



Bayesian network models as a framework for forecasting wildlife response to GCC

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Initial thoughts: *challenges ahead*

- We'd like to incorporate both empirical & experiential info
field data expert knowledge
- Graphical framework whose transparency allows dev't & evaluation by many user groups
- Causal relationships among variables may articulate mechanisms
- **Uncertainty** inherent in ecosystems leads to use of probabilities
- We'd like to know what factors model is most sensitive to



What to monitor... & what it tells us

- Conservation practitioners have wrestled with the question of what to track, given limited funds

- Umbrellas



- Flagships



- Keystones



- Key envir. correlates, Key ecological F(x)s (ICBEMP)

- Focal spp.

(Lambeck 1999)

- Indicator spp.



- Guilds

- Rare vs. common spp. (Scott et al. 1995)

Unfortunately, there simply are no silver bullets...

Bayesian network models: *Basics*

- Relate to *prior* and *posterior* probabilities

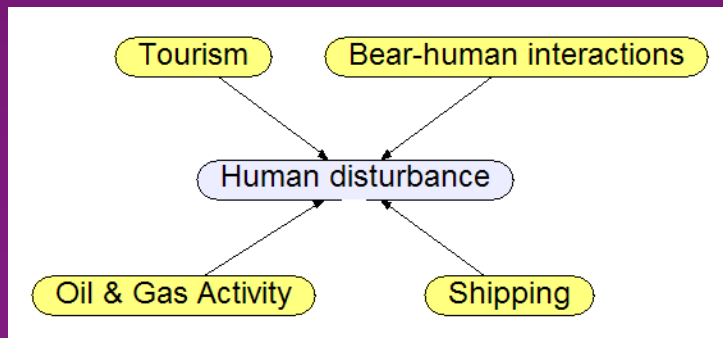
- Rely on Bayes' theorem

- $$P(S | H) = \frac{P(H | S) * P(S)}{P(H)}$$

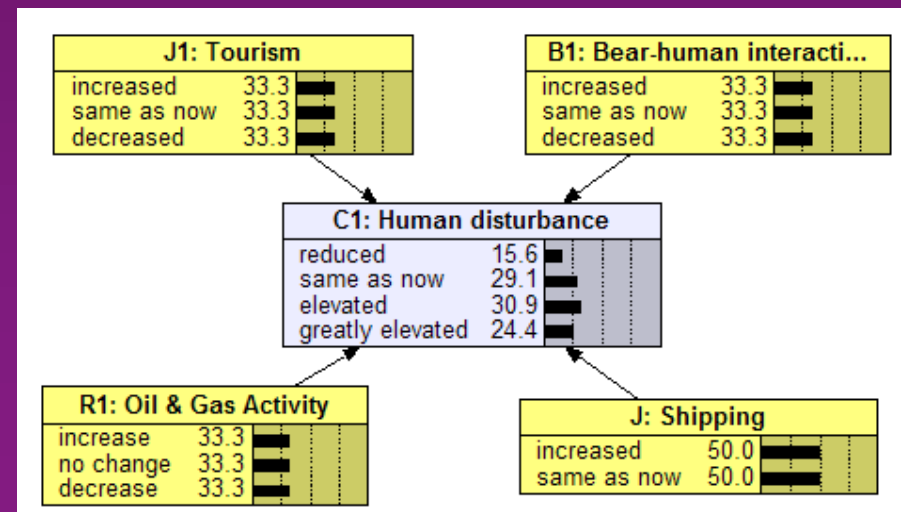
S = species abundance, presence
H = habitat conditions

- Explicitly show probabilities of each state in each node

Influence diagram (graphical)



With probabilities (quantitative)



Bayesian network models: *Strengths*

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- Allow for 'intelligent tinkering', exploration of alternative future mgmt options, & updating
- **Can use informed (hypothesis- or data-driven), or uninformed (equal prob) prior probabilities**

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- **Results can be sensitive to initial conditions; some disagreement about what to use**

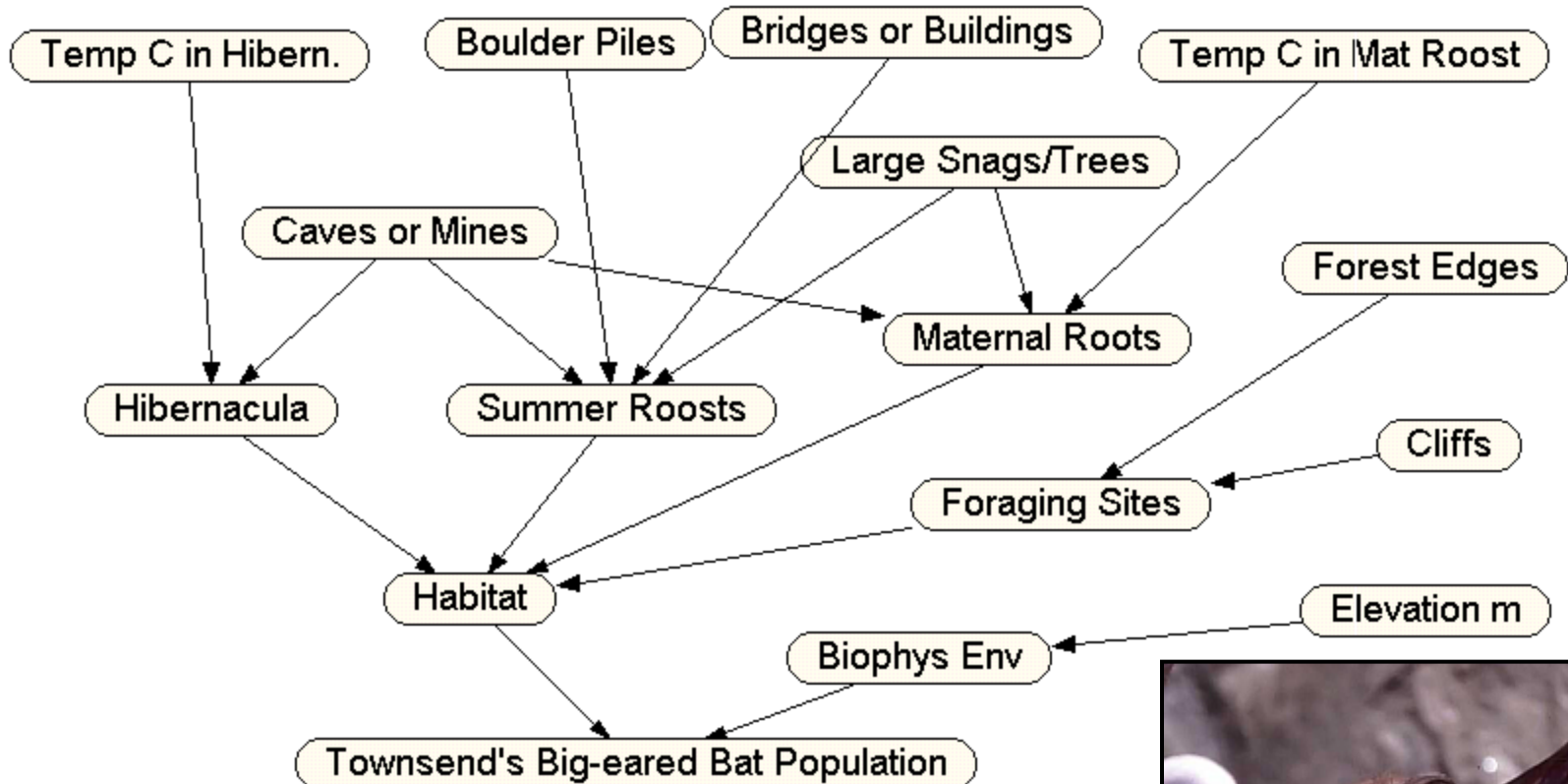
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- Others ?

Relationship to conceptual models

CMs directly convertible to Bayes networks; allow Id. of testable hypotheses

Conceptual model (=influence diagram)

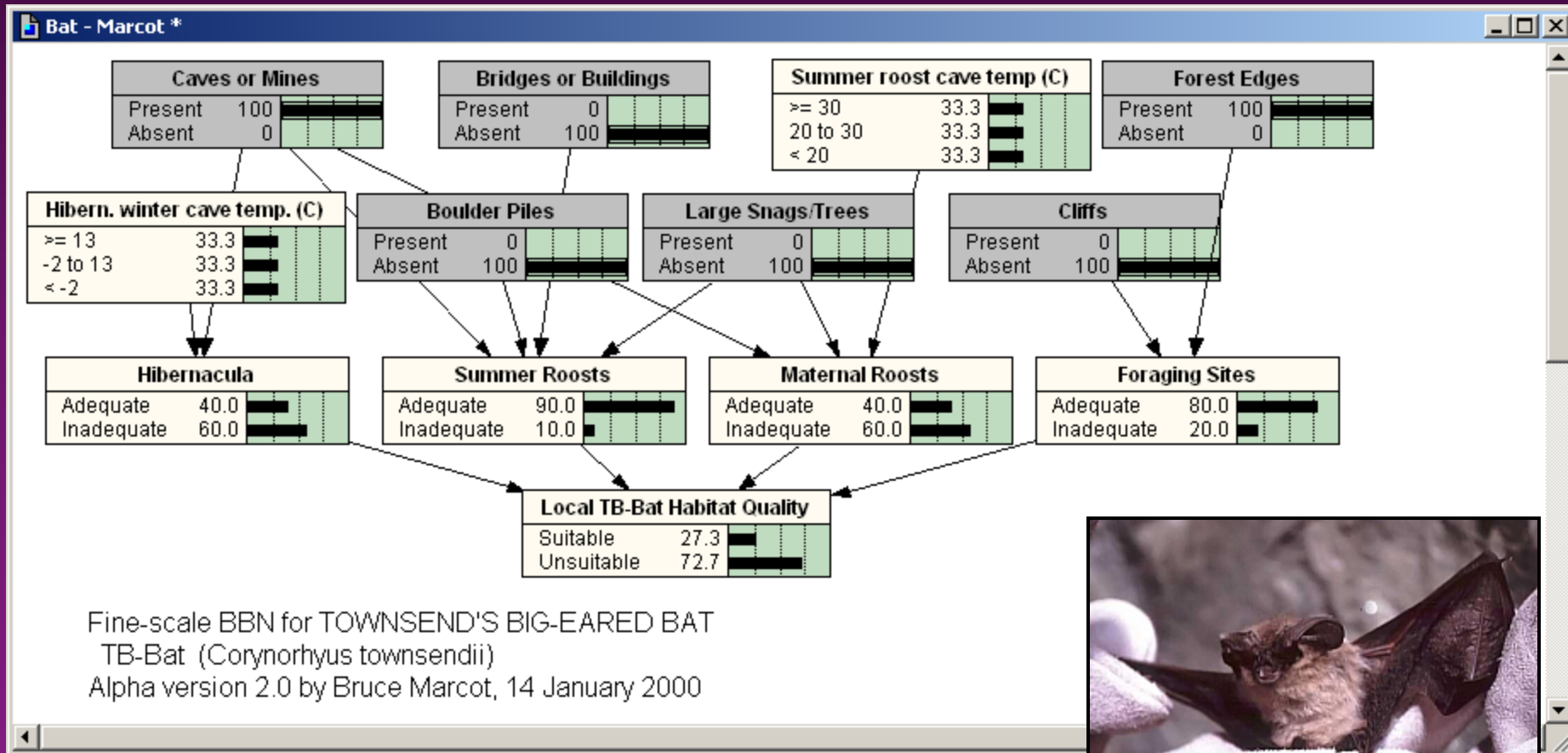


Source: Marcot, B. G., et al. 2001. Forest Ecology and Mgmt 153(1-3):29-42.



Relationship to conceptual models

Bayesian Network Model



Programs for creating conceptual models

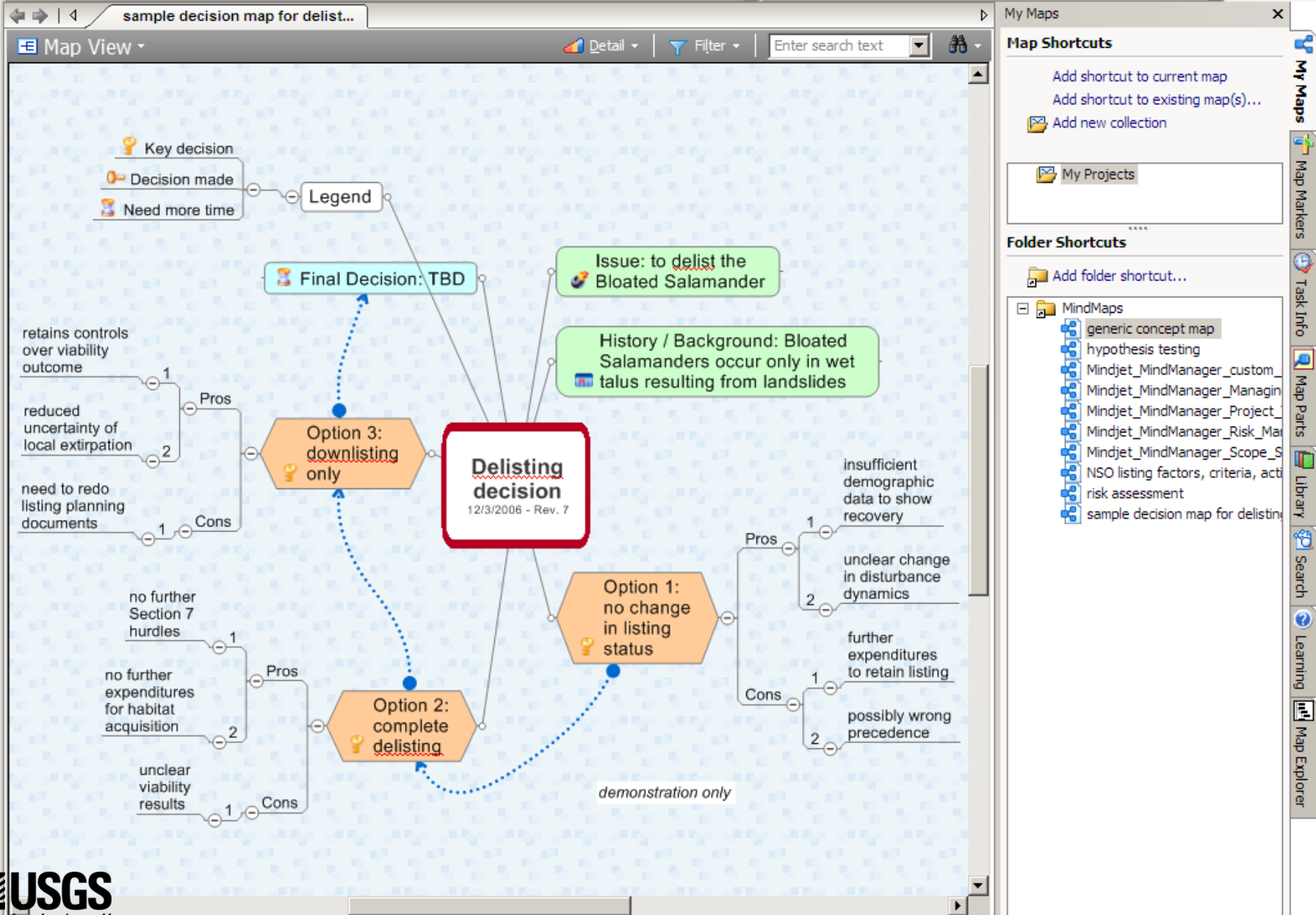
- **PowerPoint**
- **Mindjet MindManager Pro**
- **Inspiration**
- **Personal Brain**
- **Netica**
- **cMap ***
- **FreeMind ***



*** = freeware**

Mindjet MindManager Pro

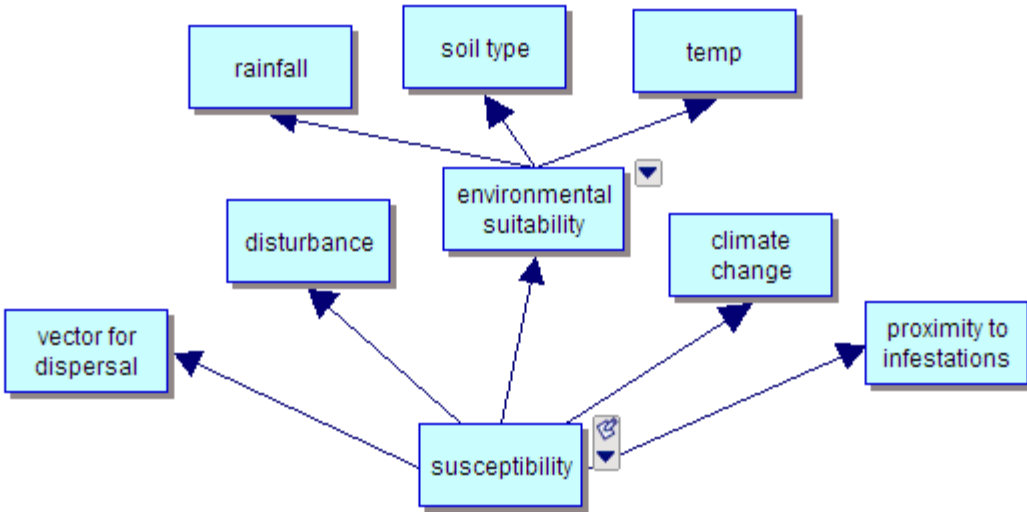
<http://www.mindjet.com>



Basic

A vertical toolbar containing various icons for drawing shapes (ovals, rectangles, diamonds, stars), text (question mark, exclamation mark, arrows), and navigation (lightbulb, globe, magnifying glass, calculator, landscape icons).

Conceptual Model of Plant Invasibility

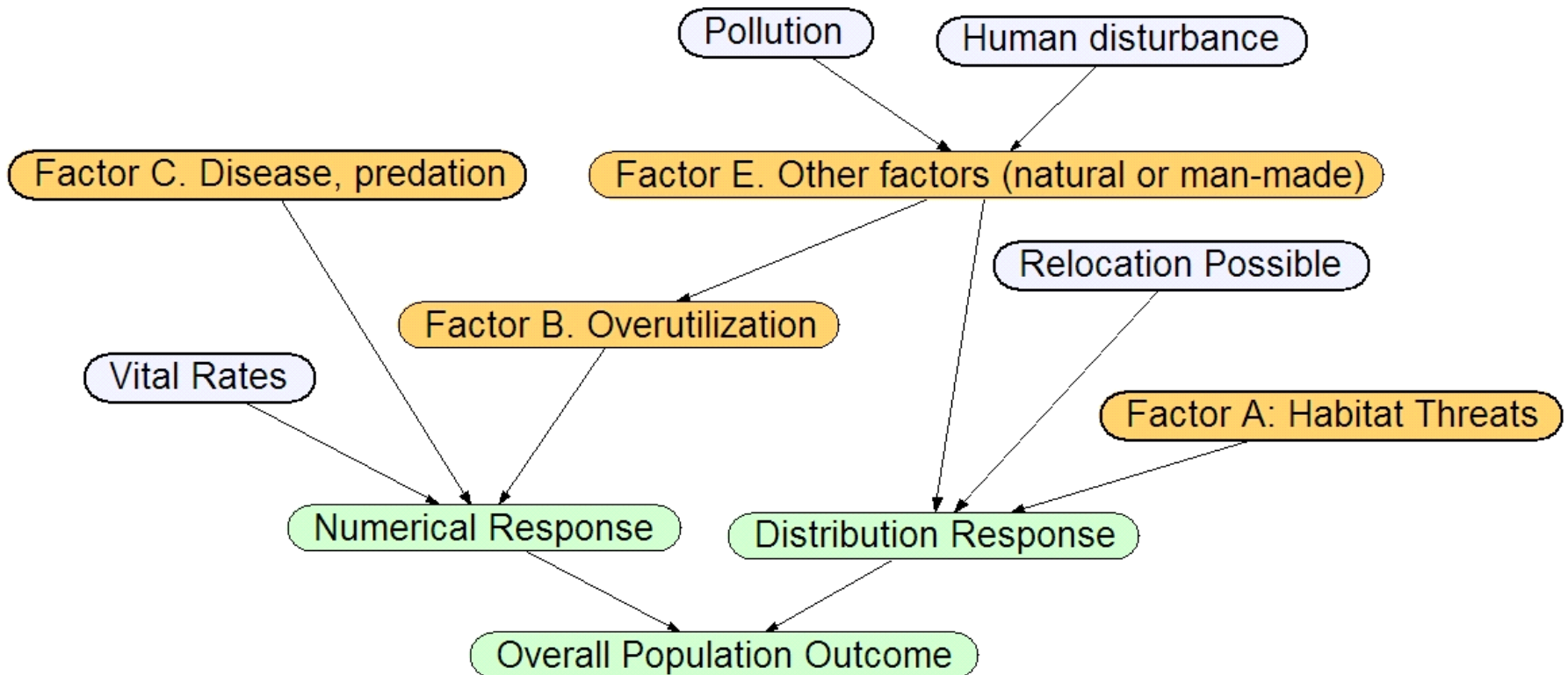


susceptibility

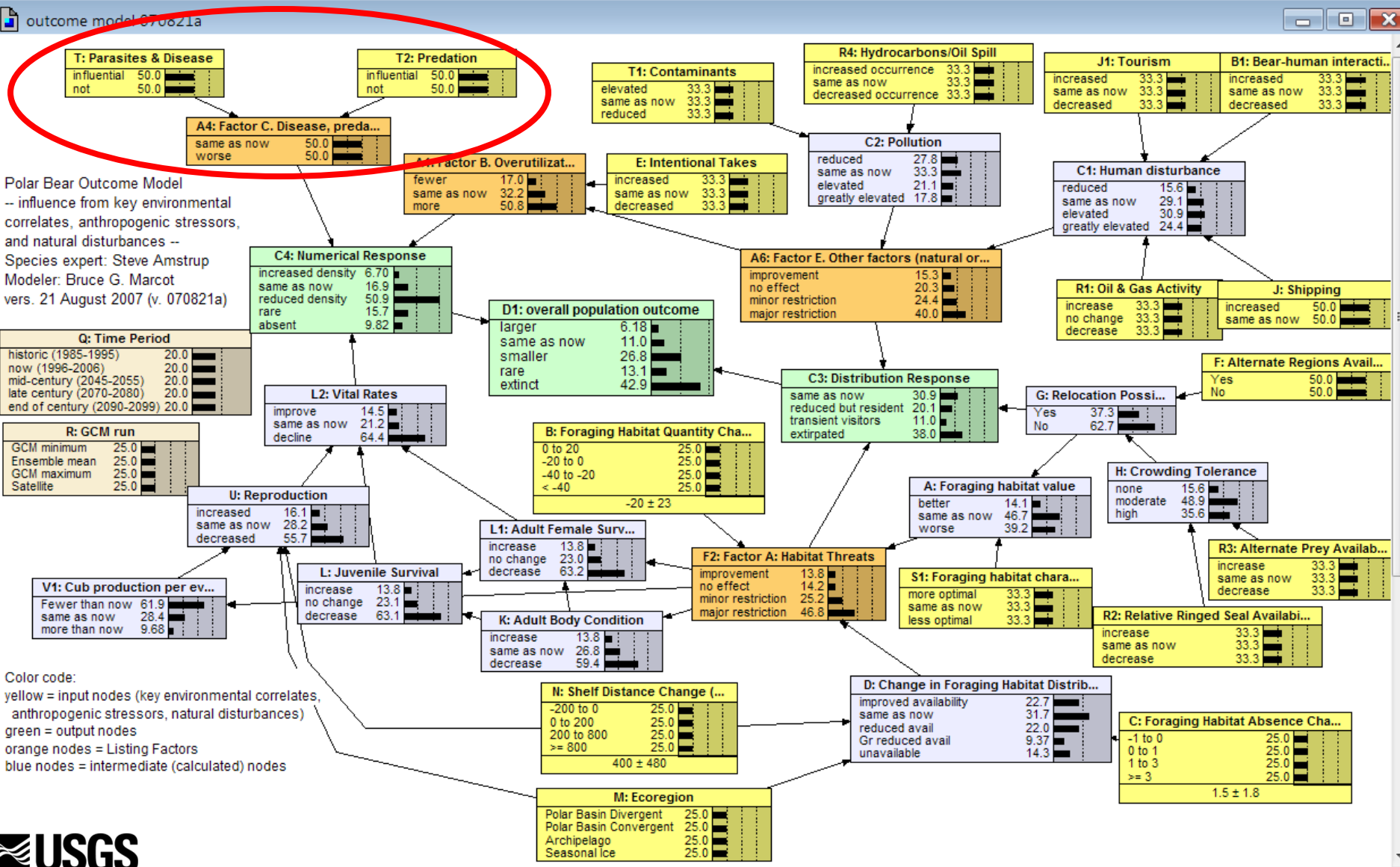
Susceptibility = the likelihood of an area to become infested with invasive plants

Bayesian Network model: *stressors on polar bear pop's*

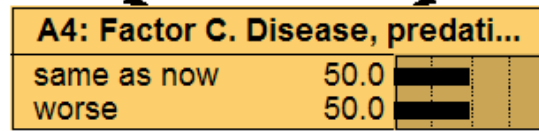
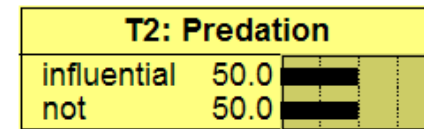
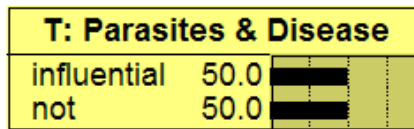
Conceptual model (=influence diagram)



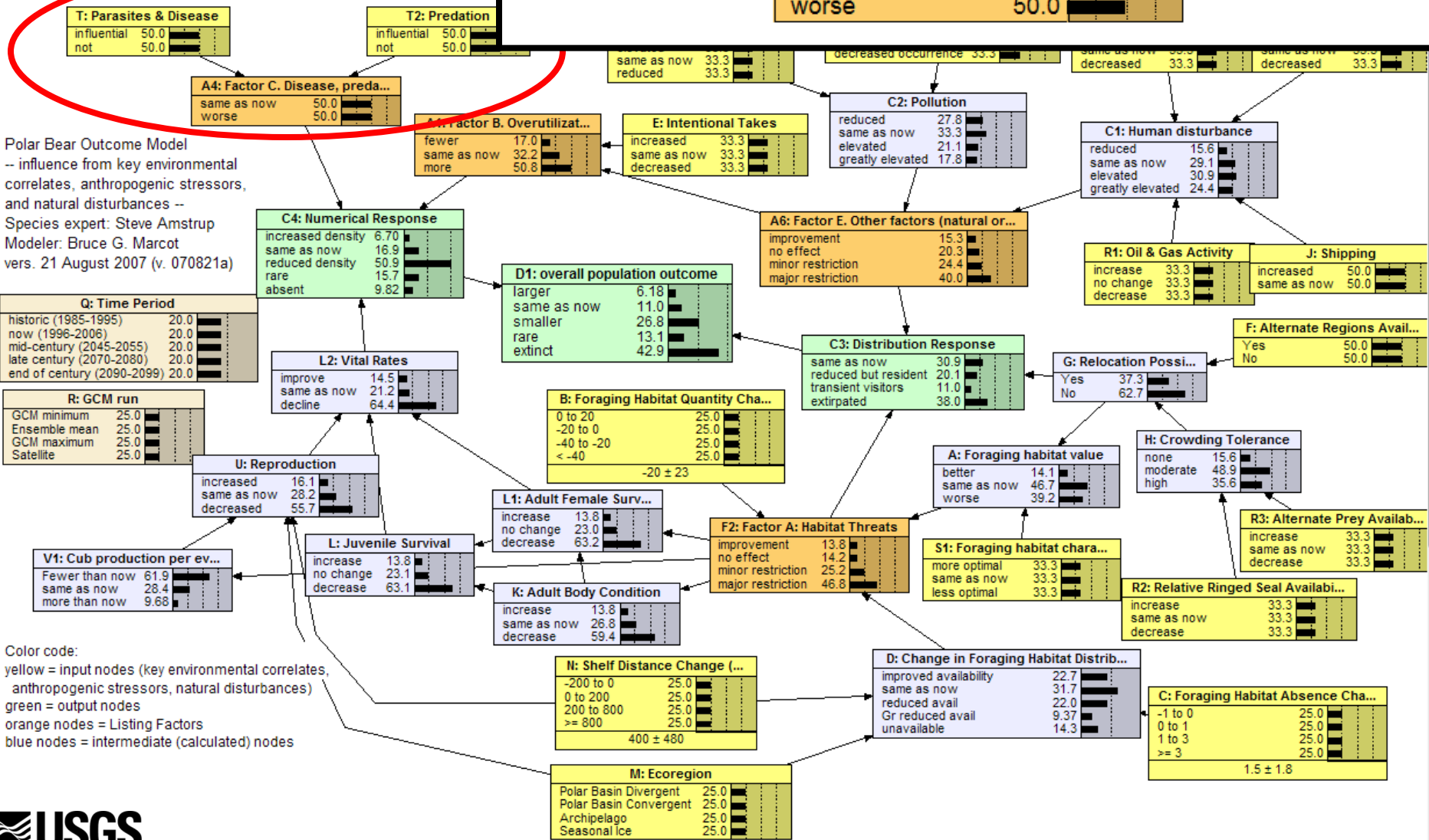
Bayesian Network model: stressors on polar bear pop's



Bayesian Network



outcome model 070821a



Bayesian Network model: *stressors on polar bear pop's*

T: Parasites & Disease		
influential	50.0	
not	50.0	

T2: Predation		
influential	50.0	
not	50.0	

A4: Factor C. Disease, predati...		
same as now	50.0	
worse	50.0	

Conditional-
probability
table

A4 Table (in net outcome_model_070821a)

Node: **A4**

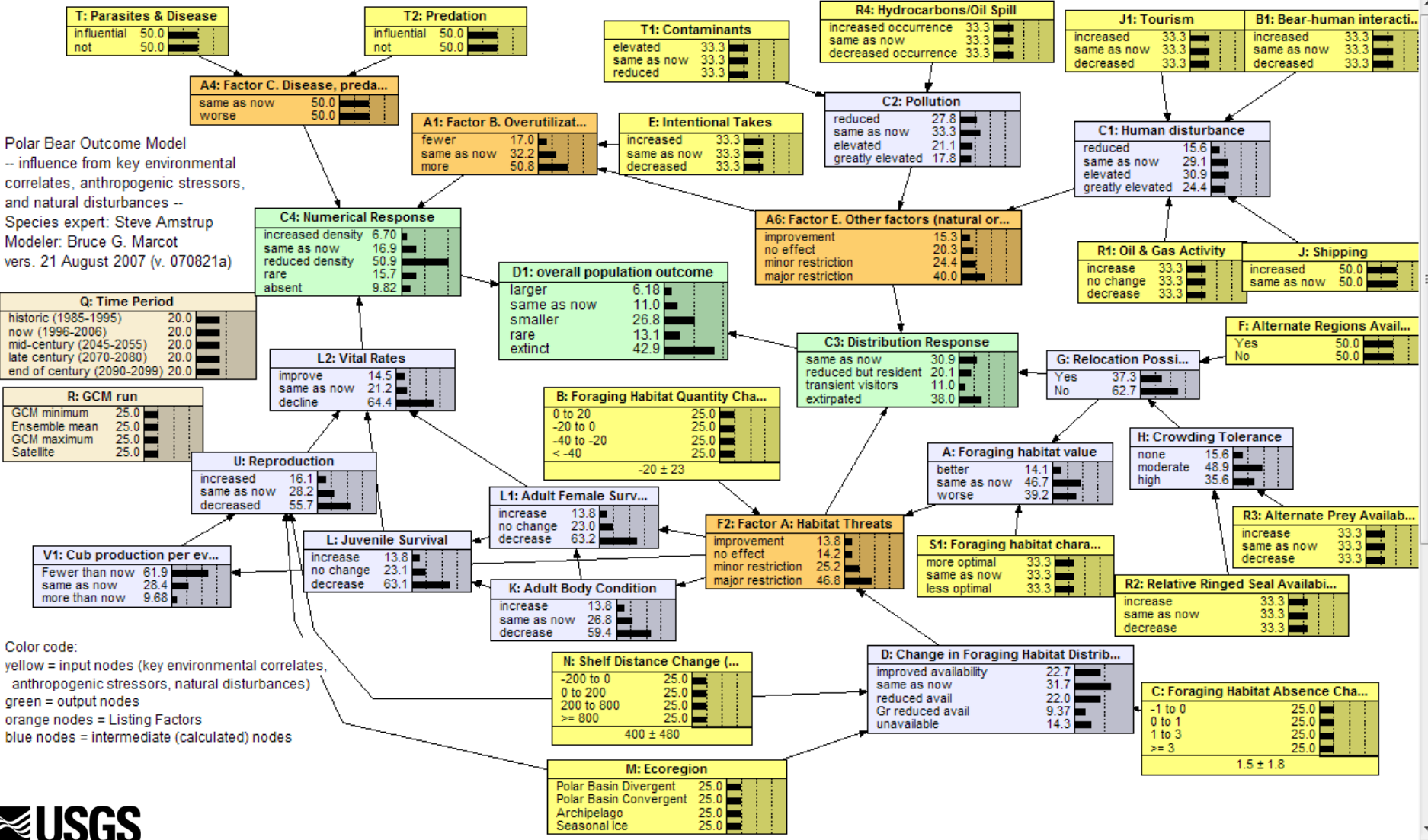
Chance ▾ % Probability ▾

Apply Okay
Reset Close

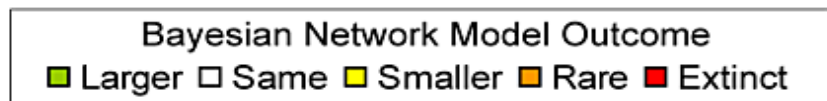
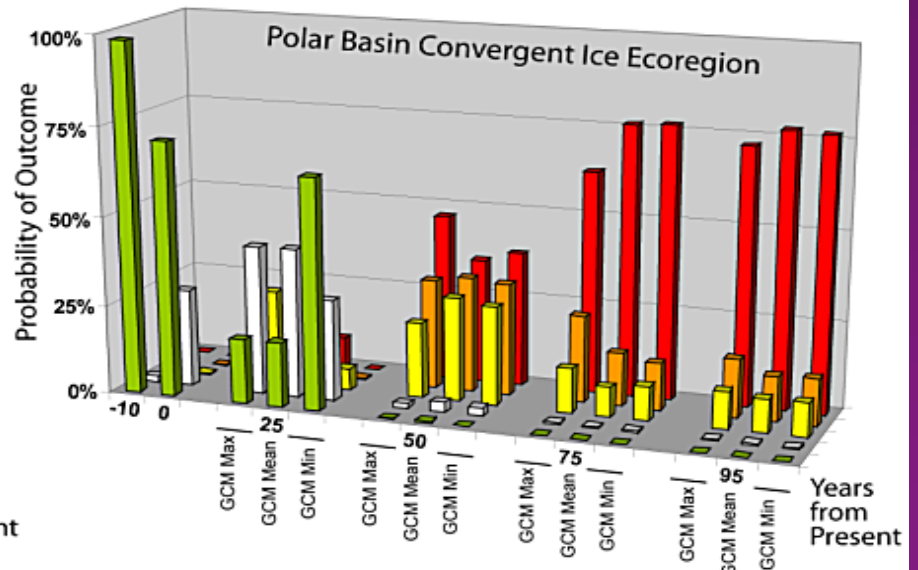
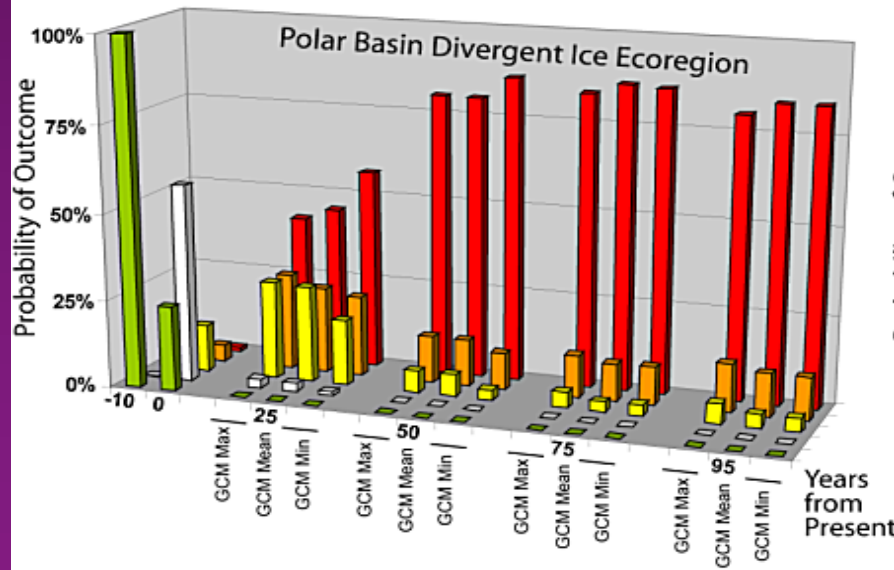
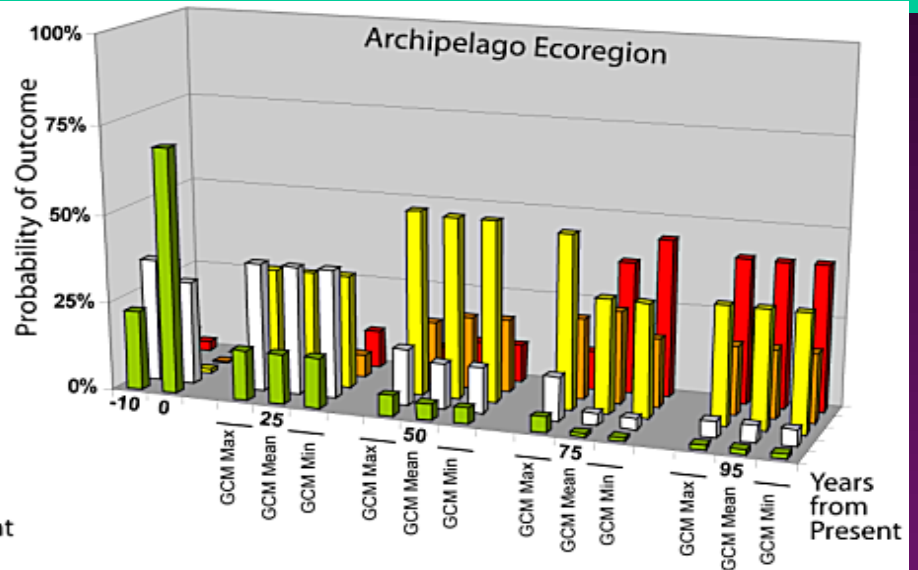
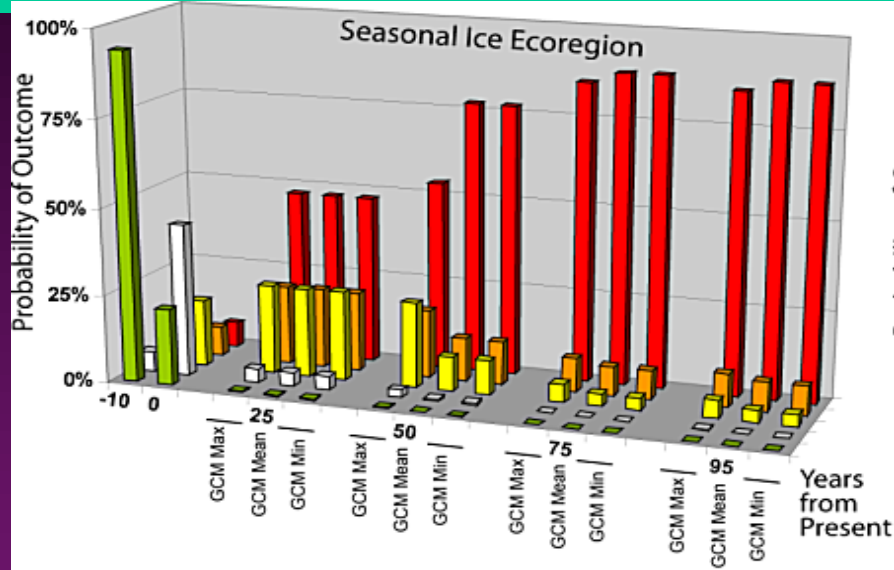
Parasites & Disease	Predation	same as now	worse
influential	influential	0.000	100.00
influential	not	30.000	70.000
not	influential	70.000	30.000
not	not	100.00	0.000

Bayesian Network model: stressors on polar bear pop's

outcome model 070821a



Bayesian Network model: *stressors on polar bear pop's*



Some of the devil(s) ...

- Complicated dynamics modeled tractably with sub-models
 - Coherency across spp., regions ??
- Spatially-explicit change requires more-intensive modeling effort, but the two can be linked by transition probabilities
- How do we handle the different dynamics of pulse vs. press disturbances? unknown trajectories of dev't? **feedbacks**, non-linear synergies, threshold dynamics, emergent properties?
- Varying resolutions of constituent data may mean reverting to coarsest scale among data sources
- Indep. of BBNs: The degree to which spp. are obligately tied to any available habitat variable differs, among spp.

Decision-support models: *useful model attributes*

- **probability-based**
- **can still provide results when missing data**
- **provides for sensitivity testing**
- **provides management hypothesis (adaptive management)**
- **incorporates new data to update model functions, probabilities, structure**
- **allows rapid prototyping**
- **combines expert judgment w/ empirical data; multiple experts.**

Take-home messages

- Work more like the human brain, compared to null-hypothesis testing
- Require specialized expertise, program(s) to build and refine (e.g., Netica, Amos?), but it's possible to learn
- Provide a transparent means by which to probabilistically bound uncertainty

