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Quantifying Uncertainty in Decisions: *Supporting Adaptive Management with Decision Analysis*

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Assessing Uncertainty in the
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Outline

Risk-Based Decision Analysis for Adaptive Management
- *What is it, and why is it useful?*
- *Steps*

Case 1: Controlling non-point sources of sediment in the Minnesota River
- *Where is the sediment coming from?*
- *Act now or wait for results of research?*

Case 2: Managing Philadelphia stormwater with Green Infrastructure
- *What is the effectiveness of GI?*
- *Should we experiment with a range of GI types?*

Case 3: Protecting the coast under climate uncertainty
- *Wetland Preservation*

opinion-forum.com/index/wp-content/uploads/2013/04/decisions.jpg

Decision analysis for adaptive management

Essential features:

1. Timing of decisions:
   - Can make commitments today, not knowing the future
   - Or we can delay, and make more informed choices later
   - Some decisions are revisited periodically
2. Uncertainty:
   - Long run uncertainties that we can get better information on
   - Shorter run variabilities that we must manage, and which mask long run trends
3. Many objectives:
   - Tradeoffs will be viewed differently by different parties

What can Risk-based Decision Analysis do, and why is it appealing? (Clemen, 2013)

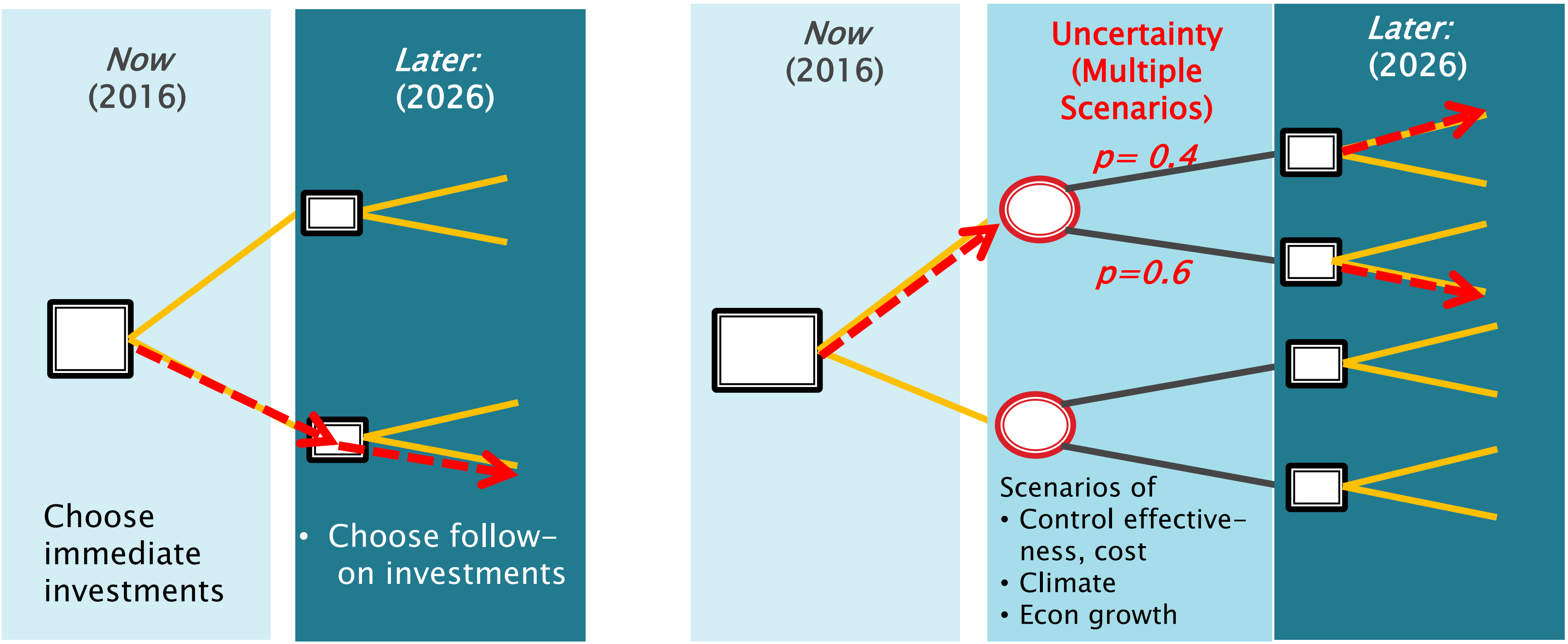
1. Useful outputs:
   - *Inferences* (parameter estimates; predictions; credible sets; hypothesis tests) *that combine diverse information* (historical data, models, expert judgment)
   - *Optimal strategies*
   - *Value of information*
   - *Value of considering risk*
2. **A comprehensive framework based on attractive ("normatively valid") assumptions, e.g.**
   - We should process information using laws of probability
   - We should systematically & consistently weigh multiple objectives & risk
3. **Practical, familiar procedures**

Basic philosophy:

Multistage decision making … *without risk*

Vs.

Multistage decision making … *with risk*



Optimal strategy:

- Best choice at each (reachable) decision node
- Today's choice considers how you'd adapt in each possible future scenario

How does Risk-based Decision Analysis do it?

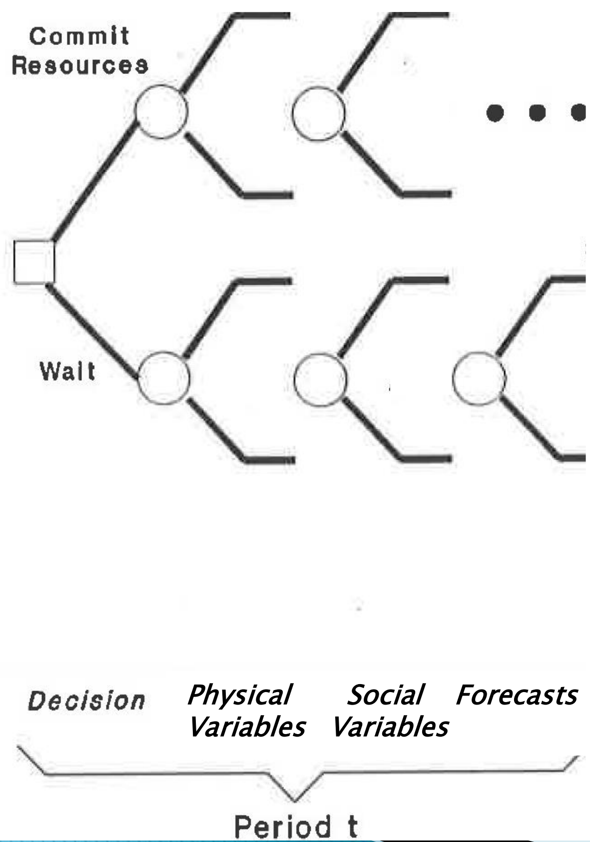
1. Specify structure of problem
2. Quantify inputs
3. Perform analysis

Step 1: Structure problem

- **What are the:**
  - Alternatives, & when are they picked? ("Decision nodes")
  - Random events, & when are they known? ("Chance nodes")
  - Sources of information, & when available?
  - Objectives?

- **Example: Classic "stopping problem" (when do you build a project?):**

Time $t \rightarrow$



Step 2. Specify inputs from data, models, expert judgment

1. "Alternatives" X
   - *Design:* what GI measures, how large a WWT?
   - *Operations:* Conowingo reservoir releases
2. Uncertain "states of nature" θ, & their "prior" probabilities $P(\theta)$
   - Susquehanna flow on 12/12/2016 ("random")
   - ΔMean precipitation in CB watershed by 2032 ("uncertain")
3. "Information" Z that might be obtained, & likelihoods $P(Z|\theta)$ of that information
   - Monitor nitrate fluxes
   - Improved downscaled GCM precipitation projections
4. "Objective(s)" O to pursue, & relationship $O(X|\theta)$ to decisions & states of nature
   - Cost
   - Distribution of D.O.

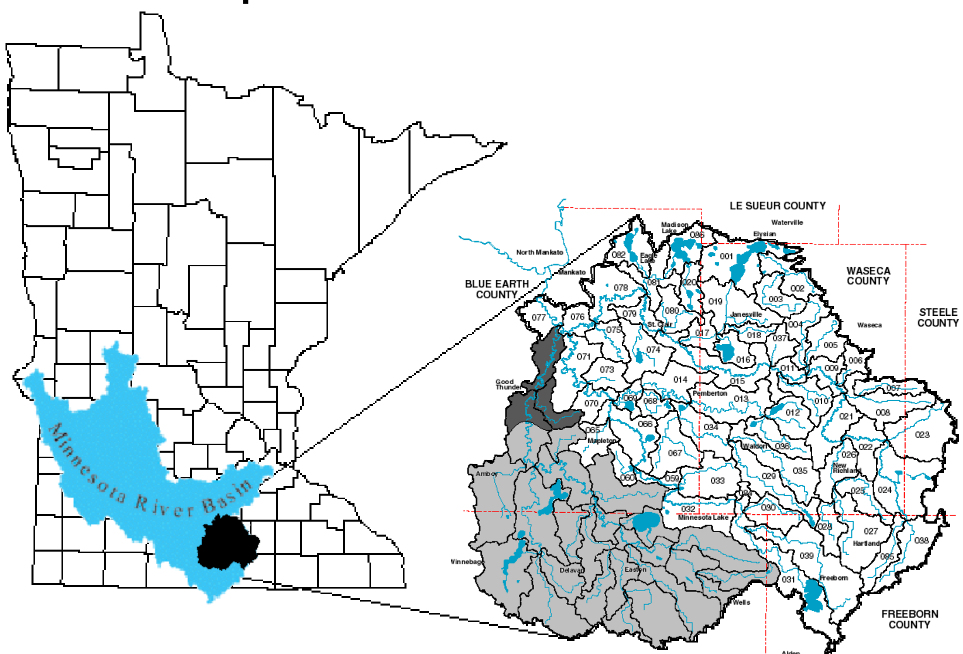
Step 3. Perform the analysis
(via "folding back", stochastic dynamic programming, multistage optimization)

1. *Posterior analysis:* After information Z is obtained, update probabilities $P(\theta|Z)$
   - E.g., improved forecasts or parameter estimates
2. *Preposterior analysis:* Considering the probabilities of outcomes θ and information Z, calculate:
   a) Best decision <u>now</u> $X_0{}^*$
   b) Best strategy <u>over time</u> and its expected performance
      - The best X^* at each decision node
      - The probability weighted value of $O(X_0{}^*|\ \theta)$
   c) $ worth of better information Z
   d) Value of the stochastic solution (VSS) = improvement in expected performance O resulting from explicitly considering risk in decision making

Case 1: Which sediment sources to reduce in the Minn. River? (Jacobi et al. 2013)

Focus: Maple River Watershed

- Impaired for turbidity under Clean Water Act
- Minnesota River contributes 85-90% of suspended sediment in Lake Pepin
- Gulf of Mexico Hypoxic Zone



Background

- Long-term sediment contributions uncertain:
  - Agricultural fields
  - Streambanks
  - Ravines
  - Bluffs

- Available Actions
  - management to reduce sediment loadings
  - research to improve understanding

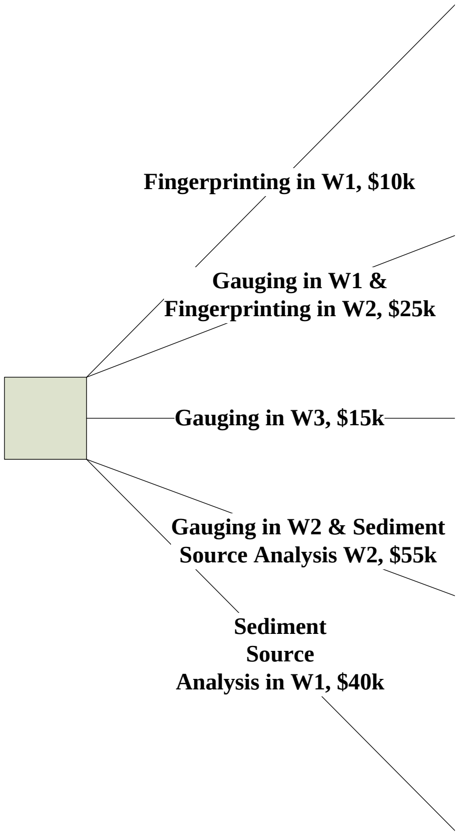
Management options in each of 3 subwatersheds

- Fields
  - Critical Area Planting
  - Conservation Tillage
- Streambank Stabilization
- Ravines
  - Land Retirement around Ravines
  - Tile Drainage at bottom of Ravines
- Bluffs
  - Toe Protection
  - Complete Stabilization

Research actions

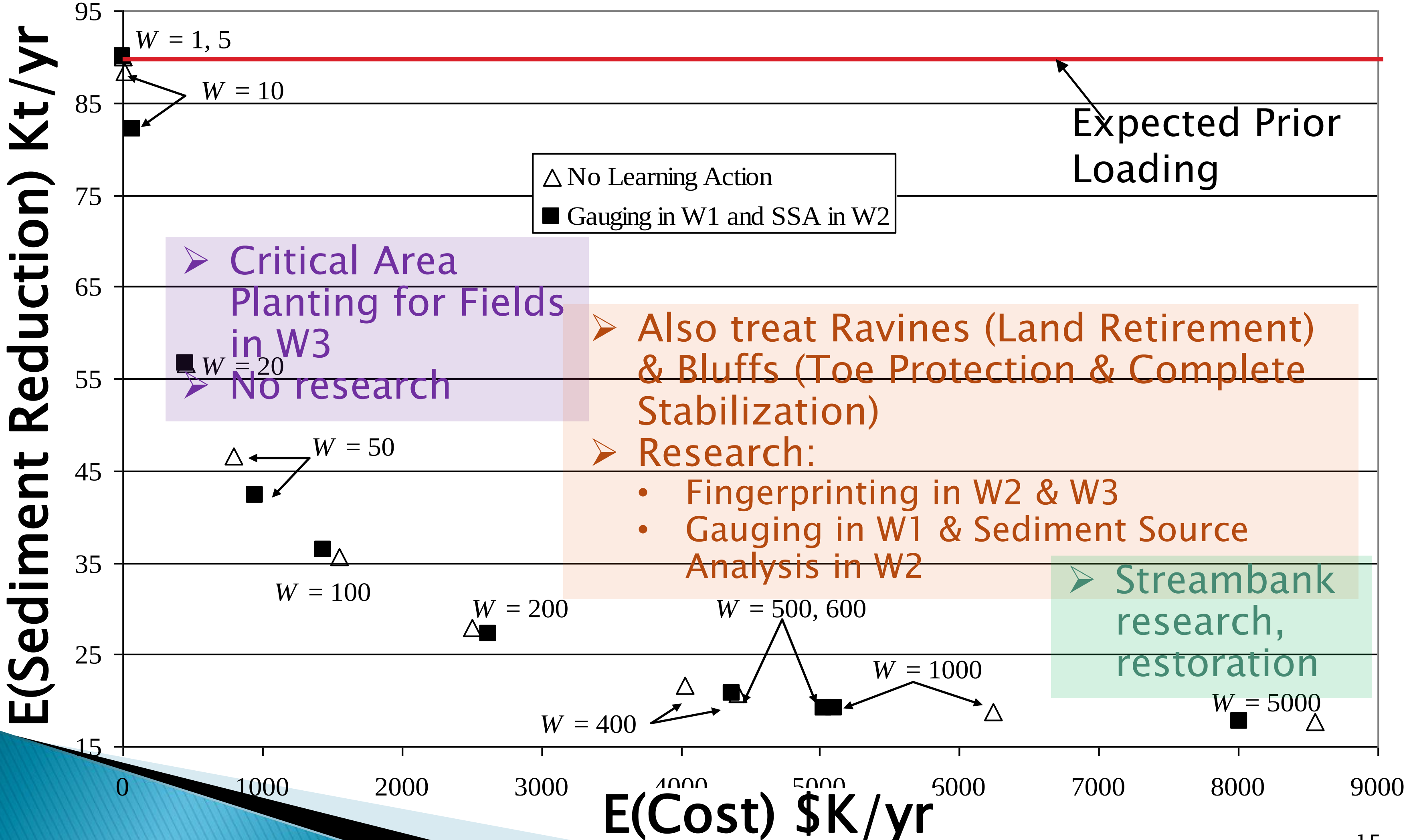
- **Gauging**: single gauge at watershed outlet ($15k/yr)
- **Fingerprinting**: atmospherically deposited radionuclides as tracers for sediment sources ($10k/yr)
- **Sediment Source Analysis**: similar to sediment budget ($40k/yr)

Decision Tree Framework



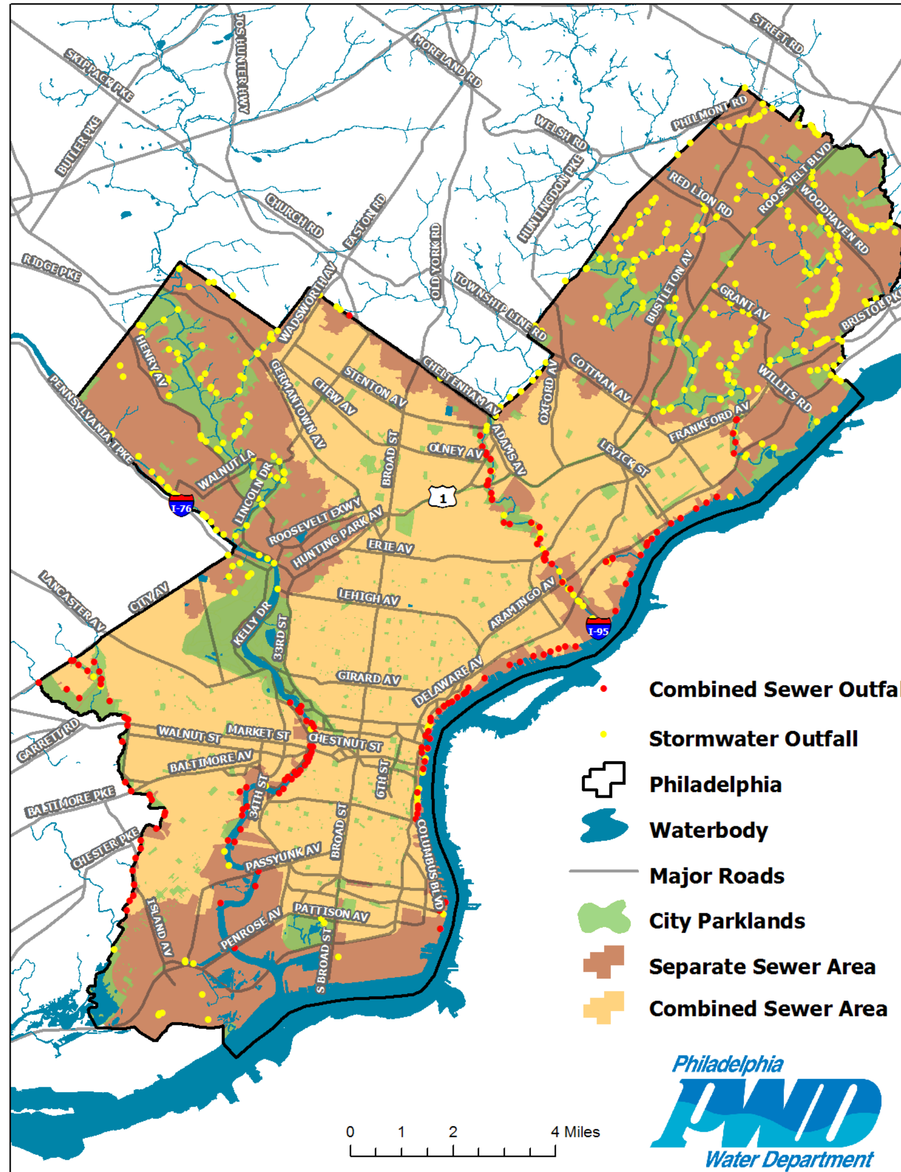
Research Actions
(45 combinations),
plus "No Learning"

Results shown as Tradeoff Curve



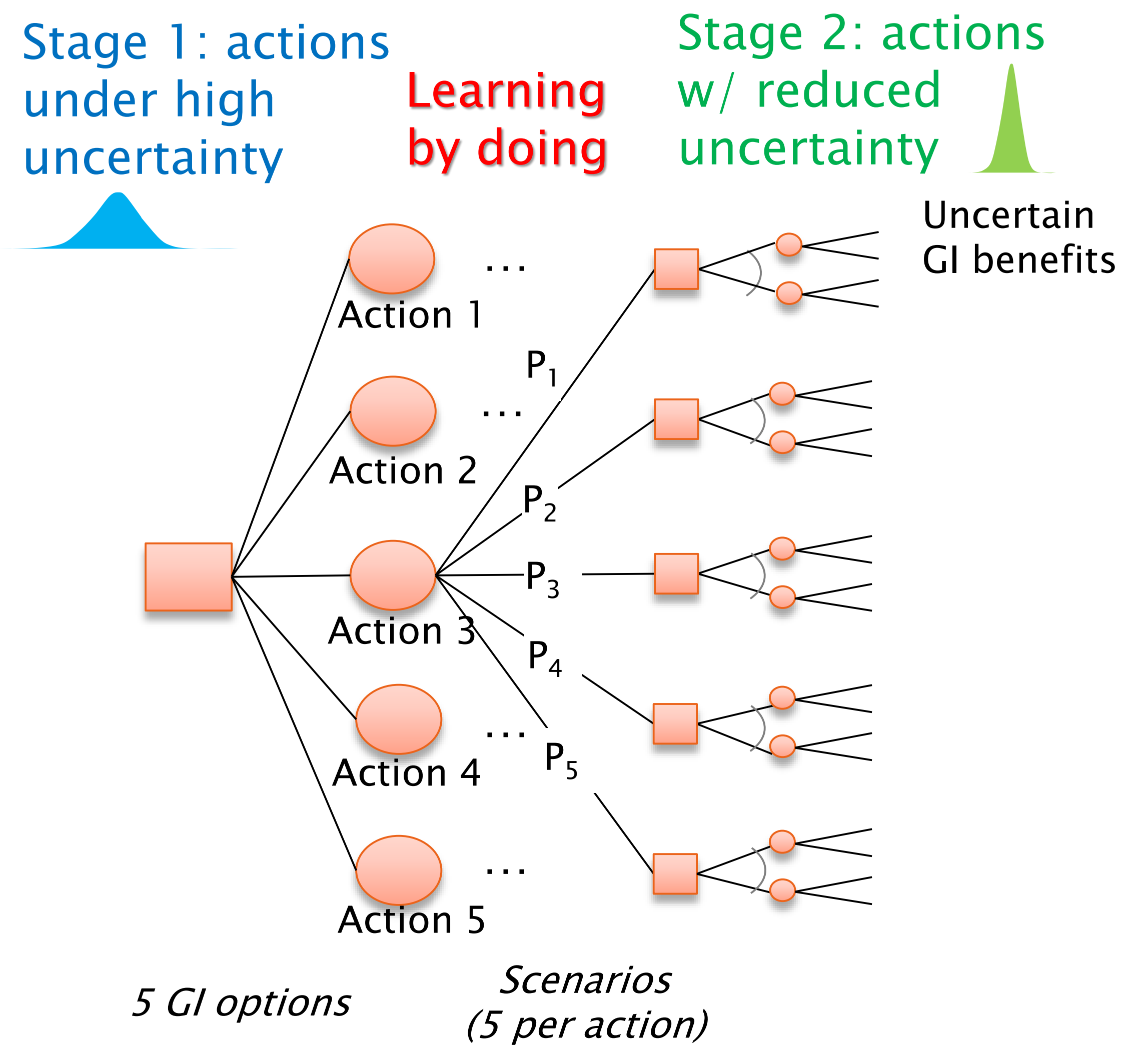
Case 2: Stormwater Management with GI in Philadelphia (Hung et al., 2015)

- City to invest $2.4B billion on Green Infrastructure (GI) over 2011-2035
  - What, where, & when?
  - Uncertain GI cost, performance
    - → Opportunity to learn



Adaptive management as a decision tree

- MAX E(loadings reductions), subject to:
  - Budget constraint
  - Risk (“CVar”) constraint
  - Solved with QP
- Learning in Stage 1 through:
  - Monitoring
  - Deliberate experimentation
- Adaptation in Stage 2
  - Optimize GIs based on what is learned



Sample numerical results:
How are choices among 3 GIs affected by "risk aversion"?

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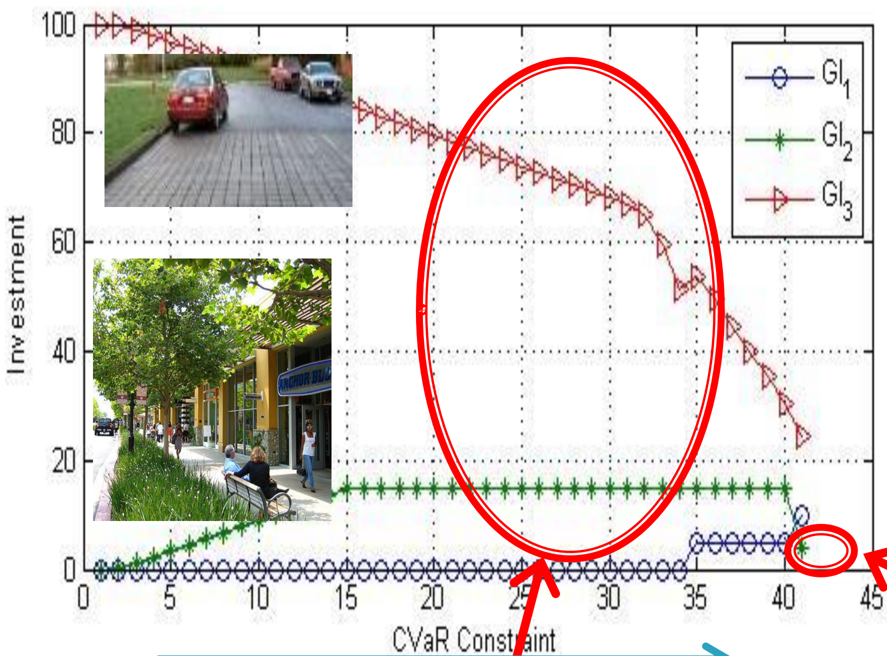
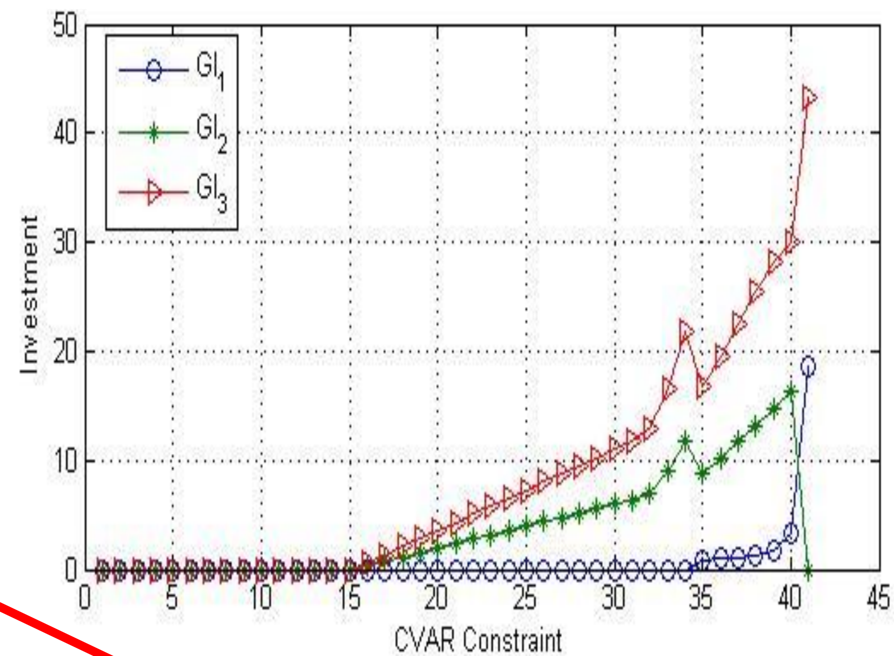
First-stage decisions



Average second-stage decisions



Increasingly averse to risk

Invest enough in Pavers & Tree trenches to learn about their performance

Invest in Rain Gardens, but not enough to learn

Case 3: Lake Erie shoreline protection under climate uncertainty

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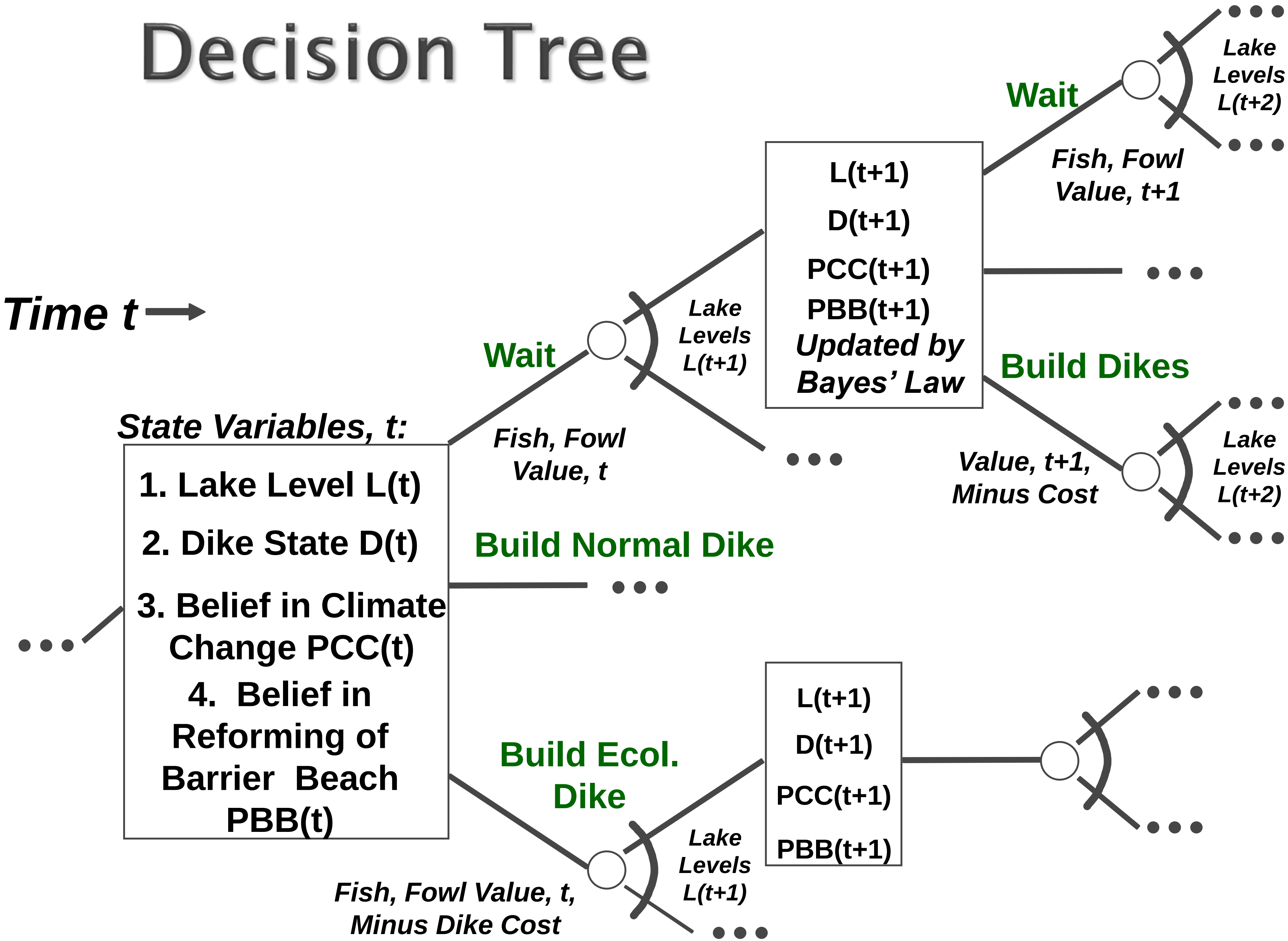
www.photography-plus.com/images/Erie/303PresqueIsle081608_320.jpg
www.skylon.com/wp-content/uploads/2013/06/Niagara-Falls-Horseshoe-Falls-view.jpg

Case 3: Metzger Marsh preservation (Bloczynzki et al., 2000)

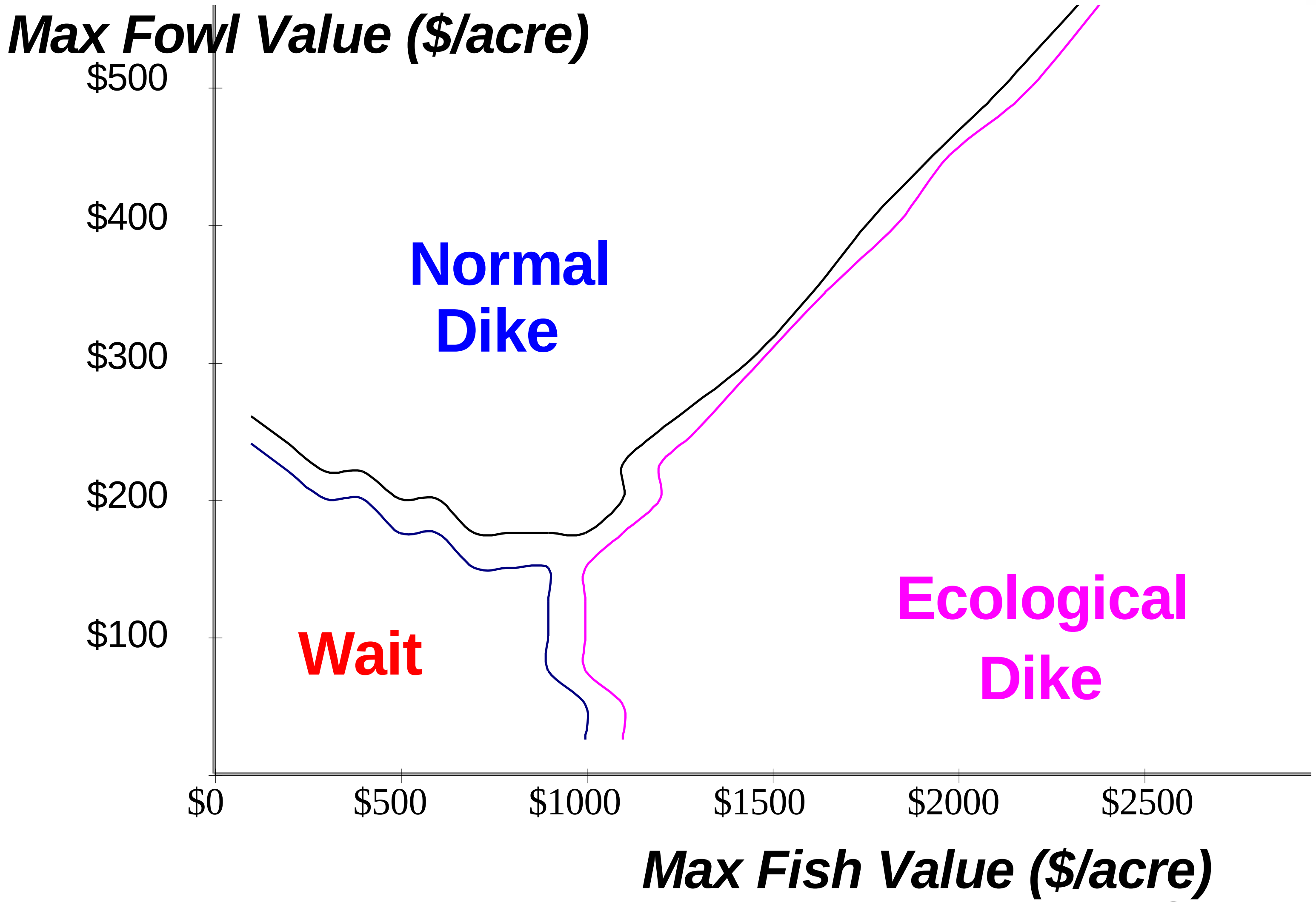
- High lake levels destroyed barrier beach
- *Alternatives:*
  - Do nothing (degraded wetland)
  - Ecological (open) dike – vulnerable to drying out if lake levels drop (Climate change!)
  - Closed dike (pump water to maintain wetland)
- *Objectives:* MAX weighted sum of:

  Fish habitat quality + Bird habitat quality – COST
- *Uncertainties:*
  - Short Run: Lake level variation
  - Long Run:
    - Climate change might permanently lower lake levels
    - Ecological value of degraded wetland
    - Whether barrier beach would re-establish at low lake levels

Decision Tree



Results of analysis: What type of wetland in Yr 1?



- Most sensitive to birds vs fish priorities
- Sensitive to value of habitat for bivalves
- But climate uncertainty is irrelevant

Conclusions

- Decision analysis can be used to identify & quantify value of adaptive management strategies
- Can integrate data, simulation models, & expert judgment
- Challenge: Curse of dimensionality
  - # scenarios
  - # alternatives
  - # simulation model runs

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