Risk-Based Environmental Remediation: What's Past is Prologue

More Data Is Not Always Better – Using Weight of Evidence Approaches in Environmental Risk Characterization

November 16, 2017

SETAC North America 38th Annual Meeting

Minneapolis, MN

John Toll, Windward Environmental LLC

Spear RC, Hornberger GM, Resource ANUCf, Studies E. 1978. Eutrophication in Peel Inlet: An Analysis of Behaviour and Sensitivity of a Poorly-defined System. Australian National University Centre for Resource and Environmental Studies.

Risk-Based Environmental Remediation: What’s Past is Prologue

Risk-Based Environmental Remediation: What’s Past is Prologue

Numerical Bayesian assessment of whether or not to collect more data before making environmental remediation decisions

- Basic principals
- Perspective on today’s opportunities and challenges

Basic principles

Hornberger GM, Spear RC. 1980. Eutrophication in Peel Inlet I: Problem-defining behavior and a mathematical model for the phosphorous scenario. Water Res 14:29-42.

Spear RC, Hornberger GM. 1980. Eutrophication in Peel Inlet II: Identification of critical uncertainties via generalized sensitivity analysis. Water Res 14:43-49.

Dilks DW, Canale RP, Meier PG. 1992. Development of Bayesian Monte Carlo techniques for water quality model uncertainty. Ecol. Modell. 62:149-162.

Dakins ME, Toll JE, Small MJ, Brand K. 1995. Risk-based environmental remediation: Bayesian Monte Carlo analysis and the expected value of sample information. Risk Anal 16(1):67-69.

Basic principles

Hornberger GM, Spear RC. 1980. Eutrophication in Peel Inlet I: Problem-defining behavior and a mathematical model for the phosphorous scenario. Water Res 14:29-42.

Spear RC, Hornberger GM. 1980. Eutrophication in Peel Inlet II: Identification of critical uncertainties via generalized sensitivity analysis. Water Res 14:43-49.

Dilks DW, Canale RP, Meier PG. 1992. Development of Bayesian Monte Carlo techniques for water quality model uncertainty. Ecol. Modell. 62:149-162.

Dakins ME, Toll JE, Small MJ, Brand K. 1995. Risk-based environmental remediation: Bayesian Monte Carlo analysis and the expected value of sample information. Risk Anal 16(1):67-69.

Numerical Bayesian assessment of whether or not to collect more data before making environmental remediation decisions

Environmental Toxicology and Chemistry, Vol. 13, No. 12, pp. 1907–1915, 1994

Printed in the USA
0730-7268/94 $6.00 + .00

Pergamon

0730-7268(94)00138-3

Annual Review

RISK-BASED ENVIRONMENTAL REMEDIATION: DECISION FRAMEWORK AND ROLE OF UNCERTAINTY

MAXINE E. DAKINS,*† JOHN E. TOLL‡ and MITCHELL J. SMALL§
†Department of Civil and Environmental Engineering, University of Idaho, 1776 Science Center Drive, Idaho Falls, Idaho 83405
‡Risk Assessment and Risk Management Programs, Enserch Environmental Corporation, 10900 NE 8th St., Bellevue, Washington 98004
§Departments of Civil & Environmental Engineering and Engineering & Public Policy, Porter Hall 119, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213

(*Received 26 May 1993; Accepted 13 May 1994*)

Abstract – A methodology for incorporating uncertainty in model predictions into a risk-based decision for environmental remediation is illustrated, considering polychlorinated biphenyl (PCB) sediment contamination and uptake by winter flounder in New Bedford Harbor, Massachusetts. Sensitivity and uncertainty analyses are conducted for a model that predicts the sediment remediation volume required to meet a biota tissue concentration criterion. These evaluations help to identify the variables that most significantly contribute to uncertainty in the model prediction and allow for calculations of the expected value of including uncertainty (EVIU) and the expected value of perfect information (EVPI) for the remediation decision. The EVIU is the difference between the expected loss of a management decision based solely on a deterministic analysis and the expected loss of the optimal management decision that considers uncertainty. For the illustrative application to New Bedford Harbor, the expected loss avoided from performing an uncertainty analysis and using the resulting information to make the optimal management decision is approximately $20 million. The EVPI, the expected decrease in loss that can be achieved by having all uncertainty eliminated, is approximately $16 million.

Keywords – Uncertainty analysis Value of information Monte Carlo analysis Risk analysis New Bedford Harbor

Risk Analysis, Vol. 16, No. 1, 1996

Risk-Based Environmental Remediation: Bayesian Monte Carlo Analysis and the Expected Value of Sample Information

Maxine E. Dakins,[1,5] John E. Toll,[2] Mitchell J. Small,[3] and Kevin P. Brand[4]

Received January 5, 1995; revised September 25, 1995

A methodology that simulates outcomes from future data collection programs, utilizes Bayesian Monte Carlo analysis to predict the resulting reduction in uncertainty in an environmental fate-and-transport model, and estimates the expected value of this reduction in uncertainty to a risk-based environmental remediation decision is illustrated considering polychlorinated biphenyl (PCB) sediment contamination and uptake by winter flounder in New Bedford Harbor, MA. The expected value of sample information (EVSI), the difference between the expected loss of the optimal decision based on the prior uncertainty analysis and the expected loss of the optimal decision from an updated information state, is calculated for several sampling plan. For the illustrative application we have posed, the EVSI for a sampling plan of two data points is $9.4 million, for five data points is $10.4 million, and for ten data points is $11.5 million. The EVSI for sampling plans involving larger numbers of data points is bounded by the expected value of perfect information, $15.6 million. A sensitivity analysis is conducted to examine the effect of selected model structure and parametric assumptions on the optimal decision and the EVSI. The optimal decision (total area to be dredged) is sensitive to the assumption of linearity between PCB sediment concentration and flounder PCB body burden and to the assumed relationship between area dredged and the harbor-wide average sediment PCB concentration; these assumptions also have a moderate impact on the computed EVSI. The EVSI is most sensitive to the unit cost of remediation and rather insensitive to the penalty cost associated with under-remediation.

KEY WORDS: Bayesian Monte Carlo analysis; decision analysis; value of information; New Bedford Harbor; PCBs.

Numerical Bayesian assessment of whether or not to collect more data before making environmental remediation decisions

Pergamon

Environmental Toxicology and Chemistry, Vol. 13, No. 12, pp. 1907–1915, 1994

Printed in the USA
0730-7268/94 $6.00 + .00

0730-7268(94)00138-3

Annual Review

RISK-BASED ENVIRONMENTAL REMEDIATION: DECISION FRAMEWORK AND ROLE OF UNCERTAINTY

MAXINE E. DAKINS,*† JOHN E. TOLL‡ and MITCHELL J. SMALL§
†Department of Civil and Environmental Engineering, University of Idaho,
1776 Science Center Drive, Idaho Falls, Idaho 83405
‡Risk Assessment and Risk Management Programs, Enserch Environmental Corporation,
10900 NE 8th St., Bellevue, Washington 98004
§Departments of Civil & Environmental Engineering and Engineering & Public Policy,
Porter Hall 119, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213

(*Received* 26 *May* 1993; *Accepted* 13 *May* 1994)

Abstract — A methodology for incorporating uncertainty in model predictions into a risk-based decision for environmental remediation is illustrated, considering polychlorinated biphenyl (PCB) sediment contamination and uptake by winter flounder in New Bedford Harbor, Massachusetts. Sensitivity and uncertainty analyses are conducted for a model that predicts the sediment remediation volume required to meet a biota tissue concentration criterion. These evaluations help to identify the variables that most significantly contribute to uncertainty in the model prediction and allow for calculations of the expected value of including uncertainty (EVIU) and the expected value of perfect information (EVPI) for the remediation decision. The EVIU is the difference between the expected loss of a management decision based solely on a deterministic analysis and the expected loss of the optimal management decision that considers uncertainty. For the illustrative application to New Bedford Harbor, the expected loss avoided from performing an uncertainty analysis and using the resulting information to make the optimal management decision is approximately $20 million. The EVPI, the expected decrease in loss that can be achieved by having all uncertainty eliminated, is approximately $16 million.

Keywords — Uncertainty analysis   Value of information   Monte Carlo analysis   Risk analysis
New Bedford Harbor

Risk Analysis, Vol. 16, No. 1, 1996

Risk-Based Environmental Remediation: Bayesian Monte Carlo Analysis and the Expected Value of Sample Information

Maxine E. Dakins,[1,5] John E. Toll,[2] Mitchell J. Small,[3] and Kevin P. Brand[4]

Received January 5, 1995; revised September 25, 1995

A methodology that simulates outcomes from future data collection programs, utilizes Bayesian Monte Carlo analysis to predict the resulting reduction in uncertainty in an environmental fate-and-transport model, and estimates the expected value of this reduction in uncertainty to a risk-based environmental remediation decision is illustrated considering polychlorinated biphenyl (PCB) sediment contamination and uptake by winter flounder in New Bedford Harbor, MA. The expected value of sample information (EVSI), the difference between the expected loss of the optimal decision based on the prior uncertainty analysis and the expected loss of the optimal decision from an updated information state, is calculated for several sampling plan. For the illustrative application we have posed, the EVSI for a sampling plan of two data points is $9.4 million, for five data points is $10.4 million, and for ten data points is $11.5 million. The EVSI for sampling plans involving larger numbers of data points is bounded by the expected value of perfect information, $15.6 million. A sensitivity analysis is conducted to examine the effect of selected model structure and parametric assumptions on the optimal decision and the EVSI. The optimal decision (total area to be dredged) is sensitive to the assumption of linearity between PCB sediment concentration and flounder PCB body burden and to the assumed relationship between area dredged and the harbor-wide average sediment PCB concentration; these assumptions also have a moderate impact on the computed EVSI. The EVSI is most sensitive to the unit cost of remediation and rather insensitive to the penalty cost associated with under-remediation.

KEY WORDS: Bayesian Monte Carlo analysis; decision analysis; value of information; New Bedford Harbor; PCBs.

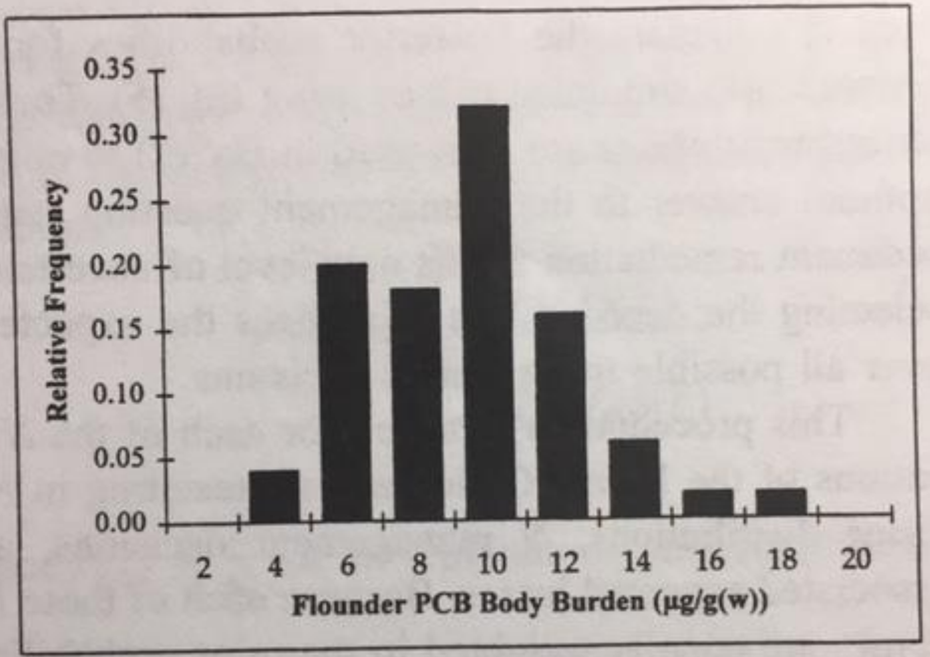


Fig. 1A. Histogram showing the prior probability distribution of total PCB body burden in 2-year-old flounder (μg/g(*w*)) in inner New Bedford Harbor, Massachusetts.[5]

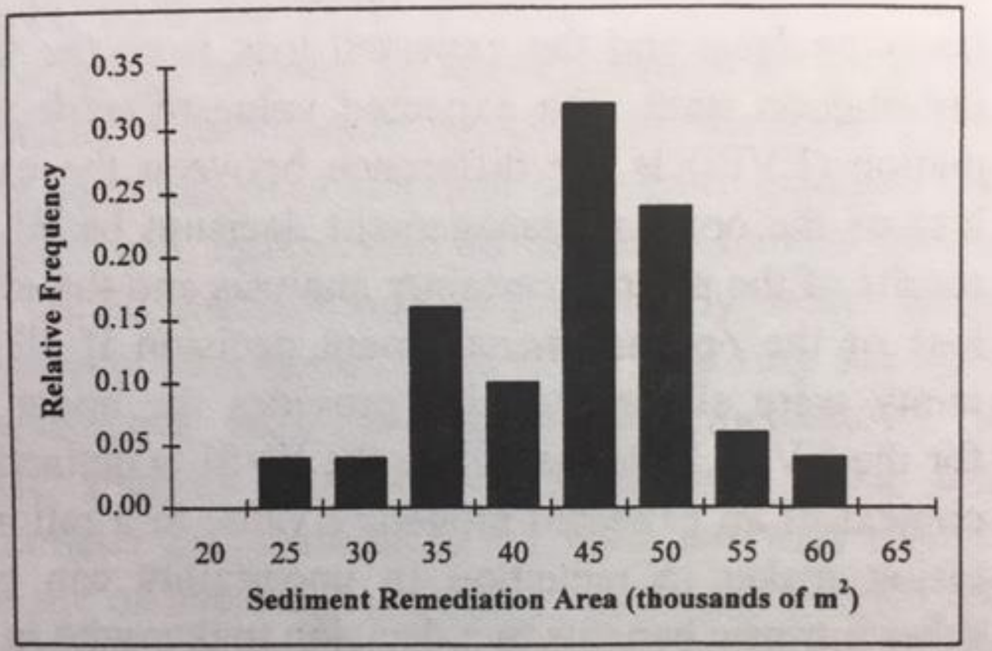


Fig. 1B. Histogram showing the required sediment remediation area (thousands of square meters) based on the probability distribution of total PCB body burden in 2-year-old flounder in inner New Bedford Harbor, Massachusetts.[5]

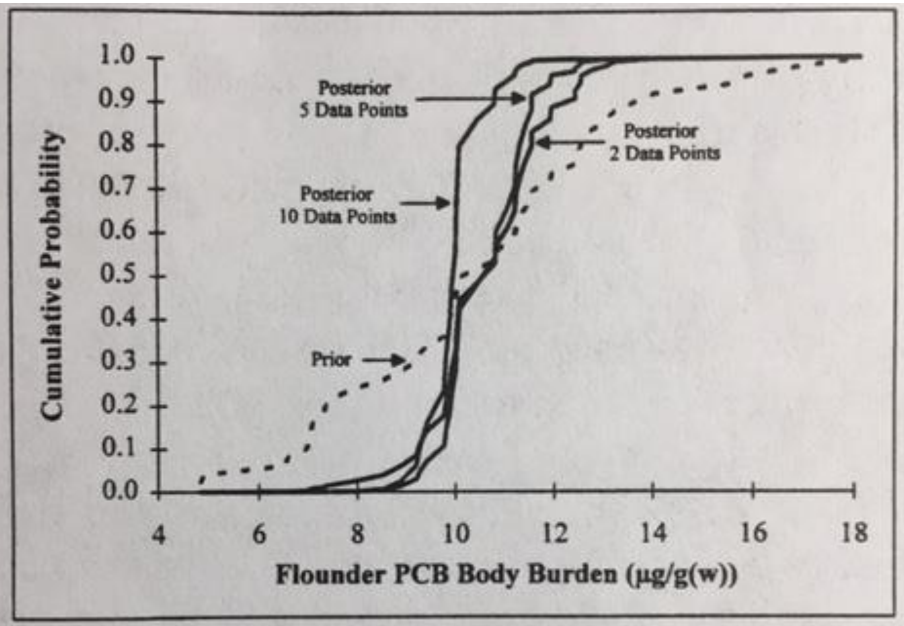


Fig. 2A. Cumulative probability distribution function for average total PCB body burden in 2-year-old flounder (µg/g(*w*)) at the prior information state and at several posterior information states for the Monte Carlo replication where predicted flounder PCB body burden is 10 µg/g(*w*).

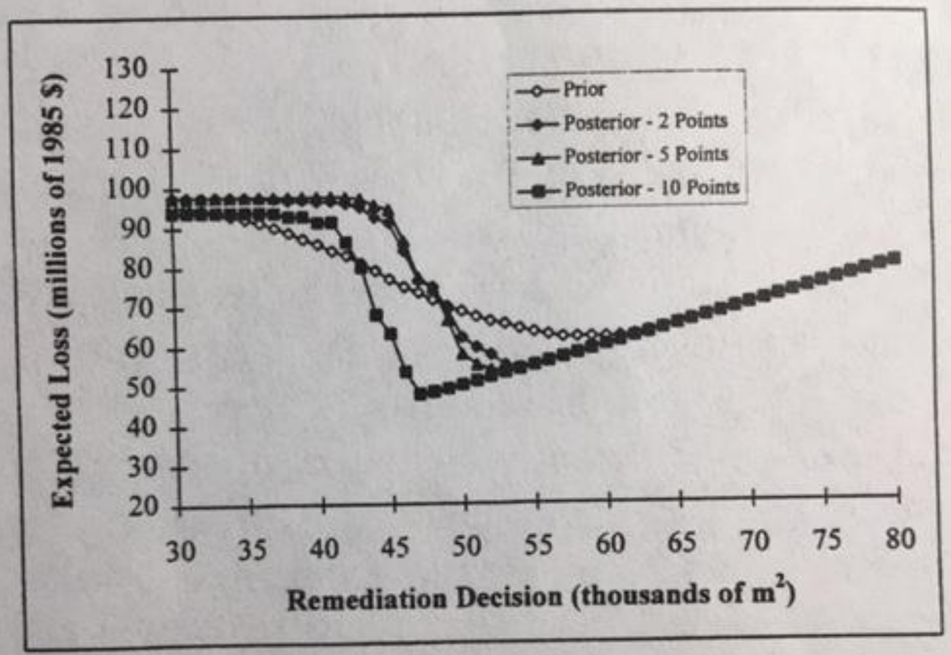


Fig. 2B. Expected loss curves at the prior information state and at several posterior information states for the Monte Carlo replication where predicted flounder PCB body burden is 10 µg/g(*w*).

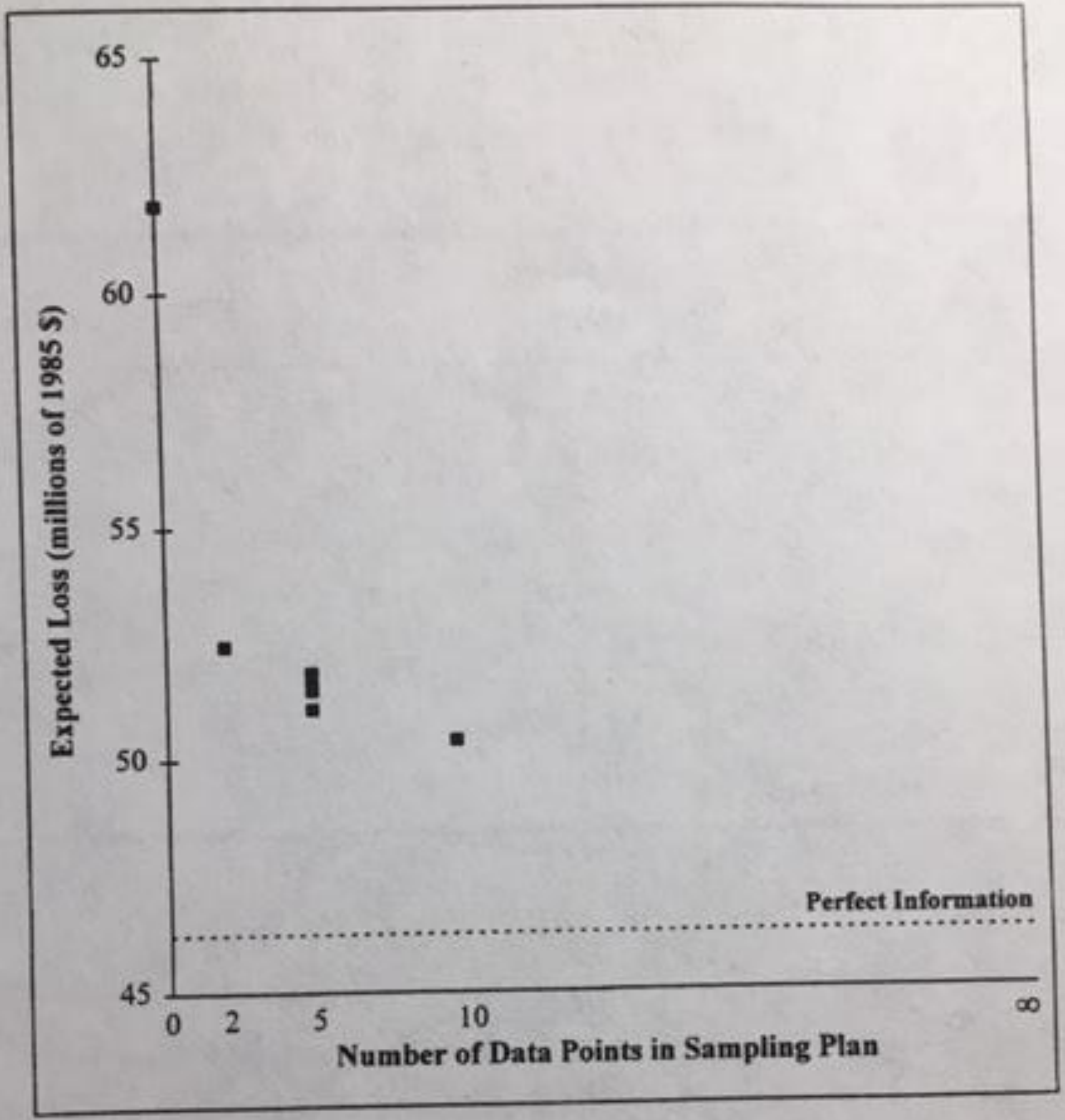


Fig. 3. Expected loss in millions of 1985 dollars for sampling plans involving zero, two, five, and ten data points. The dotted line shows the expected loss with perfect information.

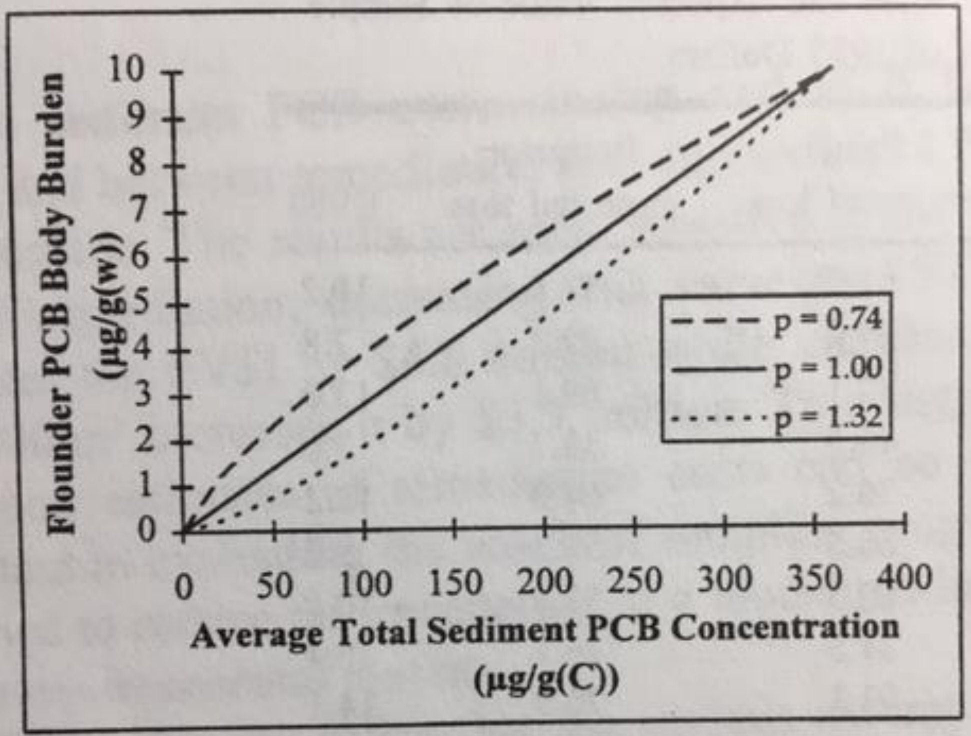


Fig. 4A. Possible relationships between average total PCB concentration in the sediment (µg/g(C)) and flounder PCB body burden (µg/g(w)).

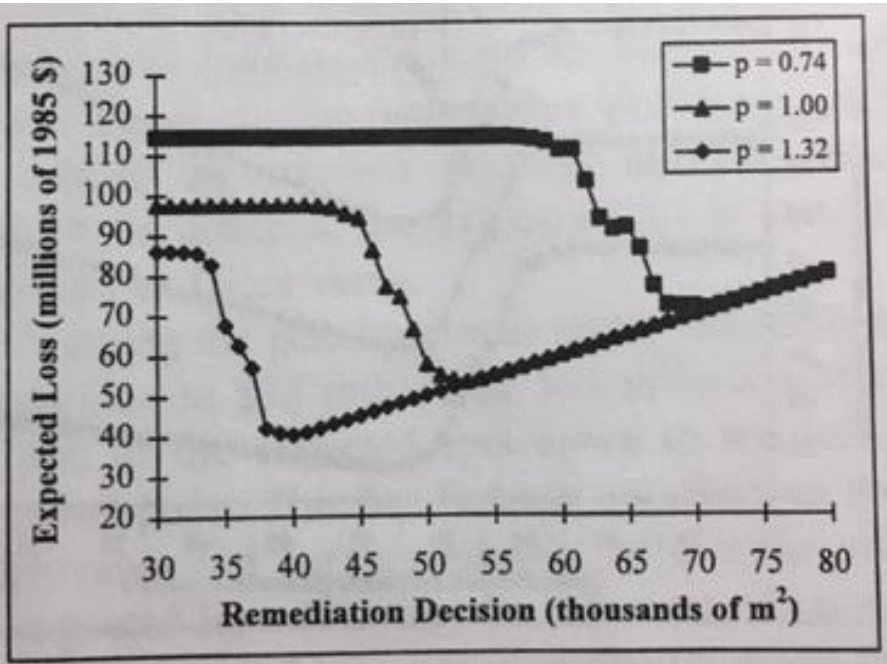


Fig. 4B. Effect of varying the relationship between PCB concentration in the sediment and flounder PCB body burden on the expected loss curves at the five-data-point posterior information state for the Monte Carlo replication where predicted flounder PCB body burden is 10 µg/g(w).

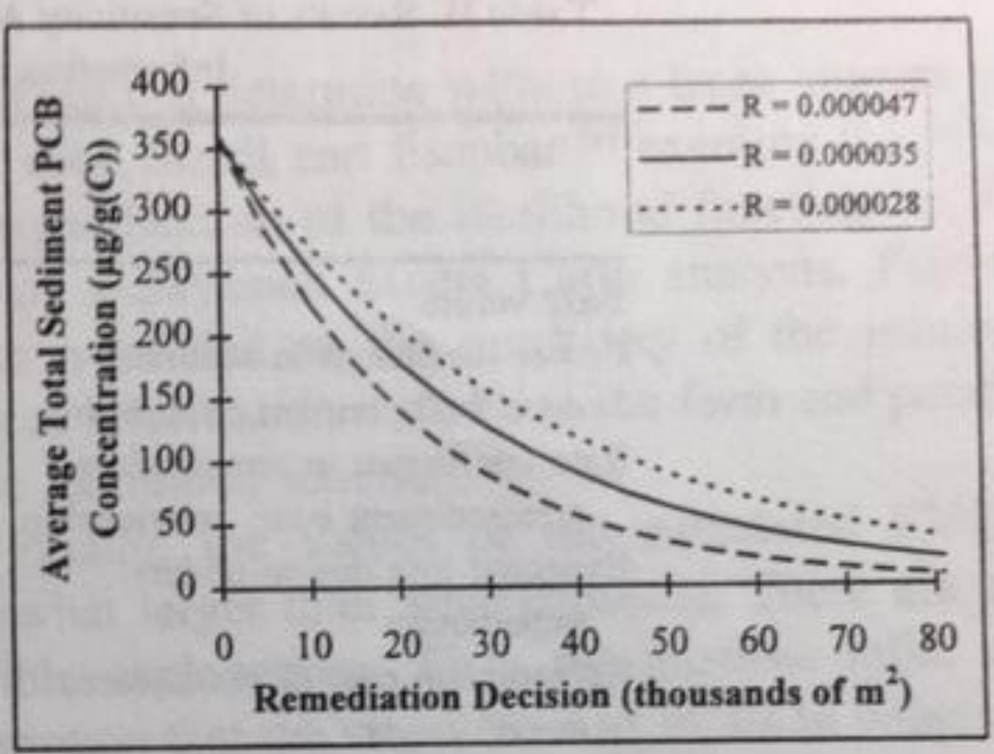


Fig. 4C. Possible relationships between sediment remediation area (thousands of square meters) and average total PCB concentration in the sediment (µg/g(*C*)).

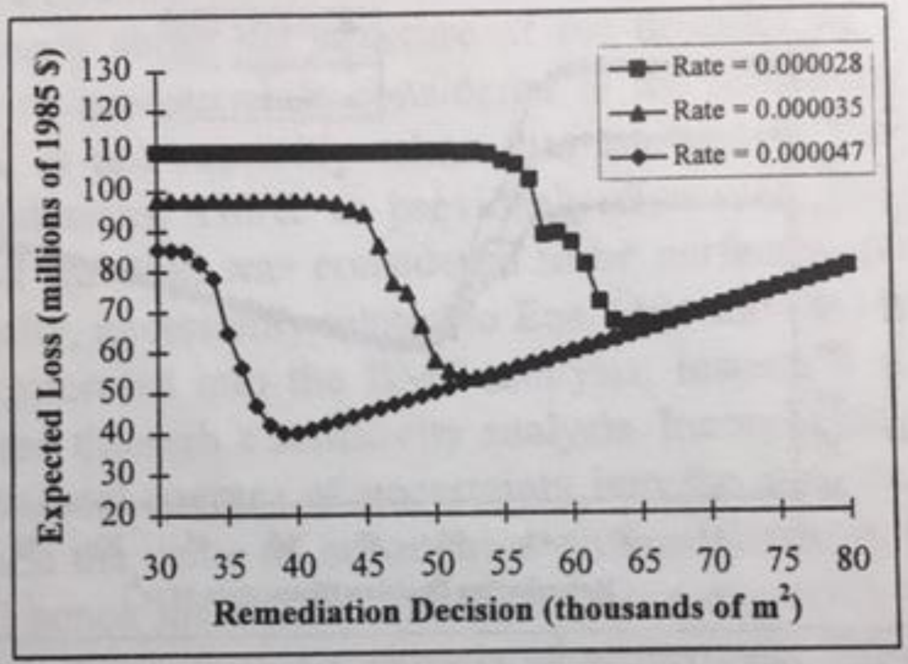


Fig. 4D. Effect of varying the relationship between sediment remediation area and PCB concentration in the sediment on the expected loss curves at the five-data-point posterior information state for the Monte Carlo replication where predicted flounder PCB body burden is 10 µg/g(*w*).

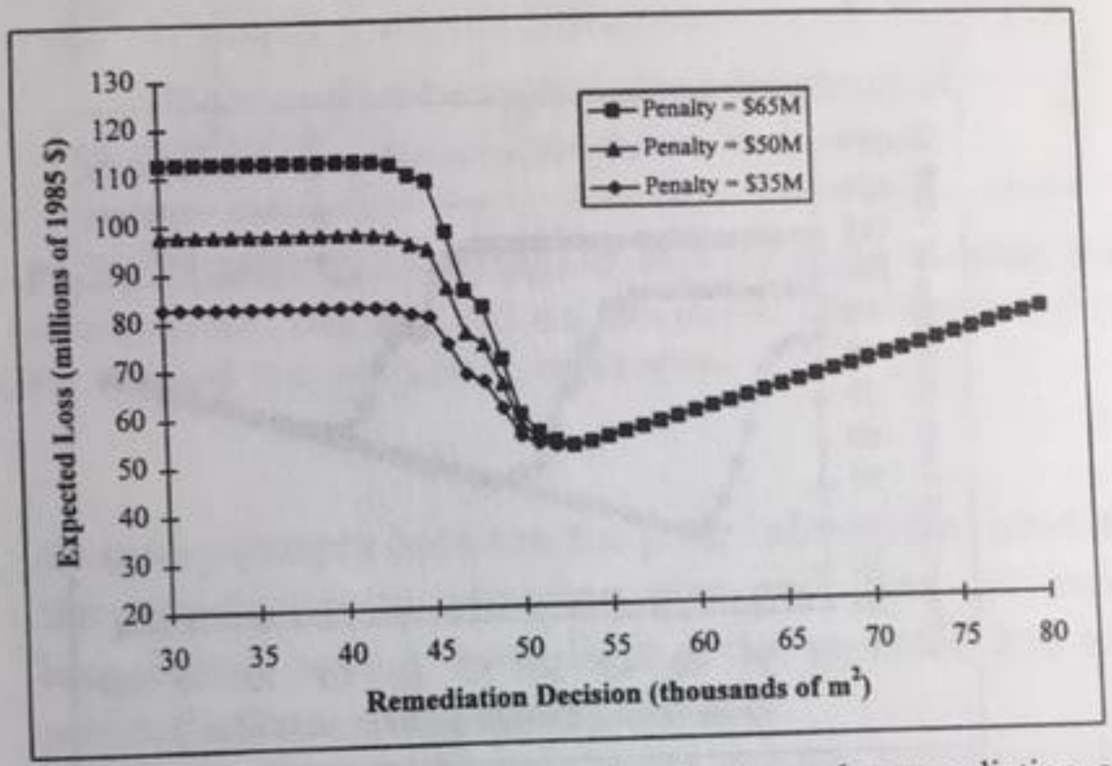


Fig. 5A. Effect of varying the penalty due to under-remediation on the expected loss curves at the five-data-point posterior information state for the Monte Carlo replication where predicted flounder PCB body burden is 10 μg/g(*w*).

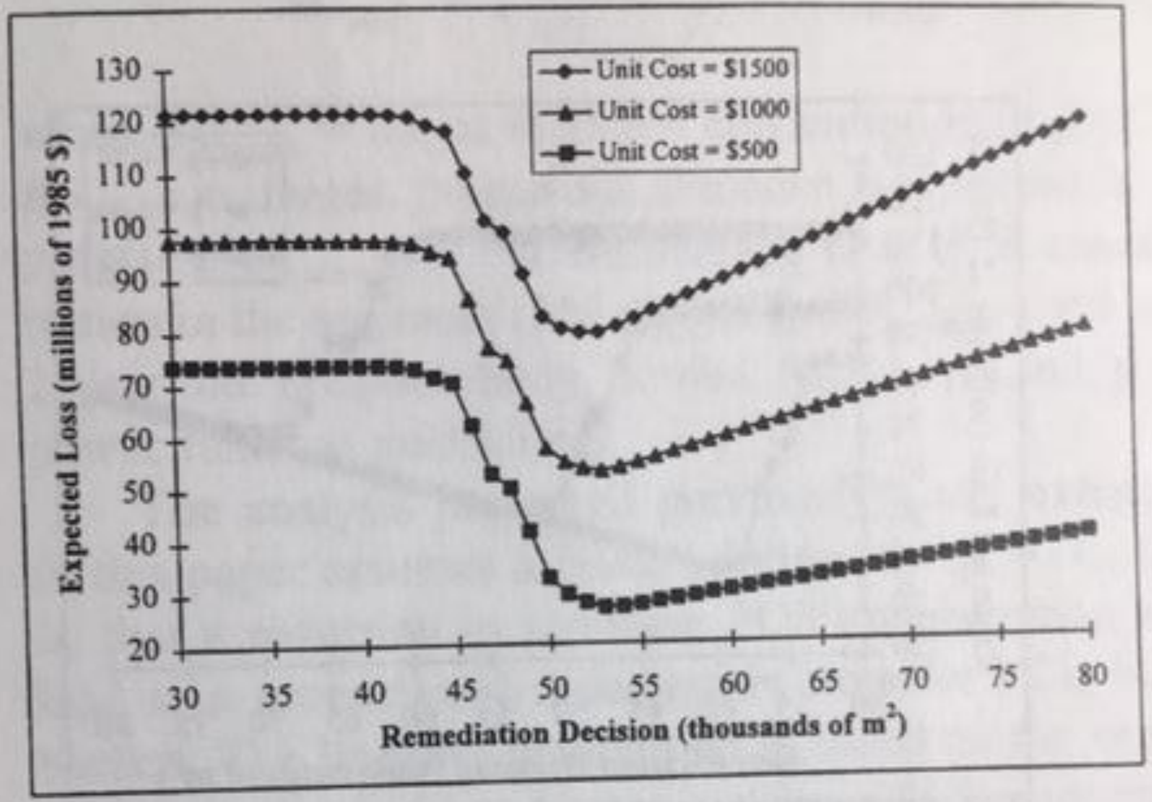
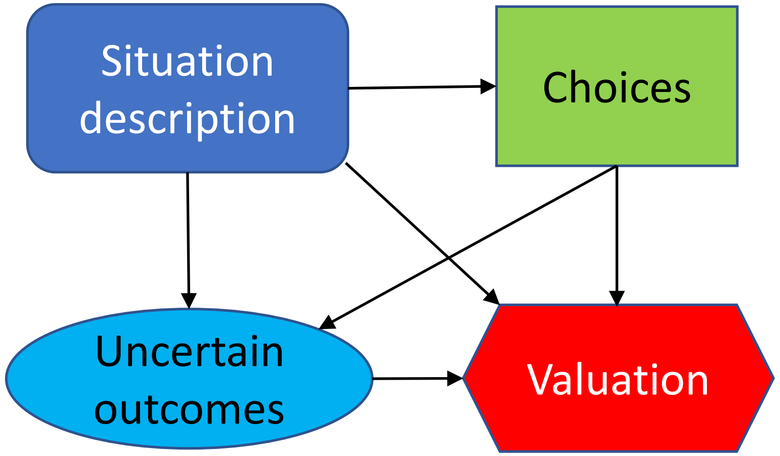


Fig. 5B. Effect of varying the unit remediation cost ($/m²) on the expected loss curves at the five-data-point posterior information state for the Monte Carlo replication where predicted flounder PCB body burden is 10 μg/g(*w*).

Perspective on today's opportunities and challenges

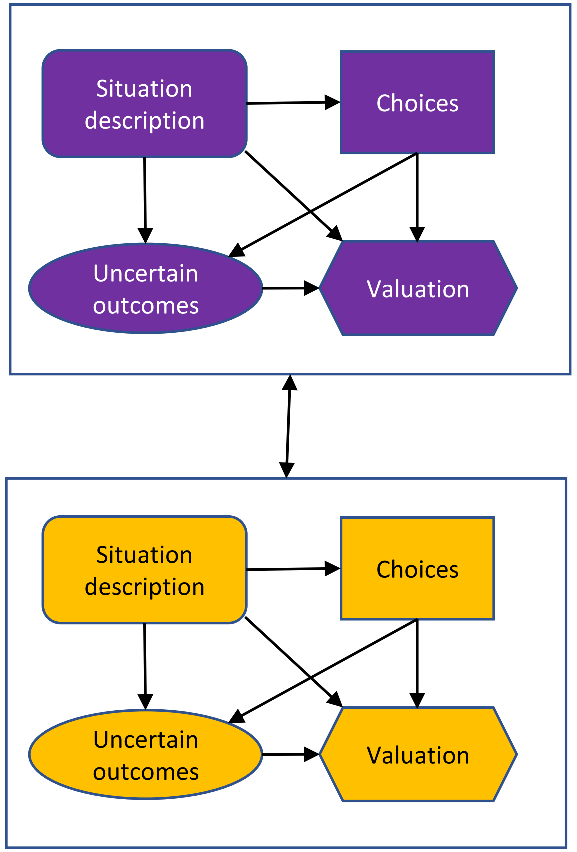
- Bayesian statistics
- Computational power
- Decision modeling tools
- Decision and predictive analytics



http://www.lumina.com/technology/influence-diagrams/

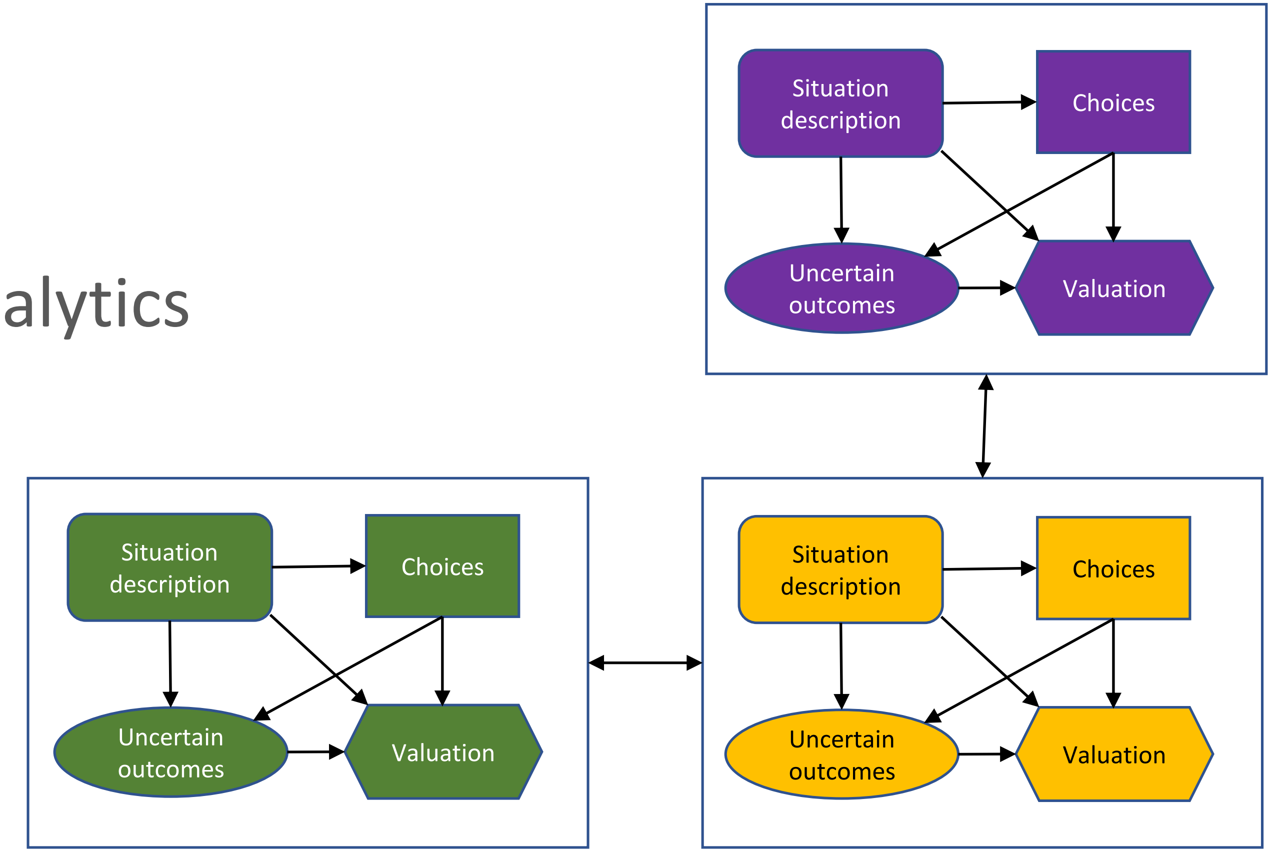
Perspective on today's opportunities and challenges

- Bayesian statistics
- Computational power
- Decision modeling tools
- Decision and predictive analytics
- Negotiation
- Compromise



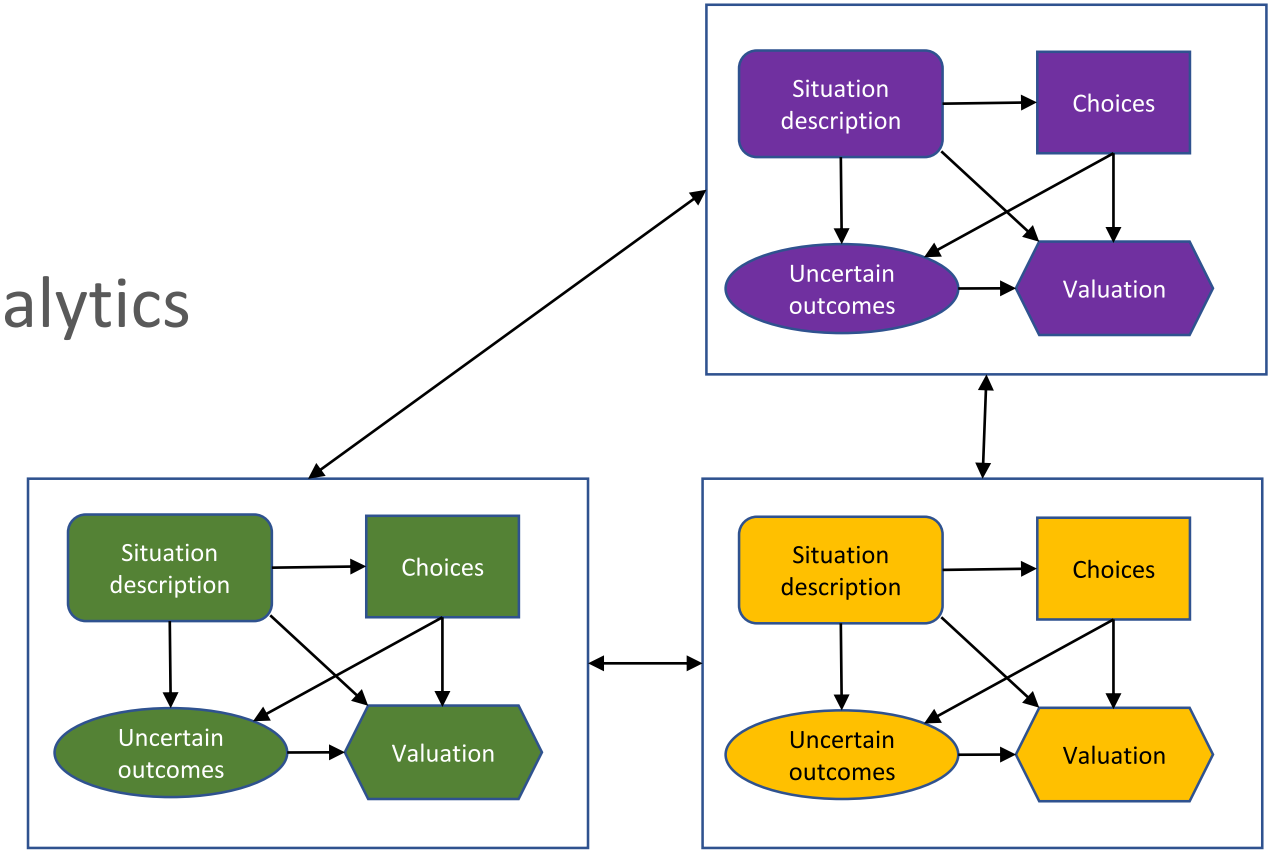
Perspective on today's opportunities and challenges

- Bayesian statistics
- Computational power
- Decision modeling tools
- Decision and predictive analytics
- Negotiation
- Compromise



Perspective on today's opportunities and challenges

- Bayesian statistics
- Computational power
- Decision modeling tools
- Decision and predictive analytics
- Negotiation
- Compromise



johnt@windwardenv.com
(206) 913-3292