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Week 6:

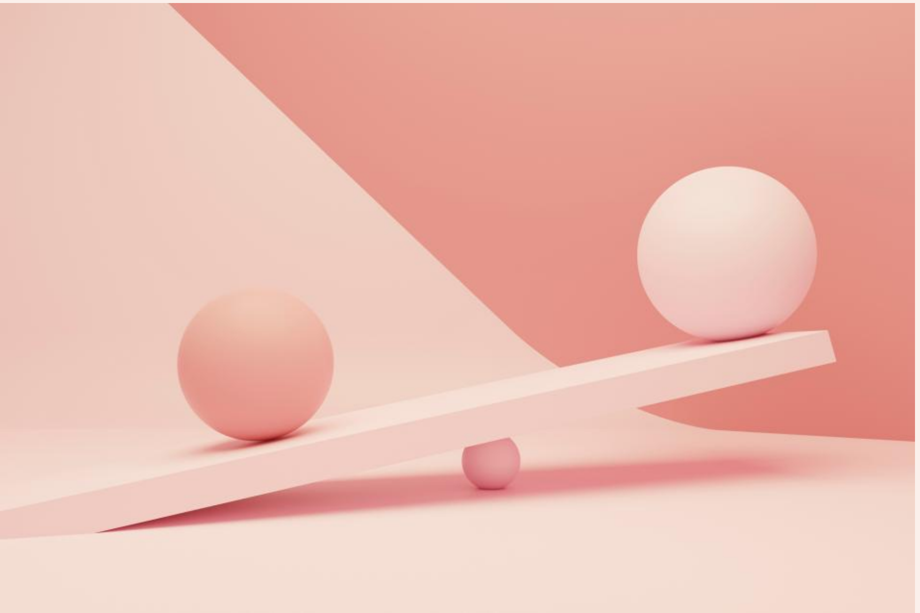
Decisions under uncertainty part 1

Instructor: Brielle K Thompson

Course: NAT_R 8001 Decision Analysis for Research and Management of Natural Resources

Review of last week

- Discussed the Tradeoffs step of SDM
- Identified tools to solve multiple objectives:
  - Simplify the problem (remove dominated alternatives, irrelevant objectives, make even swaps)
  - Reduce to single objective problem if possible
  - Negotiate a solution from a set of best compromises
  - Evaluate trade-offs explicitly
    - Tools from multi-criteria decision analysis (MCDA): SMART, swing weighting



Quick logistics

- No class next week 10/7
- Who is presenting 10/14
- Final day of class 10/21

- Decide how to submit presentations:
  - Email before class? Flash drive?

Today: How do we make decisions under uncertainty?

- Learn about uncertainty
- Methods: adaptive management, decision trees, value of information

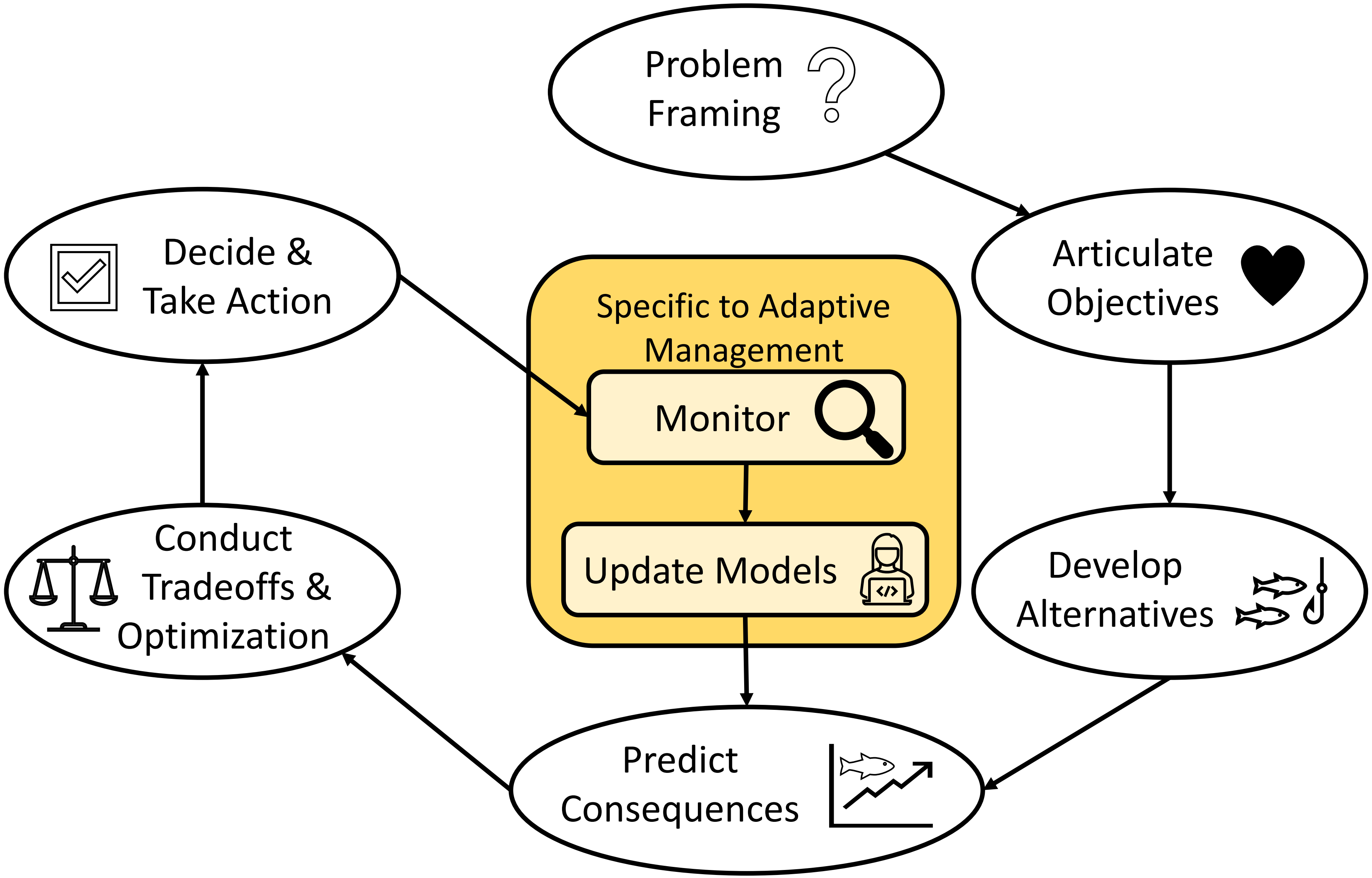
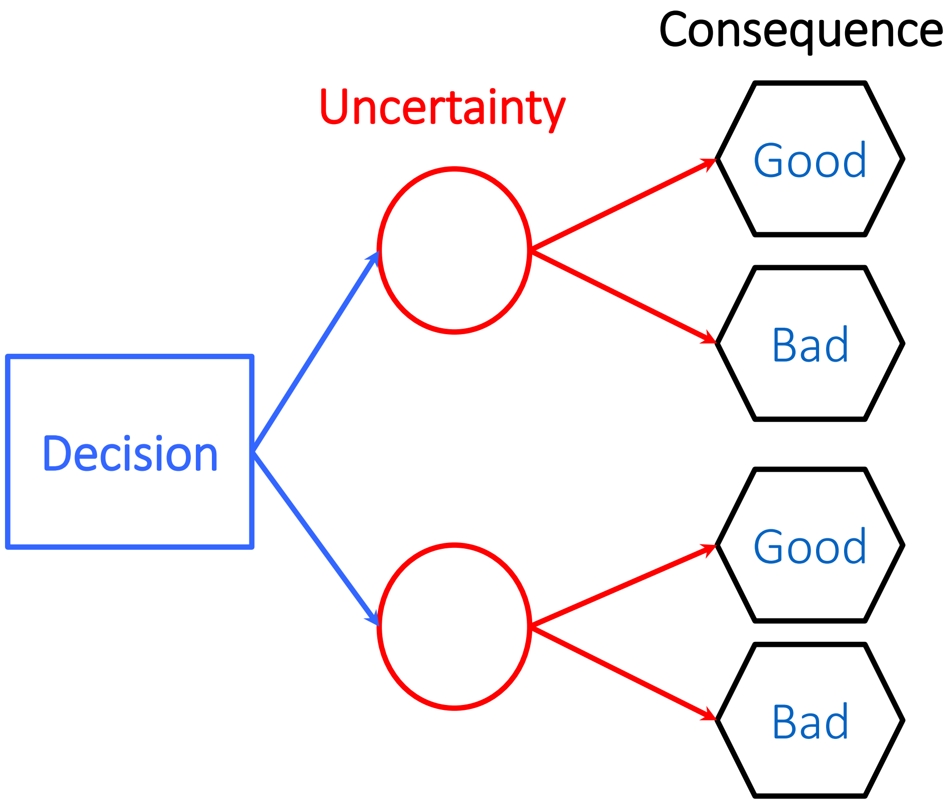


Figure Adapted from Converse et al. 2013 and Runge 2011

Uncertainty in decision making

- Desired outcomes cannot be guaranteed
- Decisions under uncertainty should be **judged by the quality of decision making**, not by the quality of the consequences (Hammond et al. 1999)



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Uncertainty in decision making @ all stages

- Problem
- Objectives
- Alternatives

Clarify ambiguities as much as possible here

- Consequences

Then identify relevant knowledge gaps

- Tradeoffs

At the end, test the sensitivity of your decision to inputs

Regan HM, M Colyvan, and MA Burgman. 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications 12: 618-628.

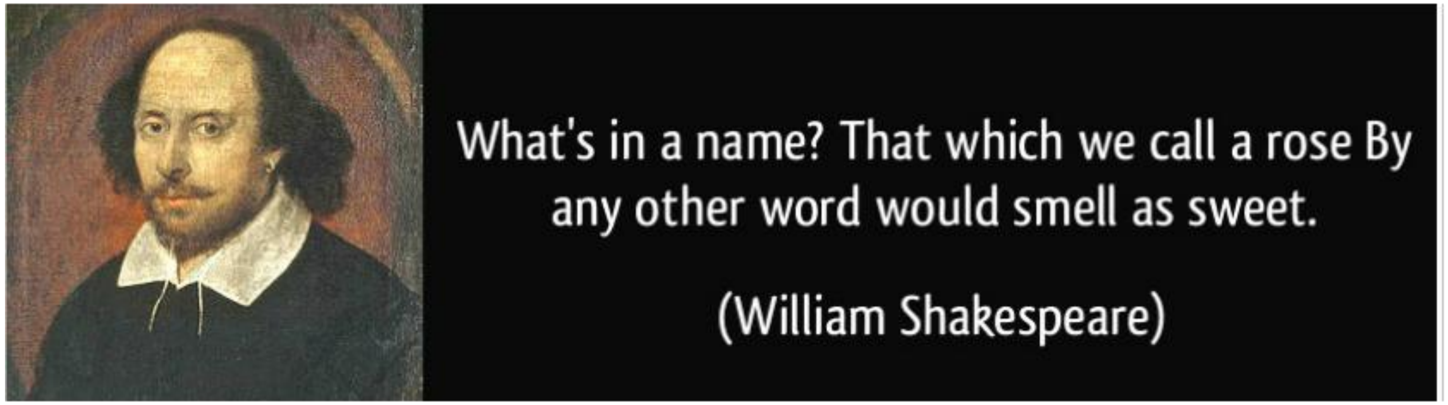
Types of Uncertainty

- **Linguistic** – uncertainty arising from our communication (can be reduced with effort)

- **Epistemic** – uncertainty about how the world works (some types can be reduced with effort)

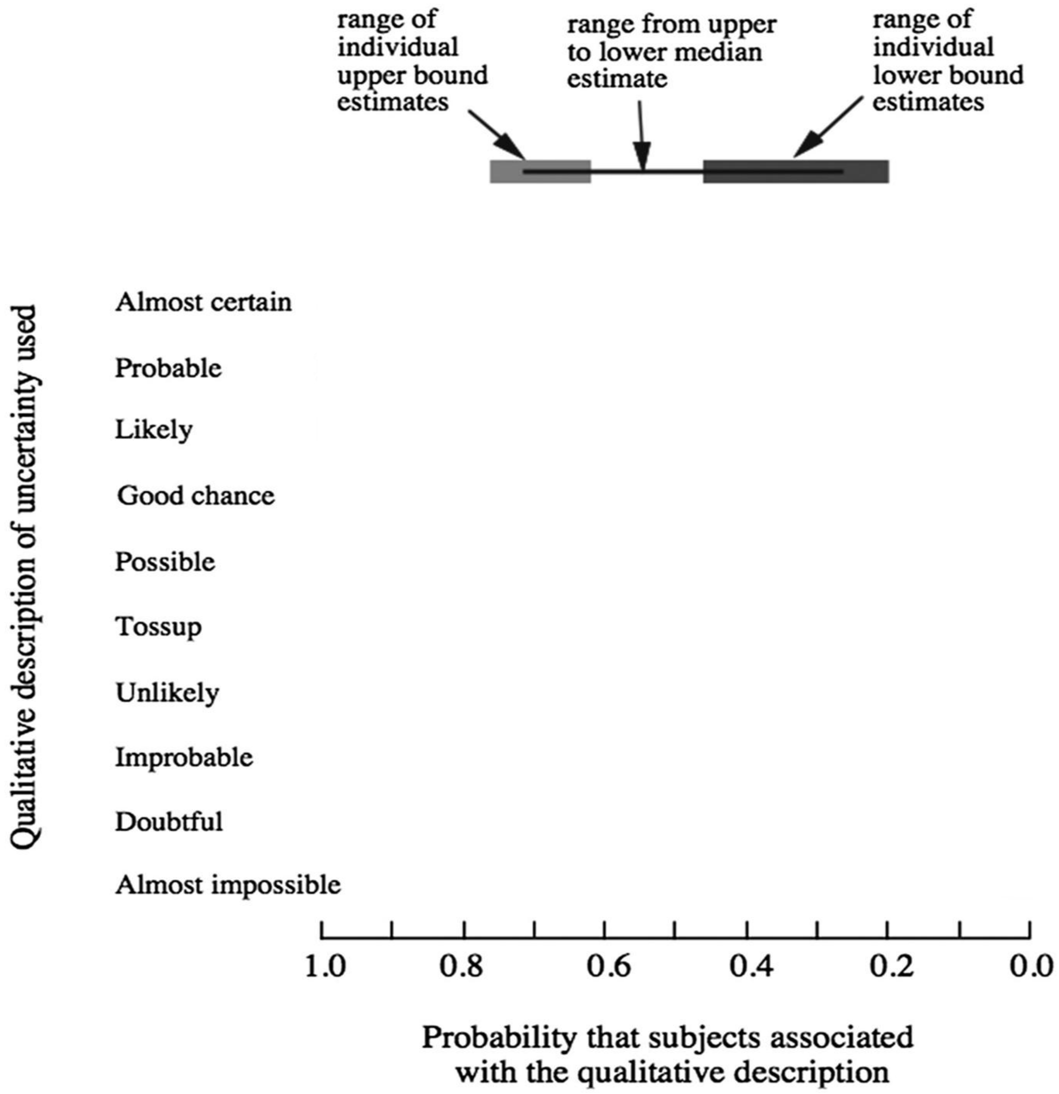
Linguistic uncertainty

- Uncertainty arising from our communication (can be reduced with effort)
  - Arises because of our natural language & our scientific vocabulary, is under specific, ambiguous, vague, context dependent, or exhibits theoretical indeterminacies
- Example: consider estimating the number of endangered species in a region. Uncertainty arises because of what constitutes an endangered species. Before we can even attempt to count the number of endangered species, it is necessary to decide what we mean by the term ‘‘endangered species’’



Morgan MG. 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. PNAS 111:7176-7184.

Linguistic uncertainty



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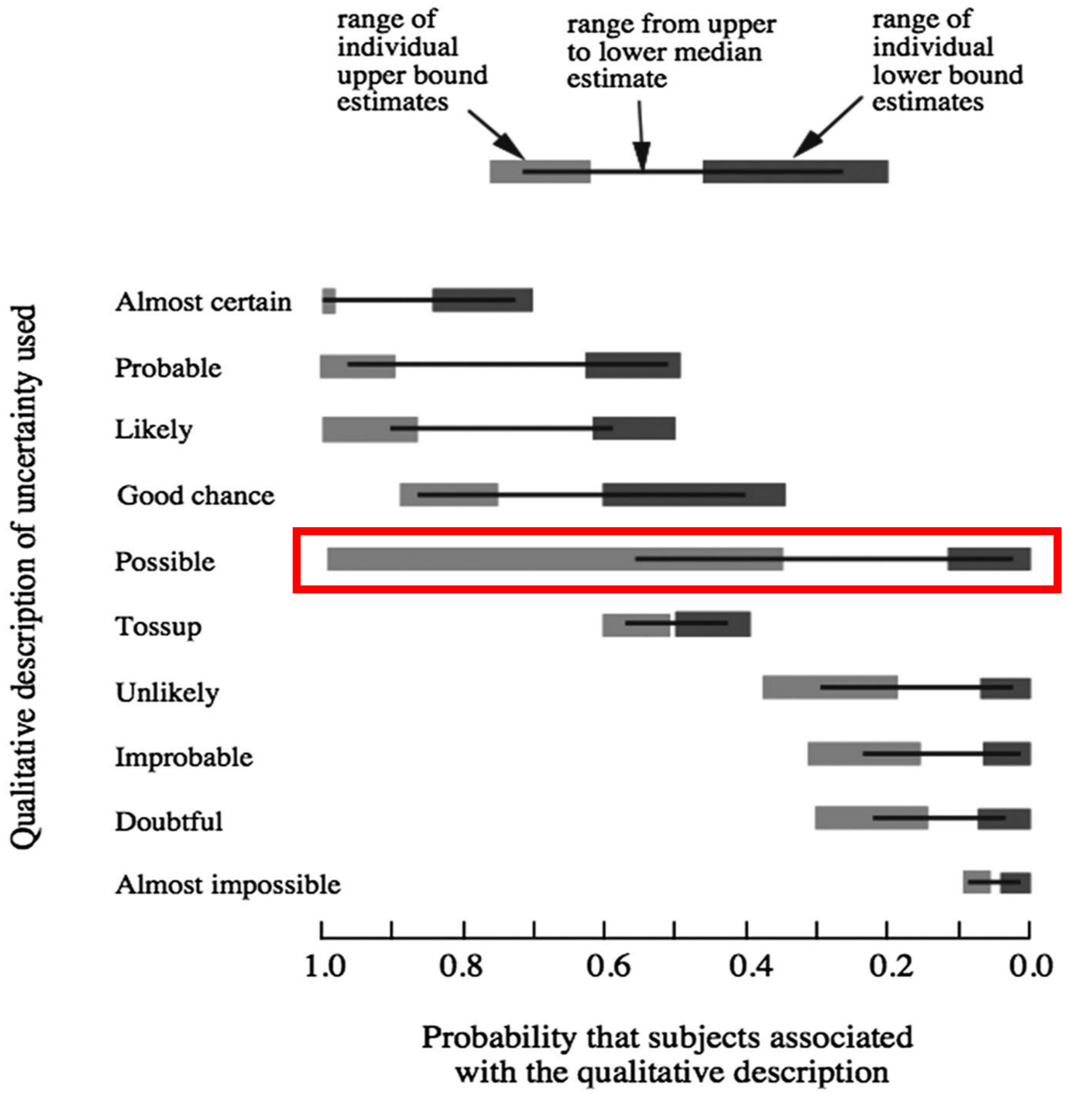
Linguistic uncertainty



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Linguistic uncertainty

Midwest vs Everybody
@midwestern_ope

Midwest language be like:

No Yeah = Yes

Yeah no = No

Yeah no for sure = Definitely

No yeah no = Oh no, you're fine

Yeah no yeah = I'm sorry, but unfortunately, the answer is yes

Epistemic uncertainty

- Uncertainty about how the world works (some types can be reduced with effort)

Epistemic uncertainty

Measurement error	Systematic error	Natural variation	Inherent randomness	Model uncertainty	Subjective judgement
Random error in equipment or operator	Bias in equipment or operator	Fluctuations that naturally occur	Unpredictable events, chaotic systems	Error representing systems (mathematically/statistically, e.g., different growth models)	How data is interpreted
Resolution: apply statistical techniques to repeated measurements	**Resolution:** Recognize bias, double sample	**Resolution:** Probability distributions	**Resolution:** Probability distributions	**Resolution:** model validation, research	Resolution: Degrees of belief in form of subjective probability

<u>Aleatoric uncertainty</u> = unpredictable variability (*alea* = Latin for dice) [applies to Natural variation and Inherent randomness]

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(see Regan et al. 2002)

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Activity: what uncertainty?

Uncertainty	Type
A field technician records fish lengths using a ruler, but the measurements vary slightly due to inconsistent technique	
A population model for elk migration fails to account for a newly constructed highway that disrupts movement	
A stakeholder group disagrees on what “sustainable harvest” means in a forest management plan	
Annual rainfall in a watershed fluctuates unpredictably, affecting streamflow and fish habitat	
A researcher estimates the impact of a proposed dam on fish populations based on expert opinion	
A sensor used to monitor water temperature consistently reads 1°C too high due to calibration issues	
A climate model predicts future temperature changes, but results vary depending on the structure of the model	
The number of deer born last year varied due to 1000-year flood that occured	

Uncertainty types:

- Linguistic uncertainty
- Measurement error
- Systematic error
- Natural variation
- Inherent randomness
- Model uncertainty
- Subjective judgement

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Activity: what uncertainty?

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A field technician records fish lengths using a ruler, but the measurements vary slightly due to inconsistent technique	Measurement error
A population model for elk migration fails to account for a newly constructed highway that disrupts movement	Systematic error
A stakeholder group disagrees on what “sustainable harvest” means in a forest management plan	Linguistic uncertainty
Annual rainfall in a watershed fluctuates unpredictably, affecting streamflow and fish habitat	Natural variation
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A climate model predicts future temperature changes, but results vary depending on the structure of the model	Model uncertainty
The number of deer born last year varied due to 1000-year flood that occured	Inherent randomness

Uncertainty types:

- Linguistic uncertainty
- Measurement error
- Systematic error
- Natural variation
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- Model uncertainty
- Subjective judgement

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Aside: model uncertainty

- Structural uncertainty – what is the overall structure of our model?
  - Example: what is the correct hypothesis regarding fish survival?
    - H1: $logit(S_t) = \beta_0 + \beta_1 * temp_t$
    - H2: $logit(S_t) = \beta_0 + \beta_2 * DO_t$
    - H3: $logit(S_t) = \beta_0 + \beta_1 * temp_t + \beta_2 * DO_t$
  - Example: do we model logistic growth or exponential growth?
- Parametric uncertainty – what is the value of a parameter within a single model?
  - Example: $\beta_0 \sim \text{Normal}(0.5, 0.25)$

Skills Check Task 1 – Identify uncertainty type

You are a wildlife manager in a refuge who is designing a prescribed burn management plan for a grassland bird

TASK 1#: For the three following uncertainties…

1) Identify the type of uncertainty 2) Suggest a way that it could be resolved

- **Uncertainty #1:** What is the correct hypothesis regarding how grassland bird nest success varies with extent of prescribed burn within territories?
  - H1: $logit(S_t) = \beta_0 + \beta_1 * burn\_ex_t$
  - H2: $logit(S_t) = \beta_0 + \beta_1 * burn_{ex_t} + \beta_2 * {burn_{ex_t}}^2$

- **Uncertainty #2:** Expert A believes that a heavy burn would be the best alternative, and Expert B believes a moderate burn would be the best choice

- **Uncertainty #3:** In a nest count survey there is variation in the number of eggs found in a nest

Working with uncertainty

First step is to acknowledge it:

- We are surrounded by uncertainty
- Simply reducing uncertainty will not guarantee a desired outcome
  - We often seek information to reduce uncertainty
  - But we should ask first:
    - Will that information change our decision and how much will it enhance our performance?

Working with uncertainty

Three Options:

1. Make decisions anyway

   Risk tools: e.g., Decision Trees, Utility Theory

2. **Conduct research to reduce uncertainty**

   Value of Information

3. Learn while managing

   Adaptive management

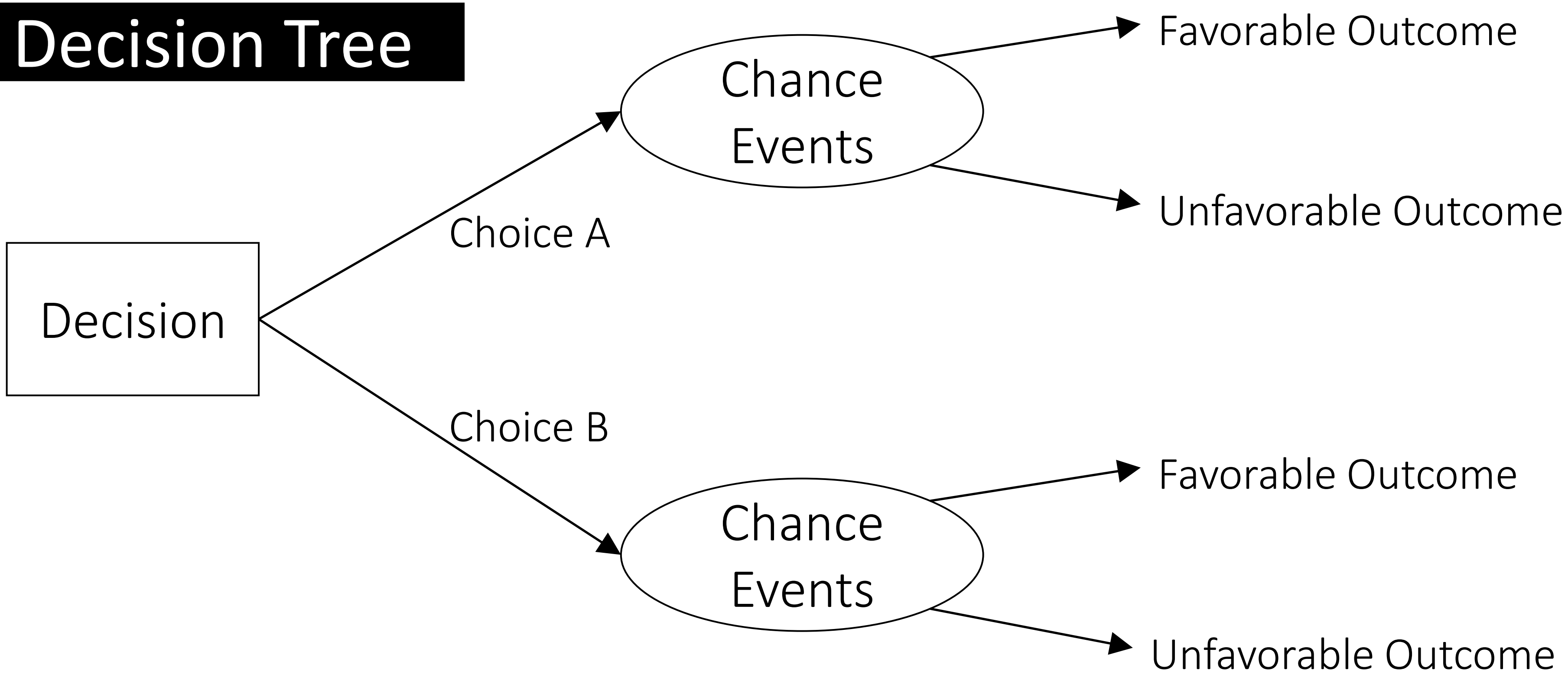
Risk = topic for next week!

Topic for today

2. Conducting research to reduce uncertainty

- Reducing uncertainty does not guarantee a desired outcome, but it can increase your chances

Decision Tree



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When to conduct research

As scientists, we have a strong tendency to:

- Want more information before taking action
- Recommend postponing a decision until we have more information
  - Why? What would we do differently based on that information?

We should ask:

- *Will the information change our decision?*
- *How much will the information improve our performance?*

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When to conduct research

NOTE:

Information has value to decision makers if, and only if

(a) It influences the selection of management actions

(b) The resulting change in management actions results in improvements in performance on the identified objectives

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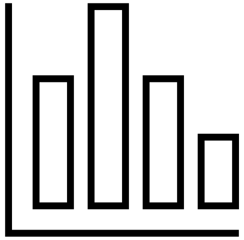
Types of data that might be collected:

- Baseline data collection (control data)
- Compliance monitoring
- Effects monitoring
- Capacity building initiatives for agencies/communities
- Co-management and trust building initiatives
- Research
- Development of assessment techniques (new predictive models)

Developed by Brielle Thompson (See Gregory et al. 2012 Ch 10)

Approaches to understand uncertainties

- Perform a sensitivity analysis



- Conduct a value of information analysis

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Sensitivity analysis

- Is the optimal alternative sensitive to uncertainty?
- *Consider the following example*
  - We are making a decision on whether to repair an impoundment, we evaluated three alternatives against four objectives:

Objectives	Alternatives		
	Status quo	Minor repair	Major repair
Cost ($M)	0	2	12
Environmental Benefit (0-10)	1	3	10
Disturbance (0-10)	0	1	7
Silt Runoff (k ft^3)	~~5~~	1	3

Sensitivity analysis

- Let's say we are uncertain about predicted environmental benefits for **Minor Repair** – we think they are 3 but they could be as large as 6

Objectives	Alternatives		
	Status quo	**Minor repair**	Major repair
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Sensitivity analysis

- Let’s say we are uncertain about predicted environmental benefits for **Minor Repair** – we think they are 3 but they could be as large as 6

	Status Quo	Minor Repair	Major Repair	Weight	Status Quo	Minor Repair	Major Repair
Cost	0	2	12	0.2	1	0.83333	0
Environ Benefits	1	3	10	0.6	0	0.22222	1
Disturbance	0	1	7	0.1	0	0.85714	0
Silt Runoff	5	1	3	0.1	0	1	0.5
					0.2	0.48571	0.65

When value = 3 we would select major repair

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Sensitivity analysis

- Let's say we are uncertain about predicted environmental benefits for **Minor Repair** – we think they are 3 but they could be as large as 6

	Status Quo	Minor Repair	Major Repair	Weight	Status Quo	Minor Repair	Major Repair
Cost	0	2	12	0.2	1	0.83333	0
Environ Benefits	1	5	10	0.6	0	0.44444	1
Disturbance	0	1	7	0.1	0	0.85714	0
Silt Runoff	5	1	3	0.1	0	1	0.5
					0.2	0.619044	0.65

When value = 5 we would still select major repair

Sensitivity analysis

- Let's say we are uncertain about predicted environmental benefits for **Minor Repair** – we think they are 3 but they could be as large as 6

	Status Quo	Minor Repair	Major Repair	Weight	Status Quo	Minor Repair	Major Repair
Cost	0	2	12	0.2	1	0.83333	0
Environ Benefits	1	6	10	0.6	0	0.55556	1
Disturbance	0	1	7	0.1	0	0.85714	0
Silt Runoff	5	1	3	0.1	0	1	0.5
					0.2	0.68571	0.65

When value = 6 we would now <u>select minor repair</u>

Thus, this uncertainty is *decision-relevant*

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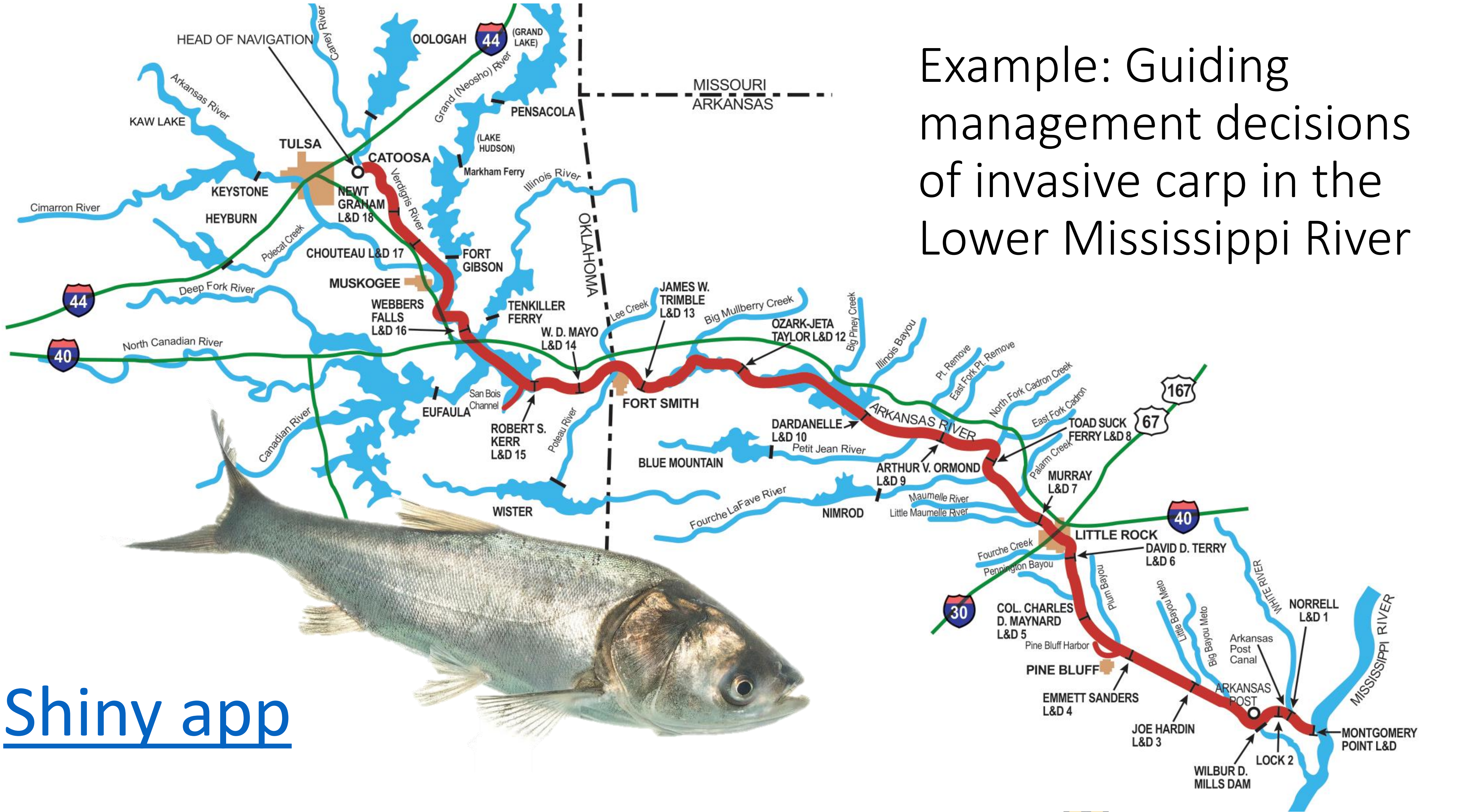
Example: Guiding management decisions of invasive carp in the Lower Mississippi River



[Shiny app](#)

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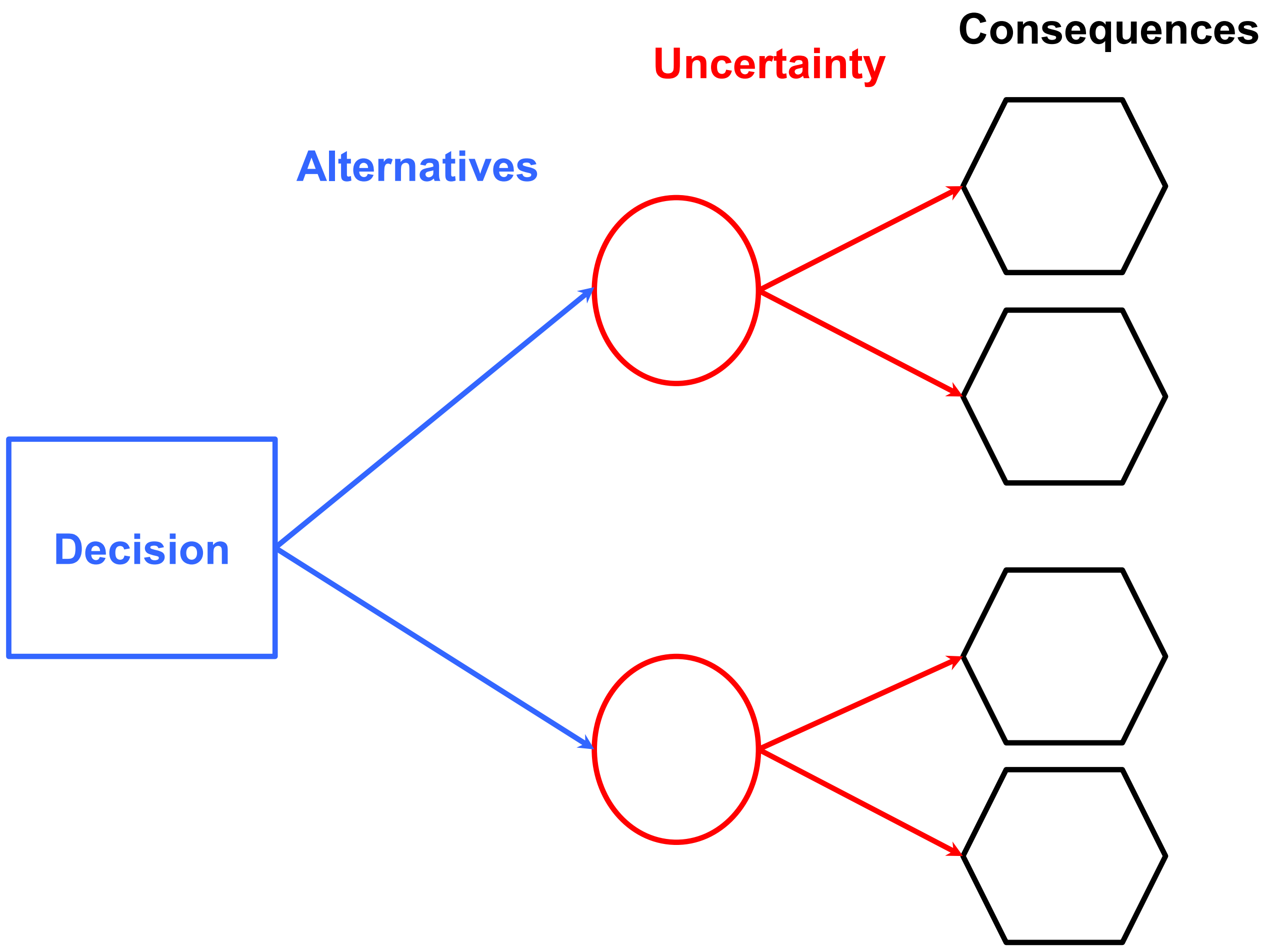
Decision trees:

- A useful tool for dealing with uncertainty



Value of information

- If the decision is not sensitive to uncertainty, then there is no decision value in additional information
  - However, if the decision is sensitive to uncertainty, what is the value of new information?
- **Value of Information** (VoI) offers a suite of tools to quantify the improvement of an outcome if uncertainty is resolved

Expected value of perfect information (EVPI)

- Expected Value of Perfect Information (EVPI): how much would we expect our management outcomes to improve it we could eliminate uncertainty?

$$EVPI = E_s[\max_a U(a,s)] - \max_a E_s[U(a,s)]$$

a = action taken, s = model of the system (a hypothesis),

$U(a,s)$ = utility associated with taking action a under model s

Aka: the difference between the expected value of an optimal action after new information has been collected and the expected value of an optimal action before the new information has been collected

- Aka aka: best outcome with information – best outcome without information

Runge MC, SJ Converse, and JE Lyons. 2011. Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. Biological Conservation 144: 1214-1223.

Developed by Sarah Converse

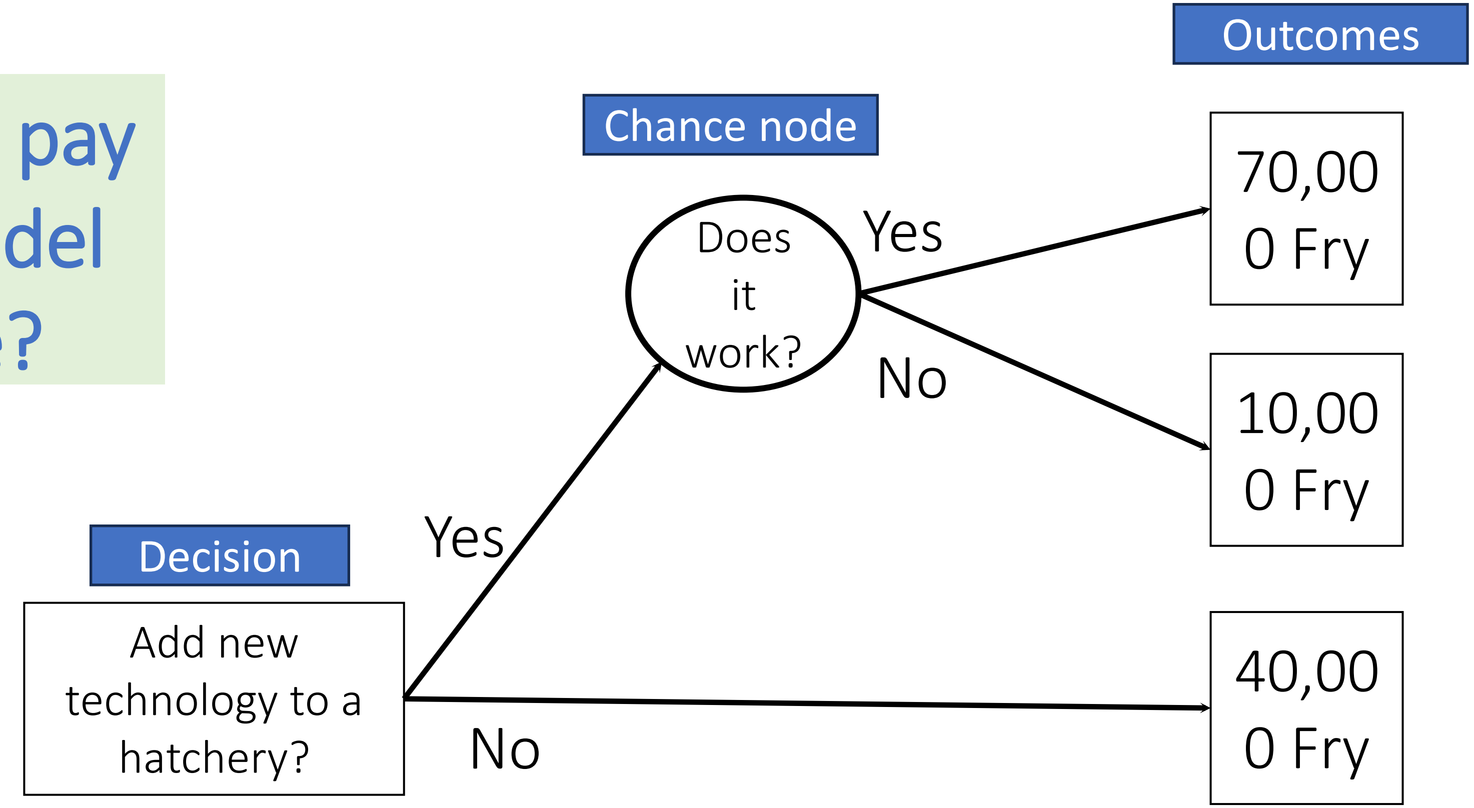
Expected value of perfect information (EVPI)

- Example: Hatchery problem – will a new technology improve the hatchery?

How much would you pay to find out which model (hypothesis) is true?

Optimistic (Model 1):
Probability that it works = 0.8

Pessimistic (Model 2):
Probability that it works = 0.4



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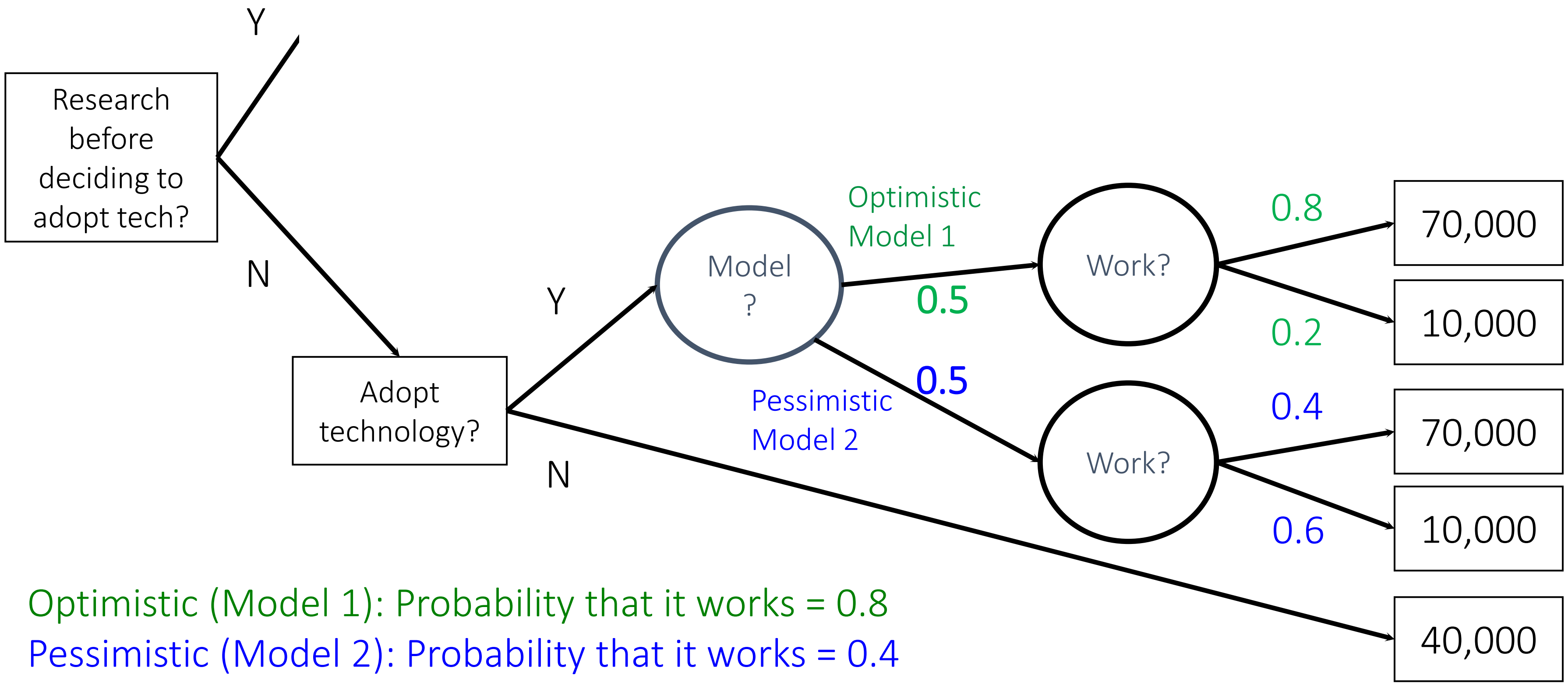
Expected value of perfect information (EVPI)



Example: Hatchery problem – will a new technology improve the hatchery?

And how much would you pay to find out which model (hypothesis) is true?

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Optimistic (Model 1): Probability that it works = 0.8

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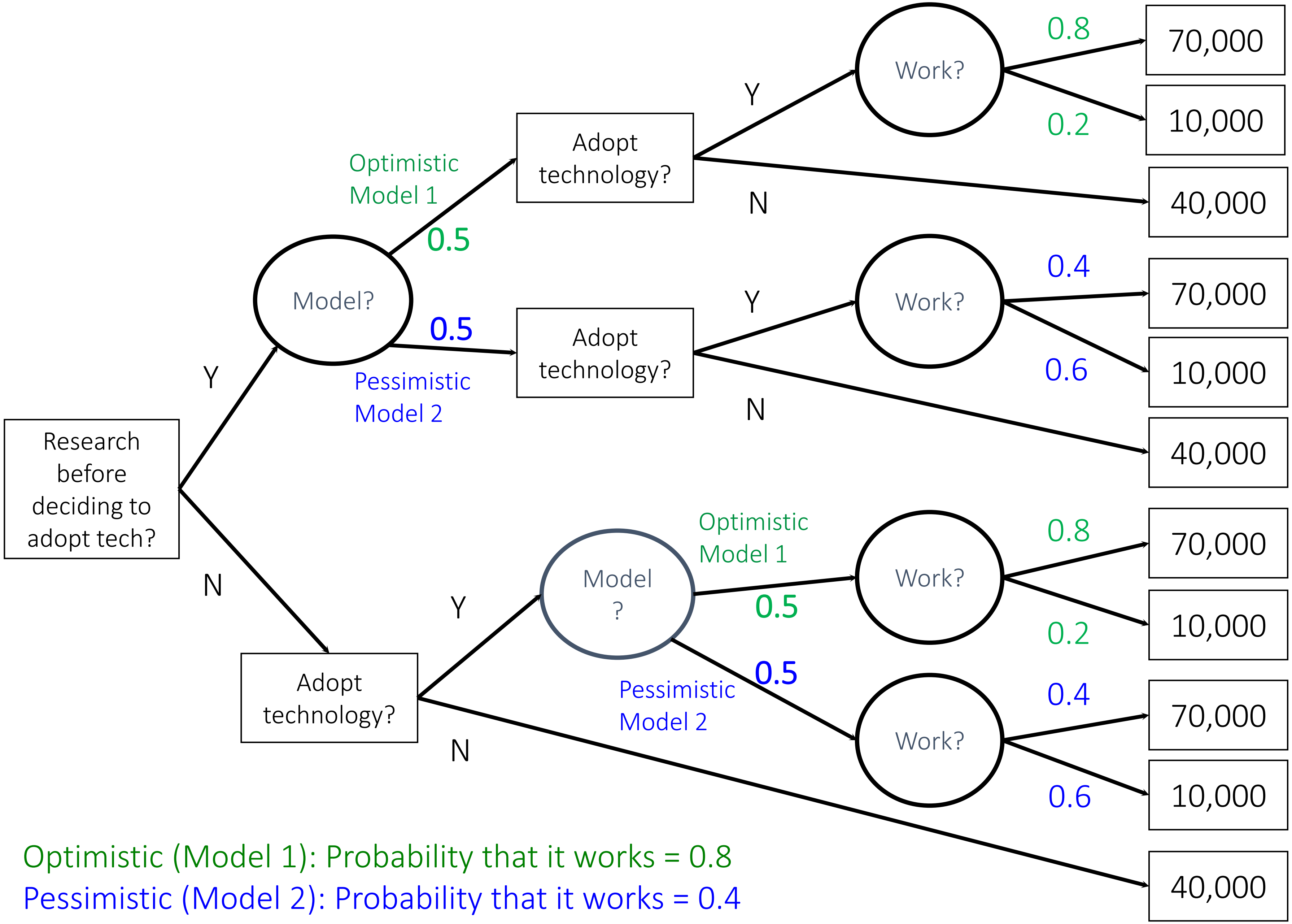
Expected value of perfect information (EVPI)



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Example: Hatchery problem – will a new technology improve the hatchery?

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Expected value of perfect information (EVPI)

EVPI: Hatchery Example

Model	Prior	Adopt the Technology?		EV with perfect information
		Yes	No	
1 (optimistic)	0.5	(0.8)*70+(0.2)*10=58	40	
2 (pessimistic)	0.5			
EV with uncertainty				

EVPI calculation

1. Calculate EV for each model and alternative

= Probability it works * Frys (in 1000s) +
probability it doesn't work * Frys (in 1000s)

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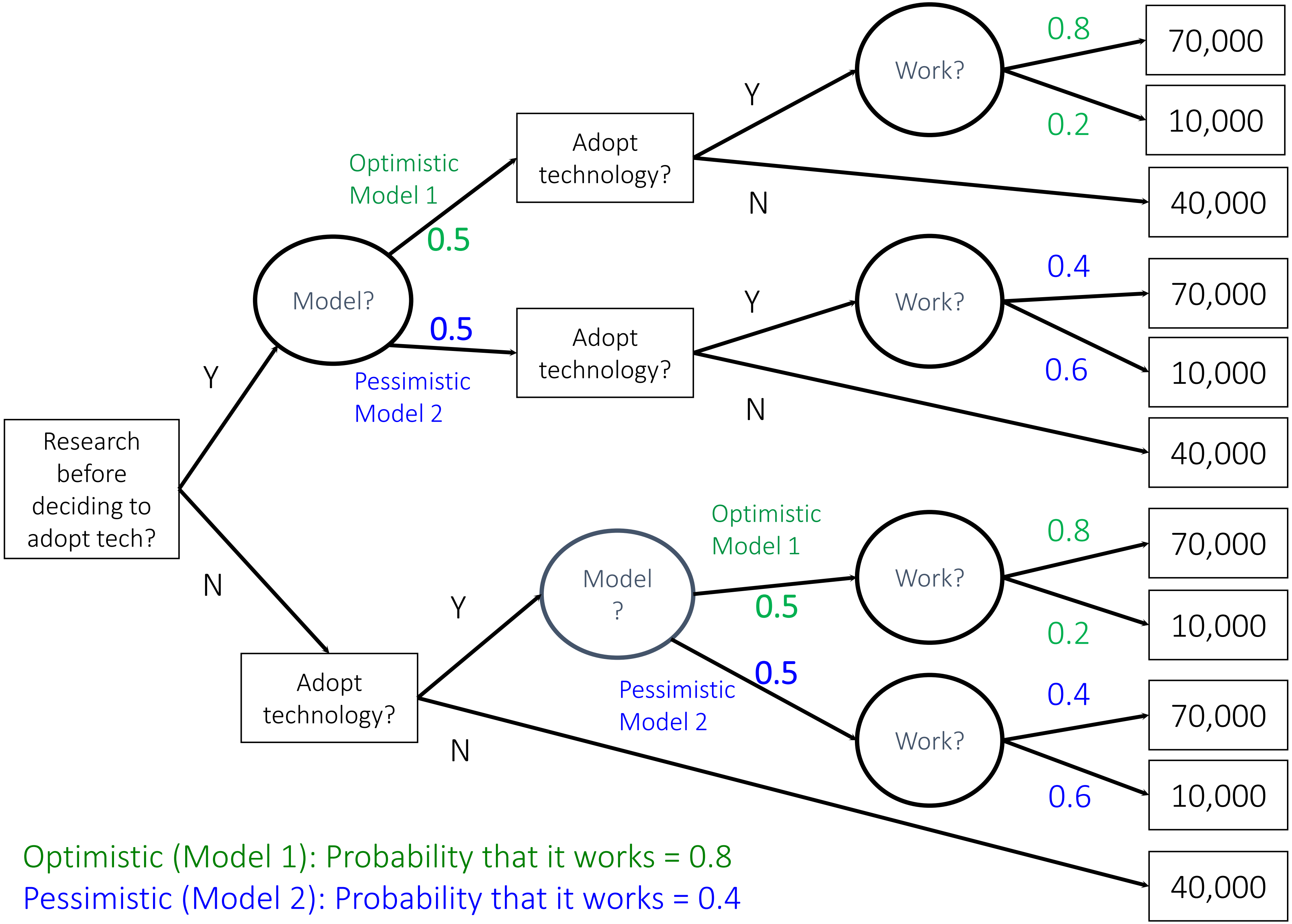
Expected value of perfect information (EVPI)



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Expected value of perfect information (EVPI)

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EV with uncertainty				

EVPI calculation

1. Calculate EV for each model and alternative

= Probability it works * Frys (in 1000s) +
probability it doesn't work * Frys (in 1000s)

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Expected value of perfect information (EVPI)

EVPI: Hatchery Example

Model	Prior	Adopt the Technology?		EV with perfect information
		Yes	No	
1 (optimistic)	0.5	(0.8)*70+(0.2)*10=58	40	(0.5)*58
2 (pessimistic)	0.5	(0.4)*70+(0.6)*10=34	40	(0.5)*40
EV with uncertainty				(0.5)*58 + (0.5)*40 = 49

EVPI calculation

1. Calculate EV for each model and alternative
2. Calculate EV **under certainty** **= 49**

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Expected value of perfect information (EVPI)

EVPI: Hatchery Example

Model	Prior	Adopt the Technology?		EV with perfect information
		Yes	No	
1 (optimistic)	0.5	(0.8)*70+(0.2)*10=58	40	(0.5)*58
2 (pessimistic)	0.5	(0.4)*70+(0.6)*10=34	40	(0.5)*40
EV with uncertainty		(0.5)*58 + (0.5)*34 = 46	40	(0.5)*58 + (0.5)*40 = 49

EVPI calculation

1. Calculate EV for each model and alternative
2. Calculate EV **under certainty** **= 49**
3. Calculate EV **under uncertainty** **= 46**

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Expected value of perfect information (EVPI)

EVPI: Hatchery Example

Model	Prior	Adopt the Technology?		EV with perfect information
		Yes	No	
1 (optimistic)	0.5	(0.8)*70+(0.2)*10=58	40	(0.5)*58
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EV with uncertainty		(0.5)*58 + (0.5)*34 = 46	40	(0.5)*58 + (0.5)*40 = 49

EVPI calculation

1. Calculate EV for each model and alternative
2. Calculate EV **under certainty** **= 49**
3. Calculate EV **under uncertainty** **= 46**
4. Calculate EVPI = EV under certainty – EV under uncertainty **= 49 – 46 = 3**

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Skills Check Task 2 – Calculate EVPI

TASK: Calculate EVPI to determine whether we should undertake research to determine which hypothesis is true?

Notation example:
V(A1|H1) = outcome of A1 given H2 is true
$\max_A$V(A|H2) = Maximum outcomes across all alternatives if H2 is true

Hypothesis	Belief		Predicted Survival under Alternative and Hypothesis	
**See Task 1 uncertainty #1*			**Alternative 1 (A1) – Heavy Burn**	**Alternative 2 (A2)– Moderate Burn**
H1	**0.4**		**0.7**	**0.3**
H2	**0.6**		**0.45**	**0.65**

1. Calculate EV for each alternative

- EV(A1) = Pr(H1)*V(A1|H1)+Pr(H2)*V(A1|H2) = 0.4*0.7 + 0.6*0.45 = 0.55
- EV(A2) = Pr(H1)*V(A2|H1)+Pr(H2)*V(A2|H2) = ? **[You will answer!]**

2. Calculate EV(Uncertainty) = ? **[You will answer!]** *Hint the maximum between EV(A1) and EV(A2)*

3. Calculate EV(Certainty) = Pr(H1)*$\max_A$V(A|H1)+Pr(H2)*$\max_A$V(A|H2) = ? **[You will answer!]**

4. Calculate EVPI = EV(Certainty) – EV(Uncertainty) = ? **[You will answer!]**

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Other VOI analysis:

- **Expected Value of Perfect Information (EVPI):** how much would we expect our management outcomes to improve it we could completely eliminate uncertainty?

- **Expected Value of Partial Perfect Information (EVPXI):** how much would we expect our management outcomes to improve if we could completely eliminate one source of uncertainty?

- **Expected Value of Sample Information (EVSI):** how much would we expect our management outcomes to improve if we could get a sample of information?

- **Qualitative Value of Information (QVoI):** a measure of EVPI based on a qualitative analysis

VOI summary:

- Reducing uncertainty before taking action is a sequence of decisions with trade-offs and risks
- Value of information is useful for evaluating how much management can be improved by reducing uncertainty and gauging how much one should pay for applied research
- If you can't do it quantitatively, think about it conceptually or qualitatively

Developed by Sarah Converse

Working with uncertainty

Three Options:

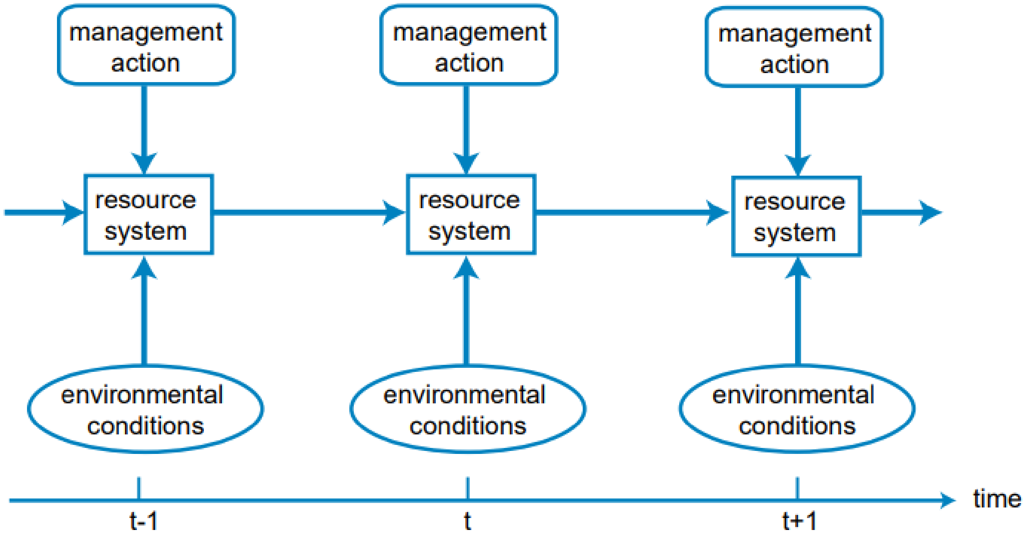
1. Make decisions anyway
   Risk tools: e.g., Decision Trees, Utility Theory
2. Conduct research to reduce uncertainty
   Value of Information
3. **Learn while managing**
   Adaptive management

Risk = topic for next week!

Topic for today

3. Learn while managing

- Recurrent Decisions - decisions we make over and over (e.g., annual harvest limits, hatchery releases, translocations, etc.)



DOI adaptive management guide

- Sometimes, if we are making recurrent decisions, we can use the opportunity to learn and adapt

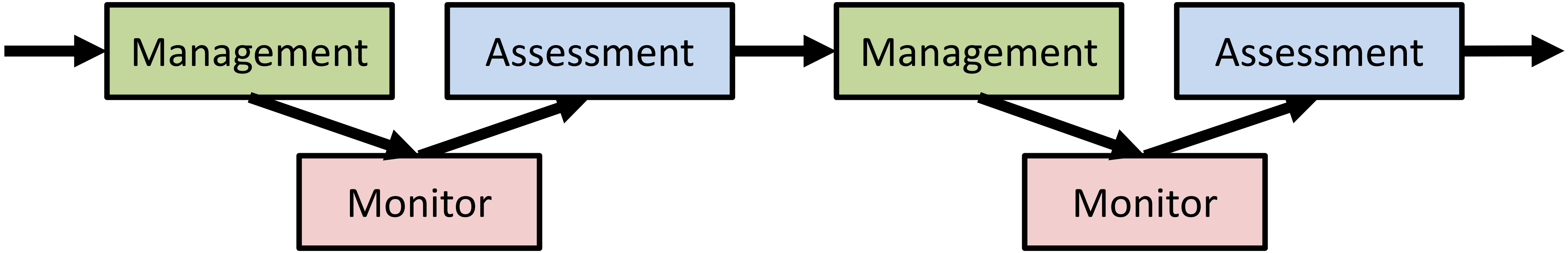
- When we use monitoring to reduce our uncertainty and adapt our management over time, we are doing ***adaptive management***

Developed by Sarah Converse

When can we use adaptive management?

- If we have:
  - Repeated decisions
  - Uncertainty that is important to management (EVPI > 0)
  - The ability to monitor to reduce our uncertainty

Adaptive Management: *learning by doing*



Questions to ask if adaptive management is needed

- Do the uncertainties affect the choice of future management actions?
- Does the spatial and temporal scale allow for formal and effective monitoring or experimentation?
- Given the multiple objectives of stakeholders and potential risks, is experimentation really an option?
- Is there sufficient institutional capacity to support an AM program?
- Are there alternative ways to reduce the relevant uncertainties?
- Do we have the capacity to collect monitoring data?

The purposes of monitoring in the context of adaptive management are to:

1. Assess the state of a system
2. Determine if objectives are being met (evaluate management performance)
3. Resolve uncertainty about how system works (foster learning)

Lyons JE, MC Runge, HP Laskowski, and WL Kendall. 2008. Monitoring in the context of structured decision-making and adaptive management. Journal of Wildlife Management 172: 1683-1692.

How does it work?

1. **Structure the decision problem**
   - Problem Framing → Objectives → Alternatives
2. **Develop predictive models that include key sources of uncertainty**
   - Distinguish between reducible and irreducible uncertainty
   - Analyze the expected value of information to determine if the uncertainty is actually worth reducing
3. **Identify a preferred management action, based on**
   - Management objective(s)
   - Weight of evidence (i.e., relative confidence in each of the alternative models)
   - Anticipated value of learning
4. **Decision is implemented, the resource evolves to a new state**
5. **A monitoring program observes the resource response** (new system state)
6. **Model-specific weights are updated to reflect the new information**
   - Weights increase for those models that more closely matched the observations
   - Weights decrease for models which showed poorer predictive capacity
7. **Return to step 3**

Developed by Runge MC, Nichols JD, Johnson FA, Eaton MJ, Romito AM, Breese G, Cochrane JF, Converse SJ, Eaton MJ, Larson MA, Lyons JE, Smith DR, Isham AF

Degrees of monitoring:
- Monitor single management action
- Monitor multiple management 'experiments'

Degrees of updating models:
- Simple as 'recording new data'
- Complex as Bayesian updating

Degrees of predicting consequences:
- Expert elicitation
- Prediction modeling
- Experiments
- Management strategy evaluation

Degrees of tradeoff & optimization:
- Negotiation
- Multi-criteria decision analysis
- Value of information
- Dynamic programming methods*

**beyond scope of class*

Specific methods used:

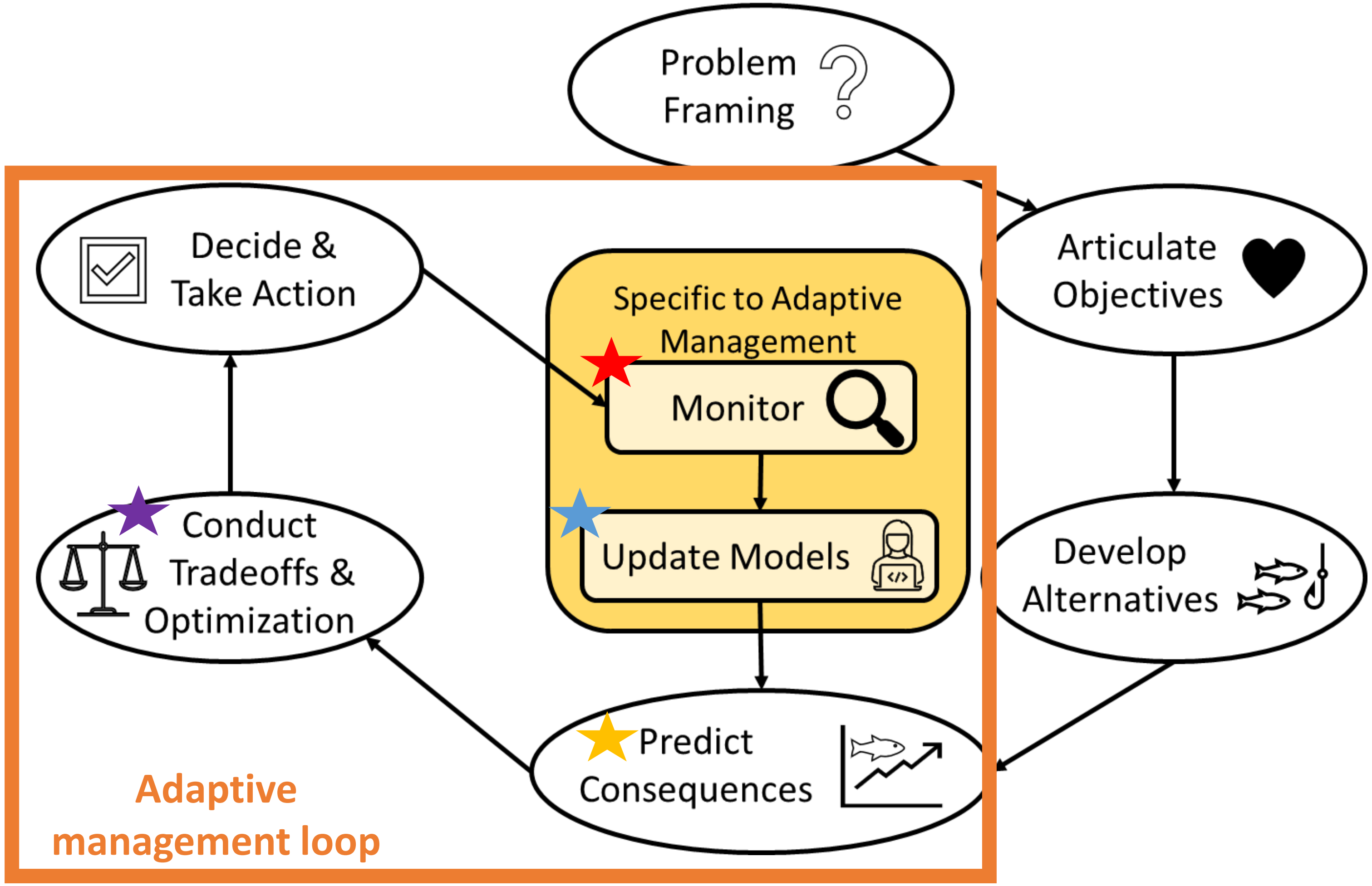


Figure Adapted from Converse et al. 2013 and Runge 2011

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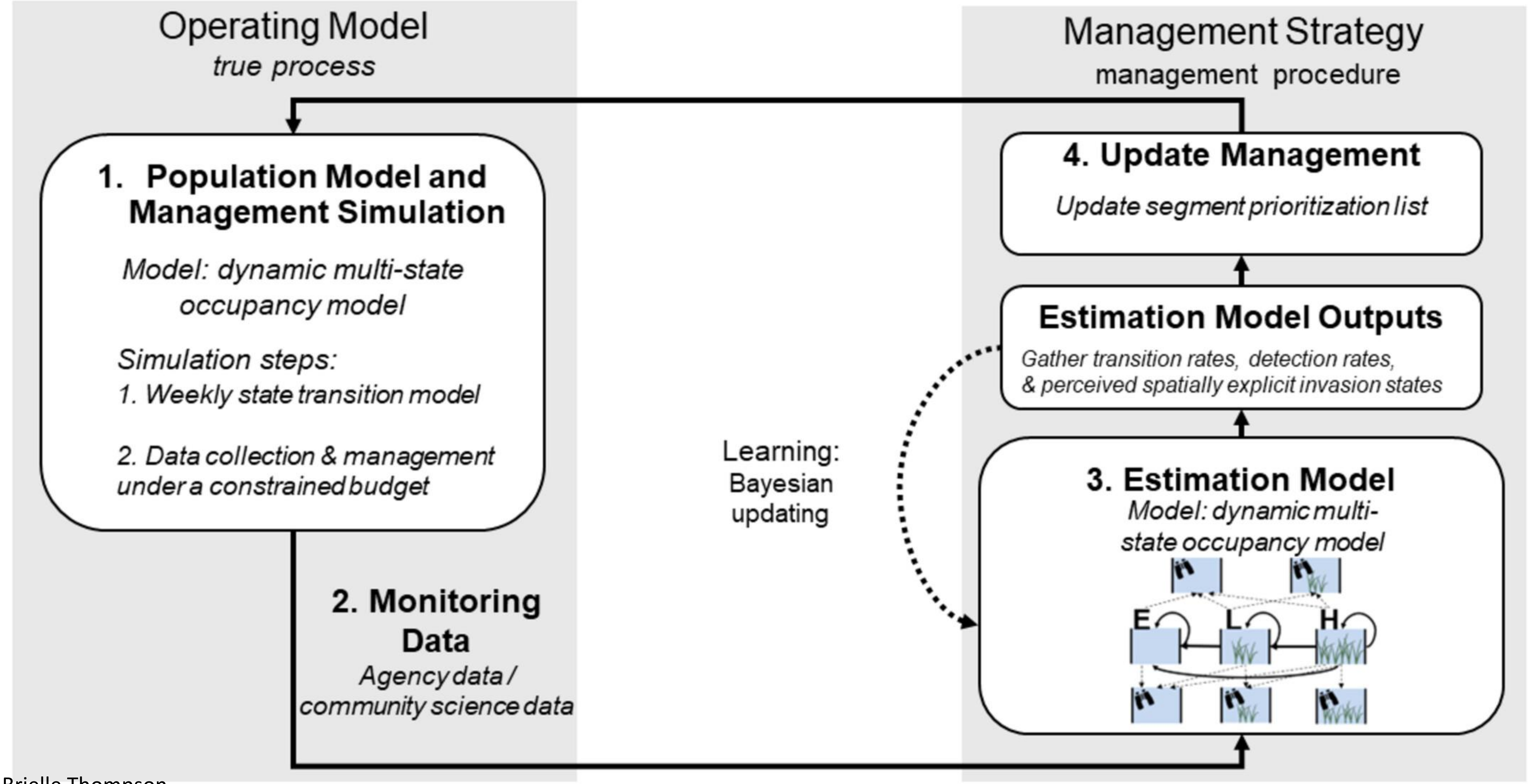
Another useful adaptive management framework:

Management strategy evaluation

Thompson et al. 2025



Missouri

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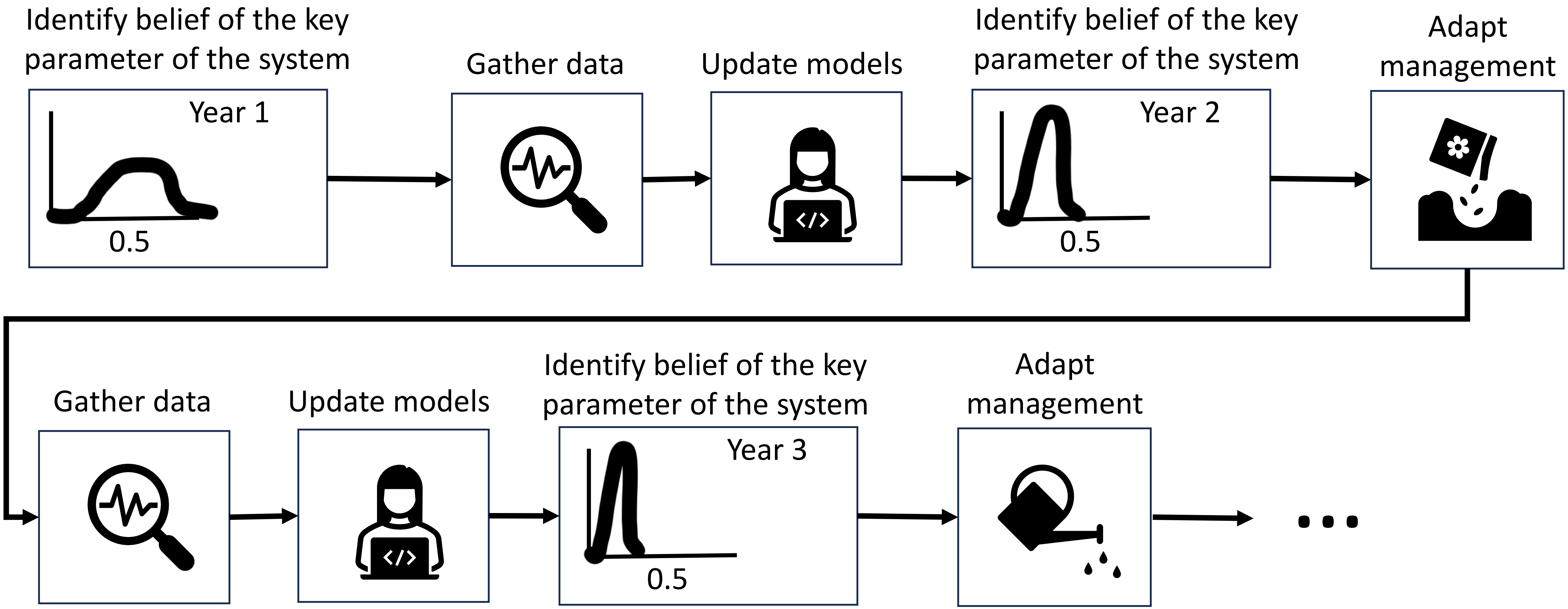
How learning can occur over time:



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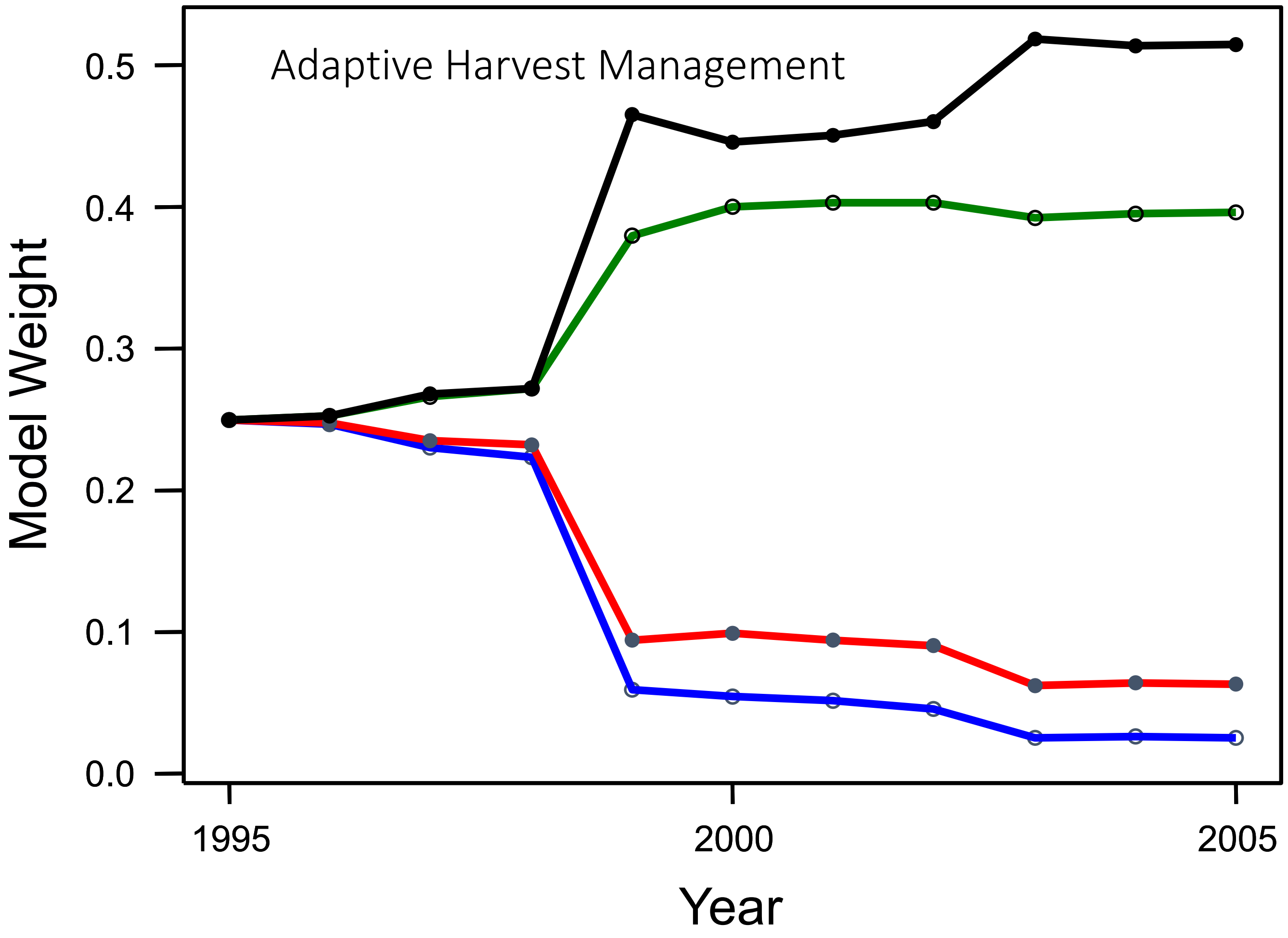
AM example- north American waterfowl harvest



Developed by Runge MC, Nichols JD, Johnson FA, Eaton MJ, Romito AM, Breese G, Cochrane JF, Converse SJ, Eaton MJ, Larson MA, Lyons JE, Smith DR, Isham AF

AM example- Glen Canyon Dam

See https://www.usbr.gov/uc/progact/amp/index.html

Other AM examples

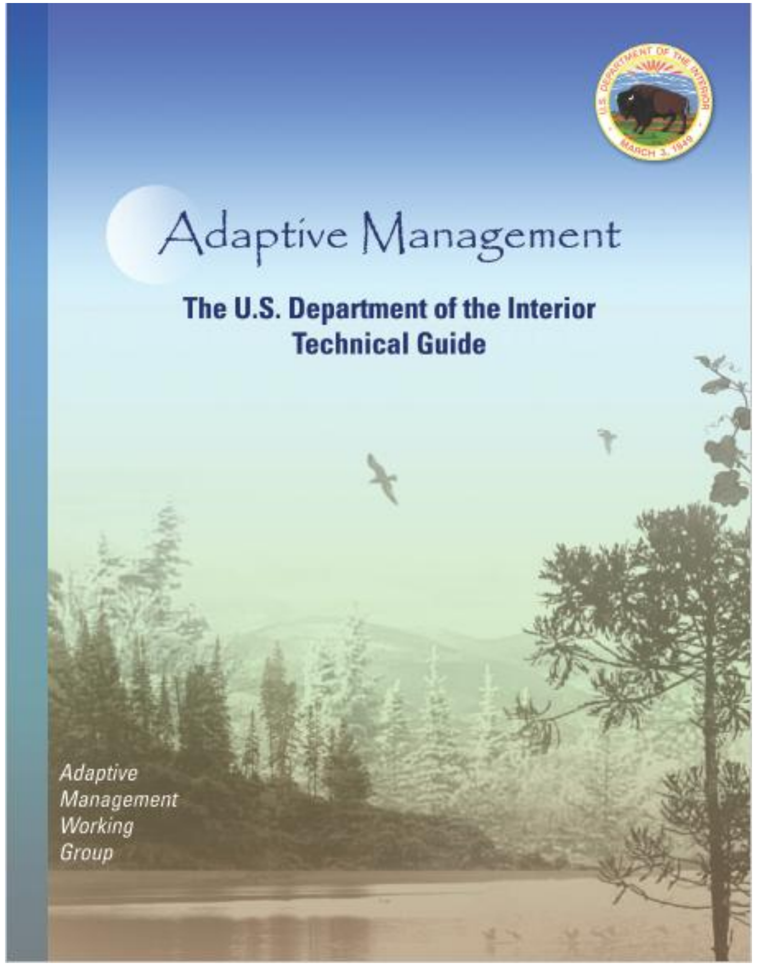
Golden Eagles in Denali

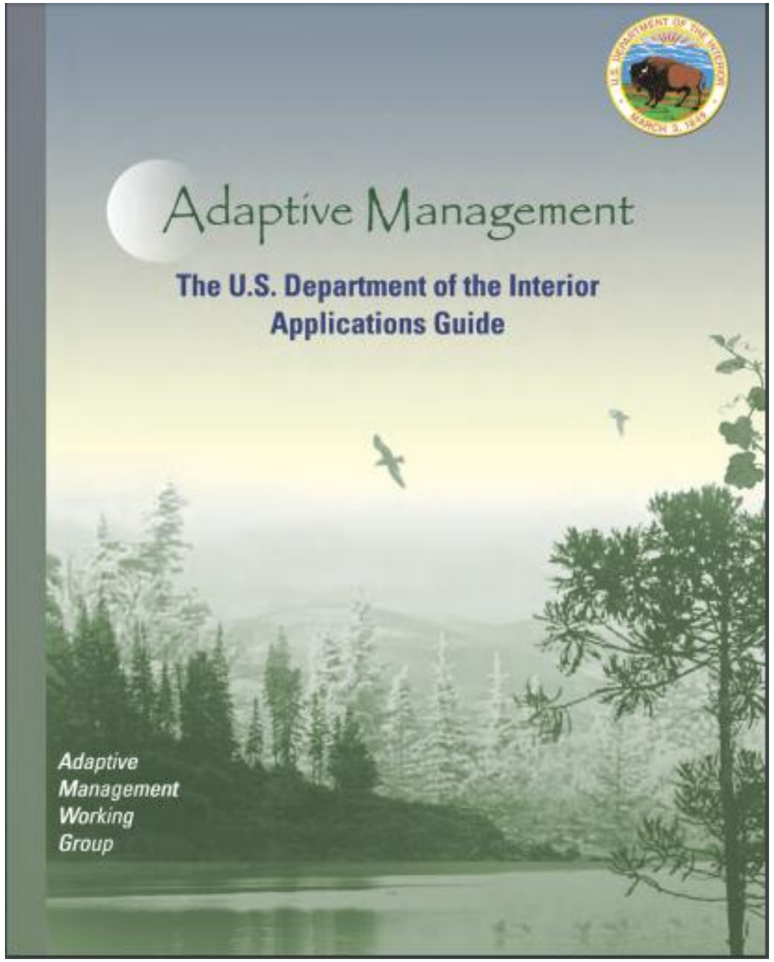
- 3 hypotheses were developed about effects of hiking on site occupancy and nest success
- Collected monitoring data each year to update hypothesis to then inform annual decisions about what trails should be restricted

Red Knots and horseshoe crabs

- Adaptive management program to identify sustainable horseshoe crab harvest strategy that protects red knots and enables learning about how the system functions
- Annual Monitoring data informs these decisions

Adaptive management resources





Impediments to adaptive management:

- Confusion with trial and error
  - It is not a ‘trial and error’ process, but rather emphasizes learning while doing
- Institutional resistance to acknowledging uncertainty
- Mistake a monitoring plan for being an adaptive management program
- Risk aversion → strategies with little or no opportunity for learning
- Lack of institutional commitment

Skills Check #3: Adaptive Management

There is still extreme uncertainty on whether hypothesis 1 or 2 is correct regarding how grassland bird nest success varies with extent of prescribed burn within territories

H1: $logit(S_t) = \beta_0 + \beta_1 * burn\_ex_t$

H2: $logit(S_t) = \beta_0 + \beta_1 * burn_{ex_t} + \beta_2 * {burn_{ex_t}}^2$

For the next 4 years, your team has four plots of land that you will experiment with doing alternative 1: a heavy burn, alternative 2: a moderate burn, alternative 3: a light burn, and alternative 4: no burns

Your task:

Explain how an adaptive management program might be performed to resolve uncertainty in our two hypotheses?

Activity: think about your decision problem

- For your final project presentation, you will quickly comment on additional tools that could be used in your problem that are beyond PrOACT
  - E.g., addressing uncertainty (sensitivity analysis, value of information analysis, and adaptive management)
  - E.g., for addressing risk **(those tools will be talked about next week)**

- How could you use these tools for your problem?

- **Feel free to go back to your other PrOACT steps!**

Developed by Brielle Thompson

Working with uncertainty

Three Options:

1. Make decisions anyway

   Risk tools: e.g., Decision Trees, Utility Theory

Risk = topic for next week!

2. Conduct research to reduce uncertainty

   Value of Information

3. Learn while managing

   Adaptive management

Topic for today

Looking ahead:

Next week: Additional SDM tools regarding uncertainty and risk & **few final presentations**

Weekly: Work through a step of the PrOACT process/ learn extra tools

Last week of class:

Elevator pitch of your research project in terms of SDM/PrOACT

Note: Abridged PrOACT story slides with a star on the upper right are good examples to use for your presentation

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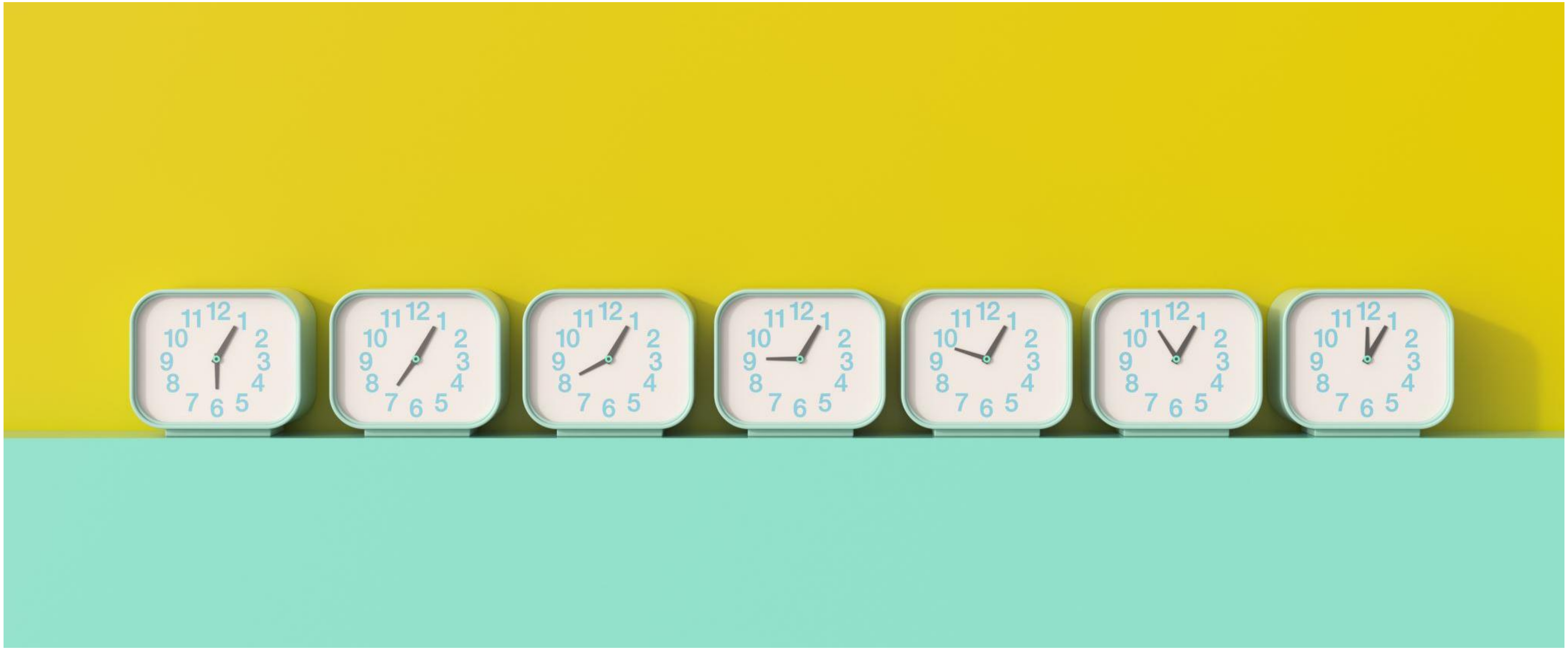
Extra time activities:



Reading discussion – Ch 10 Gregory and Long 2012

- What role does learning play throughout the SDM process, and why is it considered essential at every stage rather than just at the end?

- How does the concept of “value of information” (VOI) help prioritize research and monitoring efforts? What are the limitations of relying solely on VOI calculations?

- What are the benefits and challenges of incorporating adaptive management into SDM? How do passive and active adaptive management differ in practice?

- The authors argue that learning is a means to an end, not a fundamental objective. Do you agree? Should learning ever be treated as a primary goal in environmental management?

EXPECTED VALUE OF PARTIAL PERFECT INFORMATION (EVPXI)

- Expected Value of Partial Perfect Information: how much would we expect our management outcomes to improve if we could completely eliminate one source of uncertainty?
- Going back to the bird example: We have a new hypothesis and a new action

Hypothesis	Belief		Predicted Outcome under Alternative and Hypothesis		
			Alternative 1 – Heavy Burn	Alternative 2 – Moderate Burn	Alternative 3 – No Burn
H1	0.4		0.7	0.3	0.2
H2	0.4		0.45	0.65	0.4
H3	0.2		0.4	0.5	0.6

H1: $logit(S_t) = \beta_0 + \beta_1 * burn\_extent_t$

H2: $logit(S_t) = \beta_0 + \beta_1 * burn\_extent_t + \beta_2 * {burn\_extent_t}^2$

H3: $logit(S_t) = \beta_0$

What if I could do an experiment that would either confirm or refute H3?
Let's call our hypotheses H3 and not-H3

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EXPECTED VALUE OF PARTIAL PERFECT INFORMATION (EVPXI)

- Expected Value of Partial Perfect Information: how much would we expect our management outcomes to improve if we could completely eliminate one source of uncertainty?
- Going back to the bird example: We have a new hypothesis and a new action

Hypothesis	Belief		Predicted Outcome under Alternative and Hypothesis		
			Alternative 1 – Heavy Burn	Alternative 2 – Moderate Burn	Alternative 3 – No Burn
not-H3	0.8		0.575	0.475	0.3
H3	0.2		0.4	0.5	0.6

H1 and H2 combine to become not-H3 above ^
= EV(A1|not-H3) = (Pr(H1)*V(A1|H1)+Pr(H2)*V(A1|H2)) / (Pr(H1)+Pr(H2))
= (0.4*0.7+0.4*0.45)/(0.4+0.4) = 0.575

Developed by Sarah Converse

EXPECTED VALUE OF PARTIAL PERFECT INFORMATION (EVPXI)

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H3	0.2		0.4	0.5	0.6

<u>Then just calculate EVPI on the new table ^</u>

EV(Uncertainty) = maxA(EV(A))

- EV(A1) = 0.8*0.575+0.2*0.4 = 0.54
- EV(A2) = 0.8*0.475+0.2*0.5 = 0.48
- EV(A3) = 0.8*0.3+0.2*0.6 = 0.36

*EV(Uncertainty) = 0.54

EV(Certainty) = Pr(not-H3)*maxAV(A|not-H3)+Pr(H3)*maxAV(A|H3) = 0.8*0.575+0.2*0.6 = 0.58

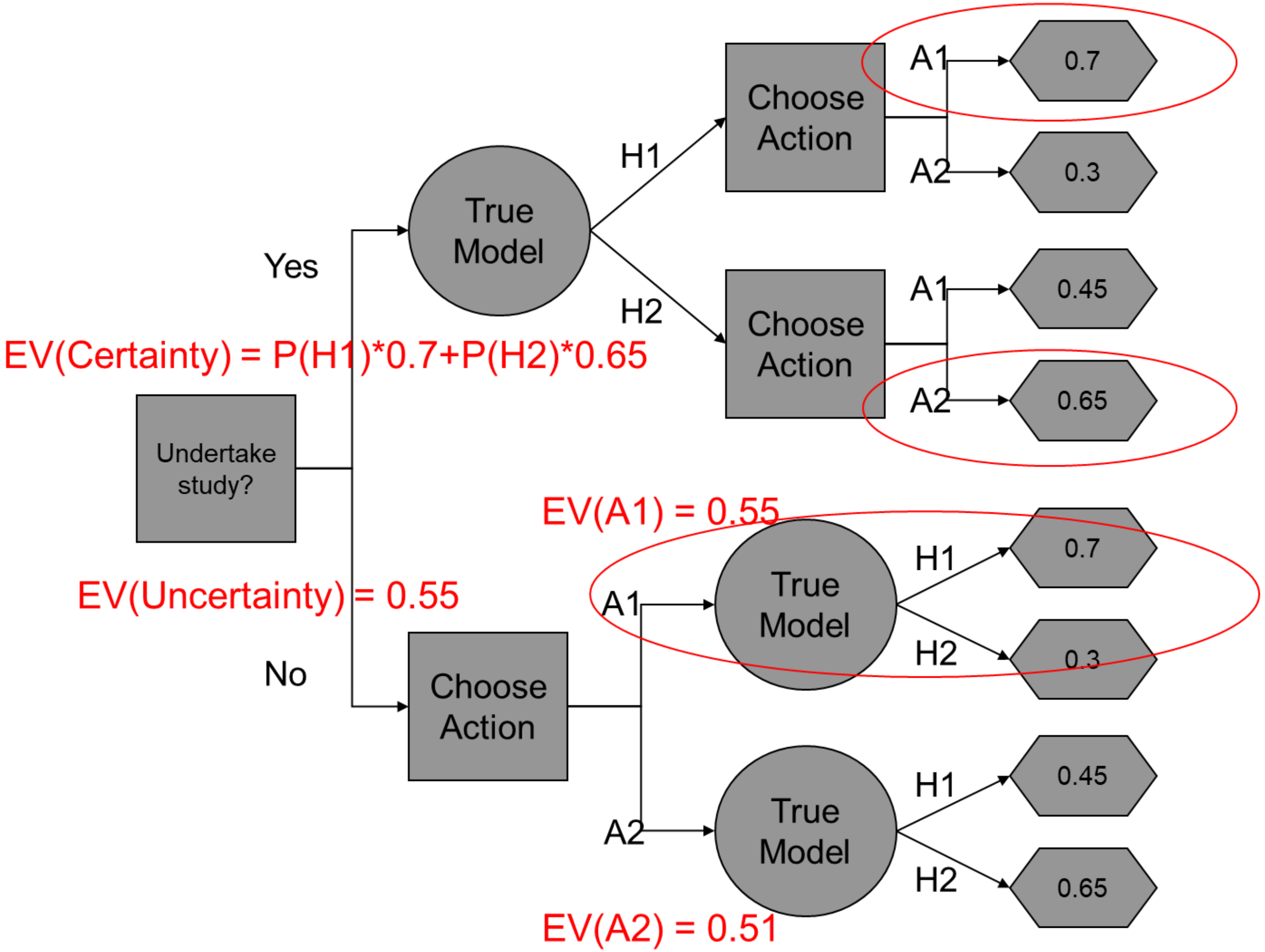
EVPXI(H3) = 0.58 – 0.54 = **0.04**

Activity: Calculate EVPXI(H1) and EVPXI(H2)

Hypothesis	Belief		Predicted Outcome under Alternative and Hypothesis		
			Alternative 1 – Heavy Burn	Alternative 2 – Moderate Burn	Alternative 3 – No Burn
H1	0.4		0.7	0.3	0.2
H2	0.4		0.45	0.65	0.4
H3	0.2		0.4	0.5	0.6

- Considering EVPXI(H1), EVPXI(H2), and EVPXI(H3), if you could confirm or refute just one hypothesis, which one would you take on?

Hints for Skills Check Task 2



Aside: Active vs passive AM

- **Passive** AM involves decision-focused monitoring
  - New information becomes available through the monitoring of outcomes, the existing data set should be updated and, if appropriate, new hypotheses constructed and new management actions undertaken.

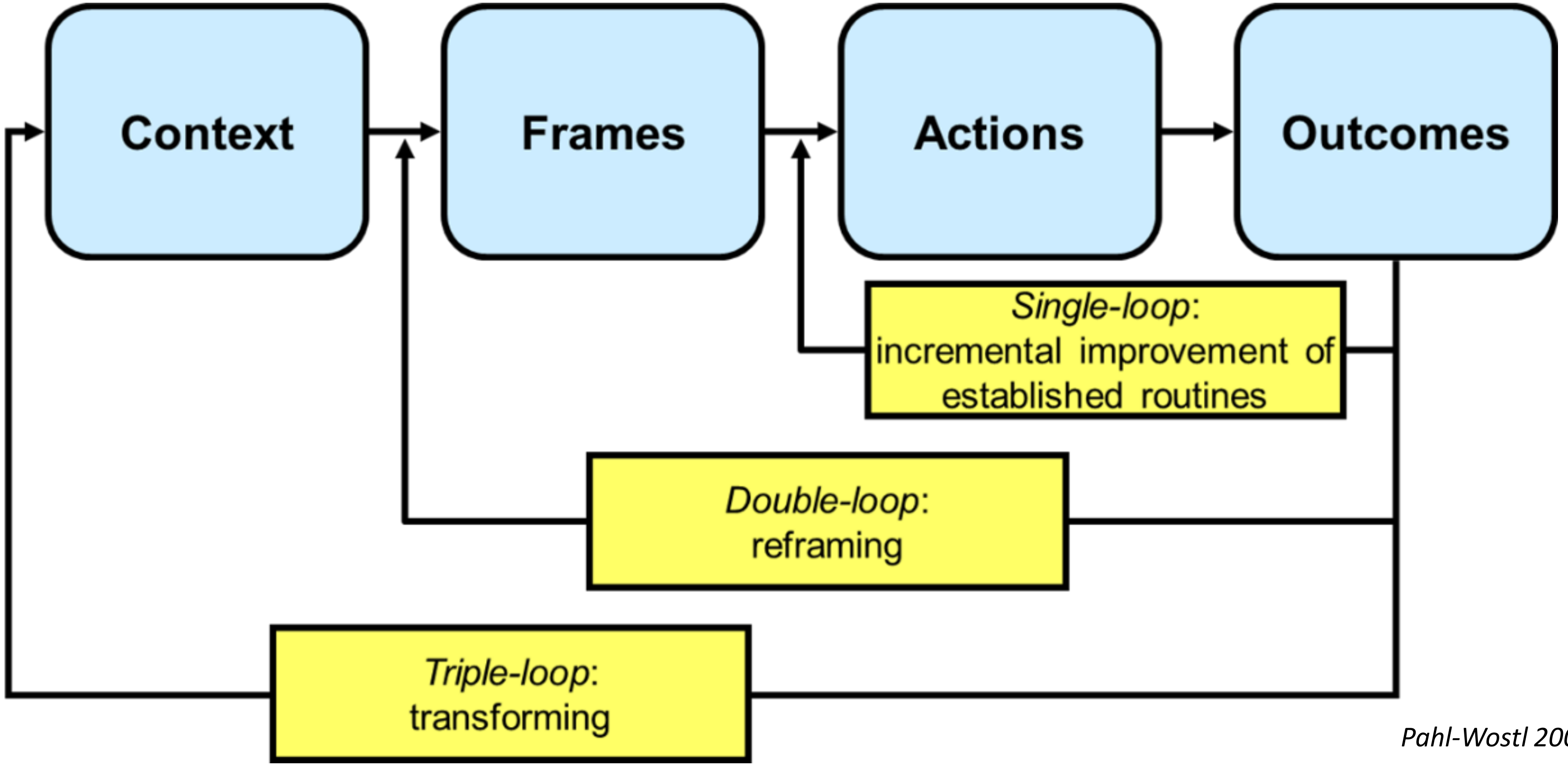
- **Active AM** involves decision-focused experimentation.
  - The implementation phase incorporates actions intended to deliberately perturb the system

Aside: Single-, double-, and triple-loop learning

- Learning occurs at several levels
- Single-loop: comparing the existing range of our understanding of the system. That is, it asks the question "are we doing things right?"
- Double-loop: describes a re-examination of the problem framing (values, objectives, alternatives, scale, etc.) following a period of single-loop learning. That is, it asks the question "are we doing the right things?"
- Triple-loop: examines the role of governance institutions, regulatory frameworks, etc., and questions their efficacy in managing resources. That is, it asks, "who has the right to do it?"

Developed by Runge MC, Nichols JD, Johnson FA, Eaton MJ, Romito AM, Breese G, Cochrane JF, Converse SJ, Eaton MJ, Larson MA, Lyons JE, Smith DR, Isham AF

Aside: Single-, double-, and triple-loop learning



Pahl-Wostl 2009

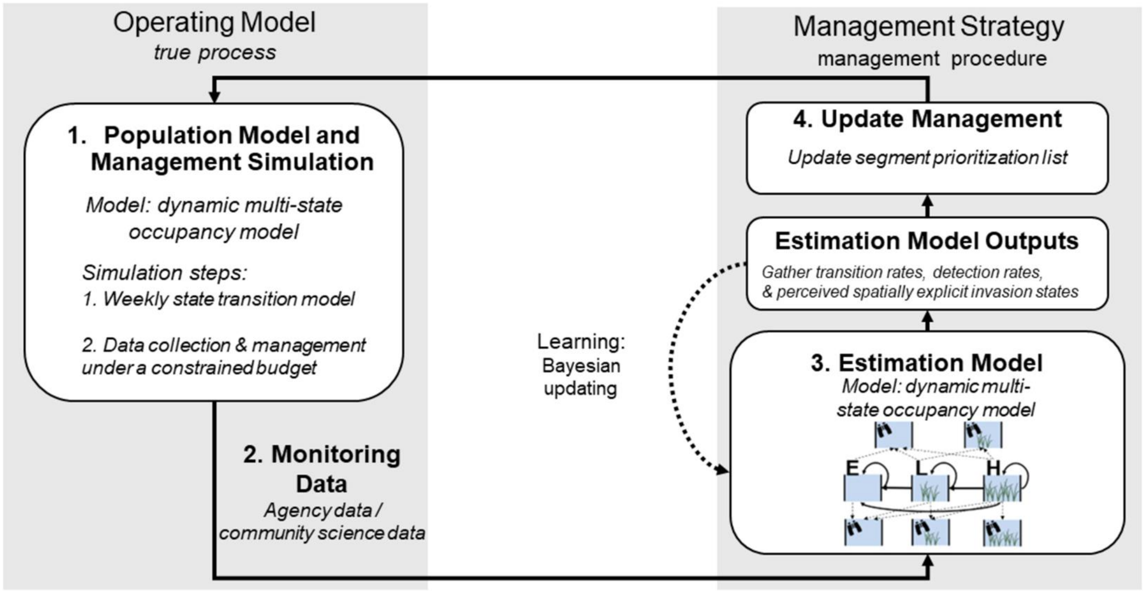
University of Missouri

Developed by Runge MC, Nichols JD, Johnson FA, Eaton MJ, Romito AM, Breese G, Cochrane JF, Converse SJ, Eaton MJ, Larson MA, Lyons JE, Smith DR, Isham AF

Management Strategy Evaluation

- Approach for identifying optimal adaptive management decisions
- Two phases:
  - **Operating model**
    - Underlying ecological process
    - Results in monitoring data
  - **Management strategy**
    - Uses monitoring data to inform estimation model
    - Estimation model then informs management decision
- Use:
  - Fisheries, invasive species, large predator management

Thompson et al. 2025



Pros: can incorporate complex ecological processes in estimation/simulation models

Cons: Does not inform mathematically optimal decisions (compared to dynamic programming processes)