Case Study: Native Prairie Adaptive Management in the USFWS Refuge System

Monitoring and Learning

Case Study Module C

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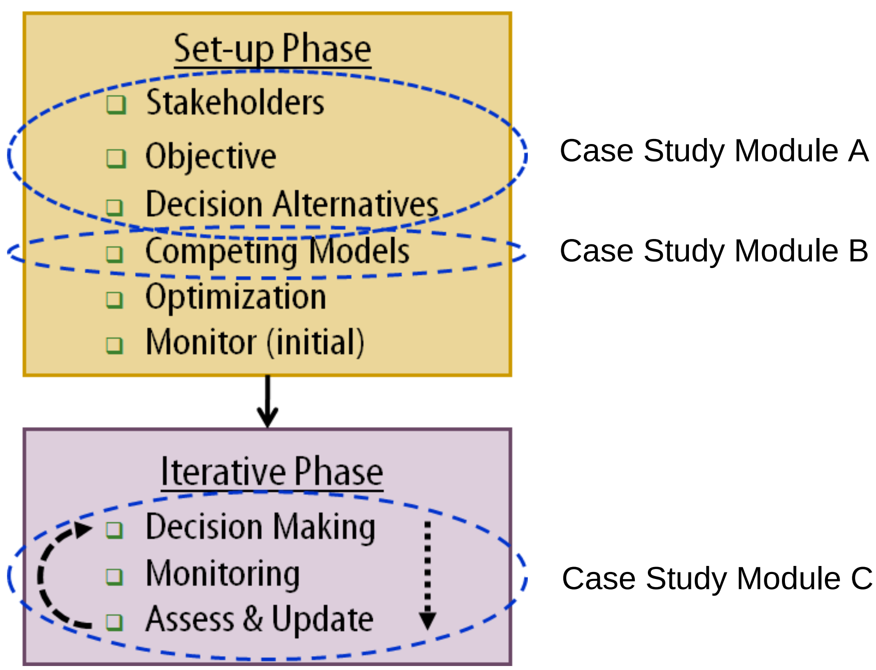
NPAM Framework Components



Objectives of Case Study Module C

- Discuss monitoring design in context of NPAM case study
- Demonstrate how structural uncertainty is reduced as a consequence of decision making, prediction, and monitoring
    - Show how we update model weights
- Consider how the rate of learning can be affected by monitoring design

<u>Native Prairie Adaptive Management</u>

- The Resource Problem
    - Loss of native prairie to cool-season invasive grasses, smooth brome and Kentucky bluegrass
- Area of focus
    - Native sod on Service-owned lands across the Prairie Pothole Region in USFWS Regions 3 and 6
    - Cooperators from 19 different refuge complexes across 4 states, with 120 management units (81 mixed, 39 tall)
- Spatial unit of focus
    - Management unit

<u>Management Objective & Decision Alternatives</u>

- Management objective
    - Increase the cover of native grasses and forbs at the least cost
- Menu of management action alternatives
    - Rest
    - Graze
    - Burn
    - Burn / Graze
- Management Cycle
    - Decisions made on an annual basis
    - Management year is 1 Sep – 31 Aug

<u>Full System State Structure</u>

Vegetation State Structure

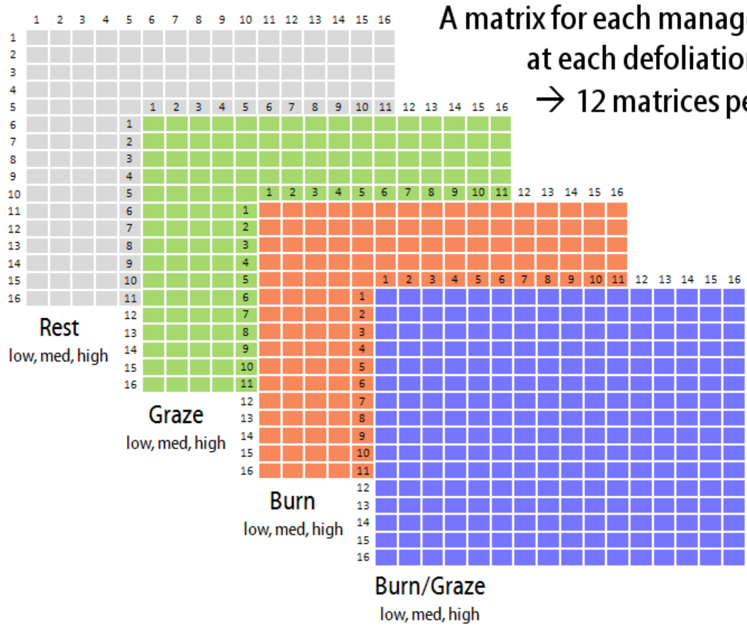
Native Cover	Dominant Invasive: SB	CO	KB	RM
60 – 100%	1	2	3	4
45 – 60%	5	6	7	8
30 – 45%	9	10	11	12
0 – 30%	13	14	15	16

Defoliation State Structure

Years Since Defoliation	Defoliation Level: Low	Med	High
5+	1		
2 – 4	2	3	4
1	5	6	7

- Combined, there are 16 x 7 = 112 possible discrete states that a unit can be in at any one time

<u>Complete Model – Vegetation</u>



A matrix for each management action (4)
at each defoliation level (3)
→ 12 matrices per model

<u>Model Input and Output</u>

- Models require as input
  - (1) Current vegetation state
    - Native cover and Dominant invasive
  - (2) Current defoliation state
    - Years since last defoliated and Defoliation level
  - (3) Proposed management action – Rest, Graze, Burn, Burn/Graze

Native Cover	Dominant Invasive: SB	CO	KB	RM
60 – 100%	1	2	3	4
45 – 60%	5	6	7	8
30 – 45%	9	10	11	12
0 – 30%	13	14	15	16

Years Since Defoliation	Defoliation Level: Low	Med	High
5+	1		
2 – 4	2	3	4
1	5	6	7

- Models predict
  - (1) Distribution of the next vegetation state
  - (2) Distribution of the next defoliation state
  - → Native cover is the target of management

	SB	CO	KB	RM
60 - 100	0	3	5	1
45 - 60	9	14	46	8
30 - 45	1	4	8	1
0 - 30	0	0	0	0

	Low	Med	High
5+	4		
2-4	37	59	0
1	0	0	0

Monitoring – What it Provides

- Monitoring is driven by the decision context and designed specifically to provide what we need to know
    - Current prairie composition (vegetation state)
        - To make state-based management decision
    - Outcome vegetation state
        - To assess the predictive abilities and credibility of the competing models
    - Amount of native cover
        - To gauge progress towards the management objective

Monitoring – What Data are Necessary

- Monitoring that is needed for decisions and learning
    - Management-unit level vegetation composition: cover of NP, SB, KB, and RM
        - Annual basis, during growing season, post management
    - Management actions implemented
- Monitoring that is not needed for the decision
    - Litter depth, Soil moisture, Slope/Aspect, Seed bank
- Some considerations
    - Must be logistically feasible by Refuge staff
    - Must be sustainable for the long-term

Monitoring – Vegetation

- Belt-transect vegetation monitoring (Grant et al. 2004)
    - Familiar
    - Quick
    - Short learning curve for seasonal staff (high turnover)
    - Robust to multiple observers
    - Provides exactly the data needed to inform the decision

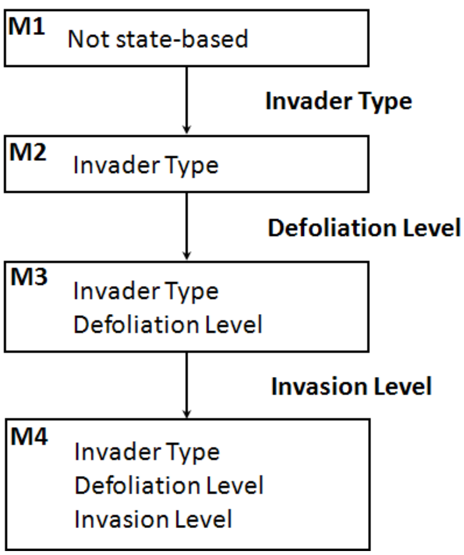
Monitoring – Management

- Past management history for all newly enrolled units
    - Basis for initial defoliation state
- Management actions and details of application
    - Type of action – Rest, Graze, Burn, Burn/Graze
    - Timing and length of application
    - Intensity (fire heat, stocking rate, utilization)

Monitoring – Centralized Database

- Centralized Database (Hunt et al. *in press*)
    - Hosted on SharePoint
    - Accessible to cooperators
    - Data entry/access is password protected
    - Observations are immediately captured and centrally stored
    - Standardization, validation, and quality control
    - Built in queries generate cooperator-level data summaries

Competing Predictive Models



Model 1: All management is equally effective and better than rest regardless of system state (i.e., vegetation and defoliation state ignored)

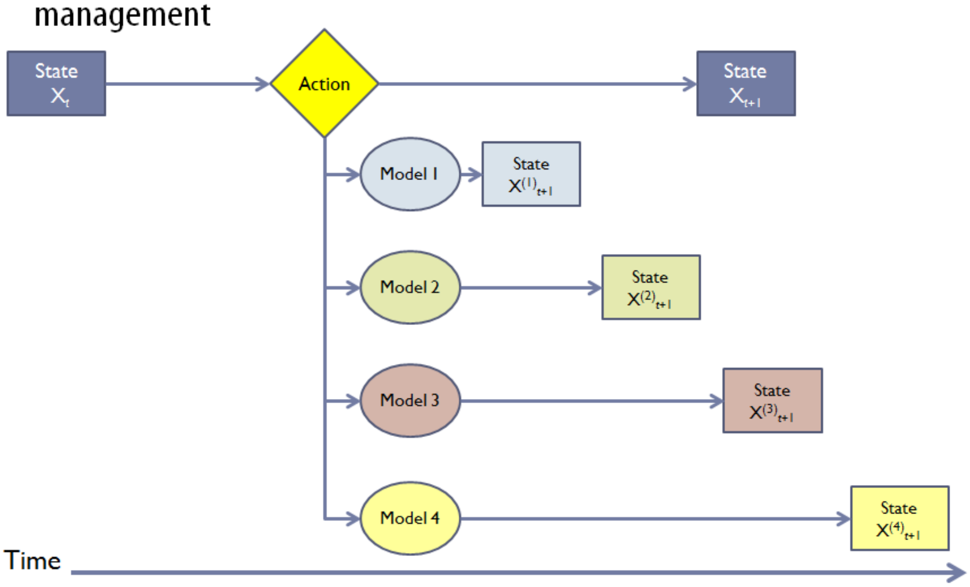
Model 2: Management is differentially effective depending on the type of dominant invasive

Model 3: **Model 2 +** History of frequent defoliation creates momentum, where rest is less detrimental and active management is more effective

Model 4: **Model 3 +** Management effectiveness declines as the level of invasion increases, such that at high levels of invasion, active management is no better than rest

Implications of Competing Models

- Competing models make different predictions of system response to management



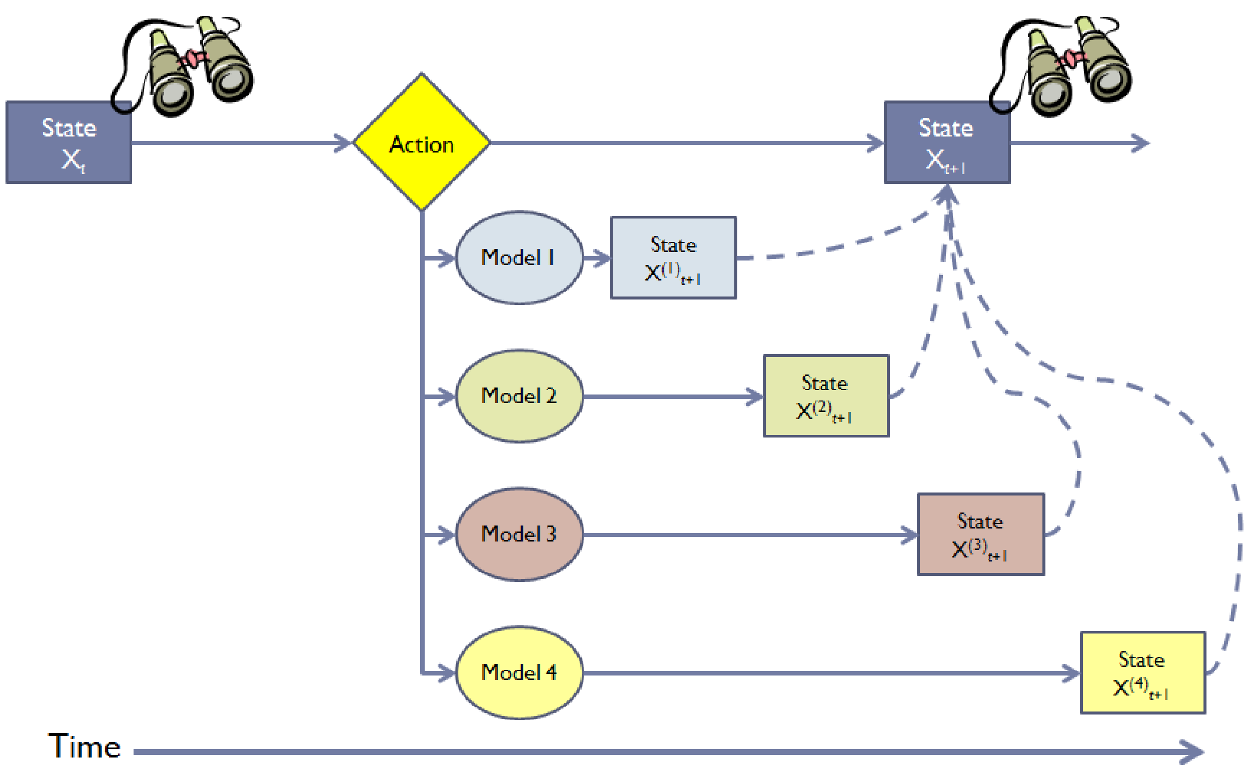
Model Weights

- Model weights represent our belief in each competing model as the "true" representation of system behavior
- Weights per model range from 0 (no belief) to 1 (full belief or certainty) and sum to 1 over all models
- We have a set of models that represent 4 different notions of how the system responds to management
- Complete uncertainty among models is represented by equal model weights $w_{m1} = 0.25$, $w_{m2} = 0.25$, $w_{m3} = 0.25$, $w_{m4} = 0.25$
  - Each model has equal influence on the decision

Updating Model Weights

- Aim of AM is to reduce uncertainty about system response to management actions, thereby allowing us to make better management decisions based on improved understanding of system behavior
- We accomplish this through the annual cycle of decision making and monitoring, which provides the information feedback necessary to update our belief in each model for later decisions
  - Updating model weights **IS** reducing uncertainty

Monitoring & Updating



Updating Model Weights – Ingredients

- Ingredients for model weight updating
  - Observation of unit prior to implementing action (vegetation state and defoliation level at time *t*)
  - Management decision to implement at time *t* +1
  - Prediction by each model of the outcome after implementing the action (predicted vegetation state at time *t*+1)
  - Observation of the actual outcome after implementing the action (observed vegetation state at time *t* + 1)
  - Set of initial model weights at time *t*

Updating Model Weights – Iterative Cycle

(1) Record system state at time *t*, implemented management action at time *t*+1, and observed vegetation state at time *t*+1 (*per unit*)

(2) Compare model specific predictions to observed outcomes and calculate model likelihoods (*per unit*)
  - Paired monitoring data from consecutive years and intervening management action

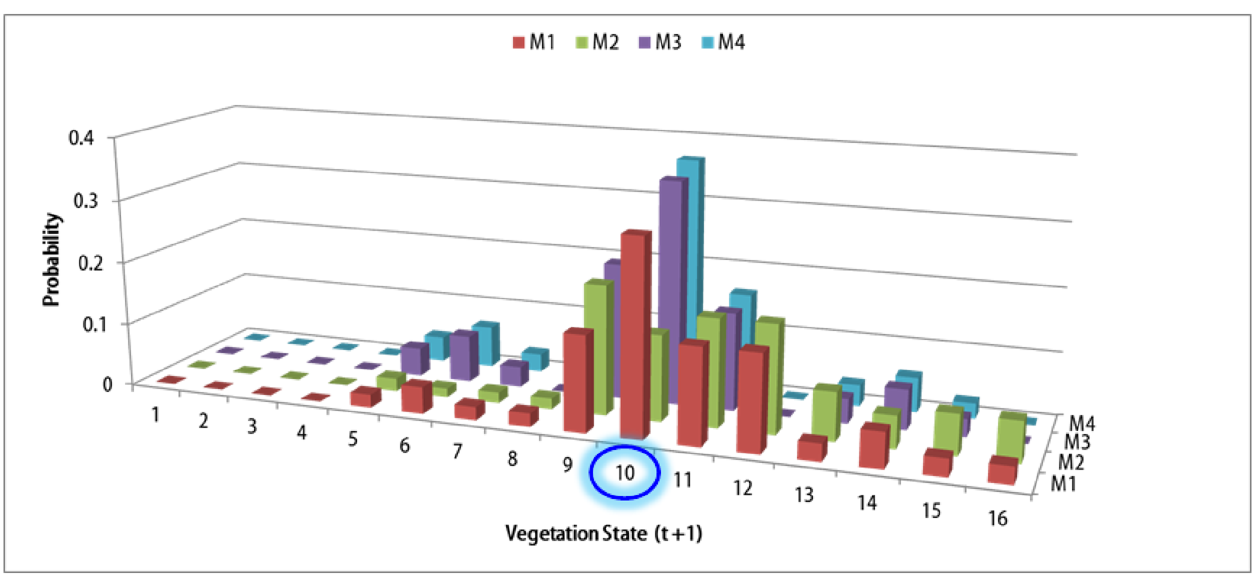
(3) Update model weights via Bayes Theorem (*all units*)
  - Greater agreement → increase in model weight
  - Lesser agreement → reduction in model weight

Updating Model Weights – Single Unit

Model Input	
Veg State (t)	30-45, CO
Defol level (t)	Med
Action (t+1)	Rest

Monitoring Feedback	
Veg State (t+1)	30-45, CO

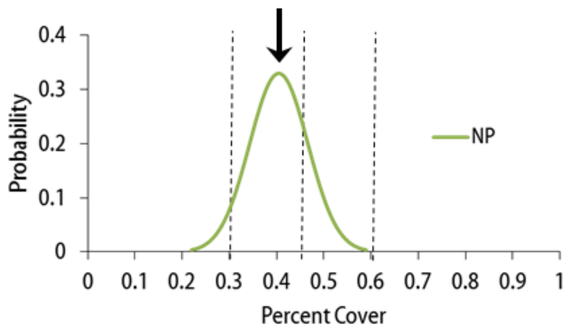
Model-Specific Predicted Outcomes

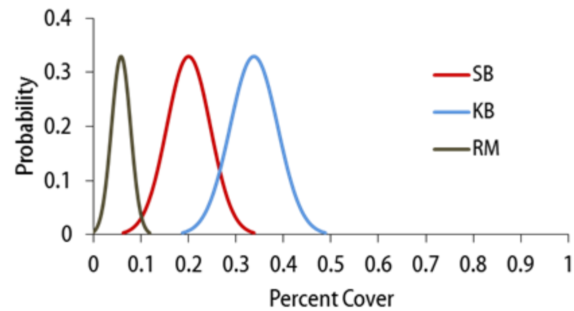


Taking into Account Partial Controllability

Monitoring Feedback	
Veg State (t+1)	30-45, CO

	NP	SB	KB	RM
Mean	0.405	0.200	0.338	0.058
Stdev	0.062	0.046	0.050	0.020





Partial observability: Inability to accurately measure the vegetation state

Observation distribution

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0.009	0.002	0
30-45	0	0.585	0.152	0
0-30	0	0.198	0.054	0

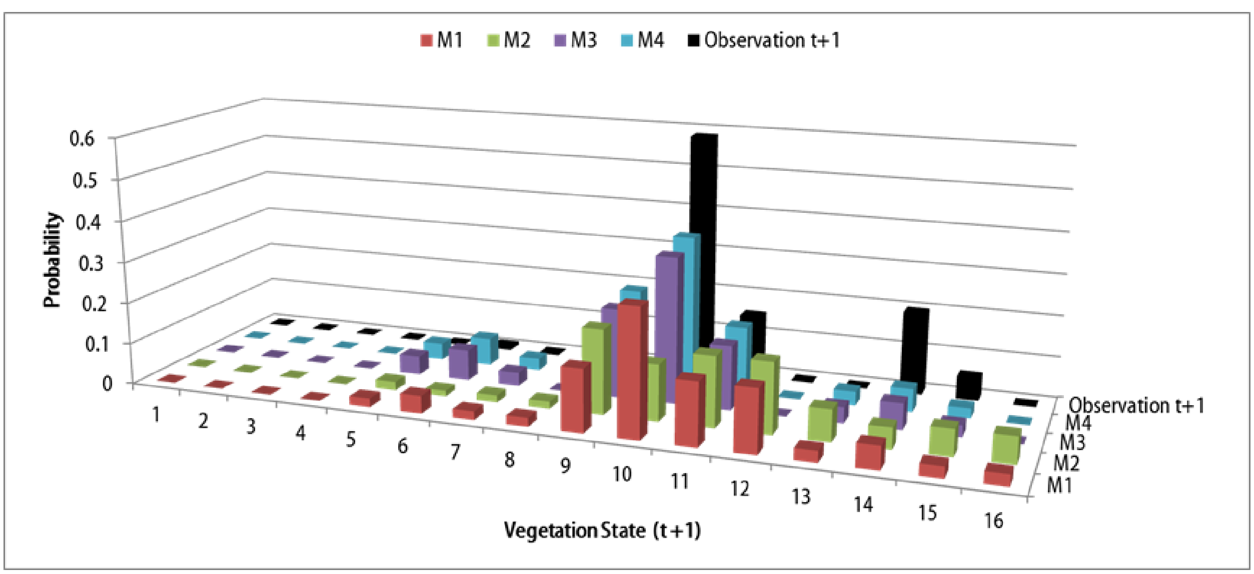
Updating Model Weights – Single Unit

Model Input	
Veg State (t)	30-45, CO
Defol level (t)	Med
Action (t+1)	Rest

Monitoring Feedback

Veg State (t+1)		SB	CO	KB	RM
	60-100	0	0	0	0
	45-60	0	0.009	0.002	0
	30-45	0	0.585	0.152	0
	0-30	0	0.198	0.054	0

Model-Specific Predicted Outcomes and Observation Outcome



Updating Model Weights – Computing Likelihoods

- Given the distributions for the model predicted outcomes and the observed outcome, we calculate model likelihoods
  - Model likelihood: The probability that the observation could have arisen as an outcome of the given model
  - We derive these, per model, by multiplying the observed probability per state by the model predicted probability per state and summing over the 16 states

Model	Likelihood
M1	0.2140
M2	0.1184
M3	0.2431
M4	0.2518

Updating Model Weights – Bayes' Theorem

- With a likelihood for each model, we update the model initial model weights by applying Bayes' Theorem

Model Likelihood

Prior, initial model weight

Posterior, updated model weight

$$p(m_i|d) = \frac{p(d|m_i)\ \ p(m_i)}{\sum_{i=1}^{4} p(d|m_i)\ p(m_i)}$$

- Initial model weights: w_{m1}=0.25, w_{m2}=0.25, w_{m3}=0.25, w_{m4}=0.25

Posterior, updated model weights per model

w_{m1}=(0.2140 x 0.25) / ((0.2140 x 0.25) + (0.1184 x 0.25) + (0.2431 x 0.25) + (0.2518 x 0.25)) = 0.259
w_{m2}=(0.1184 x 0.25) / ((0.2140 x 0.25) + (0.1184 x 0.25) + (0.2431 x 0.25) + (0.2518 x 0.25)) = 0.143
w_{m3}=(0.2431 x 0.25) / ((0.2140 x 0.25) + (0.1184 x 0.25) + (0.2431 x 0.25) + (0.2518 x 0.25)) = 0.294
w_{m4}=(0.2518 x 0.25) / ((0.2140 x 0.25) + (0.1184 x 0.25) + (0.2431 x 0.25) + (0.2518 x 0.25)) = 0.304

➢ Model Weights shifted according to model performance

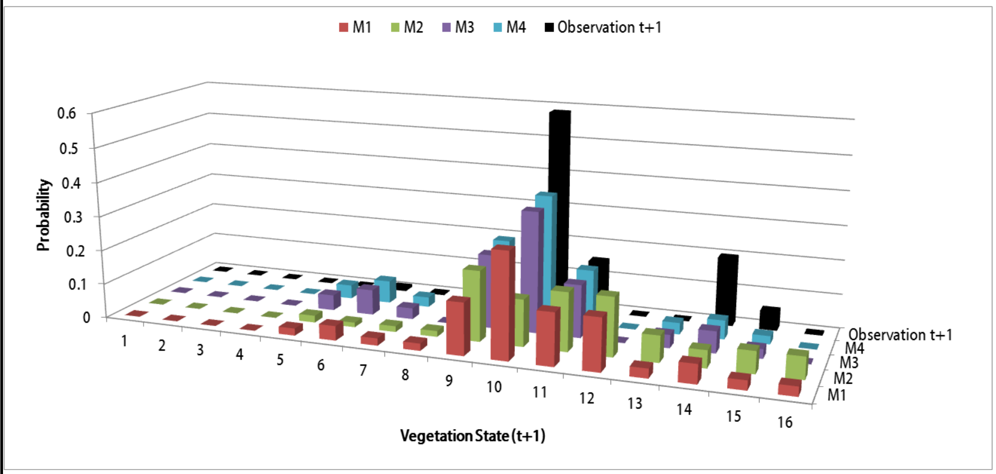
<u>Updating Model Weights – Method 1, By Unit</u>

- Use space in place of time and treat each management unit as an independent replicate
  - Go through steps 1 – 3, <u>for each unit,</u> in a sequential chain
  - The posterior model weight from one unit becomes the prior weight for the next unit in the sequential chain

- Example using 4 of 81 Units

Unit 1			Mean	SE
Veg State t	30-45, CO	NP	0.405	0.062
Defol level t	Med	SB	0.200	0.046
Action t+1	Rest	KB	0.338	0.050
Veg State t+1	30-45, CO	RM	0.058	0.020

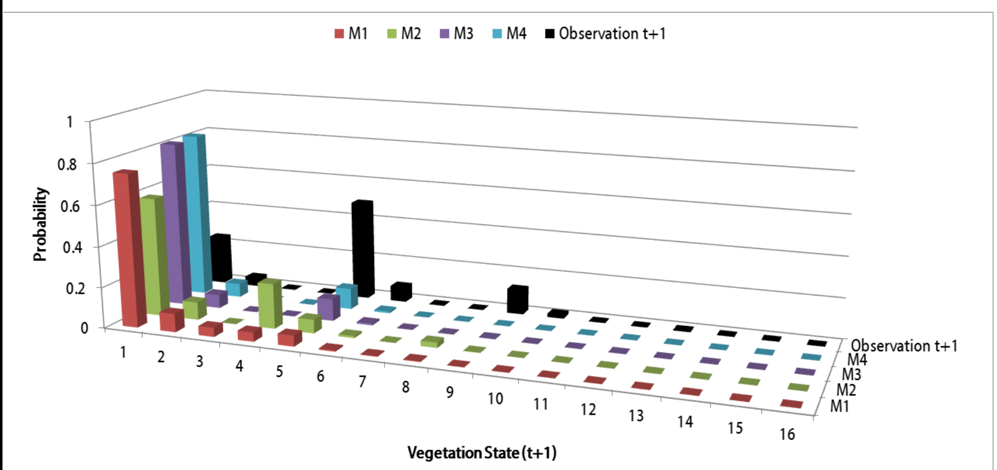
	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0.009	0.002	0
30-45	0	0.585	0.152	0
0-30	0	0.198	0.054	0



	Weight Prior	Likelihood	Weight Posterior
M1	0.25	0.214	0.259
M2	0.25	0.118	0.143
M3	0.25	0.243	0.294
M4	0.25	0.252	0.304

Unit 2			Mean	SE
Veg State t	60-100, SB	NP	0.605	0.099
Defol level t	Low	SB	0.335	0.095
Action t+1	Rest	KB	0.059	0.040
Veg State t+1	60-100, SB	RM	0.000	0.000

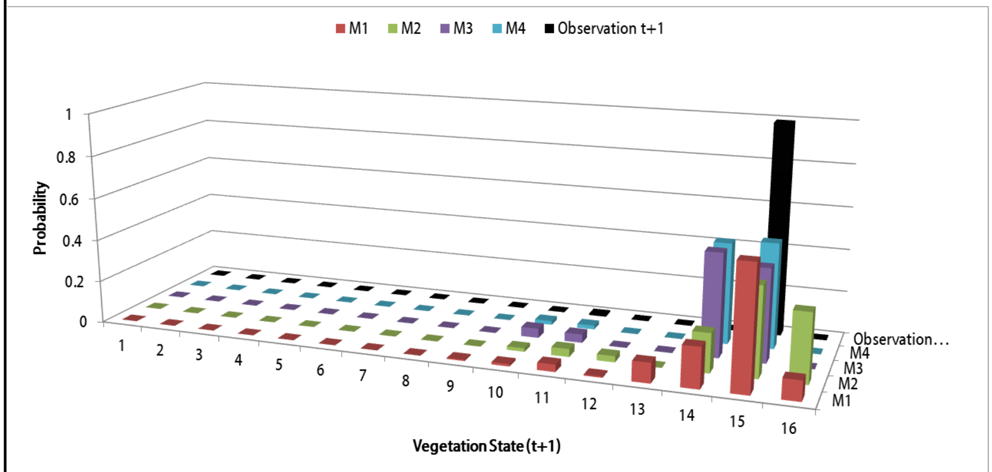
	SB	CO	KB	RM
60-100	0.243	0.044	0	0
45-60	0.493	0.077	0	0
30-45	0.123	0.017	0	0
0-30	0.003	0	0	0



	Weight Prior	Likelihood	Weight Posterior
M1	0.259	0.210	0.236
M2	0.143	0.177	0.110
M3	0.294	0.252	0.322
M4	0.304	0.251	0.332

Unit 3			Mean	SE
Veg State t	0-30, KB	NP	0.203	0.045
Defol level t	Med	SB	0.060	0.020
Action t+1	Graze	KB	0.718	0.045
Veg State t + 1	0-30, KB	RM	0.019	0.009

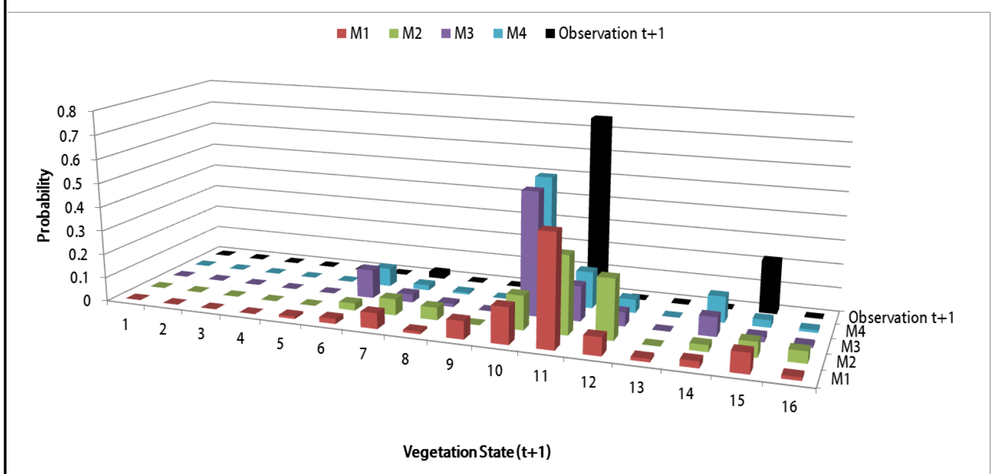
	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0	0	0
30-45	0	0	0.008	0
0-30	0	0	0.992	0



	Weight Prior	Likelihood	Weight Posterior
M1	0.236	0.566	0.279
M2	0.110	0.412	0.095
M3	0.322	0.430	0.289
M4	0.332	0.487	0.338

Unit 4			Mean	SE
Veg State t	30-45, KB	NP	0.372	0.059
Defol level t	High	SB	0.059	0.022
Action t+1	Graze	KB	0.408	0.060
Veg State t+1	30-45, KB	RM	0.161	0.048

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0	0.026	0
30-45	0	0	0.754	0
0-30	0	0	0.22	0



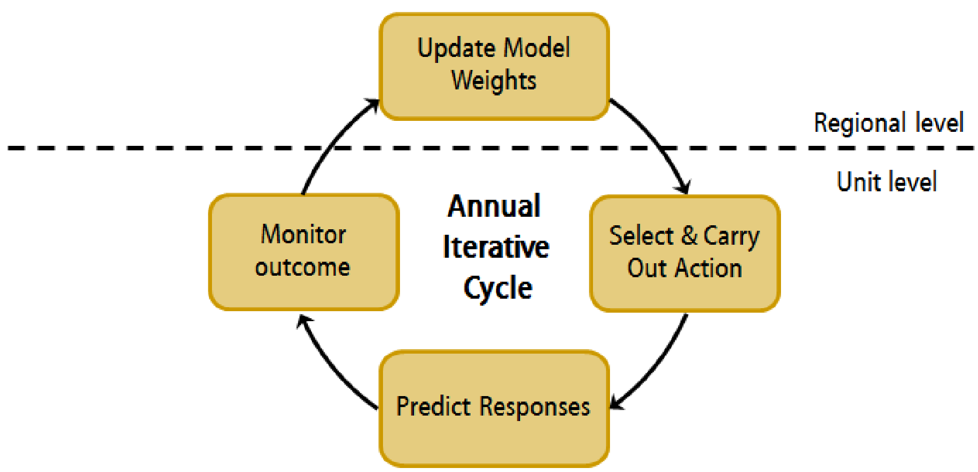
	Weight Prior	Likelihood	Weight Posterior
M1	0.279	0.365	0.506
M2	0.095	0.258	0.121
M3	0.289	0.116	0.167
M4	0.338	0.123	0.206

	Unit 1		Unit 2		Unit 3		Unit 4	
	Prior	Posterior	Prior	Posterior	Prior	Posterior	Prior	Posterior
M1	0.25	0.259	0.259	0.236	0.236	0.279	0.279	0.506
M2	0.25	0.143	0.143	0.110	0.110	0.094	0.094	0.121
M3	0.25	0.294	0.294	0.322	0.322	0.289	0.289	0.167
M4	0.25	0.304	0.304	0.332	0.332	0.338	0.338	0.206

Updating Model Weights – Method 2, Over Units

- Alternative method
  - Go through steps 1 - 2 and obtain model likelihoods for each unit
  - Calculate the median model likelihood across all units
  - Complete Step 3 – Bayes' Theorem – one time, using the median model likelihood
- We used this alternative method to annually update model weights
  - Reason: Noisy system resulted in model weights that are too sensitive to individual units that behave as outliers

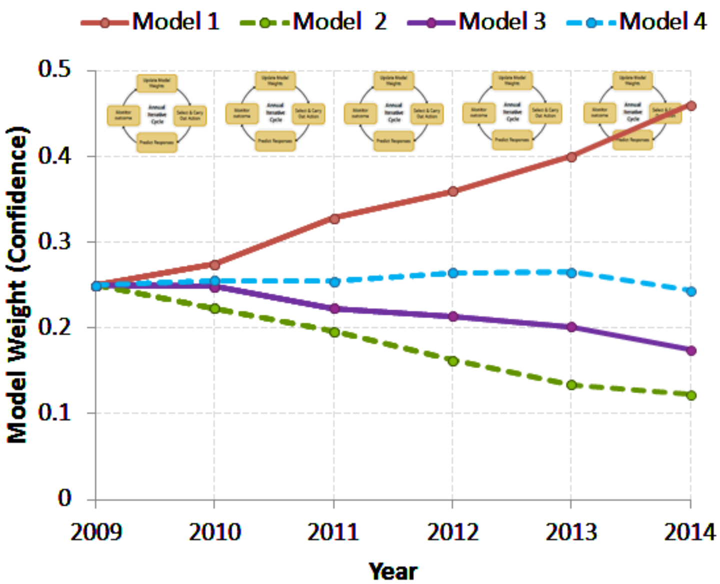
Annual Iterative Cycle: Managing & Learning



How updated model weights affect choice of next decision → Case Study Module D

NPAM Updating Cycles

- Completed five iterations of the AM decision cycle since NPAM inception



- With each annual update, we reduce uncertainty among the competing models.
- Shift in model weights is providing greater evidence for Model 1.
- By following the AM framework, we know more about the behavior of the system than we did before and can therefore make improved management decisions.

Learning Rate – Partial Observability

- Partial observability decreases the rate of learning

Unit with tight observation distribution
Point estimate: 0-30, KB

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0	0	0
30-45	0	0	0.008	0
0-30	0	0	0.992	0

Unit with wider observation distribution
Point estimate: 0-30, CO

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	0	0	0
30-45	0	0	0	0
0-30	0.002	0.815	0.183	0

Model Weights (unit with tight observation distribution)

	Prior	Ignore Partial Observability	Acknowledge Partial Observability
M1	0.25	0.299	0.299
M2	0.25	0.217	0.217
M3	0.25	0.227	0.227
M4	0.25	0.257	0.257

Model Weights (unit with wider observation distribution)

	Prior	Ignore Partial Observability	Acknowledge Partial Observability
M1	0.25	0.389	0.323
M2	0.25	0.159	0.169
M3	0.25	0.241	0.259
M4	0.25	0.211	0.249

Learning Rate – Partial Observability

- When monitoring involves sampling from the whole, partial observability is a reality
  - We cannot perfectly observe the system
- Can decrease the effect of partial observability by increasing the sampling effort
  - Decrease variation in observation distribution
- But it will always exist to some extent and therefore must be taken into account in our updating

Learning Rate – What Increases it?

- Any means that leads to distinct model predictions
  - Sharply contrasting models
    - May vary by the initial system state (vegetation state and defoliation level)
      - M1 v M2: Dominant invader
      - M2 v M3: Defoliation level
      - M3 v M4: Invasion level

Some initial states may promote faster learning than others because the models make more distinct predictions regarding the outcome of management for those states.

  - Widely-spaced decision alternatives with distinct effects on the system

Summary – Case Study Module C: Monitoring & Learning

- Monitoring design is driven by the decision context
  - Structuring the decision process leads to purposeful monitoring
- Iterative model weight updating is key to AM
  - Goal of AM is the reduction of uncertainty and thus improvement of future management through the systematic exploitation of the repeated decision and monitoring process
  - Having competing predictive models that capture uncertainty about system behavior is essential
  - Estimation of model likelihoods and application of Bayes' Theorem is central to AM
- Poor ability to measure the system decreases the ability to understand the system and thus learning rate (*partial observability*)
- Learning rate is slowed or enhanced according to the degree that model predictions are similar or distinct

Next…Case Study Module D – Dynamic Decision Making

Literature Cited

Gannon, J.J., T.L. Shaffer, C.T. Moore. 2013. Native Prairie Adaptive Management: A Multi Region Adaptive Approach to Invasive Plant Management on Fish and Wildlife Service Owned Native Prairies: U.S. Geological Survey Open File Report 2013-1279, 184 p. with appendixes, http://dx.doi.org/10.3133/ofr20131279

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