Model-driven decision support for monitoring network design based on analysis of data and model uncertainties: methods and applications

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Outline

✧ Model-driven (model-based) decision support
✧ Probabilistic vs Non-Probabilistic Decision Methods
✧ Information Gap (info-gap) Decision Theory
✧ Information Gap (info-gap) Applications:
  o Monitoring Network Design
  o Contaminant Remediation through Source Control
✧ Decision Support for Chromium contamination site @ LANL

✧ MADS: Model Analyses & Decision Support
  Open source C/C++ computational framework
  Publications, examples & tutorials @
  http://mads.lanl.gov

✧ ASCEM: Advanced Subsurface Computing for Environmental Management; Multi-national lab code development project
  http://ascemdoe.org (U.S. DOE)
Model-driven (model-based) decision support

✧ provides decision makers (DM) with model analysis of decision scenarios taking into account site data and knowledge including existing uncertainties (uncertainties in conceptualization, model parameters, and model predictions)

✧ **Model analysis:** evaluation, ranking and optimization of alternative decision scenarios

✧ **Decision metric(s):** e.g. contaminant concentration at a monitoring well (environmental risk at a point of compliance)

✧ **Decision goal(s):** e.g. no exceedance of MCL at a compliance point and/or increase chance of detecting exceedance of MCL at a monitoring well

✧ **Decision scenarios:** combinations of predefined activities to achieve the decision goal(s)
Model-driven decision support (cont.)

✧ Activities:
  o data acquisition campaigns
  o field/lab experiments
  o monitoring
  o remediation

✧ Activities are analyzed in terms of their impact on decision making process (decision uncertainties)

✧ Decision uncertainties: uncertainties associated with selection of optimal decision scenarios, or performance of specific decision scenarios

✧ The Game: Decision maker (DM) vs Nature

Important:

✧ activities are selected only to reduce decision uncertainties

✧ activities are not selected to reduce model or parameter uncertainties per se (unconstrained problem).
Non-Probabilistic Decision Methods

✧ Lack of knowledge or information precludes decision analyses requiring unbiased probabilistic distributions or frequency of occurrence (e.g. Bayesian approaches)

✧ Severe uncertainties (black swans, dragon kings) can have important impact in the decision analyses

✧ Non-probabilistic decision methods can be applied to effectively incorporate lack of knowledge and severe uncertainties in decision making process
  - Minimax (Maximin) Theory (Wald, 1951)
  - Information Gap Decision Theory (Ben-Haim, 2006)
  - There is a controversy how different are these two theories

✧ Non-Probabilistic and Probabilistic methods can be coupled (e.g. unknown probability distribution parameters can be a subject of non-probabilistic analysis, e.g. info-gap)
Information Gap Decision Theory

✧ Nominal (“best”) model prediction intended for decision making (based on nominal / “best estimates” model parameter set)
✧ Decision metric(s) / performance goal(s)
✧ Decision scenarios: vector of alternative decisions $d$ to compare
✧ Info-Gap Uncertainty Model (info-gap uncertainty metric = $\alpha$)
  o energy bound (functional uncertainties: objective function, forcing functions, etc.)
  o envelope bound (domain uncertainties: model parameters, calibration targets, etc.)
  o nested sets of uncertain model entities ranked by the largest information gap $\alpha$ that can be included in the set
  o uncertain model entities: parameters, calibrations, functions, etc. with info-gap uncertainties
  o e.g. $U(\alpha, T) = \{ T: \text{abs}(T-T') < \alpha \}$ where $T'$ is a nominal values for uncertain model entities
✧ Model predictions $C(d)$ constrained by $U(\alpha, T)$

Information Gap Decision Theory

✧ Decision uncertainty is bounded by robustness and opportuneness functions

✧ Robustness function (immunity to failure of alternate decisions $d$)
  o defines the maximum horizon of uncertainty
  o $R(d) = \max\{ \alpha: \text{performance goal is satisfied} \}$
    e.g. $R(d) = \max\{ \alpha: (\max C(d)) < MCL \}$

✧ Opportuneness function (immunity to windfall of alternate decisions $d$)
  o defines the minimum horizon of uncertainty
  o $O(d) = \min\{ \alpha: \text{performance goal is satisfied} \}$
    e.g. $O(d) = \min\{ \alpha: (\min C(d)) < MCL \}$

✧ Analyses based on Decision Robustness and/or Decision Opportuneness:
  o Model selection
  o Remedy selection
  o Performance assessment
  o ...

Info-Gap Analysis: Model parameters

- Nominal parameter set
- Nominal prediction
- MCL
- Contaminant concentration [ppb]
Bayesian Analysis: Model parameters

- Parameter 1
- Parameter 2

Contaminant concentration [ppb]

- "Best" prediction
- MCL

Probability
Bayesian Analysis: Model parameters

"Best" parameter set

Contaminant concentration [ppb]

Probability

"Best" prediction

MCL
Bayesian Analysis: Model parameters

- **Best** parameter set

- The challenge is in tail characterization
Info-Gap Analysis: Model parameters (envelope bounds)

Nominal parameter set

Contaminant concentration [ppb]

Nominal prediction

MCL

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Model parameters (envelope bounds)

Info-gap uncertainty metric = $\alpha$

$\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$
Info-Gap Analysis: Model parameters (envelope bounds)

info-gap uncertainty metric = $\alpha$

$\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$
Info-Gap Analysis: Model parameters (envelope bounds)

Info-gap uncertainty metric = $\alpha$

$\alpha_1 < \alpha_2 < \alpha_3 < \alpha_4$
Info-Gap Analysis: Calibration Targets (envelope bounds)

Calibration target 1

Calibration target 2

Nominal calibration target

Contaminant concentration [ppb]

Nominal prediction

MCL

Nominal parameter set

Inversion

Parameter 1

Parameter 2

Info-gap uncertainty metric α

0.1 1 10 100

Contaminant concentration [ppb]
Info-Gap Analysis: Calibration Targets (envelope bounds)

- Nested calibration sets

- Calibration target 1

- Calibration target 2

- Contaminant concentration [ppb]

- Nominal prediction

- MCL

- Info-gap uncertainty metric $\alpha$

- Parameter 1

- Parameter 2

- Nominal parameter set

- Inversion
Info-Gap Analysis: Calibration Targets (envelope bounds)

Nested calibration sets

Parameter sets

Inversion

Nominal prediction

MCL

Contaminant concentration [ppb]

Info-gap uncertainty metric $\alpha$

- Calibration target 1
- Calibration target 2

- Inversion

- Parameter sets

- Nested calibration sets

- Info-gap analysis

- Nominal prediction

- MCL

- Contaminant concentration [ppb]
Info-Gap Analysis: Calibration Targets (envelope bounds)

Nested calibration sets

Parameter sets

Calibration target 1

Calibration target 2

Inversion

Parameter 1

Parameter 2

Info-gap uncertainty metric $\alpha$

Contaminant concentration [ppb]

Nominal prediction

MCL

$\min\{\alpha_1 \cdot C\}$

$\min\{\alpha_2 \cdot C\}$

$\min\{\alpha_3 \cdot C\}$

$\max\{\alpha_1 \cdot C\}$

$\max\{\alpha_2 \cdot C\}$

$\max\{\alpha_3 \cdot C\}$

Calibration Target 1

Calibration Target 2

Contaminant concentration 

MCL

Nominal prediction

Info-gap uncertainty metric $\alpha$

Parameter 1

Parameter 2

Nested calibration sets

Parameter sets

Calibration target 1

Calibration target 2

Inversion

Contaminant concentration [ppb]

Nominal prediction

MCL

$\min\{\alpha_1 \cdot C\}$

$\min\{\alpha_2 \cdot C\}$

$\min\{\alpha_3 \cdot C\}$

$\max\{\alpha_1 \cdot C\}$

$\max\{\alpha_2 \cdot C\}$

$\max\{\alpha_3 \cdot C\}$

Calibration Target 1

Calibration Target 2

Contaminant concentration [ppb]
Info-Gap Analysis: Decision selection based on robustness

Contaminant concentration [ppb]

Nominal prediction

MCL

Info-gap uncertainty metric $\alpha$

Opportuneness function

Robustness
Info-Gap Analysis: Decision selection based on robustness

- Gap uncertainty metric $\alpha$
- Contaminant concentration [ppb]
- Nominal prediction
- “Strong” robustness
- MCL
Info-Gap Analysis: Decision selection based on robustness

Contaminant concentration [ppb]

Nominal prediction

MCL

“Strong” robustness

“Weak” robustness

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on robustness

Contaminant concentration [ppb]

Nominal prediction

“Strong” robustness

“Weak” robustness

MCL

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on robustness

- Gap uncertainty metric $\alpha$
- Nominal prediction
- Contaminant concentration [ppb]
- MCL
- "Strong" robustness
- "Weak" robustness
Info-Gap Analysis: Decision selection based on robustness
Info-Gap Analysis: Model selection based on robustness.

Nominal prediction

"Strong" robustness

"Weak" robustness

MCL

Contaminant concentration [ppb]

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Model selection based on robustness

Nominal prediction

“Strong” robustness

MCL

“Weak” robustness

Contaminant concentration [ppb]
Info-Gap Analysis: Model selection based on robustness

Model complexity (representativeness)
Model 1 < Model 2 < Model 3

Contaminant concentration [ppb]

Nominal prediction
“Strong” robustness

Info-gap uncertainty metric $\alpha$

"Weak" robustness

Model 1 < Model 2 < Model 3
Info-Gap Analysis: Model selection based on robustness

Model complexity (representativeness)
Model 1 < Model 2 < Model 3

Contaminant concentration [ppb]

Nominal prediction

“Strong” robustness

“Weak” robustness

MCL

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on opportuneness

Contaminant concentration [ppb]

MCL
Nominal prediction

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on opportuneness

Contaminant concentration [ppb]

MCL

Nominal prediction

“Weak” opportuneness

Decision 1

Decision 2

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on opportuneness

Contaminant concentration [ppb]

MCL

Nominal prediction

“Weak” opportuneness

“Strong” opportuneness

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision selection based on opportuneness

Contaminant concentration [ppb]

MCL

Nominal prediction

“Weak” opportuneness

Decision 1

Decision 2

“Strong” opportuneness

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision uncertainty

... duality of decision uncertainty

Contaminant concentration [ppb]

Nominal prediction

MCL

Info-gap uncertainty metric $\alpha$

propitious

pernicious

Opportuneness

Robustness
Info-Gap Analysis: Decision uncertainty

... not preferred decision bounds

Contaminant concentration [ppb]

Nominal prediction

MCL

“Weak” Robustness

“Weak” Opportunities

Info-gap uncertainty metric $\alpha$
Info-Gap Analysis: Decision uncertainty

... preferred decision bounds

Contaminant concentration [ppb]

Nominal prediction

MCL

Info-gap uncertainty metric $\alpha$

“Strong” Robustness

“Strong” Opportuneness
Info-Gap Application: Case 1

Optimization of monitoring network
Info-Gap Analysis: Network Design

✧ Two monitoring wells in an aquifer with contaminant concentrations above MCL (5 ppm)
✧ Background concentration = 0.5 ppm

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

- 4 new proposed monitoring well locations
- Which well has the highest immunity to fail in detection contaminants above MCL?

MCL = 5  Background = 0.5
Info-Gap Analysis: Network Design

Where is the contaminant source?

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

_where is the contaminant source?_

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

✨ Where is the contaminant source?

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

Where is the contaminant source?

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

MCL > 5

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

MCL = 5 Background = 0.5
**Info-Gap Analysis: Network Design**

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

MCL > 5

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

MCL = 5 Background = 0.5
Info-Gap Analysis: Network Design

• Analytical contaminant flow model:
  o 3D steady-state uniform groundwater flow in unbounded aquifer
  o 3D contaminant source at the top of the aquifer
  o 3D contaminant migration (advection, dispersion)

• Deterministic model parameters
  o contaminant flux at the contaminant source
  o contaminant arrival time
  o groundwater velocity
  o source thickness ($z_s = 1$ m)
Info-Gap Analysis: Network Design

- Unknown model parameters (8):
  - source coordinates \((x, y)\)
  - source size \((x_s, y_s)\)
  - flow direction
  - aquifer dispersivities (longitudinal, horizontal/vertical transverse)

- Uncertain observations (calibration targets) (10):
  - concentrations at the monitoring wells

- Unknown model parameters estimated using inversion

- Impact of uncertainty in calibration targets on model parameters is estimated using info-gap analyses

- Robustness and opportuneness functions associated with predicted contaminant concentrations at the proposed new well locations are applied for decision analyses

- Decision question: which of the new proposed well location has the highest immunity of failure/windfall to detect concentrations above MCL \((c > 5 \text{ ppm})\)
  i.e. which well provides the most robust/opportune decision to improve the monitoring network
Info-Gap Analysis: Network Design

- Calibration targets are highly uncertain (PDF’s cannot be defined) due to:
  - measurement errors
  - uncertain background concentrations
  - uncertain local hydrogeological and geochemical conditions
Info-Gap Analysis: Network Design

Predicted concentrations vs Info-gap uncertainty

Nominal = opportuness

robustness

MCL = 5 Background = 0.5

MCL

Wb

Wc

Wa

W1

0.5

W7

0.5

Wb

W10

0.5

W4

100

W3

40

Wa

W6

0.5

W8

0.5

Wd

W2

0.5

W9

0.5

Wc

0.5

W8

0.5

0.5

MCL = 5 Background = 0.5
Predicted concentrations vs Info-gap uncertainty

Info-Gap Analysis: Network Design

MCL = 5 Background = 0.5
Info-Gap Application: Case 2

Remediation of contamination in a aquifer through contaminant source control

Harp & Vesselinov (2011). Contaminant remediation decision analysis using information gap theory. SERRA.
Simple contaminant remediation problem:

- how much contaminant mass needs to be removed to satisfy compliance requirement $C(x', t) < \text{MCL}$
- lack of probabilistic (frequency of occurrence) information about the contaminant mass flux to aquifer $I(t)$

Harp & Vesselinov (2011). Contaminant remediation decision analysis using information gap theory. SERRA.
Info-Gap Analysis: Remediation of contaminant source

\[ I(t) = 1000 \exp(-0.05t) \]

Contaminant mass flux to the aquifer \( I(t) \)

Time since contaminant release [a]
Info-Gap Analysis: Remediation of contaminant source

Contaminant mass flux uncertainty bounds

info-gap uncertainty metric = \( \alpha \)
Info-Gap Analysis: Remediation of contaminant source

Contaminant mass flux plausible scenarios (energy bound)
Info-Gap Analysis: Remediation of contaminant source

\[ I(t) = 1000 \ (1-q) \ \exp(-0.05t) \]

Fraction of contaminant mass removed \( q \)

0.0
0.1
0.5
0.9

Contaminant flux [kg/m/a]

0
200
400
600
800
1000

0
10
20
30

Time since contaminant release [a]
Info-Gap Analysis: Remediation of contaminant source

Decision robustness defines how much contaminant mass should be removed and still be immune to failure considering lack of information about the contaminant mass flux.

Infinite robustness is achieved when all the contaminant mass is removed.
Info-Gap Analysis: Remediation of contaminant source

Decision robustness varies (increases/decreases) with the time since remediation; $\alpha_{\text{min}}$ (dashed line) defines the minimum robustness for a given fraction of the mass removed.

Infinite robustness is achieved when all the mass is removed.

Decision robustness increases with the fraction of mass removed.

Fraction of the contaminant mass removed

No mass removed

All mass removed

Time since contaminant release

$t = 1a$ $t = 2a$ $t = 3a$ $t = 5a$ $t = 10a$ $t = 30a$ $\hat{\alpha}_{\text{min}}$
Chromium plume in the regional aquifer at LANL

GOALS:

✧ provide model-based decision support related to chromium transport in the vadose zone and regional aquifer at LANL
✧ apply advanced computationally efficient methods for:
  o parameter estimation (PE)
  o model calibration
  o model-based uncertainty quantification (UQ)
  o risk analysis (RA), and
  o decision support (DS)
✧ utilize high-performance computing due to high computational demands for model simulations and model analyses
Chromium plume in the regional aquifer at LANL
Chromium plume in the regional aquifer at LANL

Vadose zone monitoring wells
Chromium plume in the regional aquifer at LANL

Los Alamos National Laboratory

Vadose zone monitoring wells
Regional monitoring wells

San Ildefonso Pueblo
Chromium plume in the regional aquifer at LANL

Supply wells
Regional monitoring wells
Vadose zone monitoring wells
Chromium plume in the regional aquifer at LANL

Supply wells
Regional monitoring wells
Vadose zone monitoring wells

Cr concentrations (~2012) [ppb]
MCL = 5 ppb
Background 5-8 ppb

Los Alamos National Laboratory
Los Alamos Canyon
San Ildefonso Pueblo
Water supply well PM-3

Vadose zone (~300 m)

Los Alamos Canyon

Sandia Canyon

Mortandad Canyon

Ground surface

Regional Aquifer

LANL boundary

1 km
Water supply well PM-3

Los Alamos Canyon

Sandia Canyon

Mortandad Canyon

Ground surface

Perched Groundwater

Vadose zone (~300 m)

Regional Aquifer

LANL boundary

1 km
Cr\(^{6+}\) ~54,000 kg

Water supply well PM-3
Cr$^{6+}$

~54,000 kg

Wetland

Los Alamos Canyon

Sandia Canyon

Mortandad Canyon

Ground surface

Perched Groundwater

Regional Aquifer

Vadose zone (~300 m)

1 km

Water supply well PM-3

LANL boundary
**Water supply well PM-3**

**Vadose zone (~300 m)**

**Los Alamos Canyon**

**Sandia Canyon**

**Mortandad Canyon**

**Ground surface**

**Perched Groundwater**

**Regional Aquifer**

**LANL boundary**

**Wetland**

$\text{Cr}^{6+} \sim 54,000 \text{ kg}$

$\text{Cr}^{3+} \sim 15,000 \text{ kg}$
Water supply well PM-3

Vadose zone (~300 m)

Los Alamos Canyon

Los Alamos

Cr$^{6+}$ ~54,000 kg

Cr$^{3+}$ ~15,000 kg

Sandia Canyon

Cr$^{3+}$ ~3,000 kg

Mortandad Canyon

Wetland

Ground surface

Perched Groundwater

Regional Aquifer

LANL boundary

Water supply well PM-3

1 km
Water supply well PM-3

Vadose zone (~300 m)

Los Alamos Canyon

Sandia Canyon

Mortandad Canyon

Ground surface

Perched Groundwater

Regional Aquifer

Cr$_6^+$ ~54,000 kg

Cr$_{3+}$ ~5,600 kg

Cr$_{3+}$ ~17,000 kg

Cr$_{3+}$ ~3,000 kg

Cr$_{3+}$ ~15,000 kg
\[\text{Cr}^{6+} \approx 54,000 \text{ kg}\]
\[\text{Cr}^{3+} \approx 15,000 \text{ kg}\]
\[\text{Cr}^{6+} \approx 5,600 \text{ kg}\]
\[\text{Cr}^{3+} \approx 3,000 \text{ kg}\]
\[\text{Cr}^{6+} \approx 230 \text{ kg}\]
\[\text{Cr}^{3+} \approx 2 \text{ kg}\]


Water supply well PM-3

Vadose zone (~300 m)

Cr$^{6+}$ ~54,000 kg

Cr$^{3+}$ ~15,000 kg

Sandia Canyon

Cr$^{3+}$ ~3,000 kg

Los Alamos Canyon

Wetland

Mortandad Canyon

Ground surface

Perched Groundwater

Regional Aquifer

Cr$^{6+}$ ~5,600 kg

Cr$^{3+}$ ~17,000 kg

Cr$^{6+}$ ~230 kg

Cr$^{3+}$ ~2 kg

Cr$^{6+}$ ~3,000 kg

Cr$^{3+}$ ~9,000 kg

1 km

LANL boundary

Water supply well PM-3
2009 model estimate of the plausible contaminant concentrations [ppb] along the regional aquifer water table

✧ Wells R-62, R-61 and R-50 were not drilled yet
✧ Locations of wells R-62, R-61 and R-50 were optimized based on model analyses
✧ Observed concentrations at R-62, R-61 and R-50 confirmed model predictions
✧ R-43 concentration were at background when the analyses were performed
✧ Since 2010, R-43 concentrations are increasing and approaching the model predicted concentration

MCL = 50 ppb
2009 model estimate of the plausible contaminant concentrations [ppb] along the regional aquifer water table

- Wells R-62, R-61 and R-50 were not drilled yet
- Locations of wells R-62, R-61 and R-50 were optimized based on model analyses
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2009 model estimate of the plausible contaminant concentrations [ppb] along the regional aquifer water table

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✧ Since 2010, R-43 concentrations are increasing and approaching the model predicted concentration
MADS is applied to perform all the presented info-gap decision analyses ...
an open-source high-performance computational framework for analyses and decision support based on complex process models

advanced adaptive computational techniques:
- sensitivity analysis (local / global);
- uncertainty quantification (local / global);
- optimization / calibration / parameter estimation (local / global);
- model ranking & selection
- decision support (GLUE, info-gap)

novel algorithms
- Agent-Based Adaptive Global Uncertainty and Sensitivity (ABAGUS)
- Adaptive hybrid (local/global) optimization strategy (Squads)

internal coupling with analytical contaminant transport solvers and test problems
external coupling with existing process simulators (ModFlow, TOUGH, FEHM, eSTOMP, Amanzi, ...)

Source code, examples, performance comparisons, and tutorials @ http://mads.lanl.gov
Advanced Subsurface Computing for Environmental Management

- an open-source interactive decision support system (Akuna/Agni) coupled a process simulator (Amanzi)
- high-performance computing (HPC)
- data- and model-driven decision support to provide standardized, consistent, site-specific and scientifically defensible decision analyses across DOE-EM complex

Challenge:
- develop tools to make better use of complex information and capabilities to explore problems in greater detail
- address the most challenging performance assessment and waste-disposal problems

Impact:
- provide technical underpinnings for current U.S. DOE-EM risk and performance assessments
- inform strategic data collection for model improvement and decision support
- support scientifically defensible and standardized assessments and remedy selections

http://ascemdoe.org
**Akuna (“no worries”):** Graphic User Interface  
(Karen Schuchardt, PNNL)  
- Open Source Eclipse/Java based  
- Incorporates data management, visualization, and model development tools

**Agni (“fire”):** Simulation controller and Toolset driver  
(George Pau, LBNL, Velimir Vesselinov, LANL)  
- Open Source C++ object oriented  
- Provides coupling between Akuna and Amanzi  
- Performs various model-based analyses (SA, UQ, PE, DS, ...)

**Amanzi (“water”):** HPC Flow and Transport Simulator  
(David Moulton, LANL)  
- Open Source C++ object oriented  
- Saturated / unsaturated groundwater flow, ...  
- Structured / unstructured / adaptive gridding  
- ...

http://ascemdoe.org
Model-Analysis Toolsets in Agni

- Sensitivity Analysis (SA) *(Stefan Finsterle, Elizabeth Keating)*
- Parameter Estimation (PE) *(Stefan Finsterle, LBNL)*
- Uncertainty Quantification (UQ) *(Elizabeth Keating, LANL)*
- Risk Assessment (RA) *(Wilson McGinn, ORNL)*
- Decision Support (DS) *(Velimir Vesselinov, LANL)*

http://ascemdoe.org
Conclusions and recommendations:

- Both Non-Probabilistic and Probabilistic uncertainties often exist in a decision problem
- Non-Probabilistic and Probabilistic methods should be applied to their appropriate uncertainties in the decision analyses
- In the case of probabilistic methods, definition of prior probability distributions for model parameters or calibration targets with unknown/uncertain distribution can produce biased predictions and decision analyses
- In the case of non-probabilistic methods, lack of knowledge and severe uncertainties can be captured
- Non-probabilistic methodologies have been successfully applied for a series of synthetic and real-world problems, though less often in hydrology
  - Remediation of unknown contaminant source
    Harp & Vesselinov (2011). Contaminant remediation decision analysis using information gap theory. SERRA
- MADS provides a computationally efficient framework for decision analyses using non-probabilistic and probabilistic methods (http://mads.lanl.gov)
- ASCEM tools are currently actively developed and will become available for testing and benchmarking in 2013 (http://ascemdoe.org)