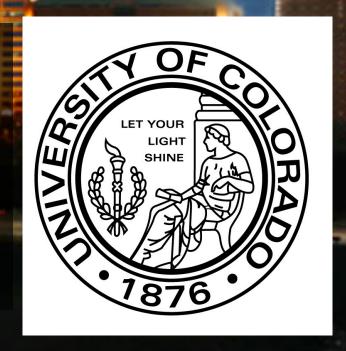
Framing Energy and Environmental Planning Problems Using Many Objective Robust Decision Making

Joseph Kasprzyk, PhD

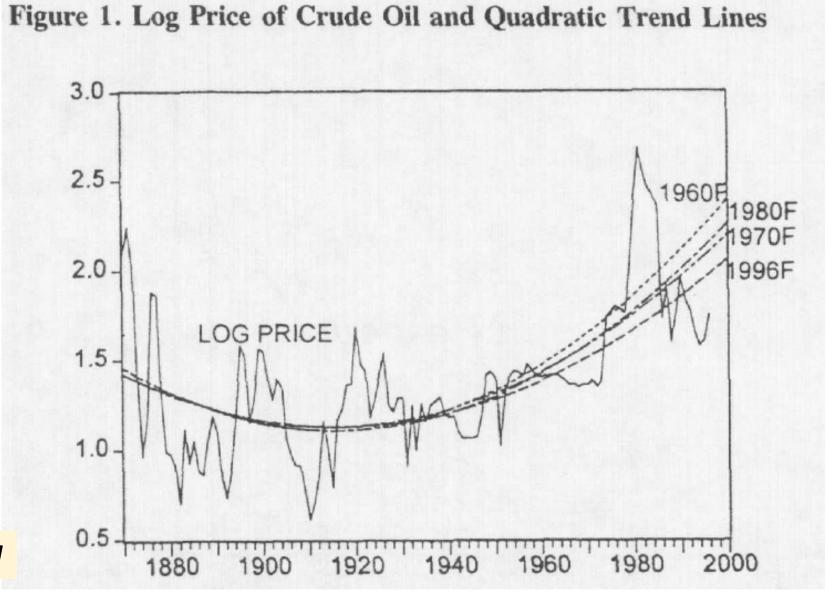
Assistant Professor

Rebecca Smith Graduate Student

University of Colorado Boulder



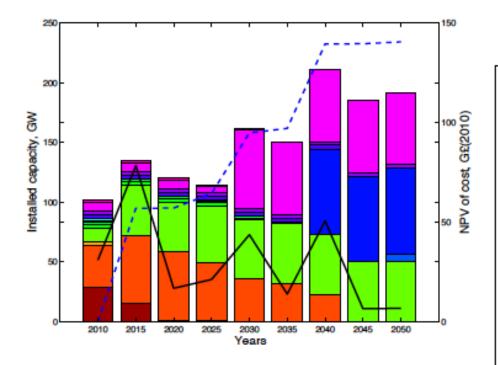
Planning requires estimates of future values of deeply uncertain exogenous "input" data.



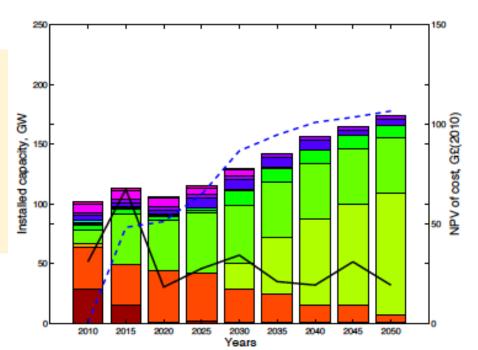
[Pindyck, 1999, Energy Journal]

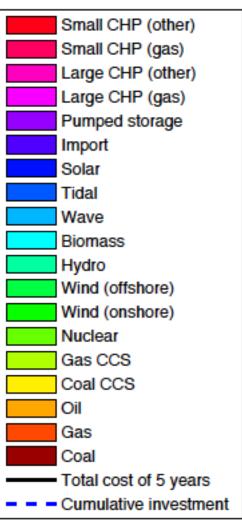


We also need the ability to **design** portfolios of stakeholder actions.



Two maximally different energy portfolios that provide near-optimal performance in a simple energy model of the UK [Trutnevyte and Strachan, 2013, International Energy Workshop]





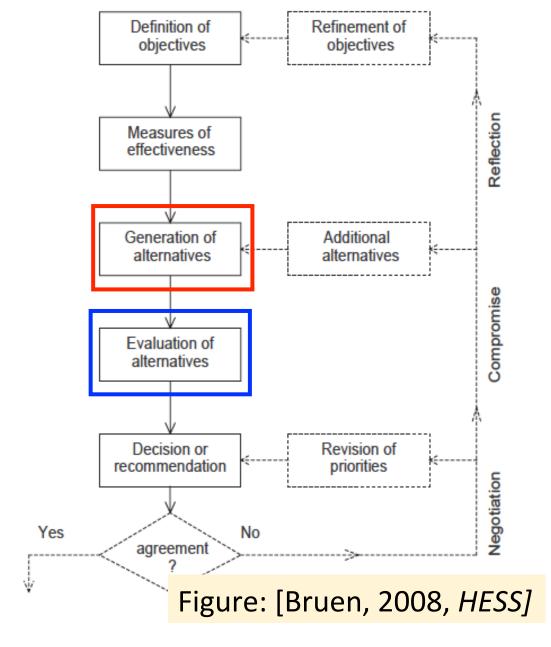


a Smith - Slide 3

Many Objective Robust Decision Making (MORDM)

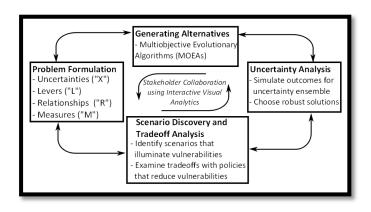
- The approach combines methods for generating new policy alternatives and evaluating them under deeply uncertain input ensembles
- Collaboration between RAND Corporation and research groups of Prof. Patrick Reed and my own
- Methods
 - Multiobjective Evolutionary Algorithm (MOEA) optimization
 - Robust Decision Making

MORDM: Kasprzyk, Nataraj, Reed, Lempert [2013], Env. Mod. Soft





Outline



1. Introduce MORDM framework



2. Show water planning case study



3. Suggest future research



Generating Alternatives

 Multiobjective Evolutionary Algorithms (MOEAs)

Stakeholder Collaboration

using Interactive Visual

Analytics

Uncertainty Analysis

- Simulate outcomes for uncertainty ensemble
- Choose robust solutions

Problem Formulation

- Uncertainties ("X")
- Levers ("L")
- Relationships ("R")
- Measures ("M")

Scenario Discovery and Tradeoff Analysis

- Identify scenarios that illuminate vulnerabilities
- Examine tradeoffs with policies that reduce vulnerabilities



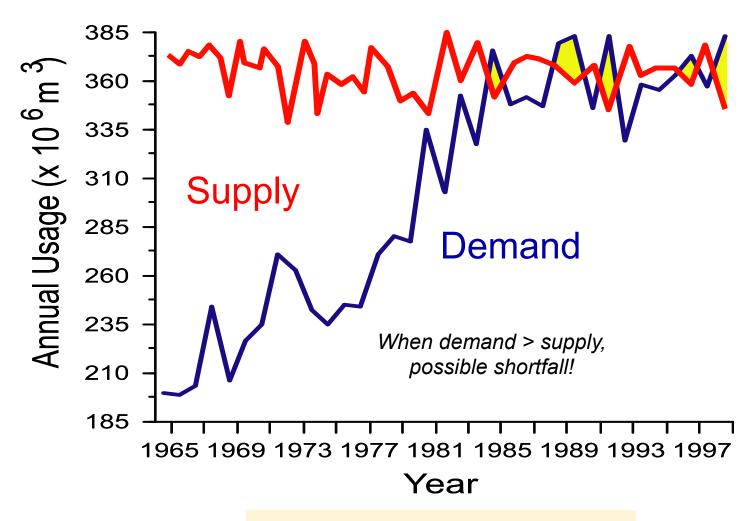
Which solutions do well under a large number of deeply uncertain trajectories?

How do we characterize values of the uncertainties that cause vulnerabilities for those robust solutions?



Lower Rio Grande Valley (LRGV) faces rising demands with variable supply.

- Rapid population growth and high irrigation water use
- Existing water market with transfers from ag to urban
- How can a single city use a water market to increase the reliability of its water supply?



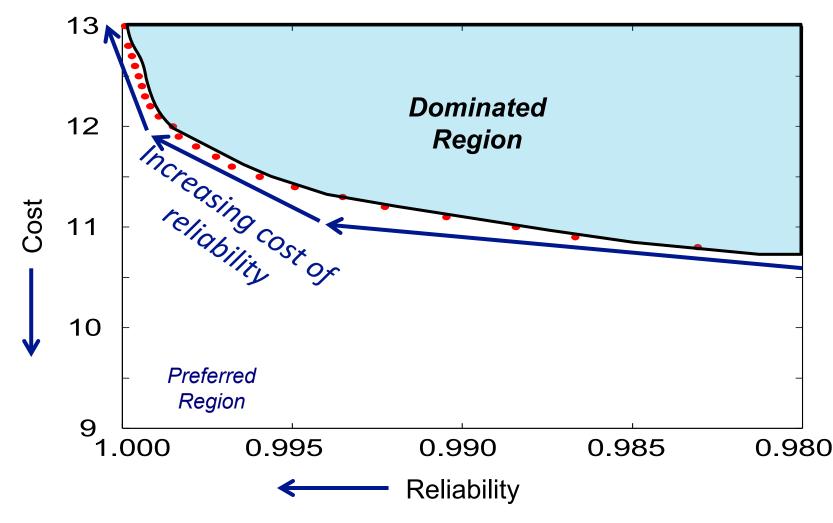


[Example data courtesy G. Characklis]

Joseph Kasprzyk and Rebecca Smith — Slide 8

What is the outcome of adding reservoir rights to meet supply?

- Each point: a volume of reservoir rights
- Non-domination (i.e., highest reliability at each cost level)
- Shows increasing cost of providing reliability





Can the market help lower costs? What other objectives are important for planning?



A many-objective approach to the LRGV helps answer these questions.

- Portfolio of 3 instruments
 - Permanent rights: non-market supply, % of reservoir inflows
 - Spot leases: immediate transfers of water, variable price
 - Adaptive options contract: reduces lease-price volatility
- Monte Carlo simulation model considers natural variability
 - Sampling of historical data for hydrology, demands, lease pricing
- Use a Multiobjective Evolutionary Algorithm to generate alternatives
 - Up to 6 objectives calculated using expected values under 10-year planning horizon

Problem Formulation



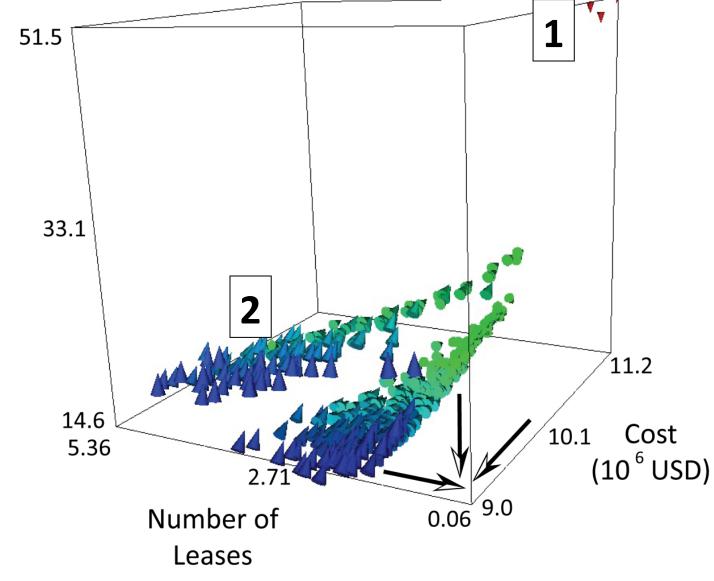
Generating Alternatives



Many-Objective Results

- Visualize rights (color), leases (orientation), options (size)
- Two distinct groups of solutions:
 - 1. rights-dominated
 - 2. market use
- Over-reliance on traditional water supply raised costs and surplus water volumes!



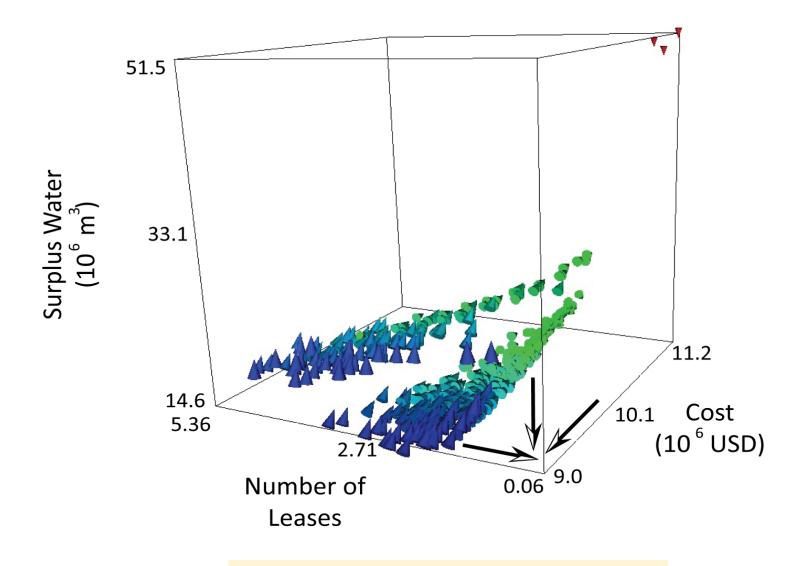




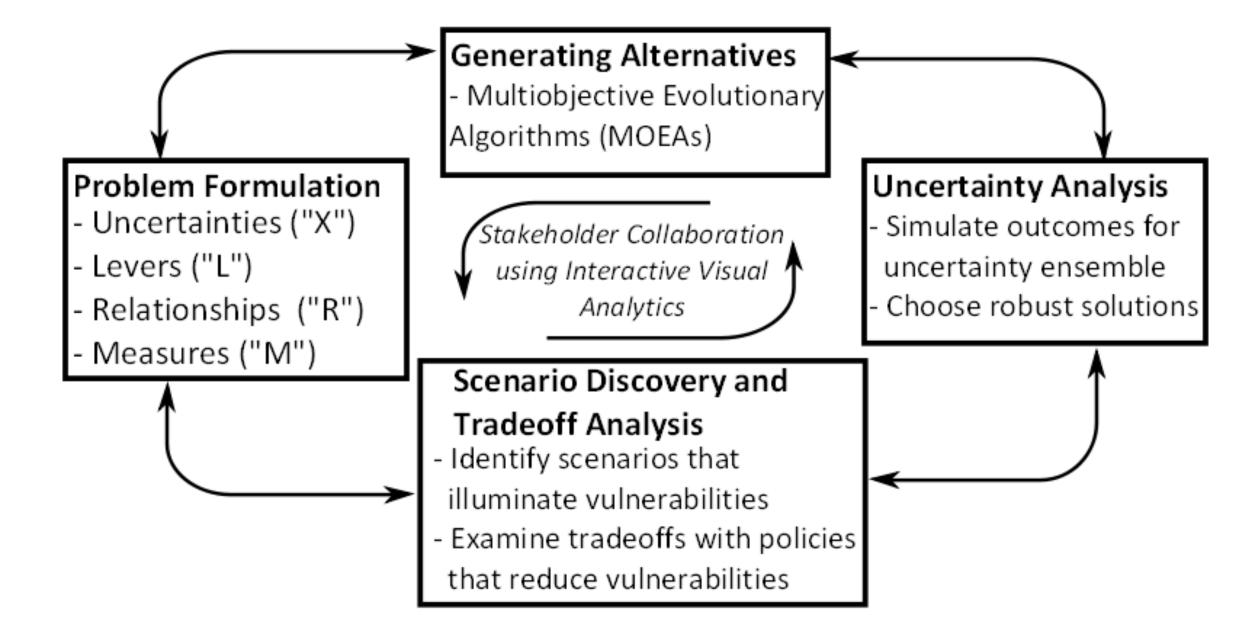
[Kasprzyk et al., 2012, Env. Mod. Soft.]
Joseph Kasprzyk and Repecca Smith — Silde 12

Our selected solutions were based on expected-value objective calculations.

- All objectives used a single distribution of input data to calculate expectation
- Issue: Is our choice of solution biased by assumptions of input data?
- Challenge: Deep Uncertainty, where decision makers can't characterize full set of events or probabilities







Scaling factors modify input data.

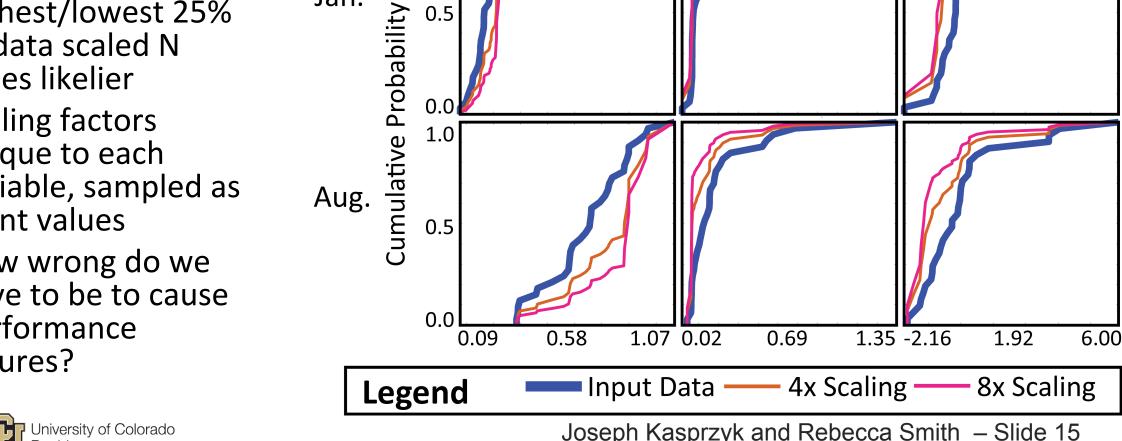
Jan.

1.0

0.5

1.0

- Baseline historical data
- Values exceeding highest/lowest 25% of data scaled N times likelier
- Scaling factors unique to each variable, sampled as point values
- How wrong do we have to be to cause performance failures?



Losses [x $10^8 \,\mathrm{m}^3$] Inflow [x $10^9 \,\mathrm{m}^3$]



Reservoir

Variation [x 10⁸m³]

Uncertainty ensemble

- State of the world (SOW): a value for each of these dimensions
- A SOW controls how input data is sampled within the Monte Carlo simulation

Table 1: Scaling Factors

Parameter	Lower Bound	Upper Bound
Low Inflows	1	10
High Losses	1	10
High Demands	1	10
High Lease Prices	1	10
Losses in Storage	1	10

Table 2: Scalar Model Parameters

Parameter	Lower Bound	Upper Bound
Initial Rights	0.0	0.4
Demand Growth Rate	1.1%	2.3%
Initial Reservoir Volume	987 mill. m ³	2714 mill. m ³



Evaluating robustness

- Apply ensemble of 10,000 LHS samples of uncertainties (SOWs) to each solution
- Sort values and calculate:
 - 10th percentile (for measures to be maximized)
 - 90th percentile (for measures to be minimized)
- Percent deviation :

$$\frac{c_{90} - c_{base}}{c_{base}} x 100 = \frac{51 - 37}{37} x 100 = 37.8\%$$

Cost Distribution for Solution N:	Cost in baseline
36	SOW
37	<
39	
40	
44	
45	
48	Cost in 90 th percentile
50	SOW percentile
51	←
55	



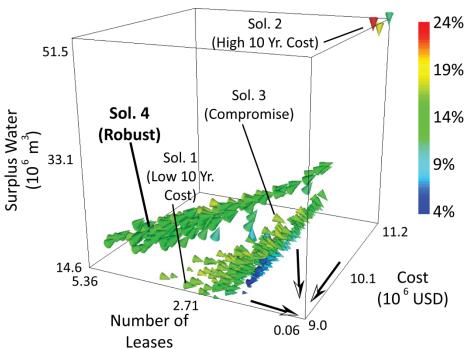
Solution X costs 37.8% more in the 90th percentile of the ensemble than it did under the baseline SOW.

We now visualize "percent deviation" across all solutions and measures.

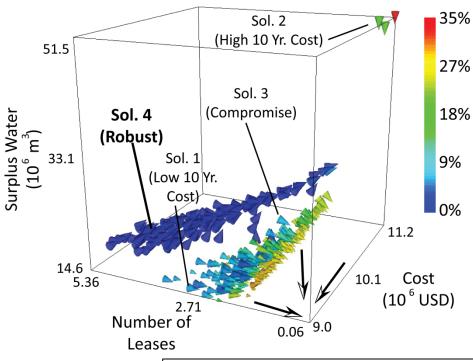


Percent deviation shows us robustness of the tradeoff space.





(b) Color: Percent Deviation in Critical Reliability



- Solution 4 exhibits low deviation in critical reliability and cost.
- It comes from a different tradeoff region than Solution 1-3.

Legend

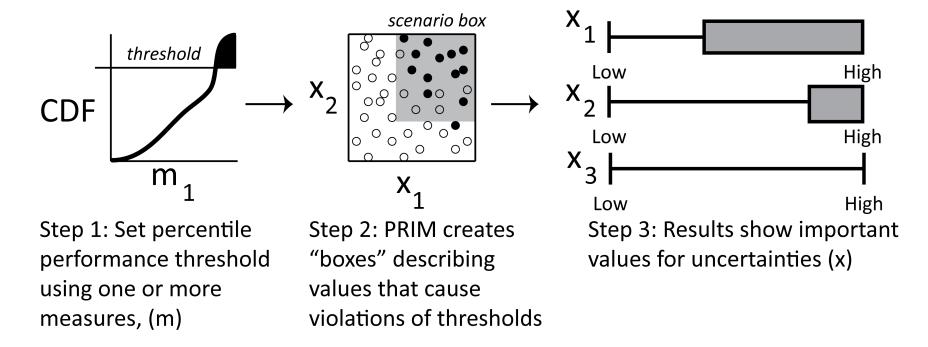
Size: Critical Reliability

Orientation: Dropped Transfers Axes: Measures in **baseline** SOW

Color: % Deviation



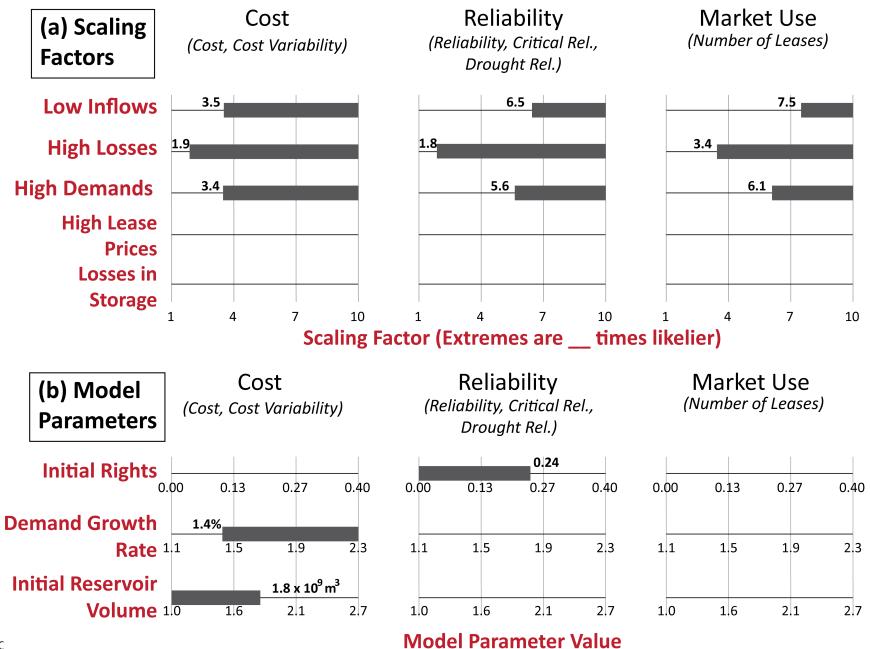
Scenario Discovery



- Patient Rule Induction Method (PRIM) is an interactive algorithm for discovering scenarios
 - Instead of specifying scenario values a priori, the discovered ranges are clearly linked to policy vulnerabilities.



Scenarios Where the "Robust" Solution Performs Poorly





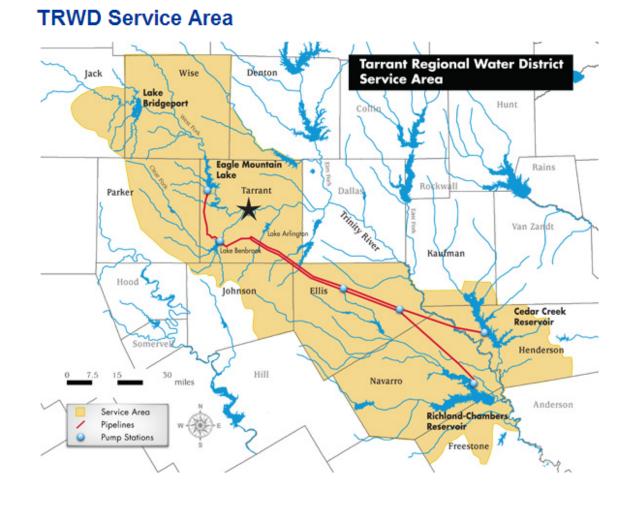
Conclusions

- Adding multiple objectives helps confront cognitive myopia
 - Aggregated, low dimensional formulations make decision makers ignore critical aspects (such as reducing surplus water)
- Ex post monitoring and adaptation: Decision makers can use scenario discovery to determine most important uncertainties for future planning
- MORDM can be applied across a wide array of problems, using simulation models of varying size
 - Screening models, regional planning, agent-based modeling



Future Research: Water planning considering energy

- Tarrant Regional Water District (TRDW) serves more than 1.7 million people
 - Cities of Fort Worth and Arlington
 - Raw water supplier
 - 7 reservoirs, over 150 miles of pipeline
- High energy costs
 - Pumping up 400 feet of elevation
 - In 2012, \$17.6 million in energy costs

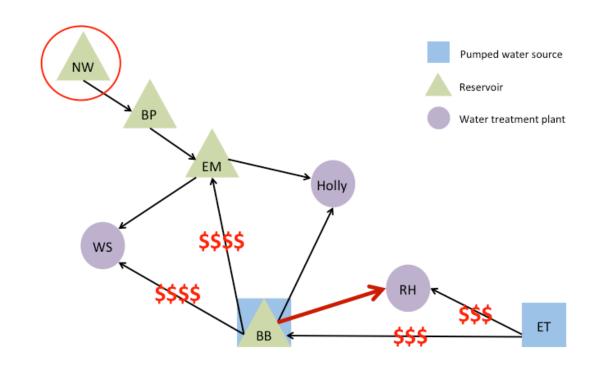




Challenges

Complex modeling

- GUI simulation models not often made to be run 1000s of times
- Node-link topology requires spatially disaggregated input data
- Integrated planning
 - TRWD buys energy in advance, not directly linked to water issues
 - In water planning, providing reliability often trumps efficiency or cost savings





Future Research: Energy planning

- Open to new collaborations!
- Use a "screening" level energy planning model to determine candidate portfolios of renewable technologies
- Optimize and evaluate portfolios using multiple objectives in addition to cost, including [Trutnevyte and Strachan 2013]:
 - Separate consideration of fixed and operating costs
 - Maximizing total installed capacity or produced energy
 - Explicit minimization of greenhouse gas emissions
 - Integration with other sectors



Thanks! Any questions?

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For more info please email joseph.kasprzyk@colorado.edu and see http://spot.colorado.edu/~joka0958/



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