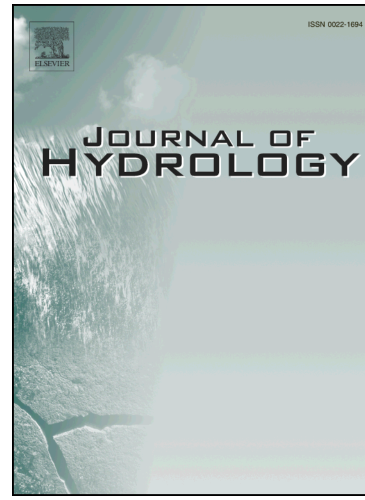
Accepted Manuscript



Research papers

Decision-making under Surprise and Uncertainty: Arsenic Contamination of Water Supplies

Timothy O. Randhir, Pallab Mozumder, Nafisa Halim

PII: S0022-1694(18)30196-3
DOI: https://doi.org/10.1016/j.jhydrol.2018.03.030
Reference: HYDROL 22663

To appear in: *Journal of Hydrology*

Received Date: 26 November 2017
Revised Date: 16 February 2018
Accepted Date: 12 March 2018

Please cite this article as: Randhir, T.O., Mozumder, P., Halim, N., Decision-making under Surprise and Uncertainty: Arsenic Contamination of Water Supplies, *Journal of Hydrology* (2018), doi: https://doi.org/10.1016/j.jhydrol.2018.03.030

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

ACCEPTED MANUSCRIPT

Decision-making under Surprise and Uncertainty: Arsenic Contamination of Water Supplies

Timothy O. Randhir*

Department of Environmental Conservation

University of Massachusetts, Amherst, MA 01003.

Pallab Mozumder

Department of Earth & Environment, Department of Economics and Social Science Lab, International Hurricane Research Center

Florida International University, Miami, FL 33199

Nafisa Halim
Department of Global Health
School of Public Health, Boston University, Boston, MA.

- Corresponding author

Acknowledgments: Research support was provided by Healey Endowment Research Grant and Department of Energy (DOE) Interdisciplinary Research Fellowship at The Environmental Institute (TEI), University of Massachusetts (Amherst, MA) and by a summer research grant at the Florida International University (Miami, FL). However, the opinions expressed herein are solely those of the authors. The code and the result files used in this paper will be made available upon request.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Decision-making under Surprise and Uncertainty: Arsenic Contamination of Water Supplies

Abstract

With ignorance and potential surprise dominating decision making in water resources, a framework for dealing with such uncertainty is a critical need in hydrology. We operationalize the 'potential surprise' criterion proposed by Shackle, Vickers, and Katzner (SVK) to derive decision rules to manage water resources under uncertainty and ignorance. We apply this framework to managing water supply systems in Bangladesh that face severe, naturally occurring arsenic contamination. The uncertainty involved with arsenic in water supplies makes the application of conventional analysis of decision-making ineffective. Given the uncertainty and surprise involved in such cases, we find that optimal decisions tend to favor actions that avoid irreversible outcomes instead of conventional cost-effective actions. We observe that a diversification of the water supply system also emerges as a robust strategy to avert unintended outcomes of water contamination. Shallow wells had a slight higher optimal level (36%) compare to deep wells and surface treatment which had allocation levels of roughly 32% under each. The approach can be applied in a variety of other cases that involve decision making under uncertainty and surprise, a frequent situation in natural resources management.

Keywords: water resource management; arsenic contamination; decision-making; uncertainty; Shackle, Vickers and Katzner (SVK) criterion; Bangladesh.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

1. Introduction

Uncertainty is pervasive in water resources and addressing uncertainty and ignorance still demands a more pragmatic approach in decision making (Ganguly et al. 2015; Hollings, 1986; Kalman, 1983). Water resources management often deals an inherent uncertainty in hydrologic processes (Borgomeo et al. 2014), especially in information access, infrastructure, hydrologic modeling, and decision making under extreme events. Uncertainties in climate change impacts, water quantity (floods and droughts), water quality (emerging contaminants, eutrophication), and social processes (communication and response) dominate research and decision making in water resources. Knowledge of uncertainty is important for robust management of water resources in order to sustain societies (Tracy, 2008). In decision making, risk (probabilities and outcomes are all known) and uncertainty (probabilities are unknown but outcomes are known) (Faber et al., 1992) dominate in water resource management. In many decisions, neither probabilities nor outcomes are clearly known; thus, ignorance and surprise is often predominant in decision making. While earlier theoretical works have made substantial progress in utilizing the probability information and nature of preferences through approaches like the expected utility theory, the shortcomings of such frameworks are tucked in its assumptions or in the complacency of the large number theory. These models use assumptions on complete information about water resource risk and have the advantage of elegance and simplicity, but are less applicable to decision making under uncertainty and ignorance that is prevalent in water resources. Several distinguished economists (Hayek 1945; Hicks 1976; Shackle 1972; Vickers 1985) have recognized this fact in analyzing uncertain choices and decisions. Metlay and Sarewitz (2012) identify that such decision strategies are complex, messy problems having: (i) a high degree of uncertainty linking options to outcomes; and (ii) substantial controversy over tradeoffs among values.

ACCEPTED MANUSCRIPT

The quantification of probabilities of future outcomes in water resources is often constrained by the unavailability or lack of information, leading to outcomes with potential for surprises. Shackle (1969) identifies that instances of surprise arise from the possibility of unknown outcomes, the non-replicability of frequency based probabilistic outcomes, and insufficient knowledge of future outcomes. In many cases, the existing scientific knowledge cannot adequately explain the system dynamics to generate information for decisions with certainty. Uncertainty and surprise also exist with respect to the sustainable use and potential future benefits derived from water resource systems. Incorporating uncertainty into water resource decision-making models requires a clear specification of the nature and sources of uncertainty. Given that a probability-based framework has limited application in such situations involving uncertainty, there is a need for alternative approaches and theories that will guide water resource decision making under uncertainty (Baudry 2018; Starmer 2000). Following the work of Shackle (1969), Vickers (1987), and Katzner (1998), we propose an alternative framework for decision making under uncertainty and ignorance, and apply it to a pragmatic case of managing water supply systems under uncertainty in Bangladesh. We incorporate non-probabilistic uncertainty and surprise in decision-making to deal with the exogenous uncertainty in water supplies. Our general objective is to derive and apply a framework that can guide prudent decision making in such cases. Bangladesh, like many other developing nations, faces an exceptionally high level of arsenic contamination in its groundwater which is leading to serious public health hazards (Smith et al. 2000). The existing scientific knowledge is limited on managing arsenic contamination (Yunus et al. 2016; Tsur and Zemel 1995; Tsur and Zemel 2004) and this study fills this gap by developing a unique operational approach to deal with water resource uncertainty. Another unique contribution is that very few studies (e.g. Horan et al. 2002) mention the SVK framework as a possible option to model uncertainty and surprise, but do

ACCEPTED MANUSCRIPT

not provide an operational framework. Our study is thus unique in developing an operational framework to apply the SVK approach and apply it to a water resource management problem.

Specific objectives of this study are: (i) to review current and develop an uncertainty framework for applications in water resource decisions; (ii) to optimize decisions on water supplies under uncertain contamination processes; (iii) to identify strategies to apply uncertainty into decision models in hydrology and water resource management. We hypothesize that: (i) the SVK uncertainty framework is suited under conditions of ignorance and potential surprise; (ii) diversified allocation is optimal for reducing uncertainty in water supply decisions; and (iii) there is potential to improve decisions involving uncertainty in water resource management.

2. Towards an operational Framework

Hydrology has recognized the importance of nonstationarity in planning and decision making (Milly et al. 2008; Borgomeo et al. 2014). Many policy decisions are also required to recognize the competing uses of water resources. Decisions often aim at avoiding risk and are made under a high degree of uncertainty (Arrow 2004). The commonly used expected utility (EU) approach assigns a numerical payoff value and a probability of state-contingent outcomes of decisions. However, in practice, decision makers are unwilling to apply expected utility methods to important decision problems (Moskowitz 1990, Moskowitz et al. 1993). Several alternative theoretical frameworks are proposed, that include reliability theory (Heiner 1983, Milon and Bogess 1988), Bayesian optimization (Zhang et al 2017), robust interactive decision analysis (Chu et al. 1989, Moskowitz et al. 1990), potential surprise framework (Shackle 1969; Shackle 1972; Katzner 1998), multi-valued mapping (Dempster 1967), weight of evidence measures (Good 1985), prospect theory (Kahneman and Tversky 1979, 2013; Machina 1982; Quiggan 1982), regret theory (Savage 1951; Chisholm 1988; Palmini 1999), safe minimum

ACCEPTED MANUSCRIPT

standard (Ciriacy-Wantrup 1968), multiattribute utility theory (White et al. 1984; Fishburn et al. 1968), robust interaction decision (Moskowitz et al. 1990), robust control framework (Roseta-Palma and Xepapadeas 2004), Genetic Optimization (Tanyimboh and Czajkowska 2017; Al-Jawad and Tanyimboh 2017) and intuitive probability approach (Koopman 1940).

The EU approach is inconsistent with predictions made about people's behavior (Starmer 2000;), inefficient in modeling under low catastrophic risk (Chichilnisky 1998), and is weak in applicability to natural resource management (Chisholm 1988; Woodward and Shaw 2006; Peterson et al. 2003)). Brock and Xapapadeus (2003) suggested incorporating Knightian uncertainty (Knight 1921) to regulate natural systems with non-linear dynamics. Decision-making under uncertainty facing irreversible changes also use concepts of option value (Weisbrod 1951; Chisholm 1988; Cicchetti and Freeman 1971), quasi option value (Arrow and Fisher 1974), and existence value.

The Shackle's model of decision making under non-probabilistic uncertainty and surprise (Shackle 1969) has not been adequately extended for use in practice of decision making. Vickers (1994) and Katzner (1998) have made considerable effort to extend Shackle's basic approach to theorize decisions under uncertain environments.

3. Methodology

SVK Uncertainty Framework: Consider a situation where a decision maker is ignorant in developing a full assessment of probabilities. This difficulty often results from poor information, an imperfect perception of past and present, and unknown future. This is a scenario with a lack of knowledge of occurrence, outcome, or the basis for probabilities (epistemic nature). Hence, a probability $p(E)$ of the subset of states E is difficult to assert. The lack of reliable estimates of $p(E)$ makes the decision-making more difficult under uncertainty, compared to that of decisions

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

under risk (in the classic Knightian sense). Following Shackle (1969), Vickers (1994) and Katzner (1998), (SVK), we assume that the decision maker imagines an incomplete collection of states of the world, say Ω, and forms a non-probabilistic judgment of belief of the occurrence of various states. The states of *E* are subsets of Ω, with unknown states represented by the empty set ϕ. In general, consider only the *σ*-field over Ω that contains all subsets of Ω (Katzner 1998) and represent it as *ε*. In contrast to the states of *E* in the Kolmogorov formulation (Tikhomirov 1993) of probability analysis, the Cox formulation (Cox 1961) of probability defines *E* as representing hypotheses, propositions or a set of answers to questions. The residual hypothesis is a collection of unknowns represented by the null set ϕ (Katzner 1998).

According to SVK, the potential surprise of *E* in *ε* is the surprise the decision maker imagines now about the future occurrence of an element in *E*. This can also be interpreted as the degree of disbelief when contemplating the possible occurrence of *E* (Katzner 1998). With this definition of surprise, we can define a potential surprise function of *E* as $S: E \rightarrow [0, 1]$, a mapping of *ε* into a closed interval. When $S(E)=0$ for some *E* in *ε*, this indicates "perfect possibility" i.e., the decision maker is unable to identify any obstacle to the occurrence of an element in *E*. On the contrary, when $S(E)=1$, the decision maker believes in "perfect impossibility" in the sense that it is not possible to conceive of an element of *E* occurring. At $S(\phi)=0$, the decision maker expresses a "perfect possibility" of occurrence of something not imagined *a priori*.

Following the SVK approach, the *S(E)* is defined to satisfy three axioms: Firstly, the range of S(E) is represented by axiom (1).

$$\text{For all } E \text{ in } \varepsilon, \quad 0 \leq S(E) \leq 1 \tag{1}$$

which is a standard condition similar to the property of a probability function. This indicates that the surprise function is nonnegative and bounded above by unity, equivalent to

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

perfect impossibility. Secondly, axiom in (2) represents that the surprise of the union of all sets is equal to the least of all surprise functions.

$$\text{For any}\{E_i\} \neq \varnothing \wedge \{E_i\} \subset \varepsilon,\ S(\bigcup_i E_i) = \inf_i S(E) \tag{2}$$

This axiom is a counterpart of the additivity and mutual disjointness of E_i in probability axioms, replaced by "*inf*" and nonempty E_i. This is an important distinction from probability theory, where the surprise function does not follow traditionally defined distribution and density functions associated with probability theory (Katzner 1998).

The third axiom is that if $\{E_i\}$ is an exhaustive set of rival hypotheses, then $S(E_i) = 0$, for at least one *i*. This signifies that there is always some hypothesis that carries zero potential surprise. In using the Shacklean concepts for decision-making, the two components (complete collection of states and probability function) are replaced by incomplete collection Ω and the surprise function *S(E)*. For decision $x \in X$, define a utility function *u(x, ω)* that is defined by $X \times \omega$ that depends on decision choices and the state ω of the world. To reduce preference ordering of *u(x, ω)* to a single function of x for decision making, Shackle (1969) introduced an ascendancy function which was replaced by attractiveness function by Vickers (1987).

To derive the attractiveness function, a subset of Ψ is defined as N_X^S that consists of perfectly possible outcomes as $N_X^S = \{\psi : f_X^S(\psi) = 0\}$. This set represents a situation where the decision maker is unable to perceive a hindrance to its occurrence. Then identify some elements of N_X^S, say ψ_X^S, to distinguish potential gain spaces and loss spaces. Potential gain spaces are defined as (3) and the potential loss spaces are defined as (4).

$$\Psi_X^+ = \{\psi : \psi \geq \psi_X^S\} \tag{3}$$

$$\Psi_X^- = \{\psi : \psi \leq \psi_X^S\} \tag{4}$$

ACCEPTED MANUSCRIPT

Such that $\Psi_x^{+} \cap \Psi_x^{-} = \psi_x^{s}$. We use ξ to denote potential surprise values over a range E, such that $\xi = f_x^{s}(\psi)$, where $\xi = [0, 1]$.

Given this framework, each pair of (ψ, ξ) has an attractiveness to the decision-maker associated with decision, x. The decision maker's objective is to select $x \in X$ on pairs of (ψ, ξ) in $\psi_x^{+} \times E$ and $\psi_x^{-} \times E$ that have maximum attractiveness, subject to the potential surprise density function (Figure 1). If attractiveness is measured in ordinal terms as real numbers, then denote it as g_x^{s} that map $\psi_x^{+} \times E$ and $\psi_x^{-} \times E$ into a real line. The optimal solutions are where iso-attractiveness contours are tangential to the potential density curve. The optimization problem is to $Max\ g_x^{s}(\psi, \xi)$, subject to $\xi = f_x^{s}(\psi)$. Substituting the constraint into the objective function, one can derive $H(\psi)$ to rewrite the problem as (5).

$$\underset{\psi}{Max}\, H(\psi) = g_x^{s}(\psi, f_x^{s}(\psi)) \tag{5}$$

The first order conditions for optima can be derived as (6).

$$\frac{dH}{d\psi} = \frac{\partial g_x^{s}}{\partial \psi} + \frac{\partial g_x^{s}}{\partial f_x^{s}} \frac{\partial f_x^{s}}{\partial \psi} \tag{6}$$

and solving for $\frac{dH}{d\psi} = 0$, one could obtain (7)

$$\frac{dg_x^{s}}{d\psi} + \frac{\partial g_x^{s}}{\partial f_x^{s}} \frac{\partial f_x^{s}}{\partial \psi} = 0 \tag{7}$$

Rearranging, and evaluating at the maximizing pairs of (ψ_x^{-}, ξ_x^{-}) or (ψ_x^{+}, ξ_x^{+}), one can obtain the first-order condition for optimality as (8).

$$\frac{\partial g_x^{s}}{\partial \psi} = -\frac{\partial g_x^{s}}{\partial f_x^{s}} \Big/ \frac{\partial f_x^{s}}{\partial \psi} \tag{8}$$

In translating this to decision making, the possible range of utility outcomes are considered by a typical decision maker to account for the values in the focus gain and focus loss spaces. That is, for $x \in X$, a decision maker looks at specific values in focus gain (*R(x)* and *r(x)*) and focus loss (*L(x)* and *l(x)*) spaces. The *x* with higher *R(x)* value is of higher utility in the focus gain space and is preferred, while a higher *r(x)* is more uncertain and is thus less desirable in this space. An x with higher *L(x)* value is less negative and is desirable, while that with higher *l(x)* makes the lowest utility value more surprising and thus less desirable. Thus, there are tradeoffs between each of the pairs of these four functions. These tradeoffs are addressed by a general function $Q^s(x)$, that has four arguments: (1) the highest potential return in the gain space, (2) the highest potential return in the loss space, (3) the lowest potential surprise in the gain space, and (4) the lowest potential surprise in the loss space. The decision maker combines these in a function defined for all values of $(\psi_x^+, \psi_x^-, \xi_x^+, \xi_x^-)$ arising from a constrained maximization of the attractiveness function, and is represented as $Q^s[\psi_x^+, \psi_x^-, \xi_x^+, \xi_x^-]$.

From the constrained optimization problem, it is expected that $\frac{\partial Q^s(x)}{\partial \psi_x^-} > 0, \frac{\partial Q^s(x)}{\partial \psi_x^+} > 0,$ $\frac{\partial Q^s(x)}{\partial \xi_x^+} < 0,$ and $\frac{\partial Q^s(x)}{\partial \xi_x^-} > 0.$ This result is because the potential return in loss space comes with a negative sign, and attractiveness increases when Ψ_x^- increases (less negative). In general, attractiveness also increases when the potential return, Ψ_x^+ increases. However, greater potential surprise in the gain space is less attractive, but it is more attractive in the loss space because it is less likely to occur.

For an unconditional uncertainty averse decision maker, $\frac{\partial Q^s(x)}{\partial \xi_x^+} < 0,$ $\frac{\partial Q^s(x)}{\partial \xi_x^-} < 0,$

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

as the unconditional uncertainty averse decision maker wants to reduce potential surprise in both gain and loss pace. However, for an unconditional uncertainty neutral decision maker, $\frac{\partial Q^s(x)}{\partial \xi_x^+} = 0, \quad \frac{\partial Q^s(x)}{\partial \xi_x^-} = 0$. The signs of these derivatives by themselves may not be sufficient to rank alternatives.

The decision maker then forms a decision index or decision function that is defined on *X* by replacing the functional value arguments of $Q^s(x)$ with their associated functions and represented as in (9) (Katzner 1998).

$$D^s(x) = Q^s(L(x), l(x), R(x), r(x)) \tag{9}$$

The decision index is distinct from the attractiveness function because it is derived from different cognitive process, while attractiveness function emerges from identification of what is positive or alarming about various objectives of choice (Katzner 1998). This formulation is similar to that of a multi-attribute utility function (Keeney and Raiffa 1976, Randhir and Shriver 2009) with attributes representing attractiveness and surprise levels in focus-gain and focus-loss spaces. The decision maker can maximize $D^s(x)$ over a subset of *X*, with budgetary restrictions for deriving an unique optima.

Study Area: An exceptionally high level of arsenic is found in groundwater in Bangladesh. Prior to the 1970s, the people in Bangladesh mostly relied on surface water, which has become increasingly polluted. Pollution from poor sewage systems and chemical waste dumping has led to cholera, diarrhea and other water-borne diseases. The mortality rates from such water borne diseases were alarming. The government and donor agencies suggested the cost-effective solution of digging shallow tube-wells to provide access to safe water (Patel 2001). Millions of dollars were spent on digging shallow tube-wells, and massive pumping of groundwater took place to meet household and agricultural demand. By 2000, almost 97% of the populations in

ACCEPTED MANUSCRIPT

rural Bangladesh were drinking water from shallow-tube wells and 2.5 to 3 million wells existed in Bangladesh (Patel 2001). Initially, no one was warned to test for arsenic. In the early 1990s, it was found that most of the well water contained arsenic.

The current method of extracting water cannot be continued as arsenic is causing serious health hazards and leading to the largest mass poisoning in history (Smith et al. 2000). More than 29 million people are affected by arsenic contamination, and 35-77 million are at risk of exposure in Bangladesh (Rahman 2002). Due to arsenic related cancers (in liver, bladder, and lung), Chen and Ahsan (2004) estimate a more than doubling of lifetime mortality risk (229.6 versus 103.5 per 100 000 population) in Bangladesh. The evidence of fetal loss and infant death due to arsenic exposure during pregnancy has been documented by Rahman et al. (2007). Maddison et al. (2005) have estimated that the aggregate willingness to pay (WTP) to avoid the health impacts of arsenic in Bangladesh is $2.7 billion/year. Given the uncertainty involved in this specific water resource management case, the application of conventional cost-benefit analysis would be inadequate. In this paper, we attempt to design an analytical framework for future decision-making and mitigation measures for similar situations of uncertainty.

Most of the large arsenic contamination worldwide involves groundwater contamination as a natural outcome of hydro-geological process (see Table I for details on worldwide occurrences of arsenic contamination in water). There is an intense debate regarding the causes of arsenic contamination in Bangladesh, a country abundant in both surface and ground water (see *Science* 22 November 2002 and *Science* 25 April 2003 for a debate regarding the causes of arsenic contamination in Bangladesh). A variety of factors such as geology, hydrology and the structure of aquifers can be attributed to the causes of contamination. Arsenic is naturally transported in the river systems in Bangladesh and adsorbed into fine-grained iron or manganese oxyhydroxides. These ores were deposited in floodplains and buried in the sedimentary column

ACCEPTED MANUSCRIPT

which later released arsenic into groundwater in certain parts of Bangladesh (see Rahman 2002). Most of the highly arsenic-contaminated wells are in shallow aquifers that are 50 to 150 feet below the surface, whereas deep aquifers are nearly arsenic-free (Yu et al. 2003). However, it uncertain whether deep aquifers will remain arsenic-free over time. An alternative view is that distribution of arsenic is related to geology rather than depth since arsenic is in aquifers with newer sediments.

The complexity in sediment dynamics and a dearth of sediment analyses make it difficult to predict whether the high arsenic zone is hydrologically separate from deep aquifers. A study on natural arsenic distribution in Socorro, New Mexico (Brandvold and Frisch 2002) shows that the relationship between rock type and arsenic concentration in water is not well defined in this study area. In West Bengal (India), Mukherjee (2005) finds no significant relationship between depth and arsenic concentration in the sedimentary sequences to apply conventional groundwater modeling to locate arsenic free sites. While answers to the questions regarding the causes of arsenic contamination in Bangladesh are yet to be known with certainty, it is important to acknowledge the uncertainty and surprise potential involved in policy and decision making regarding ground water extraction.

We apply the SVK framework in decision making under environmental uncertainty associated with management of water resources. The uncertainty and surprise are related to the surprise associated with the quality of various sources of water. Our focus is on arsenic contamination of drinking water in Bangladesh. To be justified for analysis based on a non-expected utility framework, Woodward and Shaw (2006) portray ‘arsenic in drinking water’ as a situation where relevant probabilities are very small and the ambiguity related to outcomes due to lack of information have important health implications including mortality and morbidity. Thus, the behavioral anomalies that people place more weight on low probability events in gain

ACCEPTED MANUSCRIPT

space and less weight on low probability events in loss space and also show preference towards ambiguity aversion (Camerer et al. 2004) will have significant consequences in decision making in case of arsenic contamination.

Optimization Model: To apply the SVK framework to this decision problem, we consider a decision maker (water manager) who is facing uncertainty in arsenic contamination of new water sources that are being developed. The water manager is considering three alternatives in his choice set, that include shallow wells (*sw*), deep wells (*dw*), and surface water treatment (*swt*). Let $i \in I$ denote each of these sources, where $I = \{sw, dw, swt\}$. The uncertainty involved in all these options is associated with water contamination exceeding a safety threshold long after the water supply has been developed. Figure 2 shows these three options for water collection with corresponding potential outcomes.

Let B be a non-empty subset of the real line $B^i = \{b^i : (0,1]\}$, such that there is a *1-1* correspondence, γ^i, between the decision set X^i and the real line B^i. This can be expressed as $b^i = \gamma^i(x^i)$, for all $x^i \in X^i$ and $b^i \in B^i$. Let a decision-maker (water manager) hold a belief as the potential surprise density function $f^i(\psi, b)$ of a particular source i as (10).

$$f^i(\psi^i, b^i) = \begin{cases} \phi^i & if \quad b^i + 1 \le \psi^i \\ \phi^i \left(k_g^i \psi^i - b^i\right)^2 & if \quad b \le \psi^i \le b + 1 \\ 0 & if \quad -1/b^i \le \psi^i \le b^i \\ \phi^i \left(k_l^i \psi^i - 1/b^i\right)^2 & if \quad b^i \le \psi^i \le b^i + 1 \\ \phi^i & if \quad \psi \le -1/b^i - 1 \end{cases} \qquad (10)$$

Here, $\phi^i \in [0,1]$ represents a scaling factor to model the reduction in surprise resulting from treatment technologies. The constants k_g^i and k_l^i (*g* stands for the gain space and *l* for the loss space) are marginal scaling coefficients representing increased or decreased surprise

ACCEPTED MANUSCRIPT

potential at the margin for each outcome of a decision in the gain space, Ψ_x^+ and loss space, Ψ_x^-, respectively. The lower bound, say b_0^i, of B^i represents the boundary between more favorable $\{\psi^i : f(\psi^i, b^i) = 0\}$ and less favorable outcomes $\{\psi^i : f(\psi^i, b^i) = 1\}$. This formulation also defines various endpoints of intervals through which ψ^i vary.

Let $g^i(\psi^i, \xi^i)$ be the attractiveness function of the decision maker to a particular source for water augmentation, represented as (11).

$$g^i(\psi^i, \xi^i) = \begin{cases} \alpha_g^i \psi^i - \beta_g^i \xi^i, & \text{if } \Psi_x^+ \\ -\alpha_l^i \psi^i - \beta_l^i \xi^i, & \text{if } \Psi_x^- \end{cases} \tag{11}$$

Here, α_g^i and α_l^i are marginal attractiveness for the outcomes resulting from a decision in gain space and loss space, respectively. Similarly, β_g^i and β_l^i are marginal attractiveness (repulsion) for increases in surprise levels in the gain space and loss space, respectively.

To identify optimal conditions in the gain spaces and loss spaces for each *i*, a constrained maximization of $g^i(\psi^i, \xi^i)$ subject to $f^i(\psi^i, b^i)$ can be specified. Using the Lagrangean theorem at interior points of focus loss and focus gain spaces, it is easier to identify attractiveness maximizing pairs in focus gain and focus loss for $b^i \in B^i$. The optimal tangency points are identified using $\frac{dg^i(\psi^i, \xi^i)}{df^i(\psi^i, b^i)} = 0$ in focus gain and focus loss spaces for each $i \in I$. Thus ψ_g^i, ψ_l^i, ξ_g^i, and ξ_l^i are coordinates of the tangency between the iso-attractiveness function $g^i(\psi^i, \xi^i)$ and the potential surprise density function $f^i(\psi^i, b^i)$. Figure 3 shows these tangency points for three different options (*sw*, *dw*, *swt*) to develop water supply systems.

These coordinates are functions of b^i that can be used in the development of a decision index $D(b^i)$ defined as:

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

$$D(b^i) = Q(\psi_g^i, \psi_l^i, \xi_g^i, \xi_l^i \mid \forall i \in I) \tag{12}$$

This decision index ($D(b^i)$) is a function of b^i obtained by substituting constrained maximization solution values, in focus loss and focus gain spaces, into $Q(\psi_g^i, \psi_l^i, \xi_g^i, \xi_l^i)$, a continuously differential function (Katzner 1998). This index could be optimized to identify optimal b^i that maximizes the combined attractiveness in the focus gain and focus loss spaces of all choice alternatives. The parameters applied in our analysis are listed in Table II. These parameters are based on insights from published information on water resources in the Bangladesh region, our experience in water management in the region and the nature of hydrologic processes in relation to water supplies (Maddison et al. 2005, Mukherjee, 2005, Khan and Haque 2010, Khan et al. 2014). The values of each parameter are discussed in detail in the following discussion.

The b_0^i value is the lower bound of B^i that represents the boundary between more favorable and less favorable outcomes. This boundary determines the threshold interval where the potential surprise increases. The potential surprise for deep wells (*dw*) could be set at earlier levels of b^{dw} as compared to *sw* and *swt*. This threshold is set at b_0^{dw}=0.15. A higher threshold in *sw* is set at b_0^{sw}=0.3, representing a delay before one could start observing surprises. This observation is consistent with the history of contamination of shallow wells observed in Bangladesh. The surprise associated with surface water treatment (*swt*) is much later than the other choice categories and is set at b_0^{swt}=0.4, representing potential surprises that occur with larger allocations resulting from plant malfunctions, unknown health effects, capacity obsoleteness, and spikes in contamination during extreme flood events which are common in Bangladesh. The ϕ^i parameter scales the potential surprise function. For *sw* and *dw*, this is set at

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

unity indicating surprises reaching the maximum possible levels, derived from the belief that these two options are driven by hydrologic process that are difficult to predict *ex ante* to a decision. The ϕ^i value for *swt* is relatively lower (20 %) compared to *sw* and *dw* in the belief that a treatment process is controllable and within the management ability before substantial changes in concentrations are seen. The k_g^i parameter is the coefficient that increases the marginal change in the surprise in the quadratic form as (11).

$$\frac{df^i(\psi^i, b^i)}{dx} = 2k_g^i(k_g^i - b^i) \quad \text{with } b \le \psi^i \le b+1 \tag{13}$$

The values for each *i* are based on the increase in surprise potential for increased levels of the activity.

The parameter values use relative levels in the belief that a marginal increase in surprise potential in *dw* is 81 % of that of the marginal increase in *sw*. This value is based on the relatively higher uncertainty and expected surprise in installing deep well compared to that of shallow well. The k_g^{swt} value is higher indicating a higher increase in marginal surprises involved in treatment malfunction. The k_l^i value reflects the marginal decrease in surprise potential in the loss spaces and can be interpreted similarly to that of k_g^i in the gain spaces. The attractiveness function $g^i(\psi^i, \xi^i)$ is specified as a linear function with marginal coefficients (α_g^i, α_l^i, β_g^i, β_l^i) representing incremental attractiveness for each marginal change in the focus gain and focus loss spaces. The coefficient α_g^i represents the marginal increase in attractiveness in a higher outcome, while β_g^i is the marginal increase from reduction in surprise potential in the focus gain space. Similarly, α_l^i and β_l^i are marginal changes in attractiveness from a reduction in loss of outcome and reduction of surprise in the focus loss space. We assume that the water manager is

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

indifferent to different sources of water with regard to tastes and some other likely attributes that do not impose any significant treatment cost.

The functions in the focus loss and focus gain spaces were simulated in MATHCAD software (Mathsoft, 2006) using the parameter set described above and presented in Figure 4. The optimal conditions of the constrained maximization related to the parameter set are listed in Table III. These optimal conditions are used additively in building the decision function $D(b^i)$ of the decision maker. A second optimization was conducted to maximize $D(b^i)$ subject to additional restrictions on the boundaries of b^i and a budgetary condition of the decision problem. This can be represented as

$$\underset{b^i}{Max}\, D(b^i) \text{ S.T. } \sum_i c^i b^i \le B \text{ and } b_0^i \le b^i \le 1 \quad (14)$$

where, c^i is the relative cost of developing the water source and B is the total budget constraint. The estimates for c^i are based on Ahmed (2005), and were normalized for relative costs using *sw* as a numeraire for optimization. This decision problem was specified and solved using the GAMS optimization software (Brooke et al. 1998) to identify optimal allocation of the water supply by the water manager.

4. Results and Discussion

Since typical cost-benefit analysis precludes addressing these types of situations, we apply the ‘potential surprise’ criterion to develop decision rules to manage natural resources under uncertainty. In our analysis, we assign a realistic pay-off structure with intuitive beliefs regarding various uncertain events. The prime focus is to operationalize the concept of ‘potential surprise’ criterion by applying it to a practical problem that water utilities face to maintain robust supply of water. Based on the parameters used, the optimal choice for the water manager is to build the capacity to collect 36.2 % of total water allocation from *sw* (shallow well), 32.6 % from

ACCEPTED MANUSCRIPT

dw (deep well) and 31.2 % from *swt* (surface water treatment). Our findings imply that a diversified allocation strategy which is often effective under risky situations may also be applicable to situations under uncertainty and surprise. Thus, using the SVK approach in an operational framework in the context of arsenic contamination in Bangladesh, we show that a diversified approach to developing water supply systems is the optimal choice under uncertainty and surprise. This is consistent with risk and uncertainty literature in identifying the role of diversity in allocation to minimize overall risk in decisions.

There is excellent potential for using multiobjective optimization using genetic algorithms in water resource studies. Tanyimboh and Czajkowska (2017) used penalty-free genetic algorithms to model water distribution networks. Al-Jawad and Tanyimboh (2017) used an evolutionary algorithm to model reservoir operations. Rathnayake and Tanyimboh (2015) use evolutionary algorithms in control of combined sewer overflows. The focus on SVK operationalize uncertainty framework and could be used in characterizing uncertain outcomes in optimization studies.

Decision making under uncertainty and surprise is an issue of critical concern in water resource management. However, a very limited number of studies attempt to model uncertainty and surprise explicitly in the core decision making process. More specifically, in case of water management, system managers often face uncertainty in maintaining both the desired quantity and quality of water supplies. Planners and system managers often struggle with the complexity of the system dynamics which provide water for daily use. The complexity of system dynamics is much more prominent in underground sources of water compared to surface sources.

Thus, uncertainty and elements of potential surprise in decision-making are important for water resource management. In recent years, arsenic contamination has become one of the high-priority environmental issues due to public health concerns. Management of contaminated water

ACCEPTED MANUSCRIPT

resources is also a challenge to developed countries such as in the U.S. because of prohibitive remediation costs (NRC 1994). Budget constraints are much more severe in developing countries and often depend on the flow of foreign aid for such projects. The framework, we develop is crucial to make decisions regarding water supplies under environmental uncertainty and surprise related to arsenic contamination.

5. Conclusion

The framework we propose can be a very useful tool for utility managers who can incorporate subjective beliefs and expert opinions into the decision-making process to develop a robust water supply system. Under potential surprise criterion, the decision rule favors decisions involving low surprise and high net potential gain under unconditional uncertainty aversion. Thus, a water manager can identify optimal allocation among water supply alternatives by considering values of surprise density and the attractiveness of each alternative. In applying this framework in the Bangladesh context, we observe that a diversified allocation with shallow wells, deep wells, and surface water treatment can be the attractive policy choice in the face of uncertainty and surprise. Shallow wells had a slight higher optimal level (36%) compare to deep wells and surface treatment which had levels of roughly 32% each. The implication of the results for future policy design is that given the uncertainties and surprise involved in such cases, the decisions should favor actions that minimize surprise instead of conventional cost effectiveness. The diversification of the water supply system that emerges as a robust strategy to avert unintended outcomes is also along the line of evolutionary view of decision-making under uncertainty which suggests actions leading to increasing diversity and adaptive flexibility (Rammel and van der Bergh 2003).

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

The potential surprise criterion can be extended to other applications by using relevant beliefs regarding surprise densities and attractiveness contours. Uncertainty and surprise is pervasive in natural resources management (Woodward and Shaw 2006) and the potential surprise criterion can be extensively utilized in decision making in this area. This approach is based on subjective beliefs and needs informed judgment and understanding of the resource system. Since the proposed framework is flexible to incorporate a wide range of uncertain beliefs deliberative expert elicitation of beliefs (Howarth and Wilson 2006) can be used in collective decision making.

There is immense potential to extend this study to other contaminants, especially nonpoint source pollution that is uncertain over geographic space and time. There is a need for further research into elucidation of surprise potential and attractiveness functions. Further research could also focus on developing methods to evaluate tradeoffs and applicability of SVK framework in decision making at multiple scales (Randhir, 2016). Applicability of this framework to uncertainty like decisions involving climate change strategies, and policies related to disasters like hurricanes, tsunamis, and earthquakes.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

References

Ahmed, F., 2005. Arsenic Mitigation Techniques in South and East Asia, Towards a More Effective Operational Response: Arsenic Contamination of Groundwater in South and East Asian Countries, Technical Report Paper 3 (Volume II), Environment and Social Unit-South Asia Region, The World Bank, Washington, DC.

Al-Jawad, J.Y. and Tanyimboh, T.T., 2017. Reservoir operation using a robust evolutionary optimization algorithm. Journal of environmental management, 197, 275-286.

Arrow, K., 2004. The Precautionary Principle and Rational Decision Making, Paper presented at Allied Social Science Association Meeting, San Diego, USA, January 3-5.

Arrow, K. Fisher A.C., 1974. Environmental Preservation, Uncertainty and Irreversibility, Quarterly Journal of Economics. 88, 312-319.

Baudry, G., Macharis, C. and Vallée, T., 2018. Range-based Multi-Actor Multi-Criteria Analysis: A combined method of Multi-Actor Multi-Criteria Analysis and Monte Carlo simulation to support participatory decision making under uncertainty. European Journal of Operational Research, 264(1), 257-269.

Borgomeo, E., Hall, J. W., Fung, F., Watts, G., Colquhoun, K., & Lambert, C., 2014. Risk-based water resources planning: Incorporating probabilistic nonstationary climate uncertainties. Water Resources Research. 50(8), 6850-6873.

Brandvold, L.A., Frisch P.L., 2002. Natural Arsenic Distribution in Groundwater in Socorro, NM area of the Middle Rio Grande Rift, New Mexico Geological Society, Proceedings Volume (abstracts only) Annual Spring Meeting, pp.9.

Brock, W., Xepapades, A., 2003. Regulating Nonlinear Environmental Systems under Knightian Uncertainty, in: Arnott, R., Greenwald, B., Kanbur, R. Nalebuff, B., (Eds.), Economics for an Imperfect World: Essays In Honor of Joseph Stiglitz, MIT Press, Cambridge, MA.

Brooke, A., Kendrick, D., Meeraus, A., Raman, R., 1998. GAMS: A User's Guide, GAMS Development Corporation, Washington, DC, USA.

Chen, Y., Ahsan, H., 2004. Cancer Burden from Arsenic in Drinking Water in Bangladesh, American Journal of Public Health. 94, 741-744.

Chichilnisky, G., 1998. The Economics of Global Environmental Risks, in: T. Tietenberg, H. Folmer, (Eds.), The International Yearbook of Environmental and Resources Economics, 9. Edward Elgar, Cheltenham.

Chisholm, A.H., 1988, Sustainable Resource Use and Development: Uncertainty, Irreversibility and Rational Choice, Technological Change, Development and the Environment, in: Tisdell, C., Maitra, P. (Eds.), Socio-economic Perspectives, Routledge, New York and London, pp. 188-216.

ACCEPTED MANUSCRIPT

Chu, P.Y., Moskowitz, H., Wong, R.T., 1989. Robust Interactive Decision Analysis (RID): Concepts, Methodology, and Systems Principles, Proceedings of the Twenty Second Annual Hawaii International Conference on System Science, Kailua-Kona, Hawaii, January,

Cicchetti, C.J., Freeman III, A.M., 1971. Option Demand and Consumer Surplus: Further Comments, Quarterly Journal of Economics. 85 (3), 528-539.

Ciriacy-Wantrup, S.V., 1968. Resource Conservation: Economics and Policies, 3rd Ed., University of California Press, Berkley, CA,

Cox, R.T. 1961. The Algebra of Probable Inference, Johns Hopkins University Press, Baltimore, MD.

Dempster, A.P. 1967. Upper and lower probabilities induced by a multivalued mapping, Annals of Mathematical Statistics. 38: 325-339.

Faber, M., Manstetten, R, Proops J.LR. 1992. Humankind and the environment: an anatomy of surprise and ignorance. Environmental Values. 1(3), 217-241.

Fishburn, P.C. Murphy, A.H., Issacs, H.H., 1968. Sensitivity of decisions to pProbability estimation errors: a reexamination, Operations Research. 16 (2), 254-267.

Ganguly, A., Kumar, D., Ganguli, P., Short, G. and Klausner, J., 2015. Non-stationarity and Deep Uncertainty: Water Stress on Power Production. Computing in Science & Engineering, (1), 1-1.

Good, I. J. 1985. Weight of Evidence: A Brief Survey, in: Bernardo, J.M., DeGroot, M.H., Lindley, D.V., Smith, A.F.M. (Eds.), Bayesian Statistics 2, North-Halland, Amsterdam.

Hayek, F.A., 1945. The Use of Knowledge in Society, American Economic Review. 35, 519-530.

Heiner, R.A., 1983. The Origin of Predictable Behavior, American Economic Review. 73, 560-595.

Hicks, J.R. 1976. Some Questions of Time in Economics, in: Tang, A.M., Westfield, F.M., Worley, J.S. (Eds.), Evolution, Welfare, and Time in Economics, D.C. Health, Lexington, , pp. 135-151.

Hollings, C.S. 1986. The Resilience of Terrestrial Ecosystems: Local Surprise and Global Change, in: Clark, W.C., Munn, R.E. (Eds.), Sustainable Development of One Biosphere, Cambridge University Press, Cambridge, pp. 292-317.

Horan, R., Perrings, C., Lupi, F., Bulte, E., 2002. Biological Pollution Prevention Strategies under Ignorance: The Case of Invasive Species, American Journal of Agricultural Economics. 84, 1303-1310.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Howarth, R. B., Wilson M.A., 2006. A Theoretical Approach to Deliberative Valuation: Aggregation by Mutual Consent, Land Economics. 82(1), 1-16.

Kahneman, D., Tversky, A., 1979. Prospect Theory: An Analysis of Decision Under Risk, Econometrica. 47 (2), 263-91.

Kahneman, D., Tversky, A., 2013. Prospect theory: An analysis of decision under risk. In Maclean, L.C., Ziemba, W.T., Handbook of the fundamentals of Financial Decision Making: Part I, World Scientific Publishing Company, Hackensack, NJ. (pp. 99-127).

Kalman, R.E., 1983. Identifiability and Modeling in Econometrics, in: Krishnaiah, P.R. (Ed.), Developments on Statistics, Vol. 4, Academic Press, New York.

Katzner, D.W. 1998. Time, Ignorance, and Uncertainty in Economic Models, University of Michigan Press, Ann Arbor, pp. xvi, 486.

Khan, M.Z.H., Haque, A.K.E., 2010. Economic Cost of Arsenic Disaster: Policy Choices for Bangladesh. ERG Occasional Paper. Economic Research Group, Bangladesh.

Khan, N.I., Brouwer, R., Yang, H., 2014. Household's Willingness to Pay for Arsenic Safe Drinking Water in Bangladesh, Journal of Environmental Management. 143, 151-161.

Keeney, R.L., Raiffa, H., 1976. Decision with Multiple Objectives: Preferences and Value Tradeoffs, Wiley, New York.

Koopman, B.O., 1940. The Axioms and Algebra of Intuitive Probability, Annals of Mathematics. 41, 269-292.

Knight, F.H., 1921. Risk, Uncertainty and Profit, 1933 reprint, London School of Economics, London, UK.

Machina, M.J., 1982. A Stronger Characterization of Declining Risk Aversion, Econometrica. 50 (4), 1069-79.

Maddison, D., Catala-Luque, R., Pearce, D., 2005. Valuing the Arsenic Contamination of Groundwater in Bangladesh, Environmental and Resource Economics. 31 (4), 459-476.

Mathsoft, 2006. Mathsoft 13: Users Guide. Mathsoft Engineering and Education Inc., Cambridge, MA, USA.

Metlay, D., Sarewitz, D., 2012. Decision Strategies for Addressing Complex, “Messy” Problems, The Bridge, The National Academy of Engineering, 42 (3): 8-15.

Milly, P.C.D., Betancourt, J., Falkenmark, M., Hirsch, R.M., Kundzewicz, Z.W., Lettenmaier, D. P., Stouffer R.J. 2008. Stationarity is dead: Whither water management? Science, 319(5863), 573–574, doi:10.1126/science.1151915.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Milon, J.W., Bogess, W.G., 1988. The Implications of Reliability Theory for Environmental Institutional Design and Decision Making, American Journal of Agricultural Economics. 70(5), 1107-1112.

Moskowitz, H. 1990. Decision Analysis in Contemporary Organizations: Problems and Prospects, Organization and Decision Theory, Horowitz, I. (Ed.), Kluwer Nijhoff, The Netherlands.

Moskowitz, H., Preckel, P.V., Yang, A., 1990. Robust Interactive Decision Analysis (RID): A Tool for Information Systems Evaluation in: Marsden, J.R., and D.E. Pingry, (Eds.), Advances in Intelligent Information Technology, Jai Press Inc., Greenwich, Connecticut.

Moskowitz, H., Preckel, P.V., Yang, A., 1992. Multiple criteria robust interactive decision analysis (MCRID) for Optimizing Public Policies, European Journal of Operations Research. 56 (2), 219-236.

Moskowitz, H., Preckel, P.V., Yang, A., 1993. Decision Analysis with Incomplete Utility and Probability Information, Operations Research. 41(5), 864-879.

Mukherjee, S. 2005. Prerequisite Study for Numerical Flow Modeling to Locate Safe Water Wells in the Zone of Arsenic Polluted Groundwater in the Yamuna Sub-basin, West Bengal, India, in: Bundschuh, J., Bhattacharya, P., Chandrashekharam, D., (Eds.), Natural Arsenic in Groundwater: Occurrence, Remediation and Management, Taylor and Francis Group, London, UK.

NRC, 1994. Alternatives for Groundwater Cleanup, Committee on Groundwater Cleanup Alternatives, Water Science and Technology Board, Board on Environmental and Resources, The National Research Council, Washington, DC.

Palmini, D., 1999. Uncertainty, Risk aversion, and the Game Theoretic Foundations of the Safe Minimum Standard: A Reassessment, Ecological Economics. 29(3), 463-472.

Patel, P.H., 2001. The Crisis of Capacity: A Case Study of Arsenic Contamination in Bangladesh and West Bengal, Honors Theses, Department of Environmental Science and Public Policy, Harvard College, Cambridge, Massachusetts.

Peterson, G.D., Carpenter, S.R., Brock, W.A., 2003. Uncertainty and Management of Multistate Ecosystems: An Apparently Rational Route to Ecosystem Collapse, Ecology. 84(6), 1403-1411.

Quiggan, J.A., 1982. theory of Anticipated Utility, Journal of Economic Behavior and Organization. 3, 323-343.

Rahman, M. 2002. Arsenic and contamination of drinking-water in Bangladesh: a public-health perspective, Journal of Health, Population, and Nutrition. 20(3), 193-197.

Rahman, A., Vahter, M., Ekström, E., Rahman, M., Mustafa A.H.M.G., Wahed, M.A., Yunus, M., Persson, L. 2007. Association of Arsenic Exposure during Pregnancy with Fetal Loss and

ACCEPTED MANUSCRIPT

Infant Death: A Cohort Study in Bangladesh, American Journal of Epidemiology. 165(12), 1389-1396.

Randhir, T.O., 2016. Globalization impacts on local commons: multiscale strategies for socioeconomic and ecological resilience, International Journal of the Commons. 10(1), 387–404. DOI: http://doi.org/10.18352/ijc.517

Randhir, T.O., Shriver, D.M., 2009. Multiattribute Optimization of Restoration Options: Designing Incentives for Watershed Management, Water Resources Research. W03405, doi:10.1029/2008WR007169, 45.

Rathnayake, U.S. and Tanyimboh, T.T., 2015. Evolutionary multi-objective optimal control of combined sewer overflows. Water Resources Management, 29(8), 2715-2731.

Roseta-Palma, C., Xepapadeas, A., 2004. Robust Control in Water Management, Journal of Risk and Uncertainty. 29(1): 21-34.

Savage, L.J. 1951. The Theory of Statistical Decision, Journal of American Statistical Association. 46, 55-67.

Shackle, G.L.S., 1969. Decision, Order and Time in Human Affairs, 2nd Ed., Cambridge University Press, Cambridge,

Shackle, G. L. S. 1972. Epistemics and Economics, Cambridge University Press, Cambridge.

Smith, A.H., Lingas, E.O., Rahman, M., 2000. Contamination of Drinking Water by Arsenic in Bangladesh: A Public Health Emergency, Bulletin of World Health Organization. 78(9), 1093-1103.

Starmer, C., 2000. Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice Under Risk, Journal of Economic Literature. 38, 332-382.

Tanyimboh, T.T. and Czajkowska, A.M., 2017. Joint entropy and multi-objective evolutionary optimization of water distribution networks. Water Resources Management. DOI10.1007/s11269-017-1888-y

Tikhomirov, V.M., 1993. Selected Works of A.N. Kolmogorov, Translated from the Russian by V.M. Volosov, Kluwer Academic Publishers, Dordrecht, The Netherlands.

Tracy, J.C., 2008. Understanding complexity and uncertainty in water resources management: an introduction. Journal of Contemporary Water Research and Education. 140, 1-2.

Tsur, Y., Zemel, A., 1995. Uncertainty and Irreversibility in Groundwater Resource Management, Journal of Environmental Economics and Management. 29(2), 149-161.

Tsur, Y., Zemel, A., 2004. Endangered Aquifers: Groundwater Management under Threats of Catastrophic Events, Water Resources Researc. (W06S20, doi: 10.1029/2003WR002168) 40: 1-10.

ACCEPTED MANUSCRIPT

Vickers, D., 1985. On Rational Structures and Non-equilibrium in Economic Theory, Eastern Economic Journal. 11: 384-403.

Vickers, D., 1987. Money Capital in the Theory of Firm, Cambridge University Press, Cambridge.

Vickers, D., 1994. Economics and the Antagonism of Time: Time, Uncertainty and Choice in Economic Theory, University of Michigan Press, Ann Arbor.

Weisbrod, B. 1951. Collective Consumption Services of Individual Consumption Goods, Quarterly Journal of Economics. 78, 471-477.

White III, C.C., Sage, A.P., Dezono, S., A Model of Multiattribute Decision-making and Trade-off weight Determination under Uncertainty, IEEE Transactions on Systems, Man, and Cybernetics. 14(2), 223-229.

WHO, 2001. Arsenic in Drinking Water, Fact Sheet. World Health Organization, Geneva, Switzerland. <http://www.who.int/mediacentre/factsheets/fs210/en/>

Woodward, R.T. Shaw, W.D., 2006. On Why Environmental and Resource Economists Should Care about Non-Expected Utility Models, Working Paper, Department of Agricultural Economics, Texas A&M University, College Station, TX.

Yu, W.H, Harvey, C.M., Harvey, C.F., 2003. Arsenic in Groundwater in Bangladesh: a Geostatistical and Epidemiological Framework for Evaluating Health Effects and Potential Remedies, Water Resources Research. 29 (6), 1-13.

Yunus, F.M., Khan, S., Chowdhury, P., Milton, A.H., Hussain, S. and Rahman, M., 2016. A review of groundwater arsenic contamination in Bangladesh: the millennium development goal era and beyond. International journal of environmental research and public health, 13(2), 215.

Zhang, J.L., Li, Y.P., Huang, G.H., Baetz, B.W. and Liu, J., 2017. Uncertainty analysis for effluent trading planning using a Bayesian estimation-based simulation-optimization modeling approach. Water Research, 116, pp.159-181.

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table I. Worldwide Occurrences of Arsenic Contamination in Water

Location	**No. of Potentially exposed population**	**Concentration (μg/L)**	**Environmental conditions**	**Source**
Argentina	2,000,000	1-2,900	Natural; volcanic rocks and thermal springs	Groundwater
Bangladesh	>29,000,000	1-4,730	Natural; alluvial sediments	Groundwater
Bolivia	50,000	N/A	Natural and anthropogenic	Surface water and groundwater
Chile	500,000	100-1,000	Natural and anthropogenic	Surface water basin lakes, thermal springs, mining
China	500	40-750	Natural; alluvial sediments	Groundwater
Greece	150,000	N/A	Natural and anthropogenic	Surface water, thermal springs and mining
Hungary, Rumania	400,000	2-176	Natural; alluvial sediments; organics	Surface water
Inner Mongolia	>400,000	1-2,400	Natural; alluvial and lake sediments; high alkalinity	Groundwater
Mexico	400,000	8-620	Natural and anthropogenic; volcanic sediments, mining	Surface water and groundwater
Nepal	N/A	N/A	Natural, alluvial sediments	Groundwater
Spain	>50,000	1-100	Natural; alluvial sediments	Surface water
Taiwan	>100,000	1-1,820	Natural	Groundwater
Thailand	15,000	1-5,000	Anthropogenic, mining	Surface water
Vietnam	>1,000,000	1-3,050	Natural; alluvial sediments	Groundwater
West Bengal, India	>1,000,000	10-3,880	Natural; alluvial sediments	Groundwater

Note: 1 μg (microgram) = 1/1000 (milligram); source: Rahman (2002)

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Table II. Parameter values used in the analysis of decision-making under uncertainty

i	b_0^i	ϕ^i	k_g^i	k_l^i	α_G^i	α_L^i	β_G^i	β_L^i
sw	0.3	1	0.8	1	0.4	0.2	0.6	0.8
dw	0.15	1	0.65	1.09	0.4	0.2	0.6	0.8
swt	0.4	0.2	1.5	1.25	0.4	0.2	0.6	0.8

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

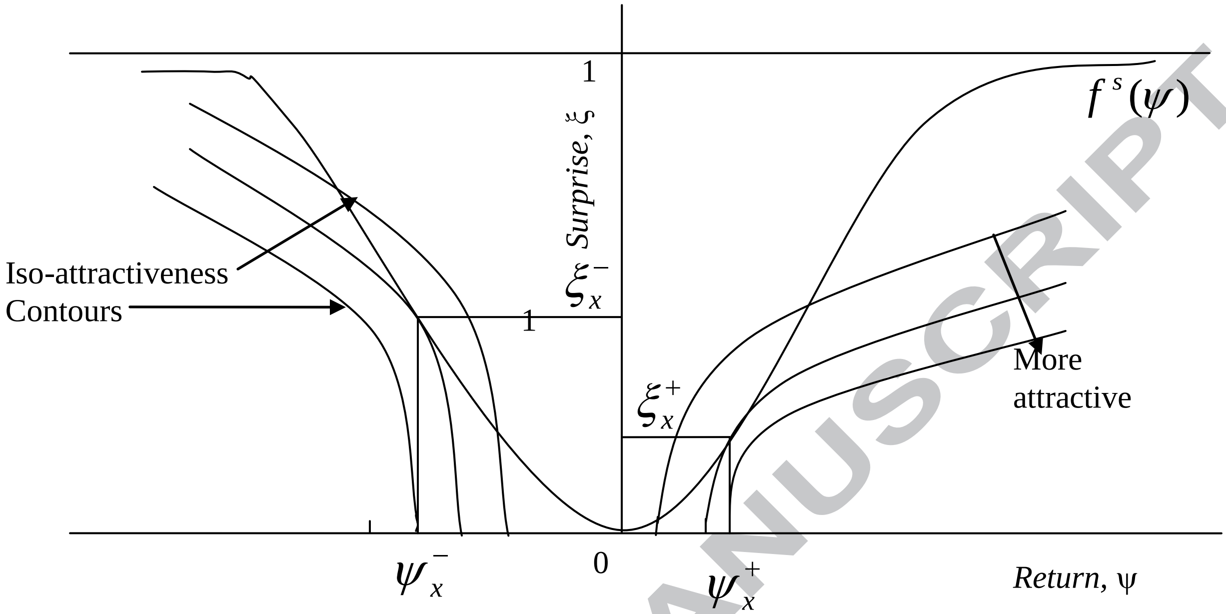
757 **Table III. Optimal tangency conditions under the constrained maximization**
758

Options	Potential surprise density in the gain (g) and loss (*l*) space
i = sw	$\psi_g = 0.1953 + \frac{b^{sw}}{0.8}$ $\psi_l = -\frac{6.2}{3.6} - \frac{1}{b^{sw}}$ $\xi_g = \left[0.8 * (0.1953 + \frac{b^{sw}}{0.8}) - b^{sw}\right]^2$ $\xi_l = (-6.2/3.6)^2$
i = dw	$\psi_g = \frac{0.4 + 2.08b^{dw}}{1.352}$ $\psi_l = \left[0.65(0.4 + 2.08b^{dw}) - b^{dw}\right]^2$ $\xi_g = \frac{1}{4.08096}\left[-0.2 - \frac{3.774}{b^{dw}}\right]$ $\xi_l = \left\{\frac{1.09}{4.08096}\left[-0.2 - \frac{3.774}{b^{dw}}\right] + \frac{1}{b^{dw}}\right\}^2$
i = swt	$\psi_g = \frac{0.4 + 0.56b^{swt}}{0.84}$ $\psi_l = \left[0.03\left\{\frac{0.4 + 0.56b}{0.84}\right\} - 0.2b^{dw}\right]^2$ $\xi_g = -\frac{1}{1.125}\left[0.2 + \frac{0.9}{b^{swt}}\right]$ $\xi_l = 0.2\left\{-\frac{1.25}{1.125}\left[0.2 + \frac{0.9}{b^{swt}}\right] + \frac{1}{b^{swt}}\right\}^2$

759

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT



Note: Attractiveness is maximized at the tangency point between potential surprise density and iso-attractiveness contour.

Figure 1. Constrained maximization of the attractiveness function in the potential surprise model

ACCEPTED MANUSCRIPT

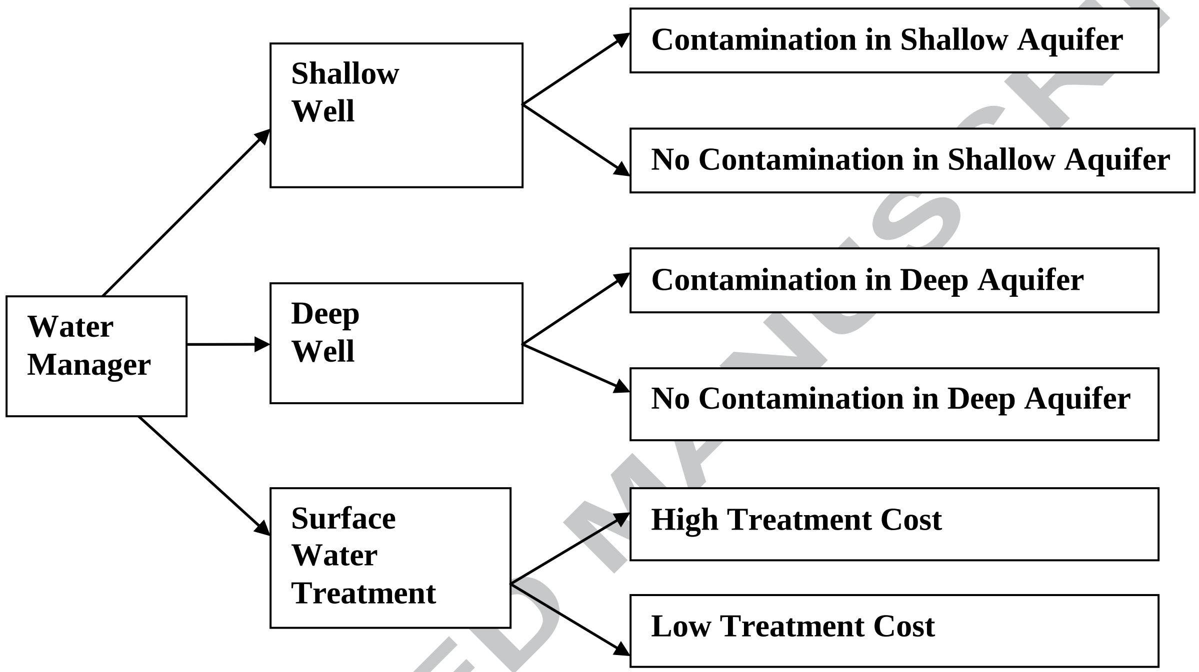


Figure 2. Options for water collection with corresponding potential outcomes

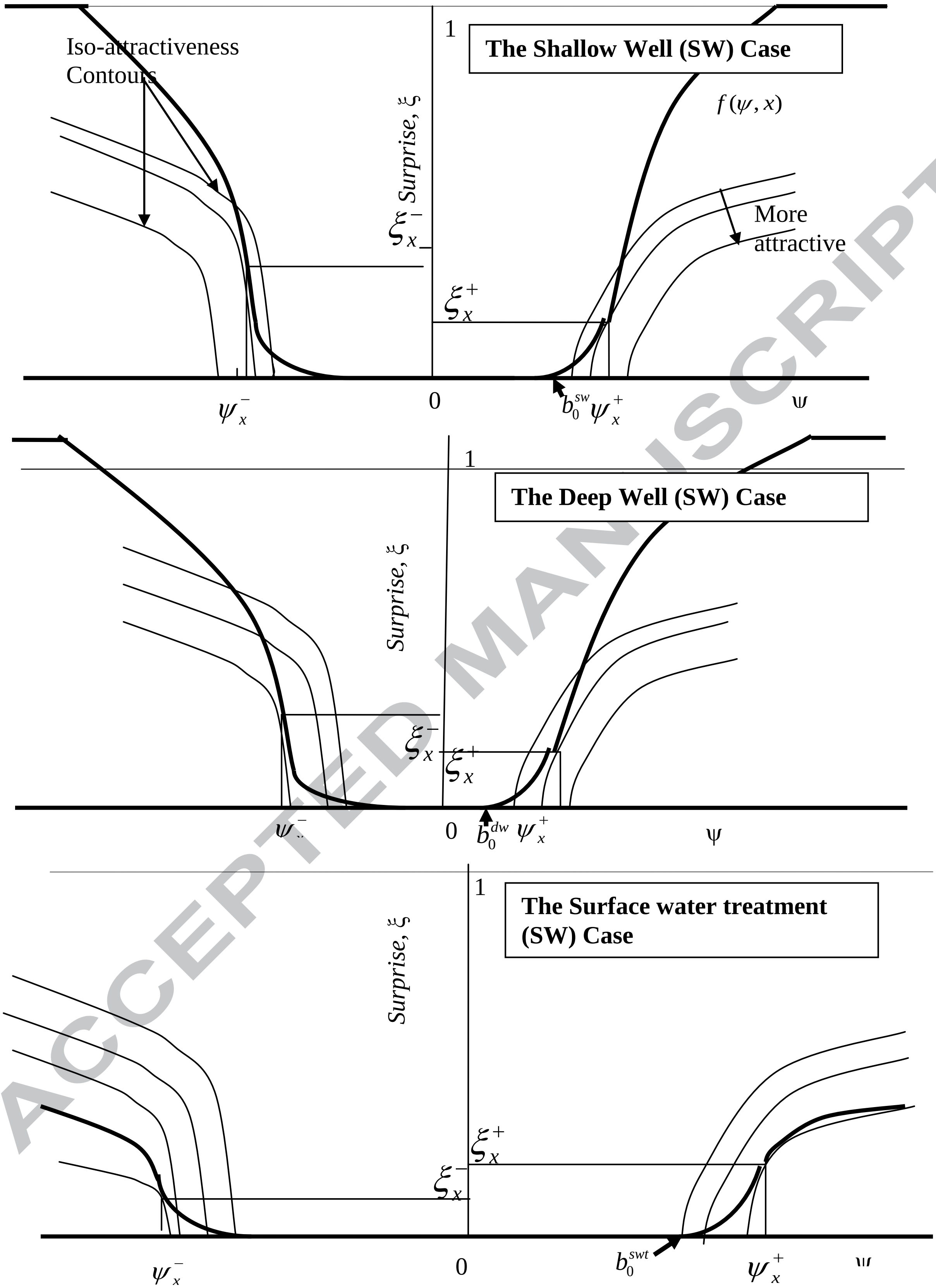


Figure 3. Potential surprise and attractiveness functions under three different options of shallow well (*sw*), deep well (*dw*), surface water treatment (*swt*).

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

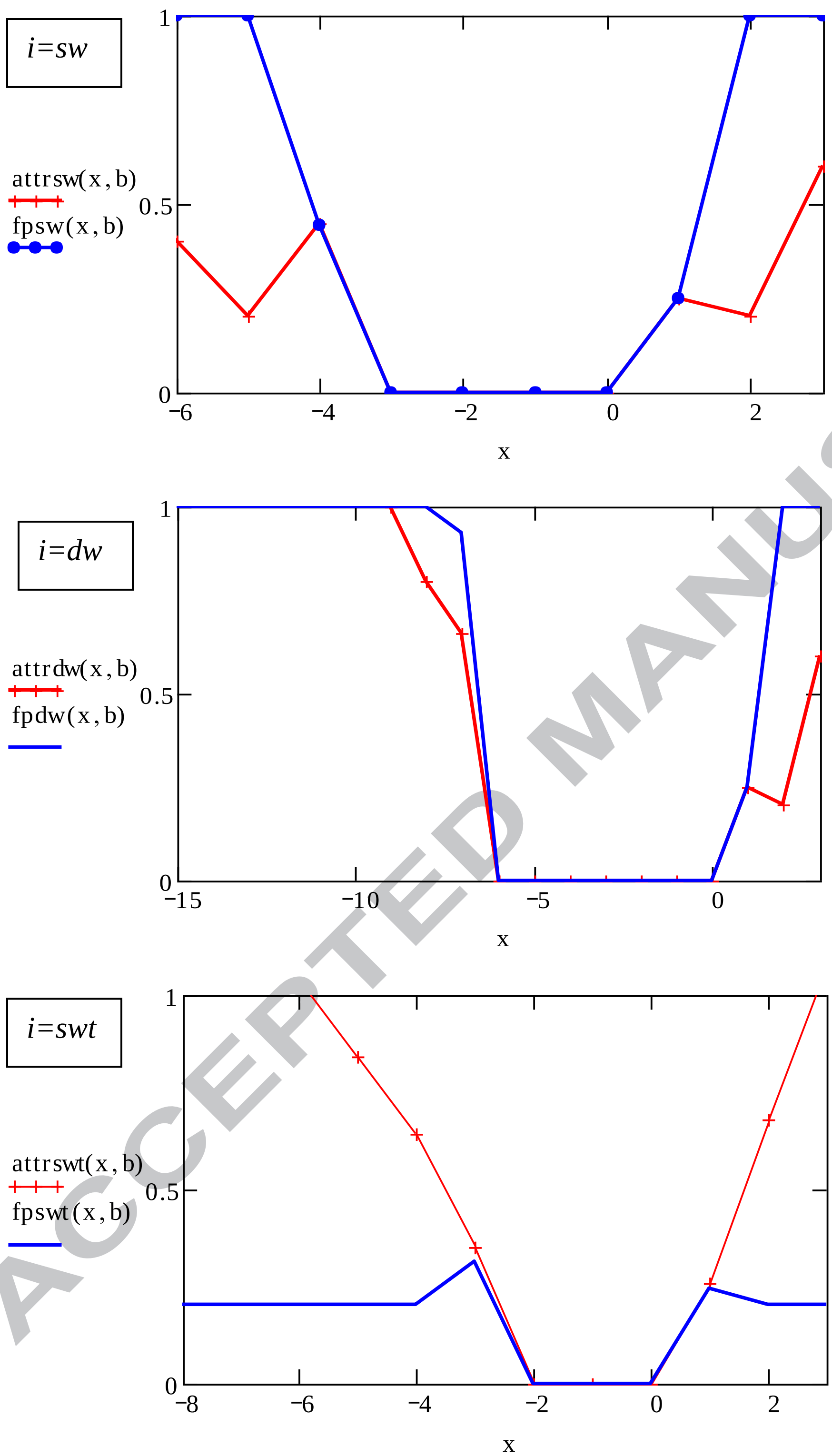


Figure 4. Simulated potential surprise and attractiveness functions under three different options of shallow well (*sw*), deep well (*dw*), surface water treatment (*swt*).

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

ACCEPTED MANUSCRIPT

Highlights

- There is a need for new approaches to uncertainty in water resources decisions
- New method to incorporate surprise potential and uncertainty into decision making
- Arsenic contamination is modeled in a nonlinear optimization framework
- Optimal investments need complex hydrologic and economic information

ACCEPTED MANUSCRIPT