Qualitative Modelling and Bayesian Belief Networks

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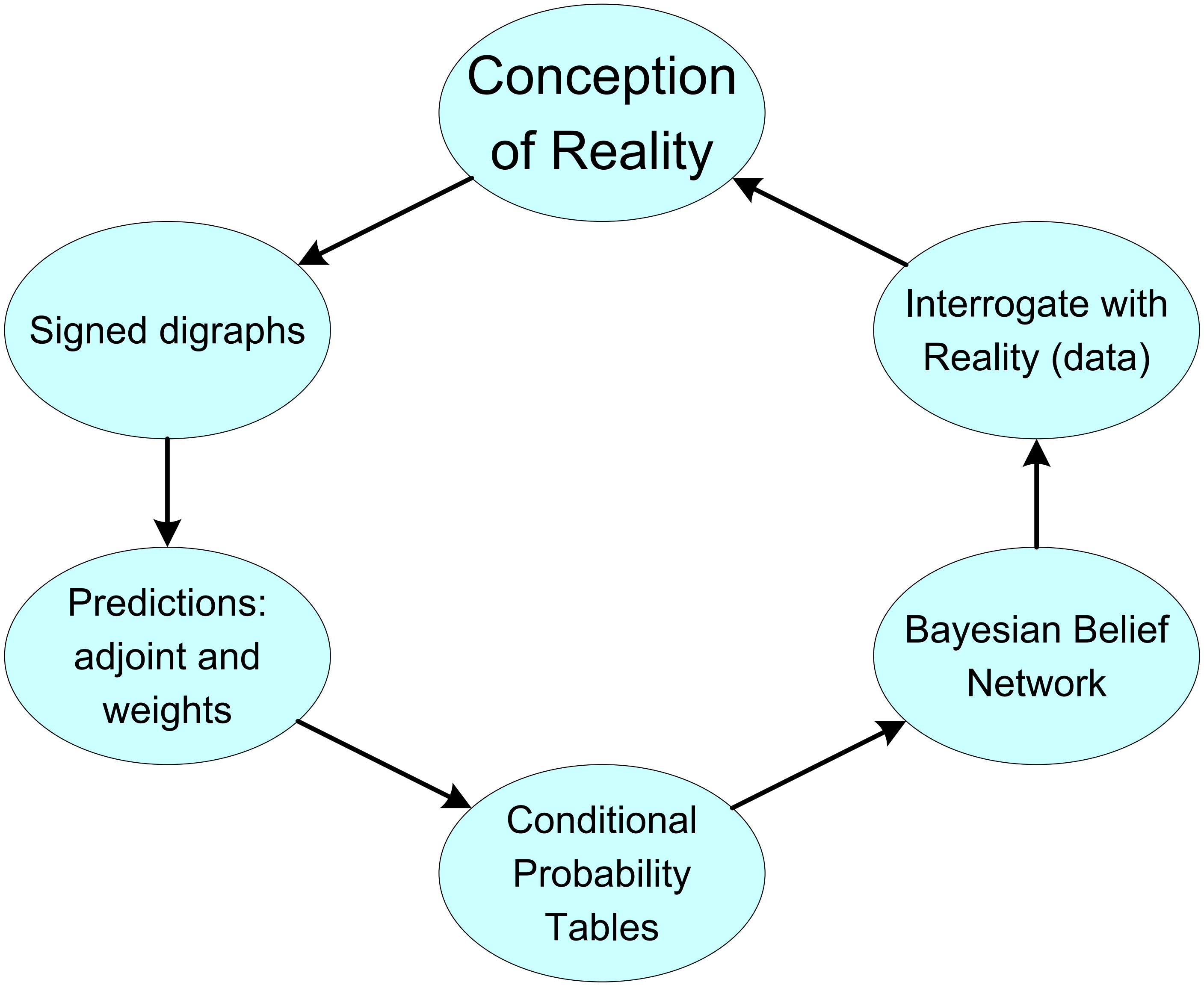
CSIRO Marine and Atmospheric Research

What does Qualitative Modelling offer BBN's?



Bayesian Belief Networks in Risk Analysis

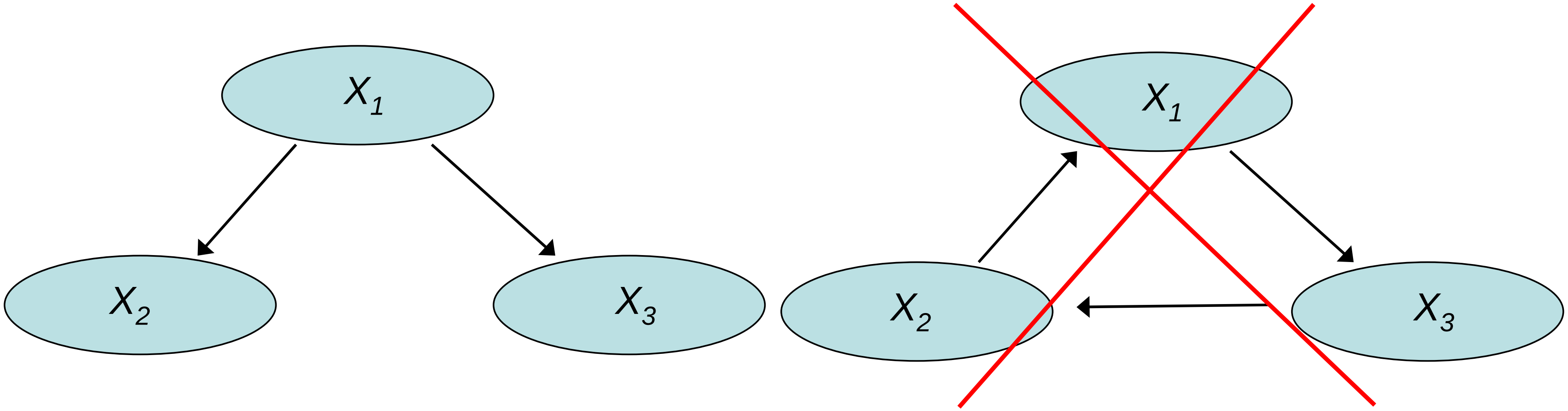
Bayesian Belief Networks (BBNs) applied to ecological risk assessment

- Prediction (Borusk et al 2004)
- Synthesis of ecological data and expert knowledge (Pollino et al 2006, Stiber et al 2004)
- Optimal decision-making (Varis 1998)

Bayesian Belief Networks

Bayesian Belief Network

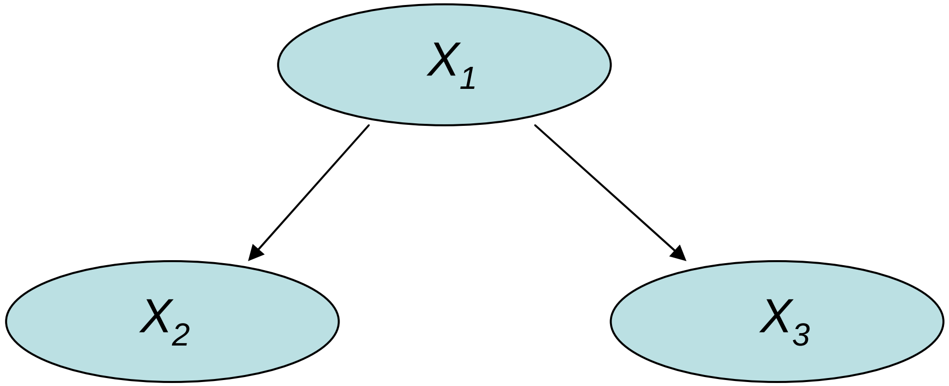
- a group of nodes connected by directed arrows such that there are no cycles (loops)



- "Child" nodes with incoming arrows are probabilistically dependent on "parents" values

Bayesian Belief Networks

- The directed graph represents conditional dependency among nodes

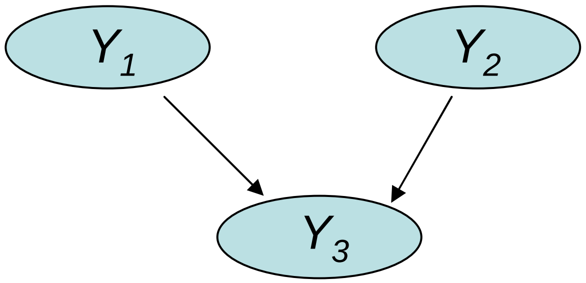


$$P(X_1 \cap X_2 \cap X_3)$$
$$= P(X_2 \mid X_1) \times P(X_3 \mid X_1) \times P(X_1)$$

- Joint probability recovered from Bayesian network
- Answer any query

An expert-informed BBN

- Ecological risk assessment starting to utilize expert opinion within BBN framework
  - Allows inference in absence of case-specific measurements
  - Well-suited for variety of ecological problems
- Set probabilities for every possible contingency in Conditional Probability Table (CPT)



CPT

Y_1	Y_2	$P(Y_3 = T \mid Y_1, Y_2)$
T	**T**	**.20**
T	**F**	**.15**
F	**T**	**.40**
F	**F**	**.25**

Conditional Probability:

Condition 1

"Given a fish population in 'poor' health, a day in which bottom water oxygen concentrations average 0.5 mg/l at mid-channel locations, and the strength and direction of winds are such that the bottom water is being brought to the surface along the windward shore, ***what is the probability of more than 100,000 fish being trapped and dying***?

Condition 2

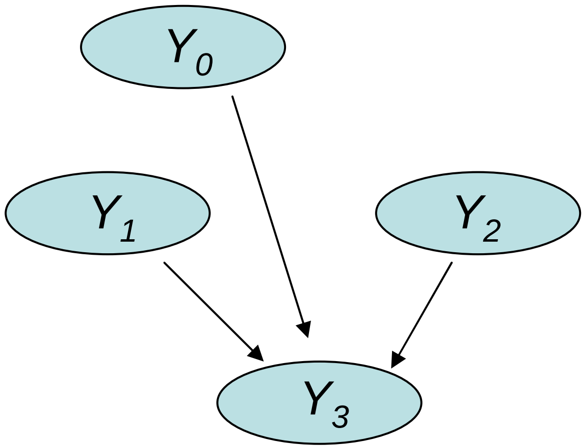
Condition 3

Probability statement

- Borusk et al 2004

Determining Conditional Probability Tables (CPT's)

Example: Adding one dichotomous variable, Y_0

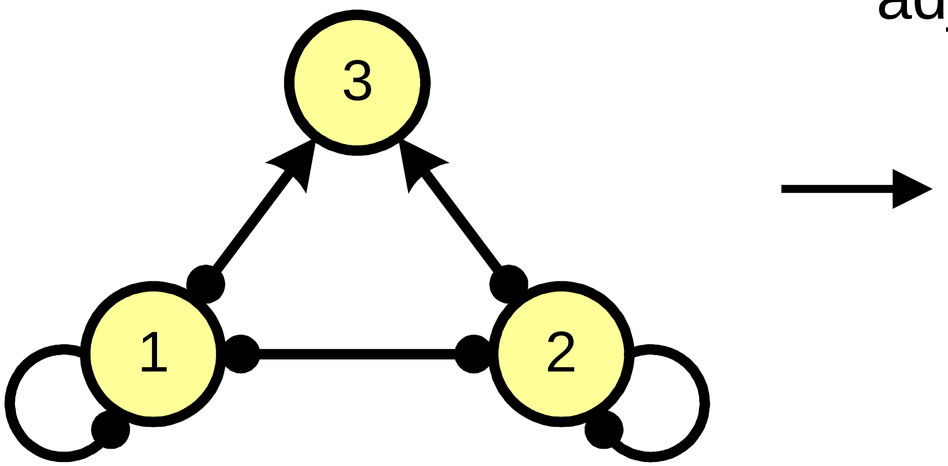


Y_0	Y_1	Y_2	$P(Y_3 = T \mid Y_0, Y_1, Y_2)$
T	**T**	**T**	**.08**
T	**T**	**F**	**.38**
T	**F**	**T**	**.04**
T	**F**	**F**	**.09**
F	**T**	**T**	**.16**
F	**T**	**F**	**.17**
F	**F**	**T**	**.06**
F	**F**	**F**	**.10**

- BBN's have difficulty incorporating unobserved or unmeasured variables since CPT becomes very large with additional contingencies (Elye-Datubo et al 2006)

Qualitative Modelling Advantages: Inclusion of feedback cycles

- Acyclic representation of BBNs disallow the incorporation of ecologically significant feedback cycles (Borusk et al. 2004)
- Qualitative models utilize feedback cycles to make predictions:



adj(-A) =

Input (columns) / Response (rows)

	V_1	V_2	V_3
V_1	-	+	+/-
V_2	+	-	+/-
V_3	+/-	+/-	0

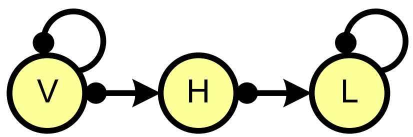
Example: Hare and Lynx

- Simple trophic chain: Vegetation – Hare – Lynx
- Krebs et al. (1995) observed non-intuitive indirect effect: experimental increase of vegetation did not significantly increase the density of hares

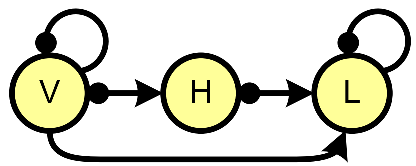
Experimental positive input to vegetation

Hare – Lynx alternative model predictions

Model A1



Model A2



Symbolic adjoints:

Model A1:

$$\begin{bmatrix} a_{2,3}a_{3,2} & -a_{1,2}a_{3,3} & a_{1,2}a_{2,3} \\ a_{2,1}a_{3,3} & a_{1,1}a_{3,3} & -a_{1,1}a_{2,3} \\ a_{2,1}a_{3,2} & a_{1,1}a_{3,2} & a_{1,2}a_{2,1} \end{bmatrix}$$

Model A2:

$$\begin{bmatrix} a_{2,3}a_{3,2} & -a_{1,2}a_{3,3} & a_{1,2}a_{2,3} \\ a_{2,1}a_{3,3}-a_{2,3}a_{3,1} & a_{1,1}a_{3,3} & -a_{1,1}a_{2,3} \\ a_{2,1}a_{3,2} & a_{1,1}a_{3,2}-a_{1,2}a_{3,1} & a_{1,2}a_{2,1} \end{bmatrix}$$

Numeric Adjoints:

Model A1:

$$\begin{bmatrix} 1 & -1 & 1 \\ 1 & 1 & -1 \\ 1 & 1 & 1 \end{bmatrix}$$

Model A2:

$$\begin{bmatrix} 1 & -1 & 1 \\ 0 & 1 & -1 \\ 1 & 0 & 1 \end{bmatrix}$$

Prediction Weights:

Model A1:

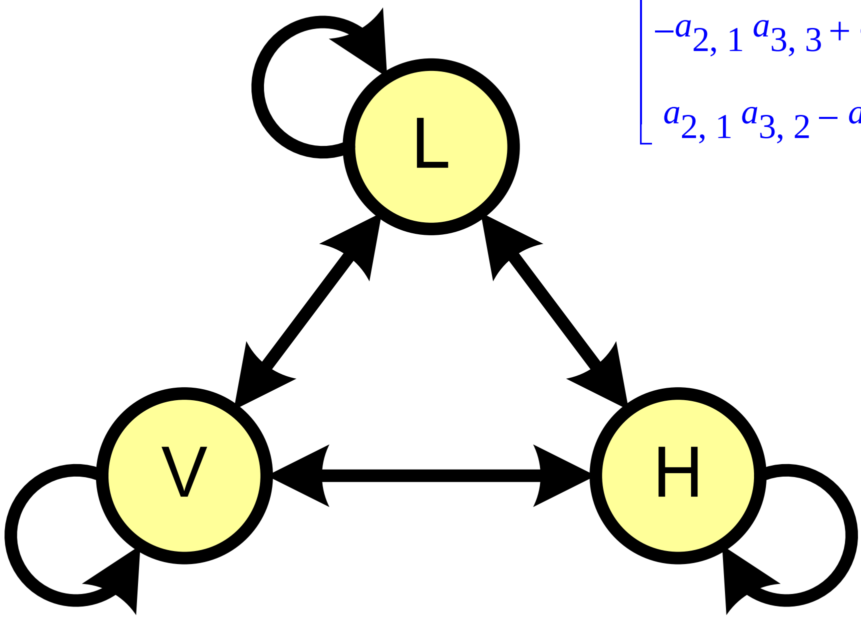
$$\begin{bmatrix} 1. & 1. & 1. \\ 1. & 1. & 1. \\ 1. & 1. & 1. \end{bmatrix}$$

Model A2:

$$\begin{bmatrix} 1. & 1. & 1. \\ 0. & 1. & 1. \\ 1. & 0. & 1. \end{bmatrix}$$

“Null” Model – Uniform probabilities of increase or decrease

Fully connected community matrix:



Symbolic Adjoint:

$$\begin{bmatrix} a_{2,2}a_{3,3}-a_{2,3}a_{3,2} & -a_{1,2}a_{3,3}+a_{1,3}a_{3,2} & a_{1,2}a_{2,3}-a_{1,3}a_{2,2} \\ -a_{2,1}a_{3,3}+a_{2,3}a_{3,1} & a_{1,1}a_{3,3}-a_{1,3}a_{3,1} & -a_{1,1}a_{2,3}+a_{1,3}a_{2,1} \\ a_{2,1}a_{3,2}-a_{2,2}a_{3,1} & -a_{1,1}a_{3,2}+a_{1,2}a_{3,1} & a_{1,1}a_{2,2}-a_{1,2}a_{2,1} \end{bmatrix}$$

Numeric Adjoint:

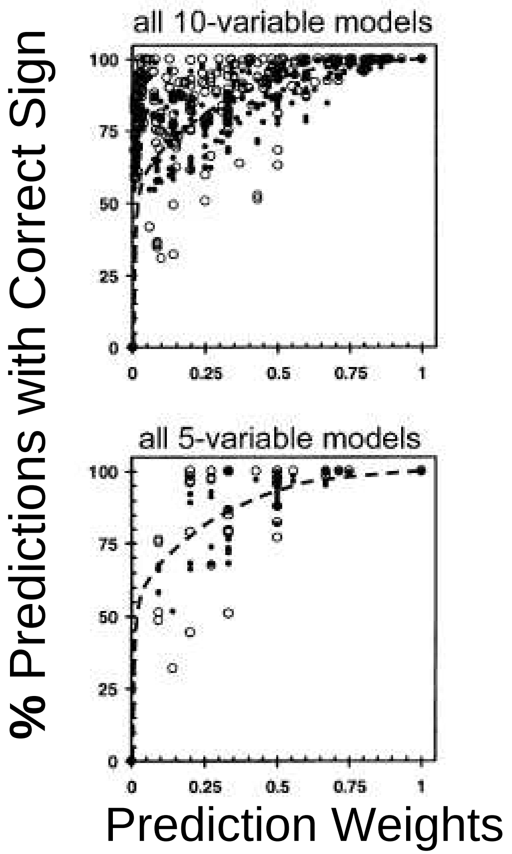
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Prediction Weights:

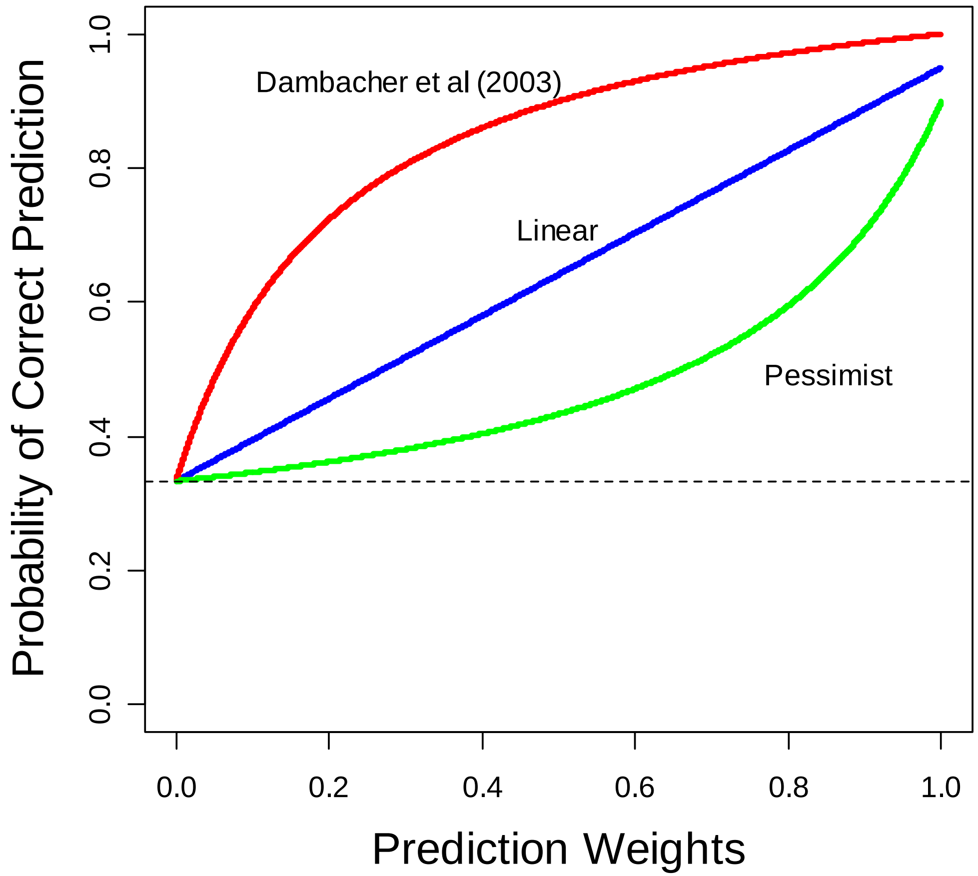
$$\begin{bmatrix} 0. & 0. & 0. \\ 0. & 0. & 0. \\ 0. & 0. & 0. \end{bmatrix}$$

Transforming weighted predictions to probabilities of increase and decrease

- **Simulations suggest weights > 0.5 have better than 90% chance of sign determinacy**
- **Functions translate predicted weights to probabilities**



Dambacher et al (2003)

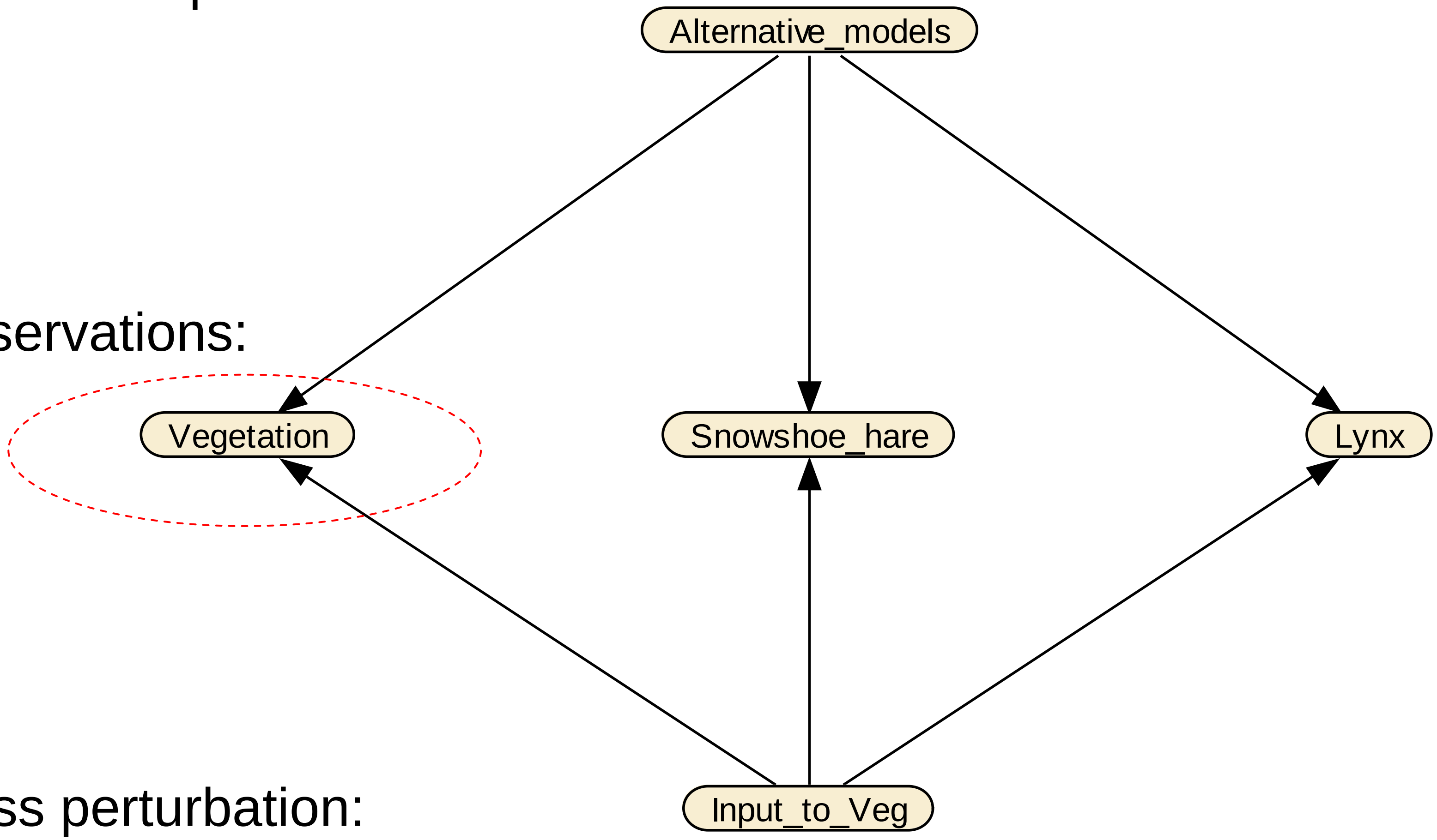


Example: Hare Lynx BBN

Model comparisons:

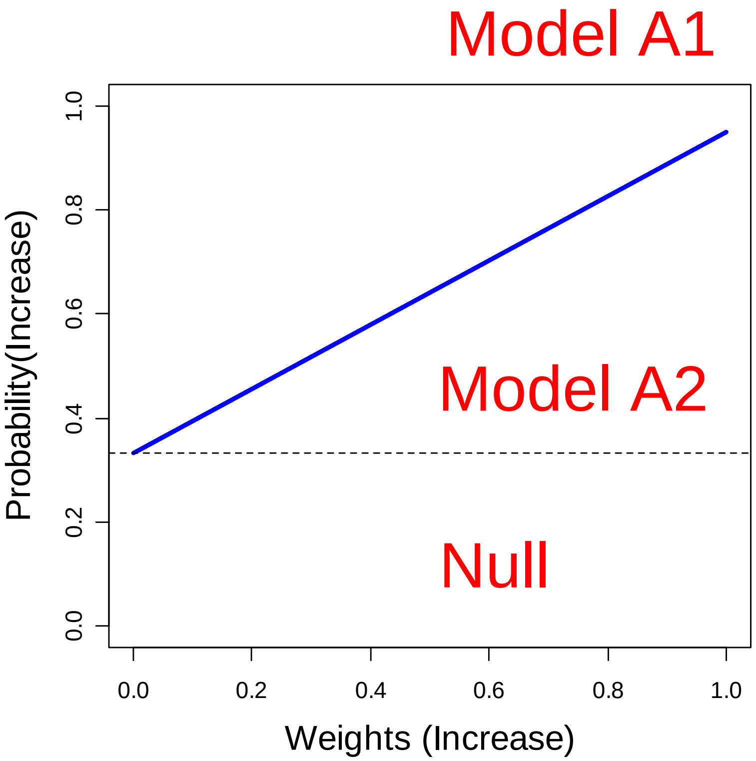
Observations:

Press perturbation:



Conditional Probability Table: Vegetation

Linear transformation:



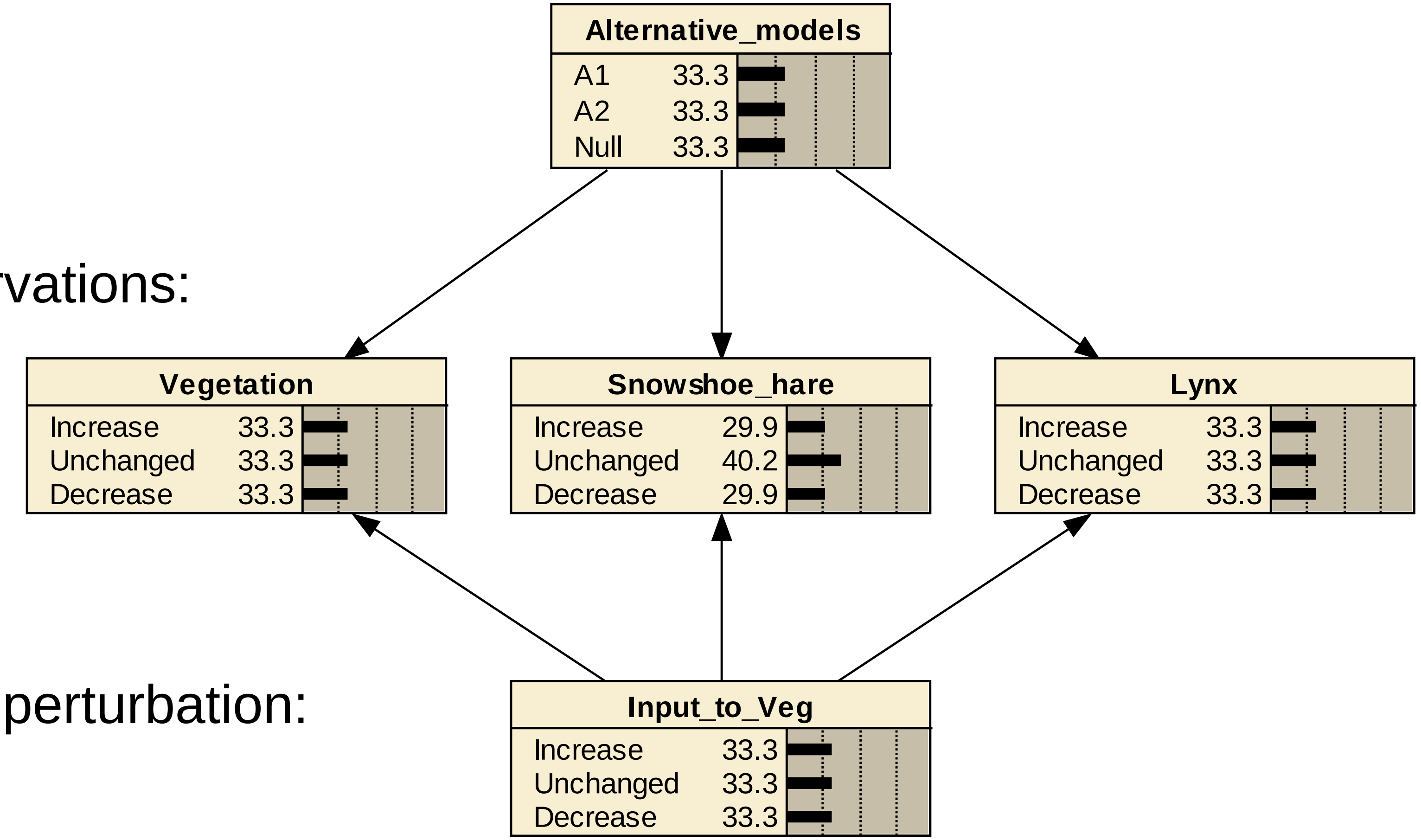
Model	Input(Veg)	Increase	Unchanged	Decrease
1	Incr	0.950	0.025	0.025
1	Unch	0.025	0.950	0.025
1	Decr	0.025	0.025	0.950
2	Incr	0.950	0.025	0.025
2	Unch	0.025	0.950	0.025
2	Decr	0.025	0.025	0.950
Null	Incr	0.333	0.333	0.333
Null	Unch	0.333	0.333	0.333
Null	Decr	0.333	0.333	0.333

Hare Lynx BBN

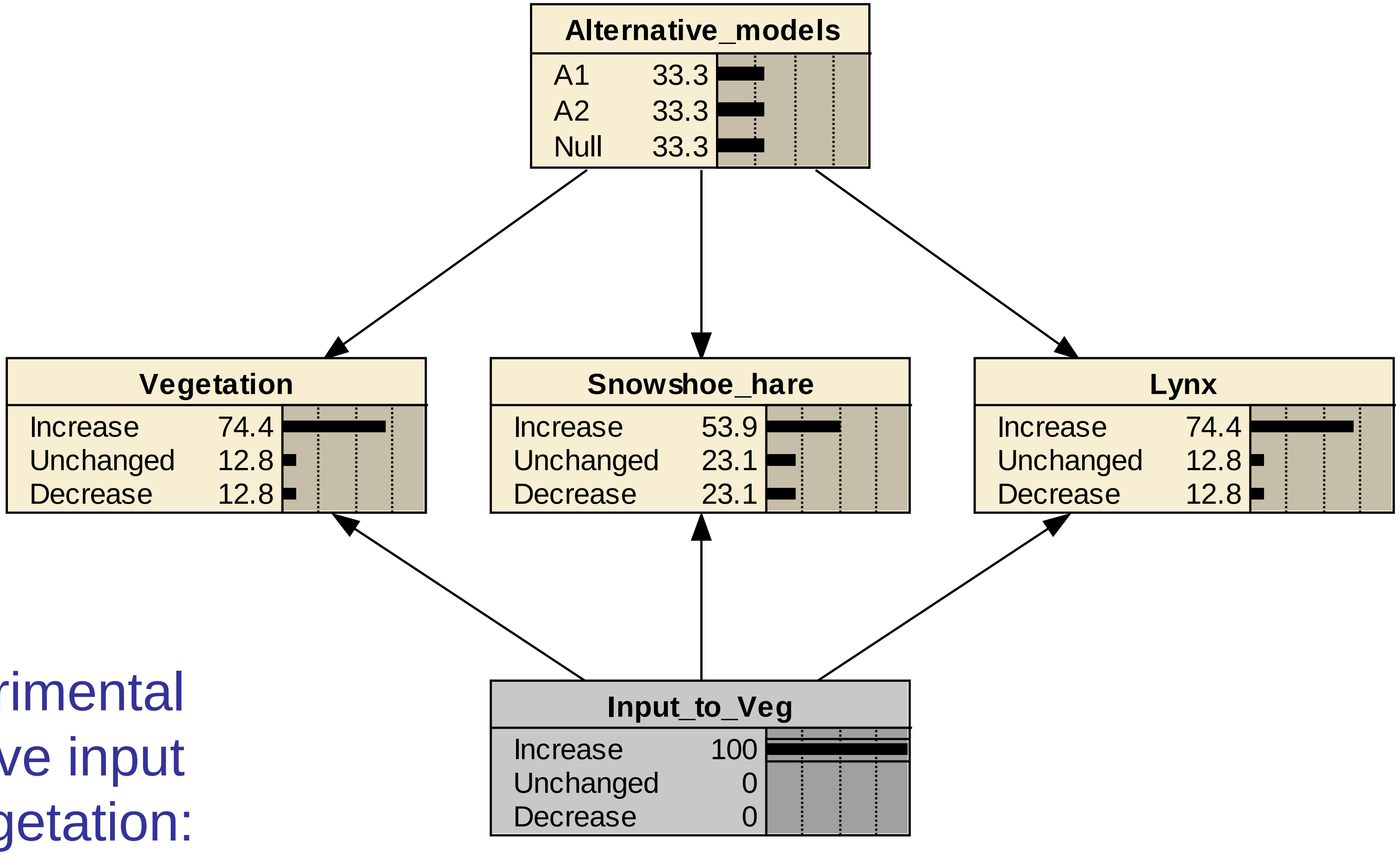
Model comparisons:

Observations:

Press perturbation:



Hare Lynx BBN



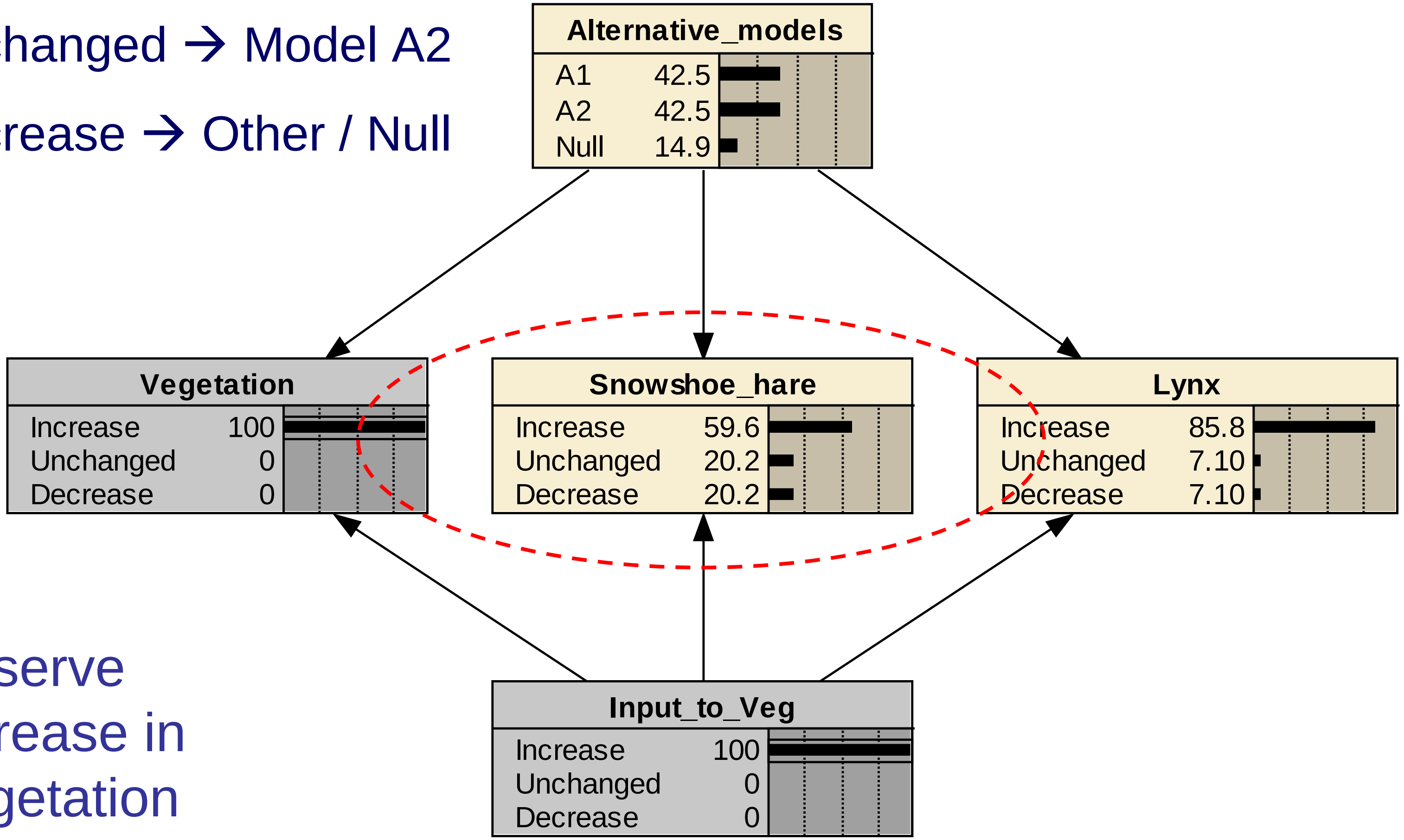
Experimental positive input to vegetation:

Hare Lynx BBN

Hare Increase → Model A1

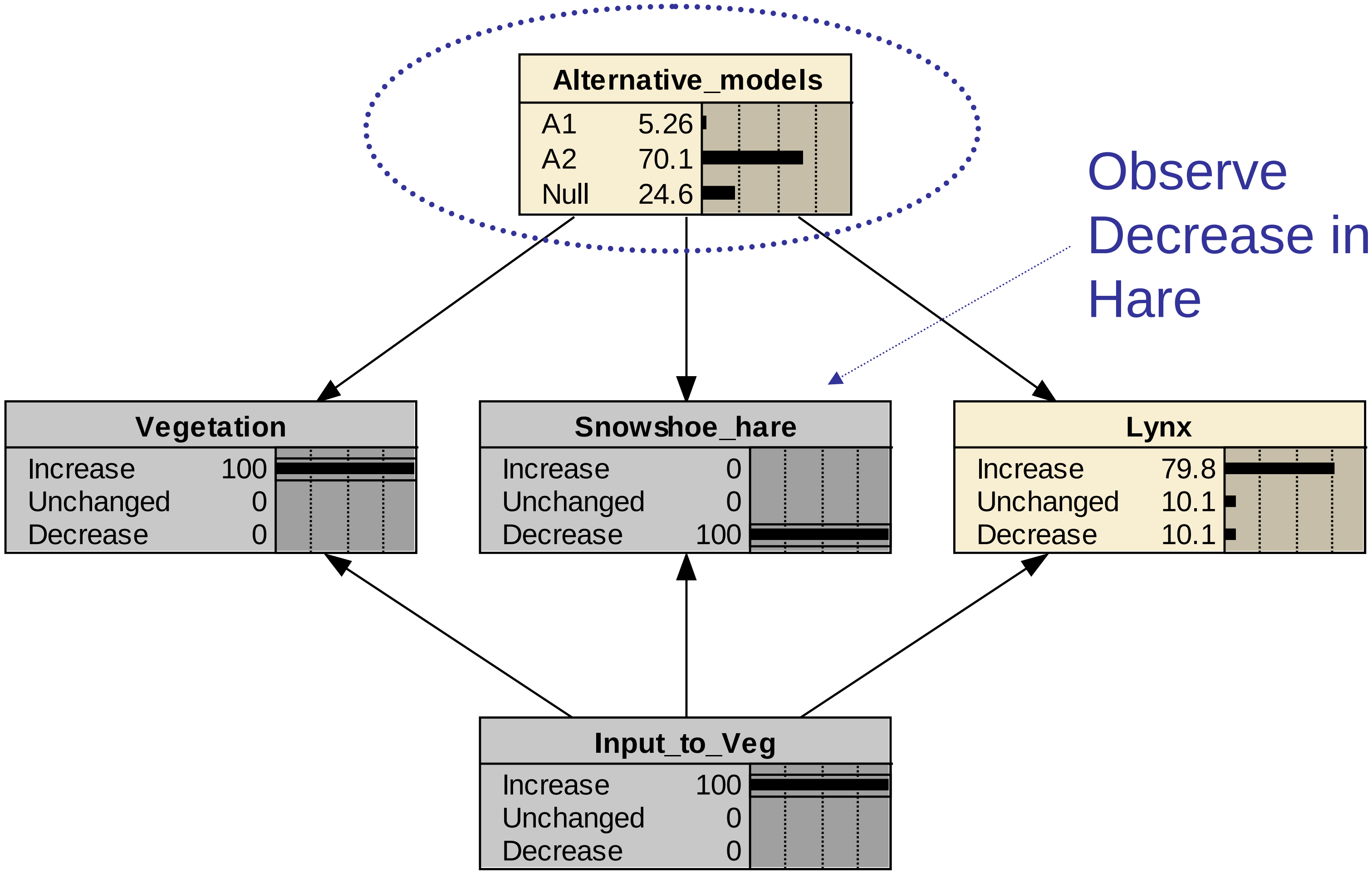
Hare Unchanged → Model A2

Hare Decrease → Other / Null



Observe Increase in Vegetation

Hare Lynx BBN

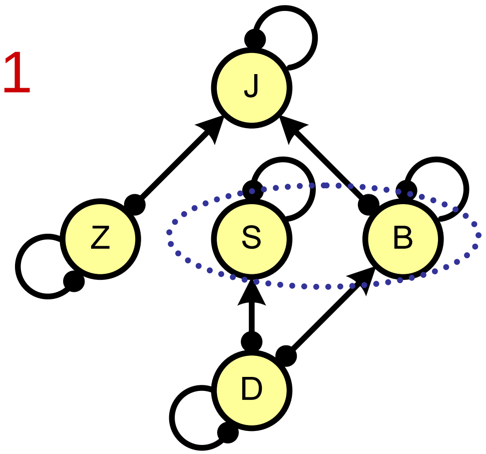


Invasive species example:
Non-native shrimp introduction

Variables of interest:

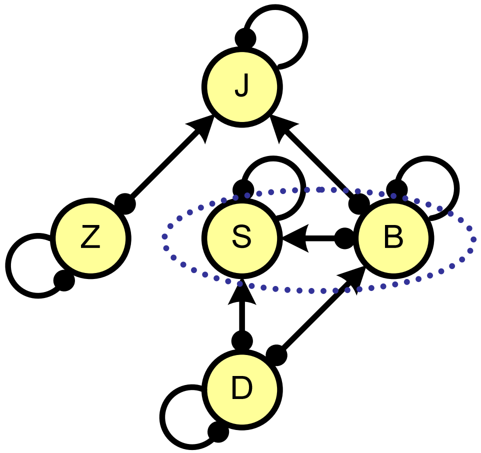
- Shrimp – Detritus – Zooplankton – Juvenile Fish – Benthic invertebrates

Model B1



Shrimp do not consume
Benthic invertebrates

Model B2



Shrimp consume
Benthic invertebrates

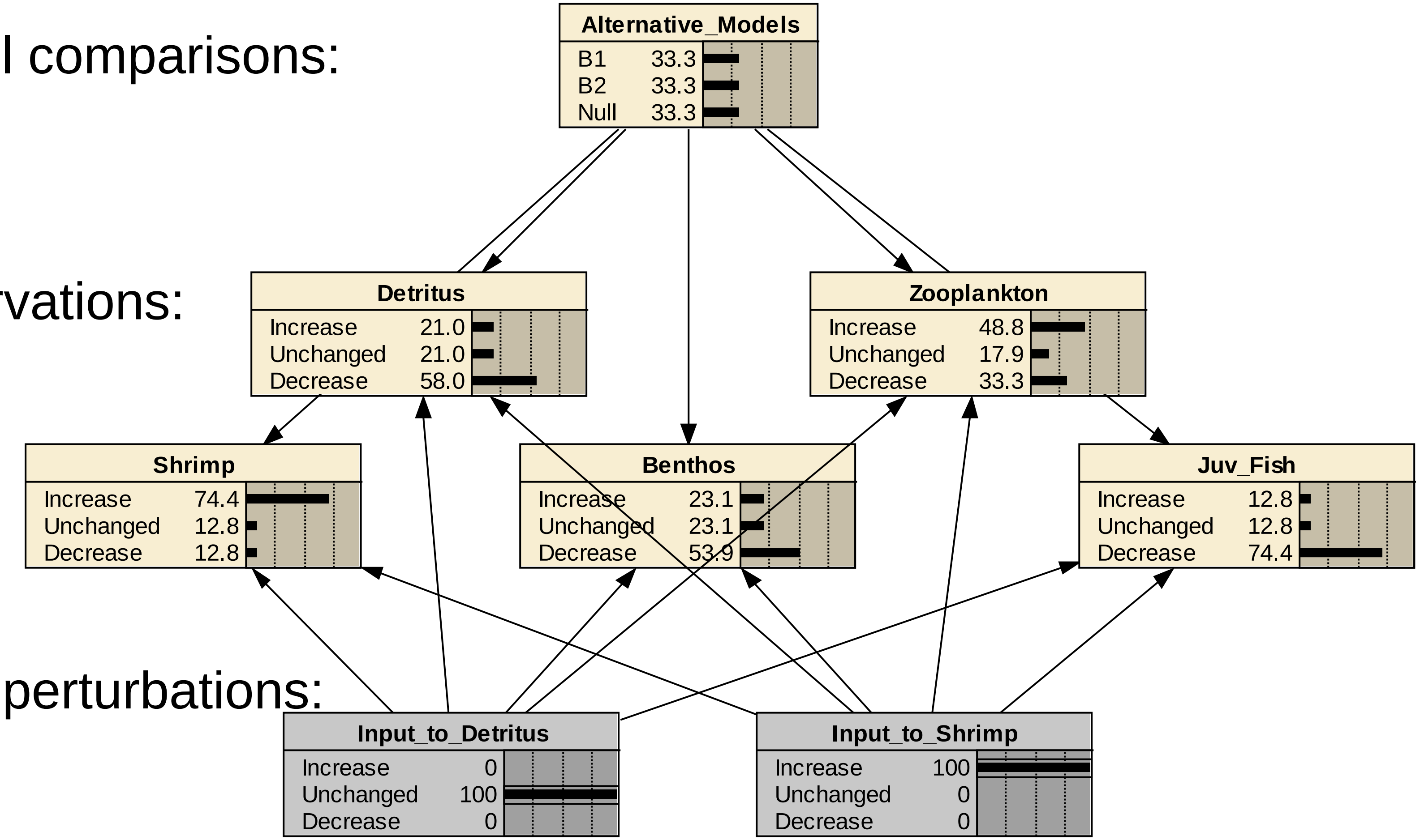
Which variable best differentiates between models?

- If only have resources to monitor one variable, which should it be?

Model comparisons:

Observations:

Press perturbations:



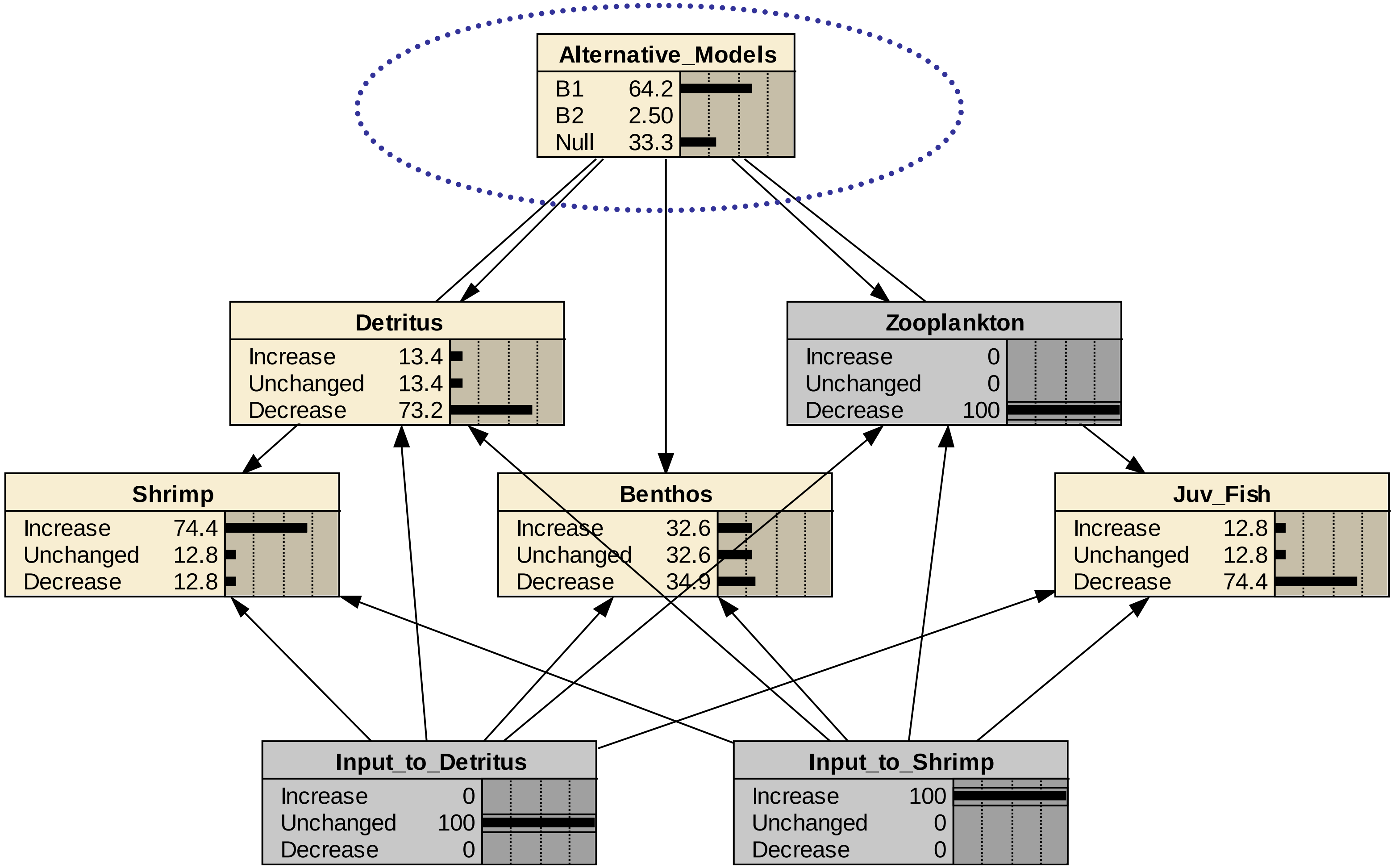
Sensitivity Analysis of BBN Informs Monitoring Strategy

- **Sensitivity findings suggest zooplankton best discriminates between competing models:**
  - Model B1: Shrimp do not prey on benthic invertebrates
  - Model B2: Shrimp consume benthic invertebrates
  - Null Model: Uniform probabilities of increase or decrease

Node	Mutual Information
Zooplankton	**.404**
Shrimp	**.323**
Juvenile Fish	**.323**
Benthic Invertebrates	**.288**
Detritus	**.248**

Observing a decrease in zooplankton suggests model B2 is incorrect

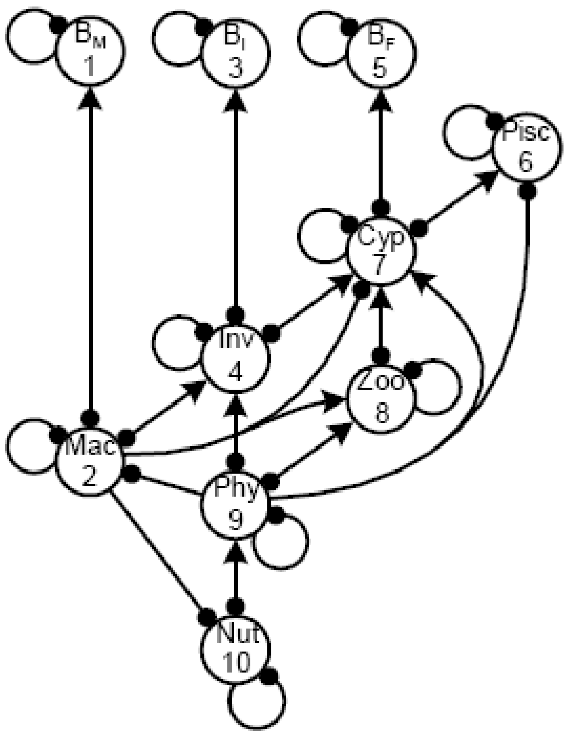
- Observation consistent with shrimp not preying on benthic invertebrates:



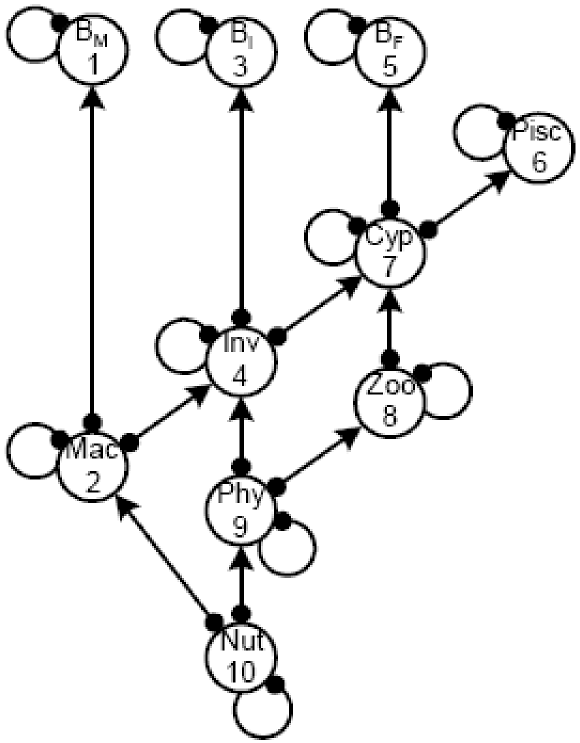
More Qualitative Modelling advantages: Alternative model falsification

- BBN's sensitive to structural uncertainty with important impacts on intervention strategy (Varis and Kuikka 1999)

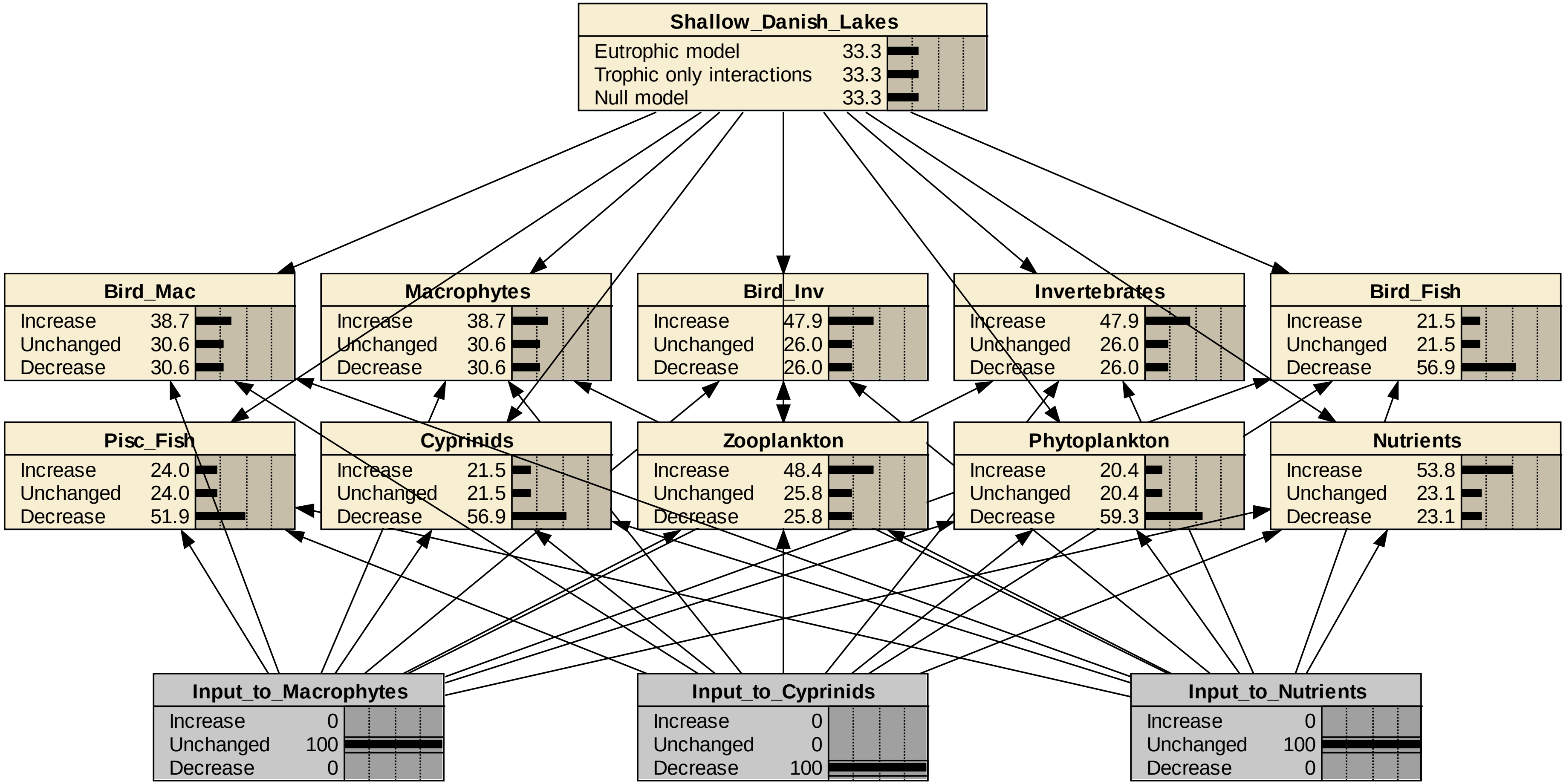
Eutrophic Lake



Trophic Interactions only

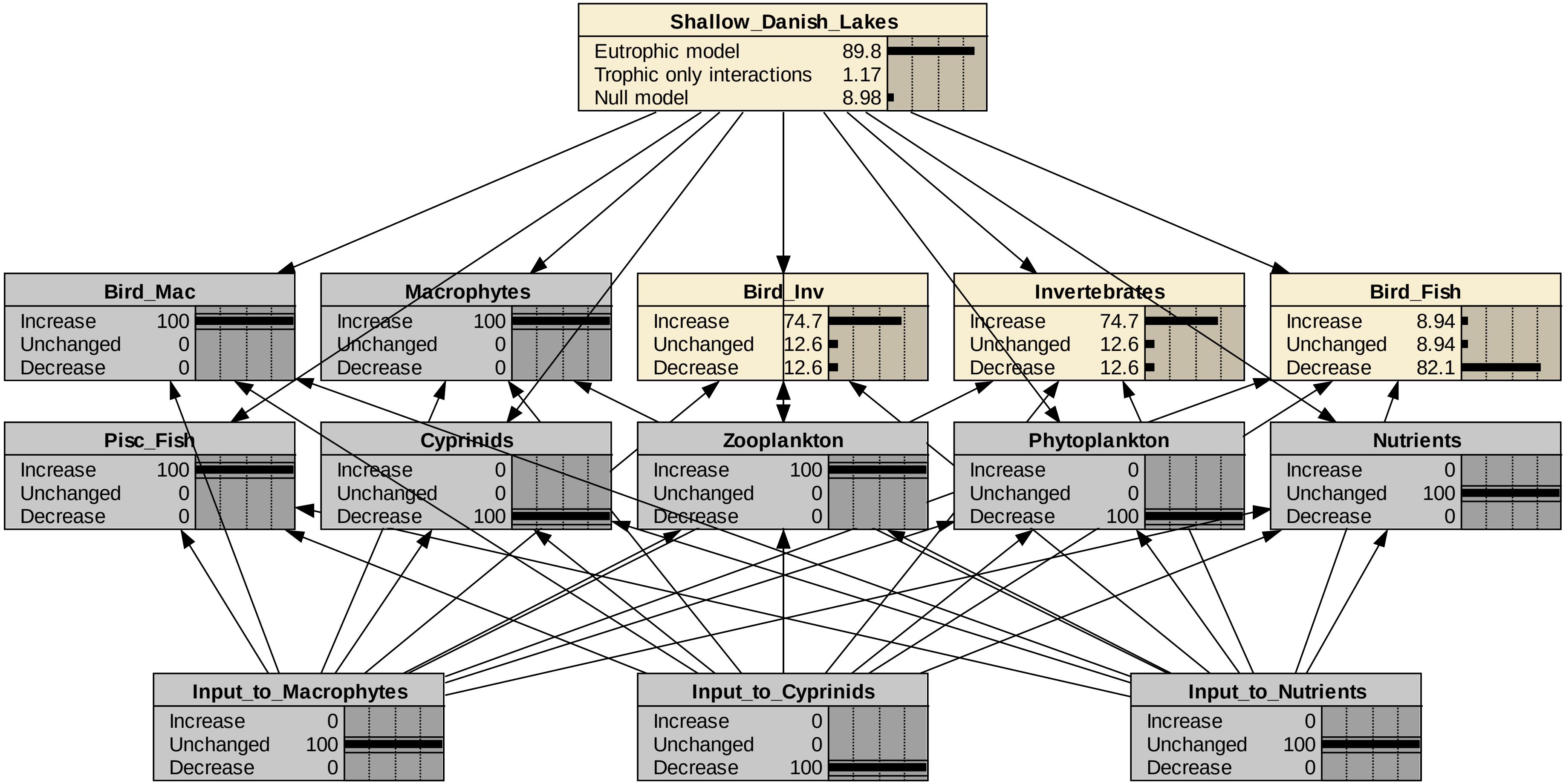


Danish Lake BBN



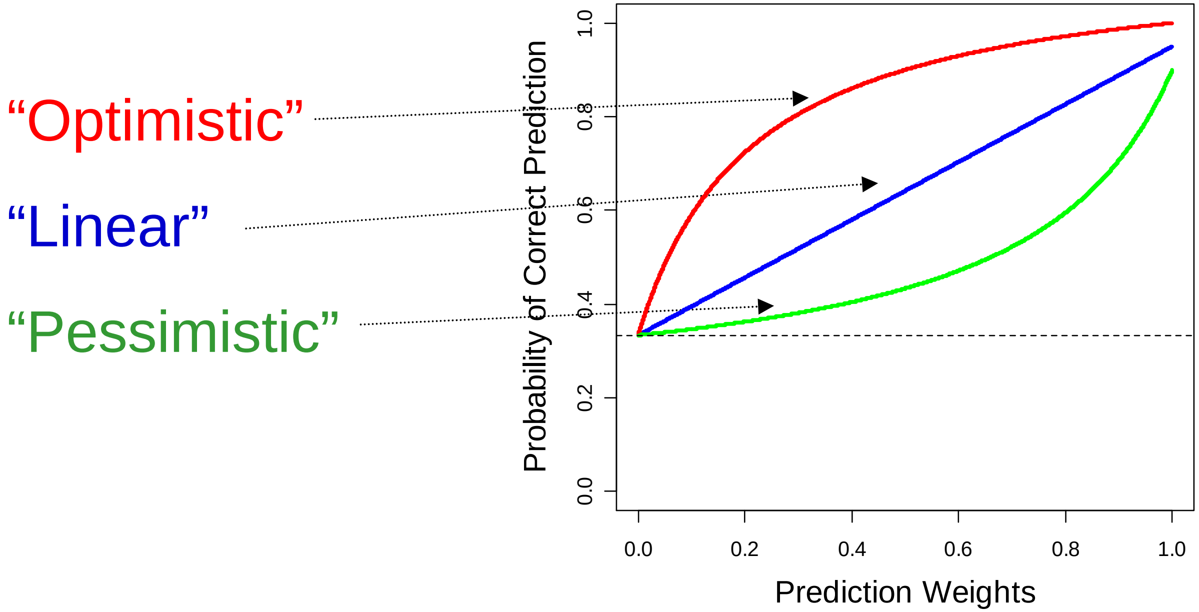
Cyprinid removal

Danish Lake BBN
“Optimistic” transformation:



Alternate models and transformations

- Observations from published studies of cyprinid removal
- Eutrophic and trophic models have predictions of same sign but different weights
- Tested three different weight-to-probability transformations:



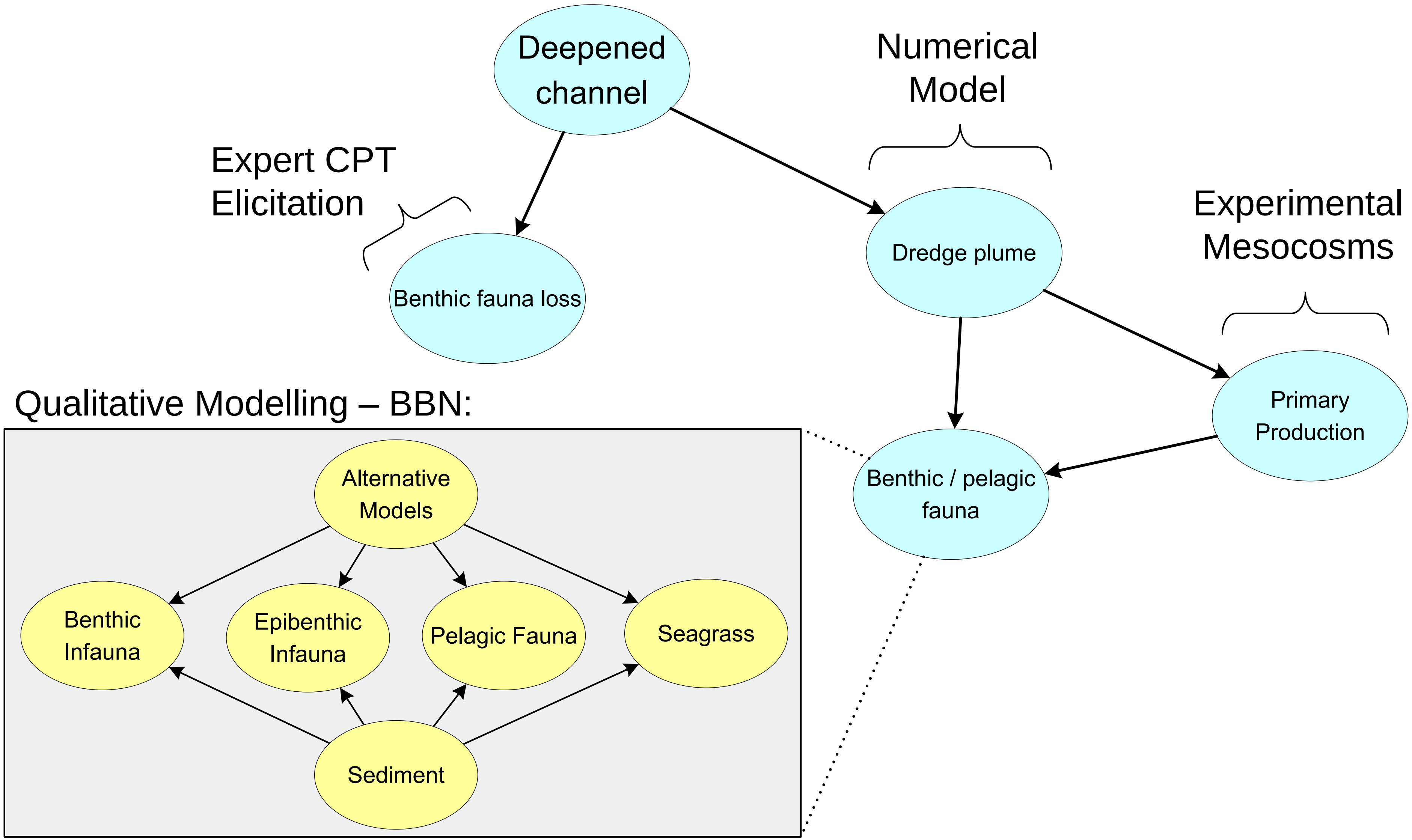
Transformations influence ability to falsify alternative models

Transformation:

Model	Optimistic	Linear	Pessimistic
Eutrophic	.90	.66	.41
Trophic	.01	.21	.38
Null	.09	.13	.22

- Eutrophic and trophic model predictions of same sign but different weights
- Each transformation suggested observations consistent with "eutrophic" model
- Optimistic transformations allow better model discrimination
  - Difficult to falsify under pessimistic transformation

BBN Modularity



BBN's and Qualitative Modelling

Advantages:

- Informed construction of large multi-conditional BBN's
- Explicit inclusion of important feedback cycles
- Represent multiple alternative models

Why important?

Incorporate both observations and model structure uncertainty in Bayesian framework to predict community response following perturbation

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Thank You

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