

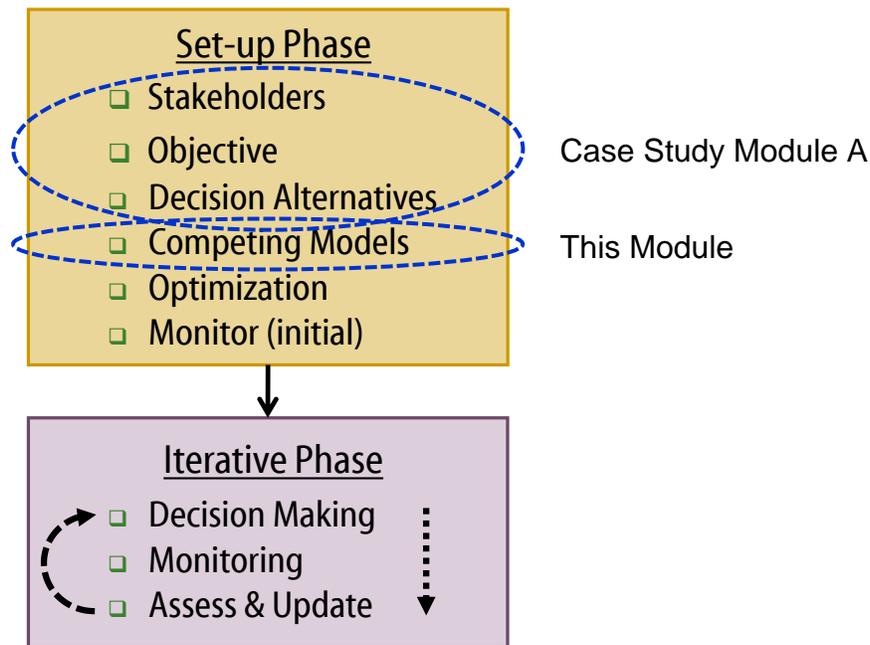
Case Study: Native Prairie Adaptive Management in the USFWS Refuge System

Model Development

Case Study Module B

Module Developed by:
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NPAM Framework Components



Objectives of Case Study Module B – Model Development

- Illustrate NPAM model structure for decision making
 - Links decision alternatives to objective by predicting the consequences of each decision with respect to the measureable attribute of the objective
- Discuss uncertainty that makes decision making difficult and identify main structural uncertainties
- Demonstrate expression of structural uncertainty via competing models
- Present an analysis of EVPI
- Express structural uncertainty via model confidence

Case Study: Model Development
Adaptive Management: Structured Decision Making for Recurrent Decisions

Native Prairie Adaptive Management

- 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

Objective & Decision Alternatives

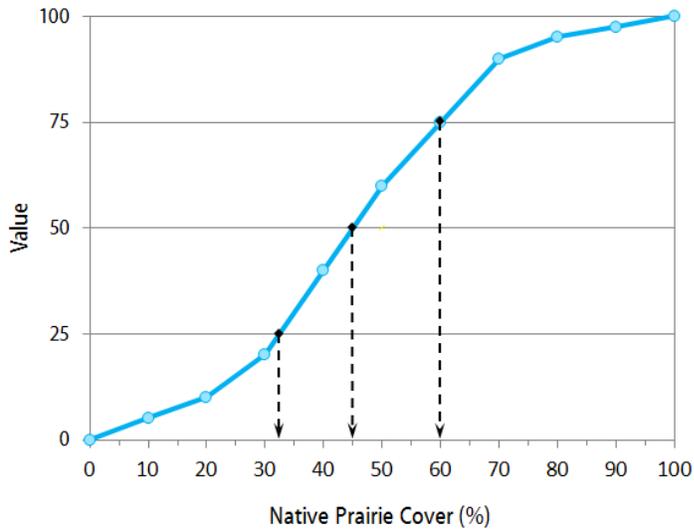
- Management objective
 - Increase the cover of native grasses and forbs at the least cost
- Menu of management action alternatives
 - Rest
 - Graze
 - Burn
 - Burn / Graze
- Management Cycle
 - Decisions made on an annual basis
 - Management year is 1 Sep – 31 Aug

Describing the System – Vegetation

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

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Adaptive Management: Structured Decision Making for Recurrent Decisions

Eliciting Vegetation Structure



Describing the System – Defoliation History

- Based on a 7-year window of past management actions
 - Two components:
 - Defoliation level: low, medium, high
 - Years since last defoliated: 1, 2 - 4 , 5+

		<u>Defoliation Level</u>		
		Low	Med	High
<u>Years Since Defoliation</u>	5+	1		
	2 - 4	2	3	4
	1	5	6	7

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Adaptive Management: Structured Decision Making for Recurrent Decisions

Full System State Structure

Vegetation State Structure

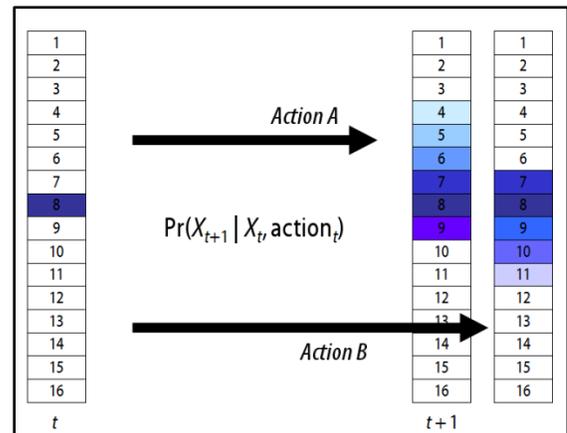
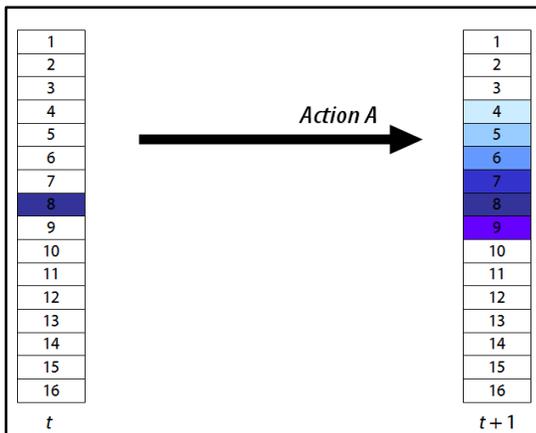
		Dominant Invasive			
		SB	CO	KB	RM
Native Cover	60 – 100%	1	2	3	4
	45 – 60%	5	6	7	8
	30 – 45%	9	10	11	12
	0 – 30%	13	14	15	16

Defoliation State Structure

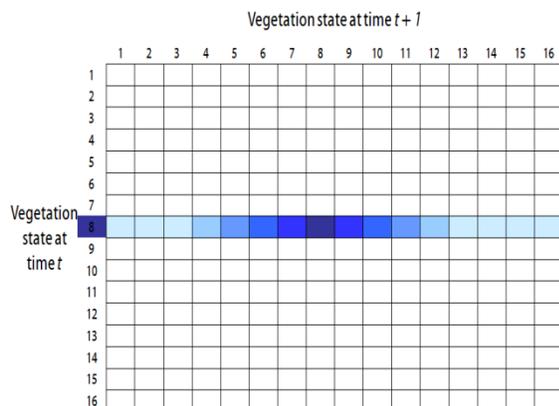
		Defoliation Level		
		Low	Med	High
Years Since Defoliation	5+	1		
	2 – 4	2	3	4
	1	5	6	7

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

State Transition Model - Vegetation



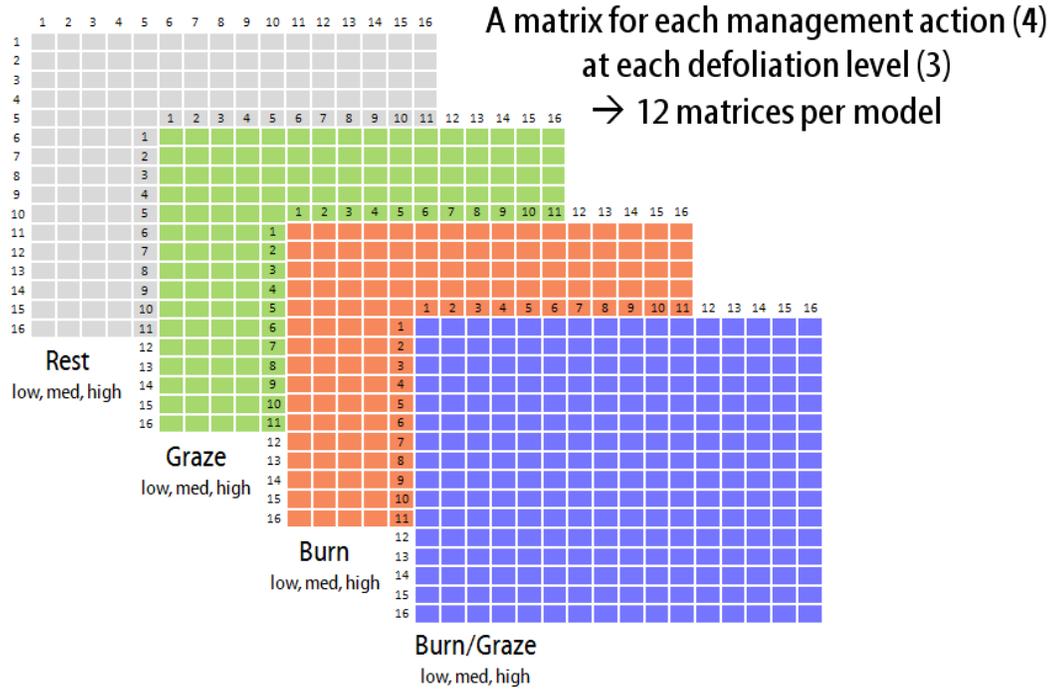
State Transition Matrix – Vegetation



Case Study: Model Development

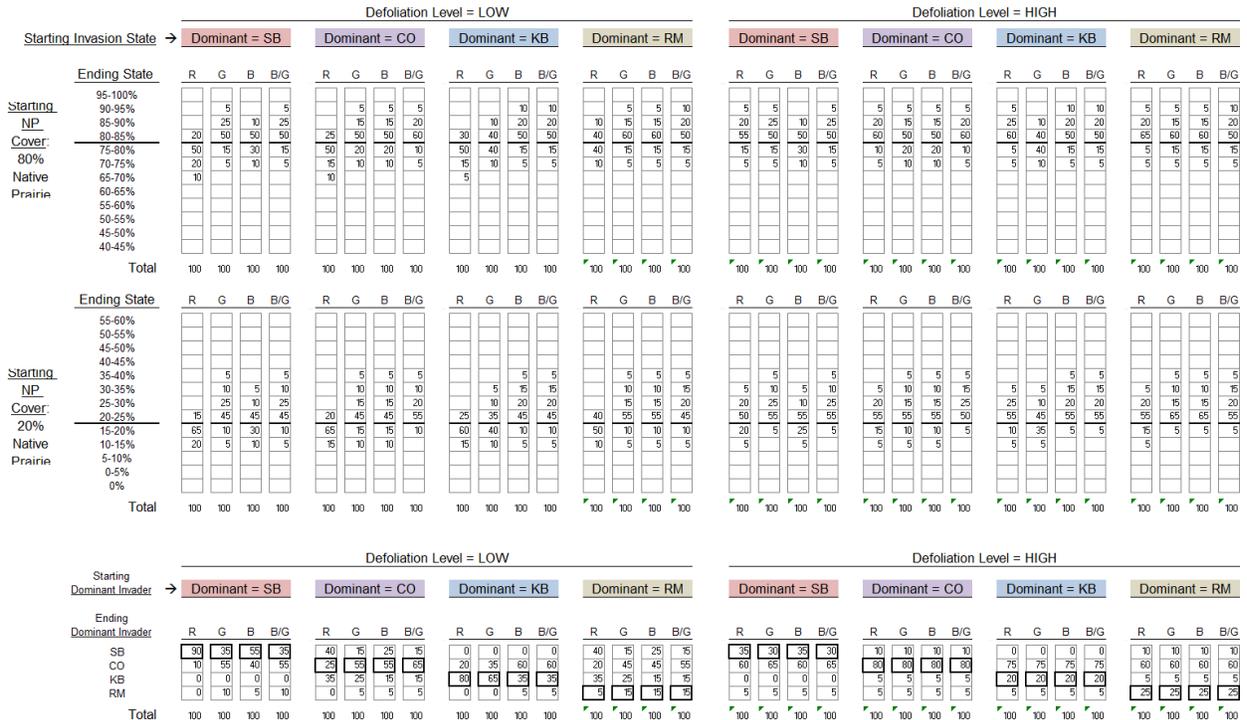
Adaptive Management: Structured Decision Making for Recurrent Decisions

Complete Model – Vegetation



Model Parameterization

- Elicitation of expert opinion



Case Study: Model Development

Adaptive Management: Structured Decision Making for Recurrent Decisions

Model Parameterization

- Linear-logistic and linear-polytomous regression models
- Transition probabilities among vegetation states given:
 - Defoliation level (low, med, high)
 - Management action (Rest, Graze, Burn, Burn/Graze)

Showing transition matrices for Rest, Graze, Burn, and Burn/Graze at Low Defoliation

Defoliation Level	Mgmt Action	NP Cover	Dominant Invader	60-100,SB	60-100,CO	60-100,KB	60-100,FM	45-60,SB	45-60,CO	45-60,KB	45-60,FM	30-45,SB	30-45,CO	30-45,KB	30-45,FM	0-30,SB	0-30,CO	0-30,KB	0-30,FM	
Low	Rest	60-100	SB	0.814428	0.067121	7.84E-07	4.83E-07	0.108008	0.008901	1.04E-07	6.4E-08	0.001423	0.000117	1.37E-09	8.43E-10	0	0	0	0	
Low	Rest	60-100	CO	0.365092	0.175613	0.341116	8.45E-06	0.048283	0.023224	0.045112	1.12E-06	0.000642	0.000309	0.0006	1.49E-08	0	0	0	0	
Low	Rest	60-100	KB	8.32E-07	0.142702	0.771896	1.08E-06	7.71E-08	0.013225	0.071535	1E-07	5.82E-10	9.99E-05	0.00054	7.55E-10	0	0	0	0	
Low	Rest	60-100	RM	0.396423	0.152629	0.370577	0.036609	0.018086	0.006966	0.016907	0.00167	2.9E-05	1.12E-05	2.71E-05	2.68E-06	0	0	0	0	
Low	Rest	45-60	SB	0.047662	0.003928	4.59E-08	2.82E-08	0.057685	0.046784	5.47E-07	3.36E-07	0.305474	0.025176	2.94E-07	1.81E-07	0.003058	0.000252	2.95E-09	1.81E-09	
Low	Rest	45-60	CO	0.002109	0.010125	0.019666	4.87E-07	0.253013	0.121702	0.236398	5.86E-06	0.138629	0.066882	0.129525	3.21E-06	0.001325	0.000637	0.001238	3.07E-08	
Low	Rest	45-60	KB	7.66E-08	0.013145	0.071105	9.94E-08	6.01E-07	0.103158	0.558	7.8E-07	0.23829	2.99E-07	1.12E-09	0.000192	0.000192	0.001038	1.45E-09	0	
Low	Rest	45-60	RM	0.066575	0.025643	0.062234	0.006148	0.282579	0.108841	0.264155	0.026096	0.065298	0.025151	0.061041	0.00603	8.71E-05	3.35E-05	8.14E-05	8.04E-06	
Low	Rest	30-45	SB	2.77E-05	2.28E-06	2.67E-11	1.64E-11	0.040872	0.003368	3.94E-08	0.24E-08	0.59467	0.049009	5.73E-07	3.52E-07	0.28829	0.023759	2.78E-07	1.71E-07	
Low	Rest	30-45	CO	2.48E-05	1.19E-05	2.32E-05	5.75E-10	0.019188	0.009226	0.017922	4.44E-07	0.266759	0.128314	0.249241	6.17E-06	0.128051	0.061594	0.119642	2.96E-06	
Low	Rest	30-45	KB	7.28E-11	1.25E-05	6.75E-05	9.44E-11	0.627E-08	0.001755	0.058175	8.14E-08	6.22E-07	0.10676	0.001998	2.34E-08	1.44E-08	0.89958	0.074138	8.67E-07	5.33E-07
Low	Rest	30-45	RM	0.000162	6.23E-05	0.000151	1.49E-05	0.050698	0.019527	0.047393	0.004682	0.294957	0.113608	0.275726	0.027239	0.068722	0.02647	0.06242	0.00346	0.00634
Low	Rest	0-30	SB	0	0	0	0	3.7E-05	3.05E-06	3.56E-11	2.19E-11	0.024242	0.001998	2.34E-08	1.44E-08	0.89958	0.074138	8.67E-07	5.33E-07	
Low	Rest	0-30	CO	0	0	0	0	4.14E-06	1.99E-06	3.87E-06	9.58E-11	0.012843	0.006178	0.011999	2.97E-07	0.401169	0.192967	3.374825	9.29E-06	
Low	Rest	0-30	KB	0	0	0	0	9.09E-12	1.56E-06	8.44E-06	1.18E-11	3.08E-08	0.005278	0.028552	3.99E-08	8.79E-07	0.150746	0.815412	1.14E-06	
Low	Rest	0-30	RM	0	0	0	0	1.24E-05	4.79E-06	1.16E-05	1.15E-06	0.019338	0.007449	0.018077	0.001786	0.395188	0.152214	0.368423	0.036495	
Low	Graze	60-100	SB	0.347405	0.531468	3E-06	0.104504	0.005864	0.008971	5.06E-08	0.001764	7.07E-06	1.08E-05	6.1E-11	2.13E-06	0	0	0	0	
Low	Graze	60-100	CO	0.145918	0.49917	0.282674	0.046188	0.003897	0.013331	0.007549	0.001233	5.99E-06	2.05E-05	1.16E-05	1.9E-06	0	0	0	0	
Low	Graze	60-100	KB	3.14E-06	0.285616	0.66703	3.72E-07	1.55E-07	0.014139	0.033021	1.84E-08	6.26E-10	5.7E-05	0.000133	7.41E-11	0	0	0	0	
Low	Graze	60-100	RM	0.146833	0.413842	0.285094	0.133081	0.003167	0.008925	0.006148	0.00287	6E-06	1.69E-05	1.17E-05	5.44E-06	0	0	0	0	
Low	Graze	45-60	SB	0.196669	0.183072	1.03E-06	0.035998	0.216081	0.330566	1.07E-06	0.065	0.017522	0.026606	1.51E-07	0.005271	3.53E-06	5.4E-06	3.05E-11	1.06E-06	
Low	Graze	45-60	CO	0.039434	0.134901	0.076393	0.012482	0.096531	0.337065	0.190875	0.031188	0.011846	0.040525	0.022949	0.00375	8.99E-06	3.08E-05	1.74E-05	2.85E-06	
Low	Graze	45-60	KB	5.45E-07	0.049563	0.115796	6.45E-08	2.26E-06	0.205296	0.479451	2.67E-07	4.33E-07	0.044819	0.104671	5.83E-06	1.25E-09	0.000114	0.000266	1.49E-10	
Low	Graze	45-60	RM	0.046089	0.11299	0.089488	0.041773	0.094823	0.267254	0.18411	0.085942	0.00909	0.025621	0.01765	0.008239	3E-06	8.46E-06	5.83E-06	2.72E-06	
Low	Graze	30-45	SB	0.001424	0.002178	1.23E-08	0.000428	0.112497	0.172101	9.71E-07	0.033841	0.224811	0.343921	1.94E-06	0.067626	0.014544	0.02225	1.26E-07	0.004375	
Low	Graze	30-45	CO	0.000291	0.000994	0.000563	9.2E-05	0.036555	0.12505	0.070814	0.011571	0.102621	0.351738	0.19185	0.032546	0.010155	0.037439	0.019672	0.003214	
Low	Graze	30-45	KB	1.28E-09	0.000117	0.000273	1.52E-10	4.76E-07	0.043296	0.101114	5.63E-08	2.36E-06	0.214465	0.500663	2.79E-07	4.61E-07	0.041935	0.097935	5.46E-06	
Low	Graze	30-45	RM	0.000494	0.001391	0.000958	0.000447	0.043161	0.121647	0.003002	0.039119	0.098816	0.278509	0.191663	0.089562	0.007535	0.021236	0.01463	0.006829	
Low	Graze	0-30	SB	0	0	0	0	0.000671	0.001027	5.8E-09	0.000202	0.062152	0.095081	5.37E-07	0.018696	0.290453	0.444342	2.51E-06	0.087372	
Low	Graze	0-30	CO	0	0	0	0	0.000154	0.000528	0.000299	4.88E-05	0.021475	0.073465	0.041602	0.006798	0.128191	0.438529	0.248333	0.400577	
Low	Graze	0-30	KB	0	0	0	0	5.6E-10	5.1E-05	0.000119	6.63E-11	2.61E-07	0.02373	0.05542	3.09E-08	3.03E-06	0.276031	0.644646	3.59E-07	
Low	Graze	0-30	RM	0	0	0	0	0.000224	0.00063	0.000434	0.000203	0.024235	0.068305	0.047055	0.021965	0.125547	0.353849	0.243765	0.113789	
Low	Burn	60-100	SB	0.551118	0.361127	2.5E-06	0.046423	0.023679	0.015516	1.08E-07	0.001995	8.05E-05	5.27E-05	3.65E-10	6.78E-06	0	0	0	0	
Low	Burn	60-100	CO	0.261957	0.503952	0.159766	0.047065	0.007328	0.014097	0.004469	0.001317	1.35E-05	2.59E-05	8.21E-06	2.42E-06	0	0	0	0	
Low	Burn	60-100	KB	2.82E-06	0.574461	0.362284	0.047932	4.38E-08	0.008926	0.005629	0.000745	5.73E-11	1.17E-05	7.36E-06	9.74E-07	0	0	0	0	
Low	Burn	60-100	RM	0.264812	0.418995	0.161842	0.13451	0.005462	0.008635	0.003338	0.002775	8.11E-06	1.28E-05	4.96E-06	4.12E-06	0	0	0	0	
Low	Burn	45-60	SB	0.017015	0.070182	4.86E-07	0.009022	0.393406	0.257784	1.79E-06	0.033138	0.07428	0.048673	3.37E-07	0.006257	8.62E-05	5.65E-05	3.92E-10	7.26E-06	
Low	Burn	45-60	CO	0.071342	0.137248	0.043511	0.012818	0.176999	0.34051	0.107951	0.031801	0.020941	0.040285	0.012772	0.003762	1.62E-05	3.11E-05	9.85E-06	2.9E-06	
Low	Burn	45-60	KB	1.01E-06	0.204977	0.129269	0.017103	1.73E-06	0.351422	0.221624	0.029322	1.32E-07	0.026976	0.017013	0.002251	1.15E-10	2.33E-05	1.47E-05	1.95E-06	
Low	Burn	45-60	RM	0.083623	0.132185	0.051107	0.042476	0.17037	0.269308	0.104123	0.086539	0.016282	0.025737	0.009951	0.00827	8.11E-06	1.28E-05	4.96E-06	4.12E-06	
Low	Burn	30-45	SB	0.000477	0.000313	2.17E-09	4.02E-05	0.093107	0.06101	4.23E-07	0.007843	0.410779	0.269168	1.87E-06	0.034601	0.070514	0.046206	3.2E-07	0.00594	
Low	Burn	30-45	CO	0.000528	0.001015	0.000322	9.48E-05	0.066317	0.127581	0.040447	0.011915	0.183782	0.35356	0.112088	0.033019	0.01867	0.035918	0.013387	0.003354	
Low	Burn	30-45	KB	1.44E-08	0.002923	0.001843	0.000244	9.39E-07	0.191291	0.120637	0.015961	1.79E-06	0.365552	0.230535	0.030501	1.16E-07	0.023633	0.014904	0.001972	
Low	Burn	30-45	RM	0.000889	0.001406	0.000543	0.000452	0.076725	0.121281	0.046891	0.038972	0.178838	0.282694	0.109298	0.09084	0.01383	0.021862	0.008453	0.007025	
Low	Burn	0-30	SB	0	0	0	0	0.000149	9.79E-05	6.79E-10	1.26E-05	0.050221	0.032908	2.28E-07	0.00423	0.524507	0.34369	2.38E-06	0.044181	
Low	Burn	0-30	CO	0	0	0	0	0.000253	0.000487	0.000154	4.55E-05	0.037904	0.072919	0.023117	0.00681	0.231141	0.444669	0.140972	0.041528	
Low	Burn	0-30	KB	0	0	0	0	6.33E-09	0.001289	0.000813	0.000108	5.17E-07	0.105222	0.066358	0.00878	2.34E-06	0.476887	0.300749	0.039791	
Low	Burn	0-30	RM	0	0	0	0	0.000387	0.000611											

Case Study: Model Development
Adaptive Management: Structured Decision Making for Recurrent Decisions

Model Prediction – Single Time Step

- Model input
 - Current vegetation state: native cover, dominant invader
 - Current defoliation level
 - Proposed management action
- Model output
 - Provides a distribution of predicted vegetation state in the next year in response to model inputs and stochastic events

NPAM Model Prediction Over a Single Time Step

Initial Starting States at time t

Defoliation Level (L, M, H)	Low
Management Action (R, G, B, BG)	Rest
NP Cover (0-30, 30-45, 45-60, 60-100)	45-60
Dominant Invader (SB, CO, KB, RM)	CO

Distribution of Predictions at time $t+1$

	SB	CO	KB	RM
60-100	2	1	1	0
45-60	27	13	18	0
30-45	11	5	21	0
0-30	0	0	1	0

State Transition Matrix – Defoliation

No Defoliation

(Rest)

		Defoliation State time $t+1$						
		5+	2 - 4			1		
Defoliation State time t	5+	Low	Low	Med	High	Low	Med	High
	5+	Low	1	0	0	0	0	0
Low		0.3889	0.6111	0	0	0	0	0
Med		0.0313	0.4063	0.5625	0	0	0	0
2 - 4	High	0	0	1	0	0	0	0
	Low	0	1	0	0	0	0	0
	Med	0	0.1429	0.8571	0	0	0	0
1	High	0	0	0.4545	0.5455	0	0	0

Defoliation

(Graze, Burn, B/G)

		Defoliation State time $t+1$						
		5+	2 - 4			1		
Defoliation State time t	5+	Low	Low	Med	High	Low	Med	High
	5+	Low	0	0	0	0	0.75	0.25
Low		0	0	0	0	0.3333	0.6667	0
2 - 4	Med	0	0	0	0	0	0.8125	0.1875
	High	0	0	0	0	0	0	1
1	Low	0	0	0	0	0.2857	0.7143	0
	Med	0	0	0	0	0	0.7143	0.2857
	High	0	0	0	0	0	0	1

Case Study: Model Development
Adaptive Management: Structured Decision Making for Recurrent Decisions

Model Prediction – Time Series

- Two parts that work together
 - Vegetation model
 - $P(x_{t+1}|x_t, d_t, a_t)$
 - Defoliation model
 - $P(y_{t+1}, d_{t+1}|y_t, d_t, a_t)$
- Next time step
 - Vegetation model uses the new defoliation level predicted by the defoliation model

x = vegetation state
 d = defoliation level
 a = management action
 y = years since last defoliation

NPAM time series simulation

Initial Starting States at time t

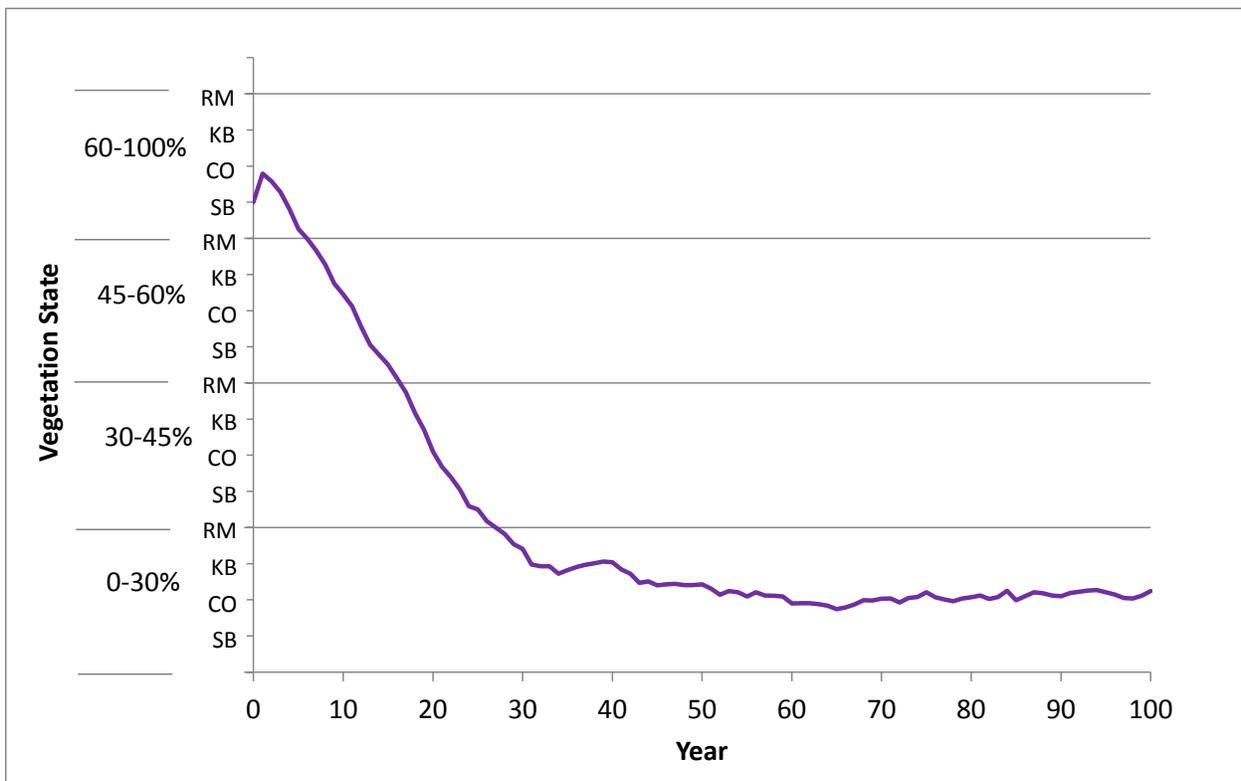
Defoliation State: Yrs Since | Level **1 | High**

NP Cover **60-100**

Dominant Invader **SB**

Management Action

Repeated Annual Action **Rest**



Case Study: Model Development
Adaptive Management: Structured Decision Making for Recurrent Decisions

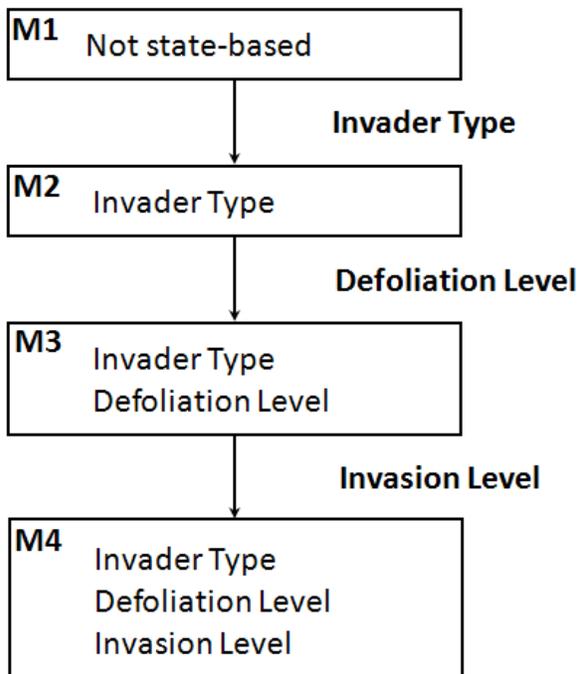
Structural Uncertainty

- Decisions are difficult due to uncertainty about system behavior
 - Which management action is best to apply depends on how the system behaves
- Elicitation of uncertainties
- Identified three key uncertainties
 - Does vegetation response to management depend on the:
 - 1) Type of dominant invader
 - 2) Past defoliation history of the unit
 - 3) Level of invasion

Structural Uncertainty: Competing Models

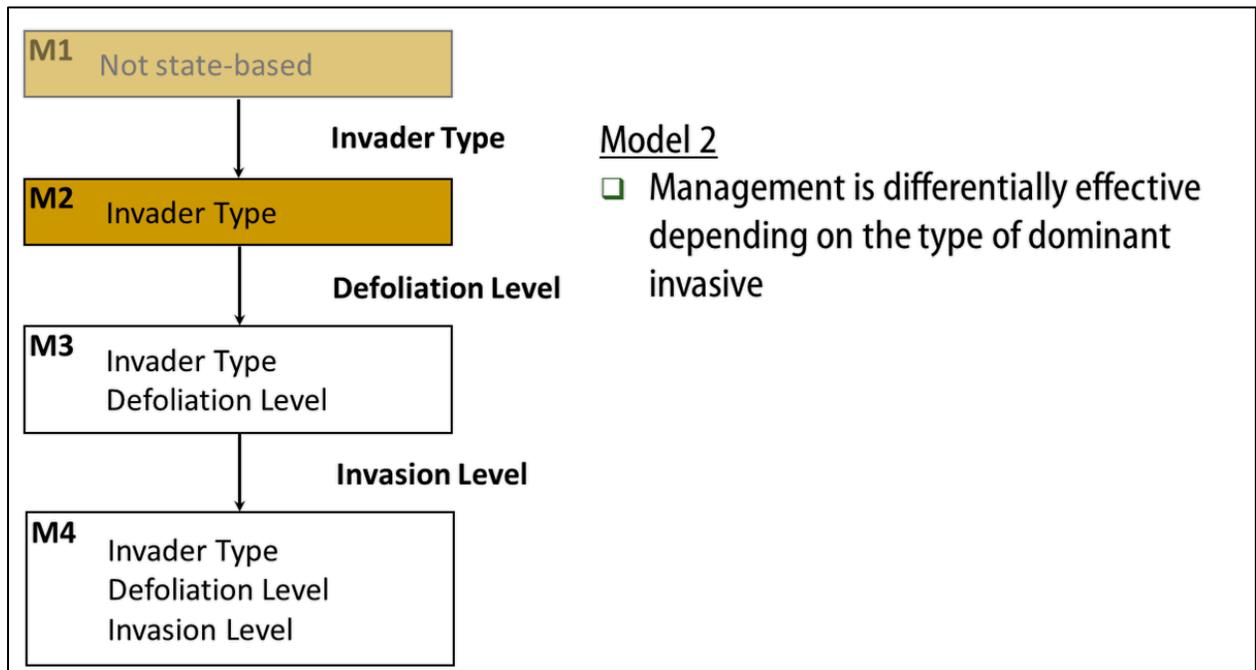
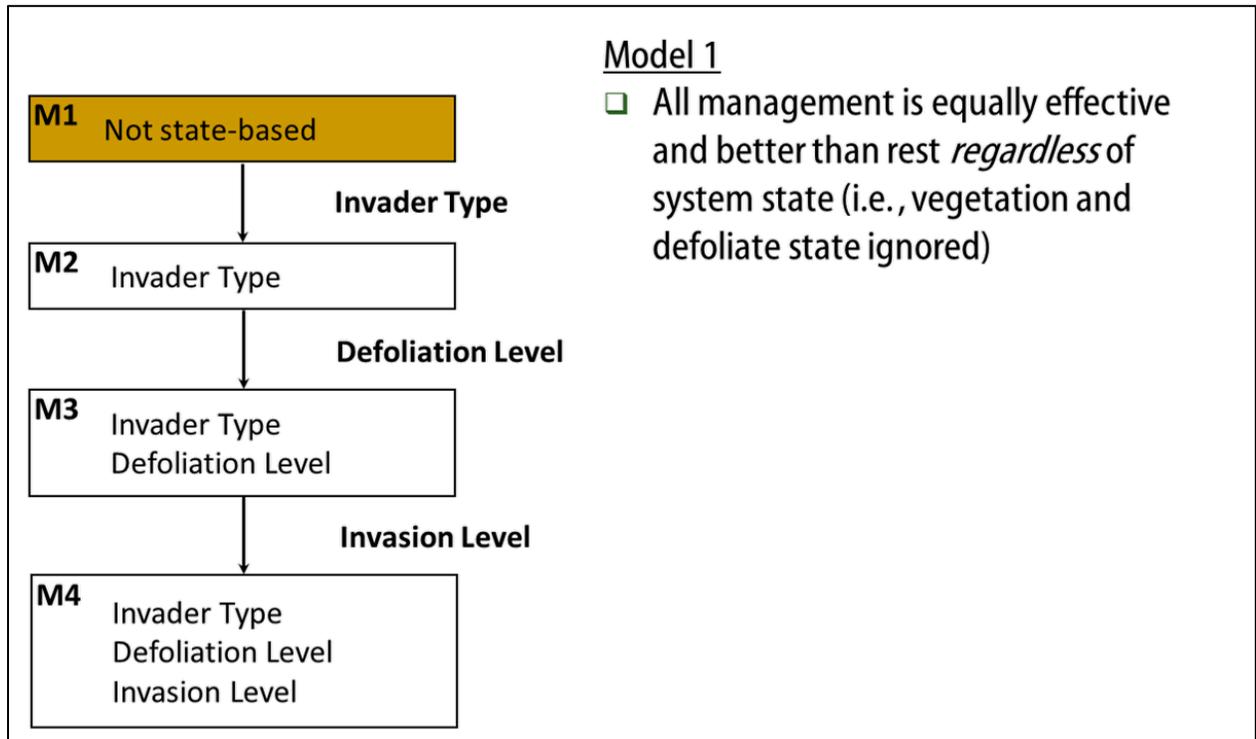
- Goal of managing under an AM framework
 - Reduce uncertainty so make better decisions based on improved understanding of system behavior
- Represent uncertainty through competing models
- Models make different predictions about how the system responds to different management actions
 - Predictions based on three identified uncertainties:
 - (1) Invader type, (2) Defoliation level, (3) Invasion level

Competing Model Set



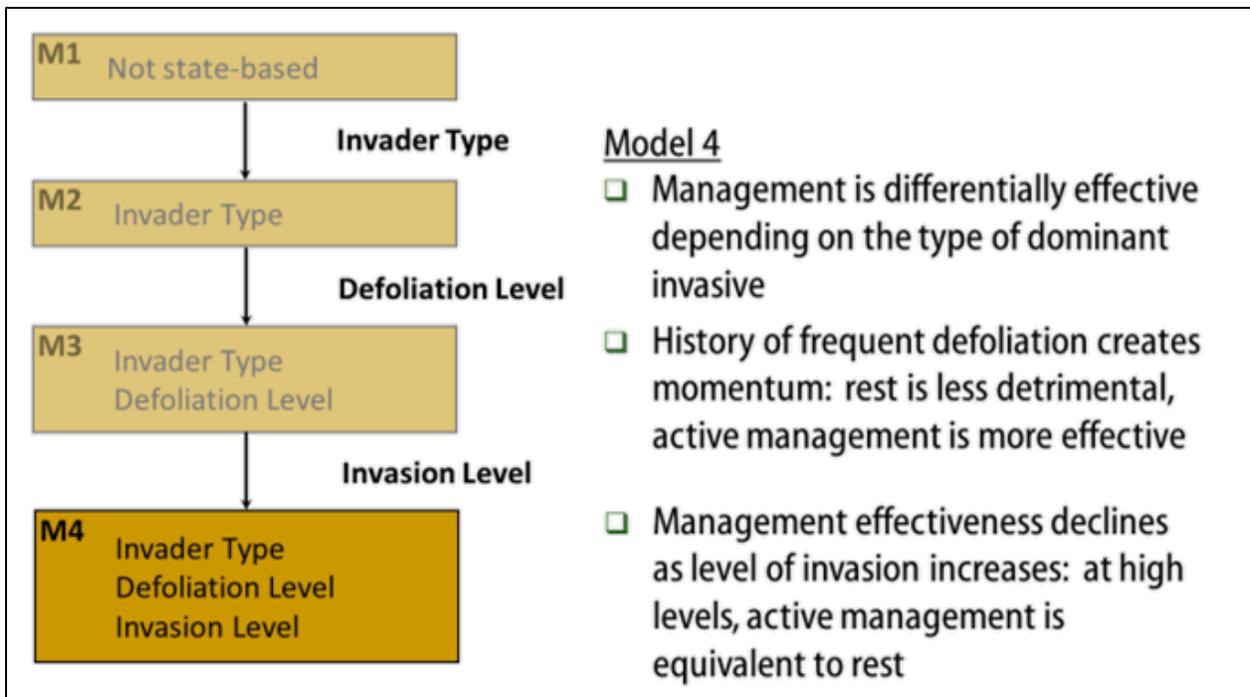
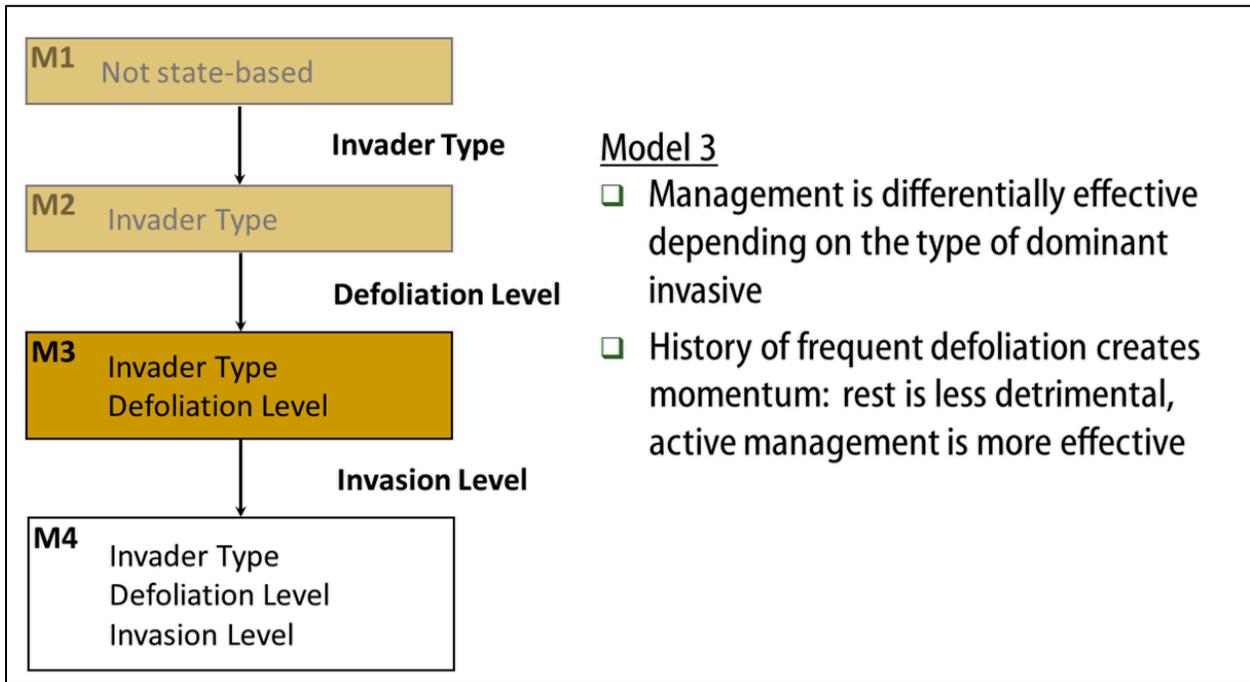
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Competing Model Set



Case Study: Model Development
Adaptive Management: Structured Decision Making for Recurrent Decisions

Competing Model Set (continued)



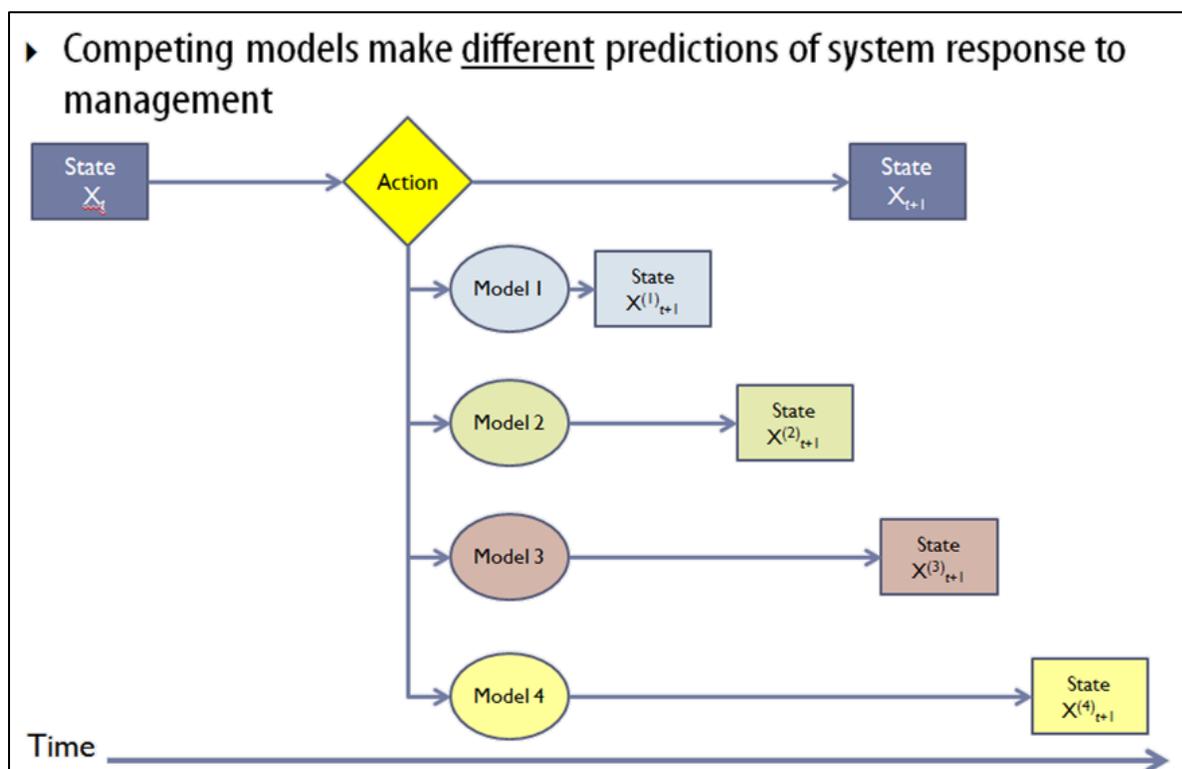
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Parameterization of Competing Models

- Original elicitation was used to parameterize Model 3
- To parameterize Models 1, 2, and 4
 - Modified the elicited values to be consistent with the specific hypotheses
 - Like before, used the values as input in a linear-logistic and linear-polytomous regression
 - Derived parameters of the state transition probability matrices for each model (12 matrices per model)

Implications of Competing Models



Implications of Competing Models – Vegetation State

- Competing models make different predictions
 - Same starting vegetation and defoliation state
 - Same management action
 - Different predicted outcome of vegetation state
- Prediction of the resulting vegetation state depends on the model used; therefore, which management action you should select depends on the model you believe

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NPAM Model Prediction Over a Single Time Step

Initial Starting States at time t

Defoliation Level (L, M, H) High

NP Cover (0-30, 30-45, 45-60, 60-100) 30-45

Dominant Invader (SB, CO, KB, RM) KB

Management Action (R, G, B, BG) Burn

Distribution of Predictions at time $t+1$

Model 1

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	1	1	5	0
30-45	7	12	52	6
0-30	1	4	9	2

Model 2

	SB	CO	KB	RM
60-100	0	1	0	0
45-60	0	6	8	11
30-45	0	26	18	26
0-30	0	1	1	2

Model 3

	SB	CO	KB	RM
60-100	0	1	0	0
45-60	0	19	6	1
30-45	0	54	11	5
0-30	0	1	1	1

Model 4

	SB	CO	KB	RM
60-100	0	0	0	0
45-60	0	7	1	1
30-45	0	55	14	6
0-30	0	12	2	2

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NPAM time series simulation

Initial Starting States at time t

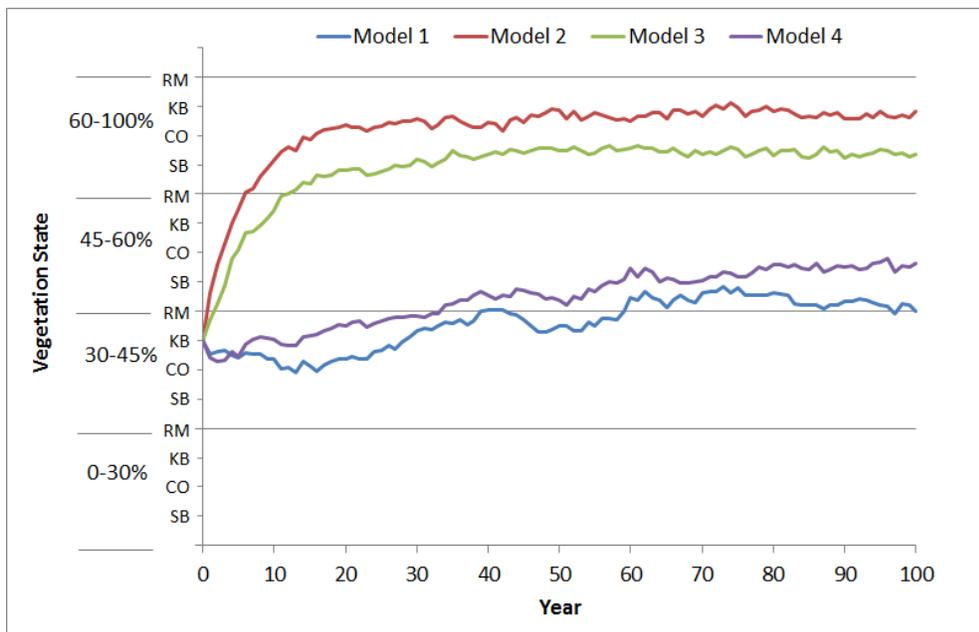
Defoliation State: Yrs Since | Level **1 | High**

NP Cover **30-45**

Dominant Invader **KB**

Management Action

Repeated Annual Action **Burn**



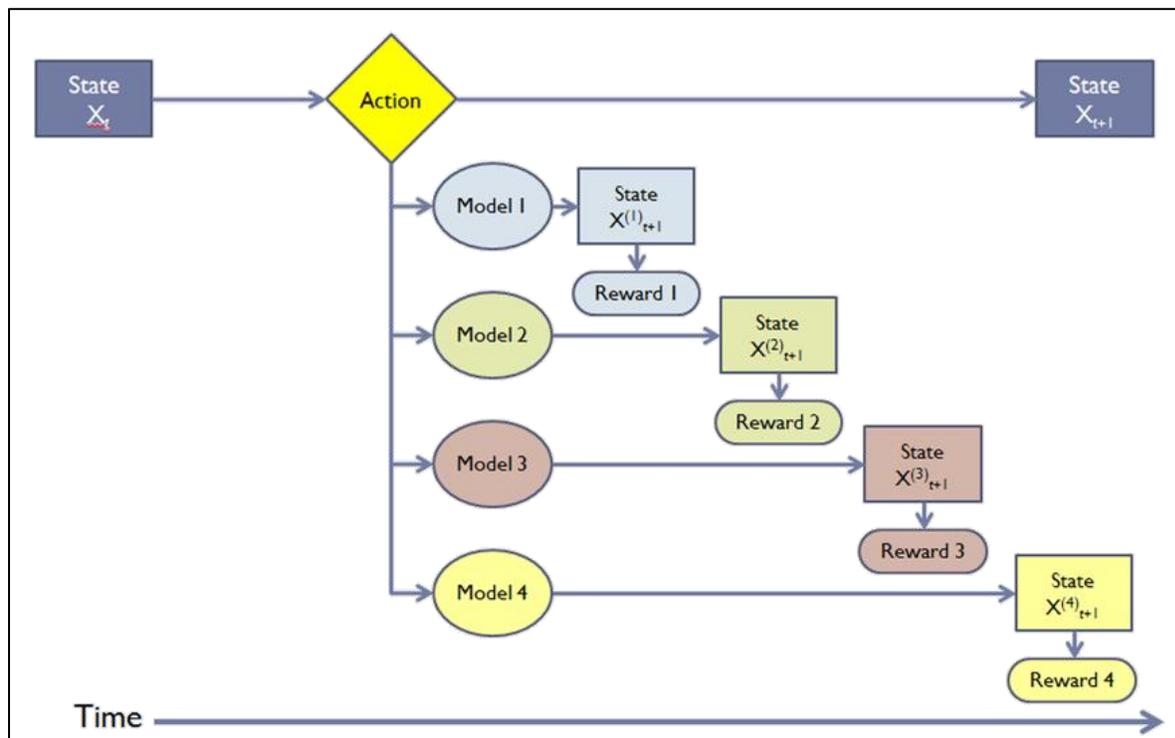
Implications of Competing Models – Reward

- We translate the resultant vegetation state into a value that represents the reward gained (utility)
- A subjective expression that quantifies how cooperators value the outcome produced by the action taken
- Combines both aspects of the management objective and is a function of
 - Native cover outcome relative to starting state (resource gain)
 - Management action applied (cost)
- Unitless number that ranges between 0 and 1
- Annual measure of what is received for what is invested
 - Larger the value, greater the payoff

More about utility in Case Study Module D...

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Implications of Competing Models – Reward



- Because reward is a function of the starting state, management action taken, and resulting state.
- And because competing models made different predictions about the resulting state given the same input.
- It follows that competing models predict different rewards for the same input.

Implications of Competing Models – Reward

- For any given vegetation state and management action taken, competing models project different rewards
- If differences aren't trivial, as rewards accumulate through the course of decision making, competing models will indicate that the objective would be best pursued along different paths of decision making

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NPAM Model Prediction Over a Single Time Step

Initial Starting States at time t

Defoliation Level (L, M, H) High

NP Cover (0-30, 30-45, 45-60, 60-100) 30-45

Dominant Invader (SB, CO, KB, RM) KB

Management Action (R, G, B, BG) Burn

Distribution of Predictions at time $t + 1$ for Competing Models

Model 1

	SB	CO	KB	RM	Sum	Utility	
60-100	0	0	0	0	0	0.4366	<u>M1 v M2</u> 20.3629
45-60	2	2	4	0	8		
30-45	8	22	39	6	75		
0-30	1	1	13	2	17		

Model 2

	SB	CO	KB	RM	Sum	Utility	
60-100	0	2	0	0	2	0.5255	<u>M2 v M3</u> 2.1337
45-60	0	6	9	22	37		
30-45	0	17	12	23	52		
0-30	0	2	4	3	9		

Model 3

	SB	CO	KB	RM	Sum	Utility	
60-100	0	2	0	0	2	0.5367	<u>M3 v M4</u> 20.0391
45-60	0	28	10	2	40		
30-45	0	40	7	4	51		
0-30	0	6	0	1	7		

Model 4

	SB	CO	KB	RM	Sum	Utility
60-100	0	0	0	0	0	0.4471
45-60	0	8	5	0	13	
30-45	0	54	10	6	70	
0-30	0	8	7	2	17	

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Structural Uncertainty: Expected Value of Perfect Information

- If management performance depends on the model used, best performance would be achieved by managing under the model that best reflects system behavior
 - Have 4 different models, that make 4 different predictions, and are uncertain which is the better representation of system behavior
 - Goal of managing under AM framework to reduce uncertainty
 - What is the value of resolving the uncertainty among competing models? What is sacrificed if fail to identify the most appropriate model and continue to manage under model uncertainty?
 - This is the Expected Value of Perfect Information (EVPI)

Expected Value of Perfect Information (EVPI)

- EVPI is the value of resolving uncertainty compared with continuing to manage under uncertainty
- EVPI is measured in units of the management reward, i.e., the utility
- To compute EVPI we need:
 - Expected value (utility) of managing under certainty with respect to each competing model
 - Expected value (utility) of managing under continued uncertainty with respect to all competing models

Expected Value of Perfect Information (EVPI)

- (1) Expected value of management under certainty for a model
 - For a given model m , optimization procedure provides the expected average maximum utility for a given starting state x , assuming the optimal policy is followed
 - Call this value $U_m(x)$
- (2) Expected value of management under continued uncertainty
 - Optimization procedure provides the expected average maximum utility by averaging all 4 model rewards
 - Call this value $U.(x)$

Optimization.....in brief

- A procedure that looks at all possible decision pathways through time and the accumulated rewards over the course of the different decision pathways
- Identifies the trajectory of decisions (i.e., management actions) for each time-step through time that is optimal (i.e., results in the highest accumulation of rewards)

More about optimization in Case Study Module D...

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Expected Value of Perfect Information (EVPI)

- Averaging over all possible starting states, x

U_{m1}	U_{m2}	U_{m3}	U_{m4}	Avg_{m1:m4}
0.71722	0.84983	0.85911	0.77048	0.79916

(1) Average of the four model-certain utilities. Average expected per annum utility if resolve uncertainty among models.

Average expected per annum utility under each respective model as if certain it is the best model (i.e., weight of 1.0)

U.
0.79053

(2) Average expected per annum utility if continue to manage without resolving uncertainty among models (i.e., always equal weight of 0.25 on each model)

- **EVPI = Avg_{m1:m4} - U. = 0.00862**

- Over all states, resolving uncertainty provides a 1.1% increase in utility over continuing to manage without resolving uncertainty
 - We get 1.1% by dividing the **EVPI** by the expected value of continuing to manage under uncertainty (i.e., the value **U.** in the green box) * 100. $(0.00862/0.790534)*100 = 1.1\%$

EVPI Differs by System State

- Value of resolving uncertainty is greater in some states than others
 - Overall: 1.1% increase
 - Amount of native prairie vegetation

0-30%	30-45%	45-60%	60-100%
0.9%	0.7%	1.1%	1.6%

- Level of past defoliation

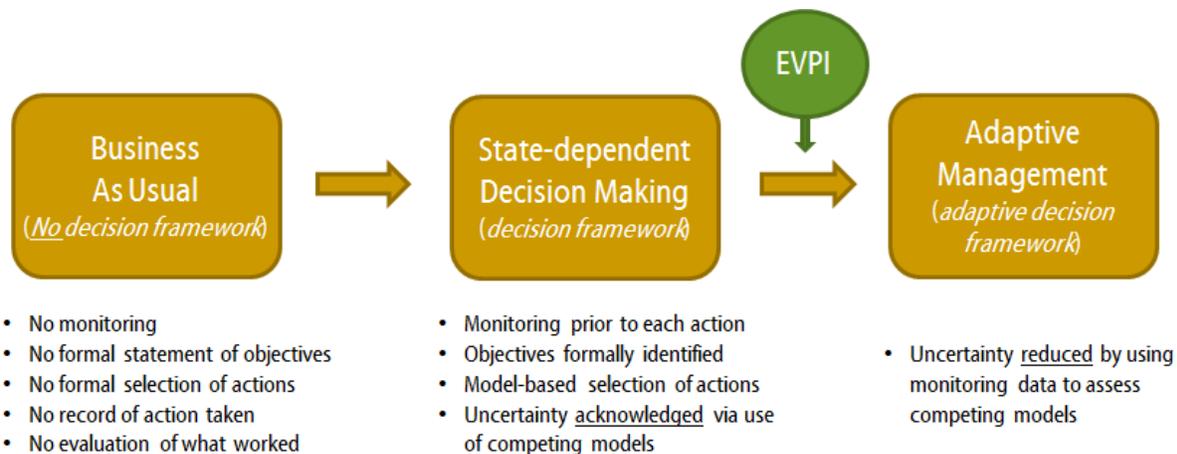
Low	Medium	High
1.0%	1.1%	1.2%

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EVPI is not Measuring Value of AM over 'Business As Usual'!

- Cooperators have already agreed to implement state-dependent decision making, with monitoring
 - EVPI is measuring the value of using the monitoring data to improve future management



Structural Uncertainty: Model Weighting

- If we're uncertain about choice of model, how do we move forward with a decision?
 - Assign initial model weights to each model, e.g.,
 $w_{m1} = 1/4, w_{m2} = 1/4, w_{m3} = 1/4, w_{m4} = 1/4$
 - This weighting reflects complete uncertainty among competing models
 - Each model initially has equal influence on the decision
 - For subsequent decisions, model weights are updated on the basis of information feedback from the monitoring program
 - Each model's influence on the decision is continually revised over time

More about this in Case Study Module C – Monitoring and Learning...

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Summary: Case Study Module B - Model Development

- NPAM models project vegetation composition through time, in response to management actions and stochastic effects
- Lacking data, model parameters were derived via expert elicitation
- Response of vegetation to management is uncertain and we express structural uncertainty through competing models
- Resolution of the uncertainty among competing models is likely to translate into increased management performance
- EVPI is the expected value of resolving uncertainty compared with continuing to manage under uncertainty

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>