchmark is arbitrary (Kühberger 1998). It has been shown that people are more sensitive to losses relative to a benchmark than to gains (Camerer 1998). This may mean that managers are strongly motivated to prevent their program from being perceived to be a failure relative to the reference point, but less strongly motivated to seek to make a program perform above the reference point, even if a stronger performance would be feasible and worthwhile.

By regular monitoring and evaluation of project outcomes, AM may help to enhance flexibility in the setting of project goals and to reduce dependence on a fixed reference point. AM, in conjunction with a DSS could help in reducing the impacts of framing effect and reference-point bias by helping managers to assess potential strategies more comprehensively and objectively. Reasons why DSSs are not more commonly used by environmental managers include: lack of adequate training, no clear policy guideline to use the best possible information or DSS, and pressure to spend money within a deadline that is too short to allow time for using the DSS (Shtienberg 2013). To address the last of these issues, in particular, agencies should ideally plan and prepare for potential programs or the next phase of an existing program well before the existing program has concluded.

Discussion

Although many natural resource managers claim to use AM, rigorous and systematic applications are rare (McFadden *et al.* 2011; Westgate *et al.* 2013; Williams & Brown 2014). This is surprising given the theoretical attractiveness of AM in the face of risk and uncertainty (Stankey *et al.* 2005). There has been little research about the impact of psychological biases on decision making by managers of environmental or natural-resource programs (Westgate *et al.* 2013). Based on a survey of the economics and psychology literature, we have identified a set of biases that have implications for AM in particular and NRM in general. As a result of this review, there are grounds to expect that: (1) the managers are likely to take on-ground actions even when these are not worthwhile (Patt & Zeckhauser 2000); (2) they could suffer from the cognitive illusion of being more in control of the system than they actually are (Koole & van't Spijker 2000); (3) they could be overconfident about the expected outcome of their decisions (Flyvbjerg 2007); (4) they may be overly optimistic in terms of expected completion time of the project (Kahneman 2012); (5) they might rely on a partial set of information for decision making even when fuller information is available (Hertwig & Pleskac 2010); (6) they might rely on trial-and-error learning and repeat their past successful choices instead of collecting and comparing information about the full set of decision options (Erev & Haruvy 2009); and (7) managers could try to achieve predefined goals rather than the best possible outcomes from a project (Kühberger 1998; Table 1).

Different biases could influence various steps of the AM cycle differently. For example, action bias could influence the design phase of the AM cycle and lead the planners and managers to design projects with more emphasis on on-ground actions and less on the expected outcomes. Similarly, overconfidence and reliance on limited information would mean the managers would fail to consider all relevant information during the design and monitoring phases. Limited use of systematic learning process would mean failure to learn from previous mistakes during the evaluation phase. Lack of systematic learning would also make mangers susceptible to framing effect and reference-point bias (Klayman & Brown 1993). Agencies should be cautious about the impact of these biases and take remedial measures (Fischhoff 1982).

First, the agencies need to promote a culture of learning (e.g., García-Morales *et al.* 2012). It needs to be recognized that both successful and failed projects generate valuable information about the future state and expected impacts of the management interventions. This could be done by providing appropriate incentives (tangible and intangible) for the managers and decision makers to consider the full range of options before making any decision (Arnott 2006), requiring them to repeat the same decision several times before finalizing it (Vul & Pashler 2008; Herzog & Hertwig 2014), or asking mangers to justify their decisions to external parties (Gollwitzer & Sheeran 2006).

Second, adoption of a DSS could facilitate retention and storing of relevant information (e.g., Behrens & Ernst 2014). It may also make learning from past projects easier and help in systematic evidence-based decision making. Relevant staff should be adequately trained and properly incentivized to use DSSs (Dicks *et al.* 2014).

Third, conducting benefit-cost analyses of planned options would help to refine and prioritize the options during the design phase of the AM cycle (e.g., Pannell *et al.* 2012, 2013). Benefit-cost analysis provides a systematic and objective framework to include all relevant costs and benefits (both market and nonmarket goods and services) related to a project. In the process of identifying benefits and costs, it also helps in identifying if there is complementarity among them (to avoid double counting) and the time lag and uncertainty attached to realization of each benefits and costs. Thus, benefit-cost analysis could be used as a tool to comprehensively assess the expected benefit of a project (Sunstein 2000; Atkinson & Mourato 2008).

Fourth, involvement of external third-party reviewers may also help in designing more realistic and feasible projects (Chen & Volden 2013; Behrens & Ernst 2014). Finally, scenario analysis should be conducted as part of the assessment and design phase of AM cycle to anticipate the expected outcomes of different options (Lautenbach *et al.* 2009). The likely impact of different types of biases, their impact and the effectiveness of potential remedial measures should be systematically analyzed and studied before making any final recommendation for use in decision making for natural resources.

Table 1 Potential psychological biases, their impacts on different steps of the AM cycle, and potential remedial measures to overcome the impact of the biases

Biases	Potential impact on behavior	Potential impact on different steps of AM cycle	Potential remedial measures
Action bias	• Tendency to rely more on actions rather than on results	• During design phase (step 2) projects with visible actions will be prioritized which may lead to wastage of valuable resources (money and time)	• Emphasize the value of information and learning from the AM cycles during the evaluation (step 5), adjustment (step 6), and assessment (step 1) phases rather than on the actions undertaken on ground • Conduct a benefit-cost analysis during the design phase (step 2) of the cycle
Planning fallacy	• Overoptimistic or wrong judgments on the expected benefits, completion time, and costs of the project	• Failure to implement the project (step 3) in due time • During the monitoring phase (step 4), all relevant indicators may not be included, which lead to inadequate assessment during the evaluation phase (step 5)	• Conduct feasibility study as part of the assessment of the problem (step 1) and design of the options (step 2) • Involve external third parties during design phase (step 2) to review proposed actions and their underlying assumptions.
Reliance on limited information	• Make quick judgment • Lack of clearly specified project goals	• During assessment of the problem (step 1), full set of information will not be considered, which will lead to faulty prioritization of projects	• Develop DSSs which will automate incorporation of available information and facilitate consideration of full range of available information during assessment (step 1) and design (step 2) phases
Limited reliance on systematic learning	• Failure to consider the full range of the options • Repetition of the "safe" options • Failure to learn from previous mistakes	• Failure to consider learning from "failed" projects during the evaluation phase (step 5) may lead to missed opportunities to learn and realize the full potential of the situation	• During the evaluation (step 5) and adjustment (step 6) phases, consider learning from all projects (complete/incomplete, successful/failed, etc.) • Always conduct a scenario analysis with a range of options and expected future states during assessment (step 1) and design (step 2) phases
Framing effect and reference-point bias	• Failure to understand the real implications of an option • Success as well as failure is measured relative to a reference point • Follow a satisficing rule rather than a maximization rule while making decisions	• Use wrong measures to evaluate a project (step 5) • Managers may not give their full efforts if they think that they have performed better than others (or with respect to a predefined goal) already (step 3)	• Use DSSs and train managers on how best to use it • A scenario analysis could demonstrate the best possible outcomes from a given situation

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