# Reflections on Bayesian analysis to support landscape ecological risk assessment in the Upper Grande Ronde Watershed of INLAS

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# Fire is more than a local impact

The sun in the middle of the afternoon near Burlington Washington-smoke from hundreds of miles away and last several days.

Being on the boarder we get it from California, Oregon, Alaska, British Columbia and occasionally from Asia.

# Short Introduction….thanks to the USFS

Our application of Bayesian Networks grew out of a program funded by Joint Venture Agreement No. PNW 06-JV-11261900–070 with the U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Terry Shaw facilitated the program and when we said that we wanted to start using Bayesian Networks-he said that this guy down the hall uses them all the time so ok. Of course, that person was Bruce G. Marcot and my research took a different path…..

# Short Introduction….

Forestry Management has multiple management goals and fire is only one of them.

Bayesian networks allow a number of questions about "current states" and then a number of "what if" questions and management alternatives.

The methods in this talk have now been applied for the cleanup of toxic sites, disease prediction, synthetic biology, invasive species and other types of questions.

# Short Introduction….

Human and Ecological Risk Assessment, 18: 705–732, 2012

ISSN: 1080-7039 print / 1549-7860 online
DOI: 10.1080/10807039.2012.688696

**RISK ASSESSMENT ARTICLES**

**A Pilot Application of Regional Scale Risk Assessment to the Forestry Management of the Upper Grande Ronde Watershed, Oregon**

**Suzanne M. Anderson and Wayne G. Landis**
Institute of Environmental Toxicology, Huxley College of the Environment, Western Washington University, Bellingham, WA, USA

Conventional Relative Risk Model

Human and Ecological Risk Assessment: An International Journal, 18: 946–970, 2012

ISSN: 1080-7039 print / 1549-7860 online
DOI: 10.1080/10807039.2012.707925

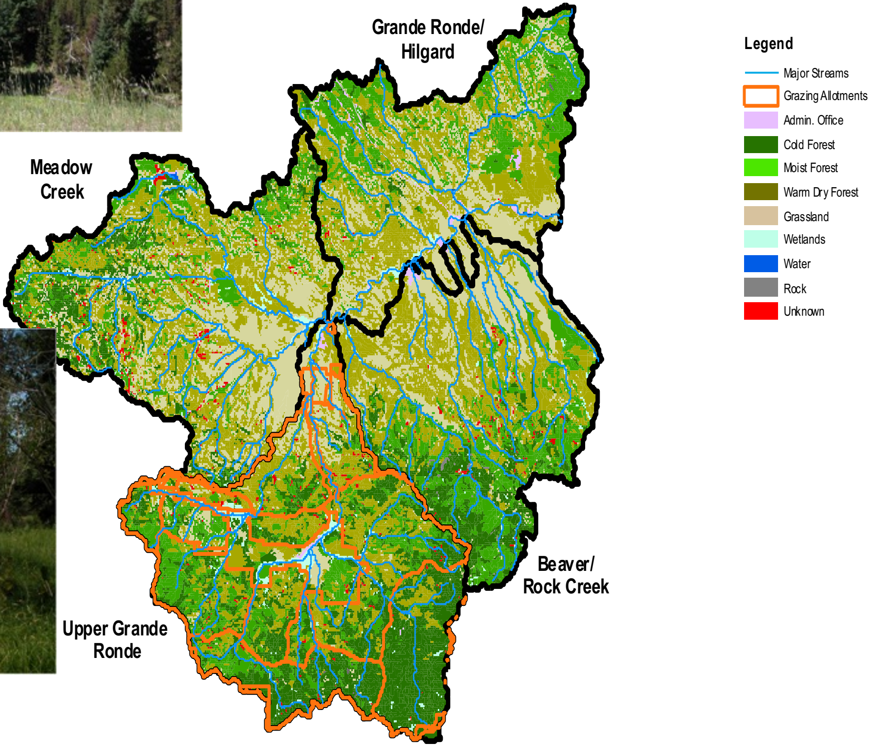
**RISK ASSESSMENT ARTICLES**

**A Bayesian Approach to Landscape Ecological Risk Assessment Applied to the Upper Grande Ronde Watershed, Oregon**

**Kimberley K. Ayre and Wayne G. Landis**
Institute of Environmental Toxicology, Huxley College of the Environment, Western Washington University, Bellingham, WA, USA

Our first application of Bayesian networks

# The study area……..

# Risk Assessment Structure and Causal Pathway

Based on Landis and Wiegers 1997, 2005.

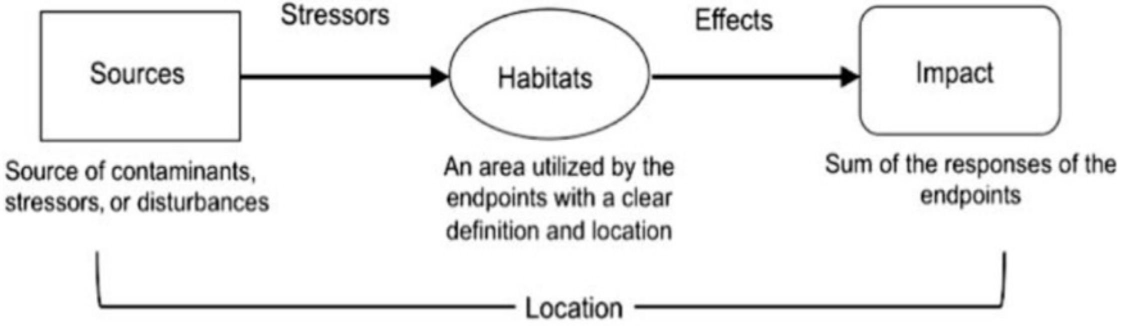



**Figure 1.** Diagram of the fundamental RRM conceptual model for regional risk assessment.

Anderson and Landis 2012

# Risk Assessment Structure and Causal Pathway

- Directed Acyclic graph
- Nodes
- Lines of influence
- Categorical
- Probabilistic

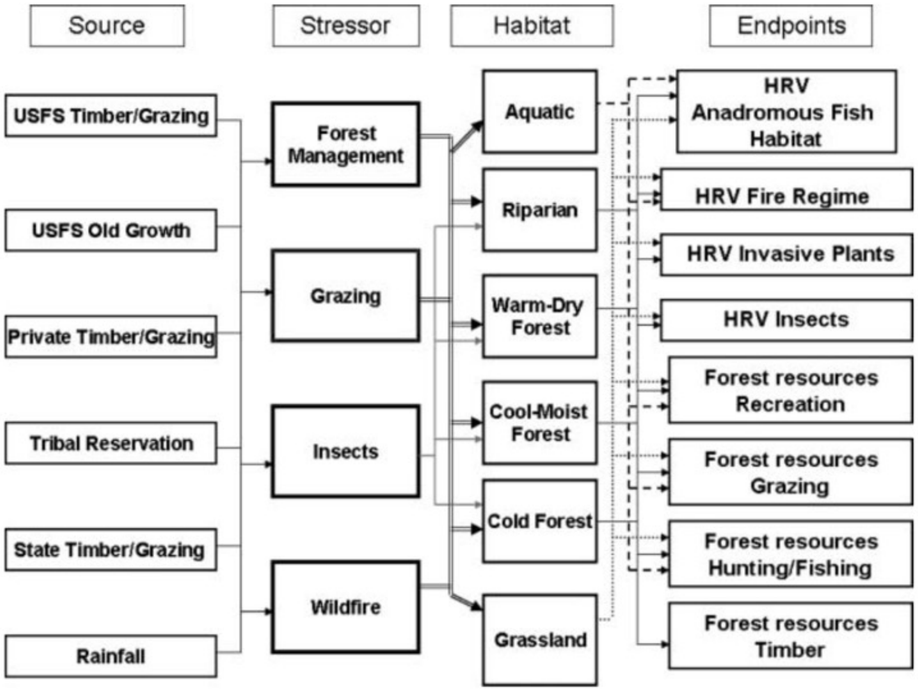


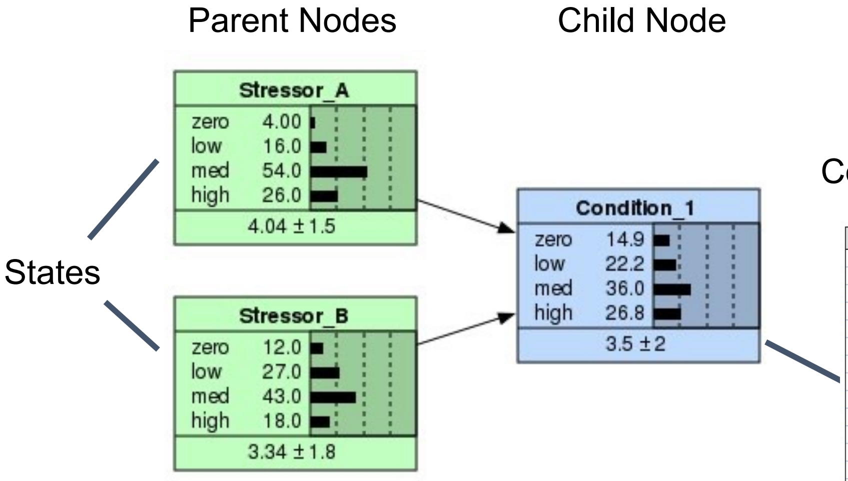

**Figure 4.** Conceptual model. Complete pathways are indicated with connecting lines. The same model is used for each risk region although the ranks and filters are altered specifically for each calculation.

# Bayesian Network Structure

- Nodes represent variables
  - Parent node has no input variables
  - Child node has input from other variables
- Variables are assigned discrete states
  - Zero, low, medium, and high
  - Similar to treatment with relative risk model
- Structure reflects causality
  - Based on conceptual model developed by Suzanne Anderson

# Bayesian Network Relative Risk Model

The methods have been published for other sites and a variety of stressors:




Conditional Probability Table

| Stressor_A | Stressor_B | zero | low | med | high |
|---|---|---|---|---|---|
| zero | zero | 100.00 | 0.000 | 0.000 | 0.000 |
| zero | low | 90.000 | 8.000 | 1.500 | 0.500 |
| zero | med | 75.000 | 20.000 | 4.000 | 1.000 |
| zero | high | 60.000 | 25.000 | 10.000 | 5.000 |
| low | zero | 75.000 | 20.000 | 4.000 | 1.000 |
| low | low | 50.000 | 35.000 | 10.000 | 5.000 |
| low | med | 25.000 | 35.000 | 30.000 | 10.000 |
| low | high | 10.000 | 30.000 | 45.000 | 15.000 |
| med | zero | 25.000 | 35.000 | 30.000 | 10.000 |
| med | low | 10.000 | 30.000 | 45.000 | 15.000 |
| med | med | 5.000 | 25.000 | 50.000 | 20.000 |
| med | high | 1.000 | 9.000 | 40.000 | 50.000 |
| high | zero | 15.000 | 25.000 | 40.000 | 20.000 |
| high | low | 10.000 | 15.000 | 35.000 | 40.000 |
| high | med | 5.000 | 10.000 | 30.000 | 55.000 |
| high | high | 1.000 | 4.000 | 20.000 | 75.000 |

# Conditional Probabilities

- Link parent and child nodes
- Value of child node is dependent upon the likelihood of states for all parent nodes
- Conditional probabilities established through spatial analysis of GIS data for all parent node variables

# Why Bayesian Networks?

1. Combine different types of data including model predictions and expert judgment
2. Uncertainty is inherently reflected in the probability distributions
3. Updateable when new information or knowledge comes available
4. Can be used to predict both input and output variable states

# The Bayesian network for UGR watershed of INLAS

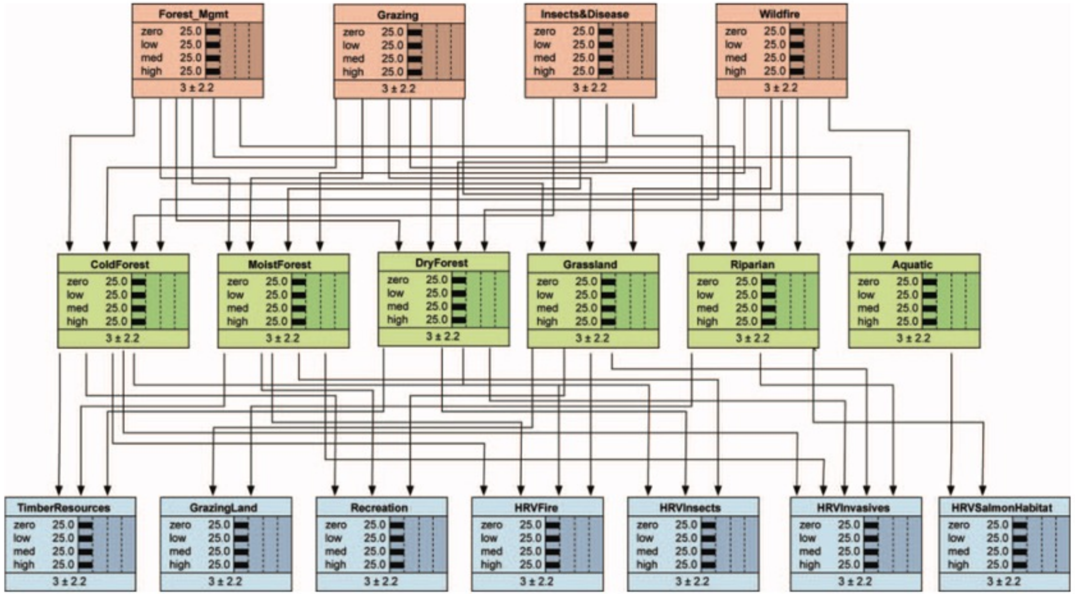



**Figure 3.** Bayesian network model developed for the analysis of ecological risk from landscape disturbances in the upper Grande Ronde watershed in northeastern Oregon. The top parameter nodes in the diagram repre-

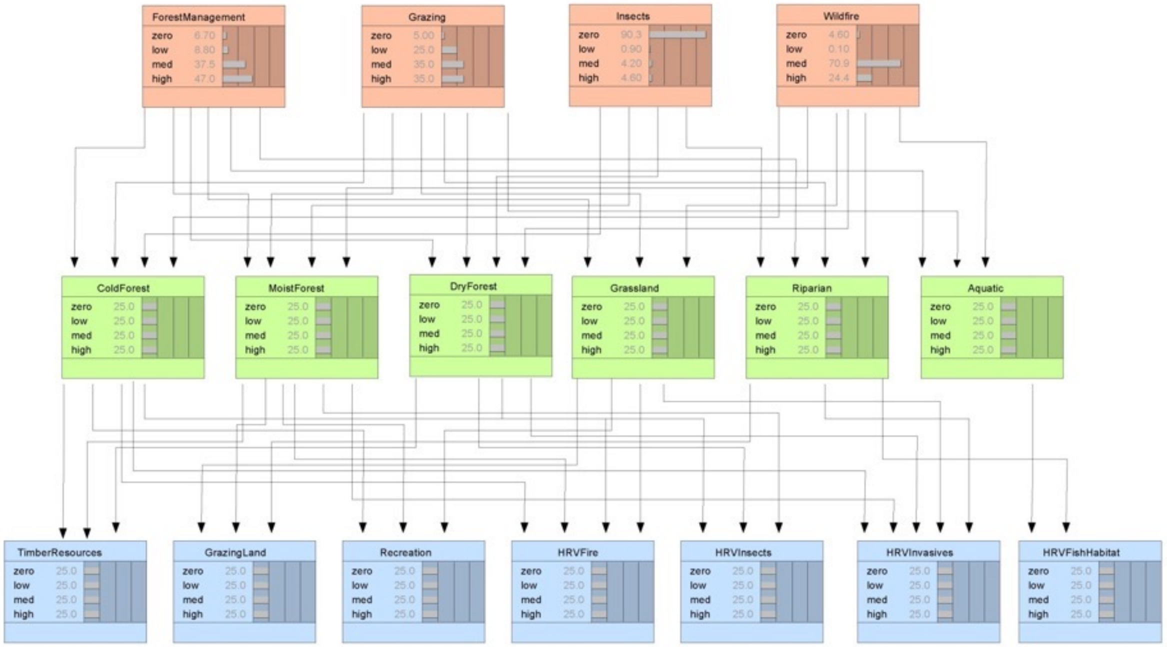
Ayre and Landis 2012

A slight rearrangement.

The inputs are now on the top row, the outcomes (impacts) are on the bottom-

Parameterized using the extensive datasets and expert knowledge of the USFS.

# The Bayesian network in Netica for UGR watershed of INLAS



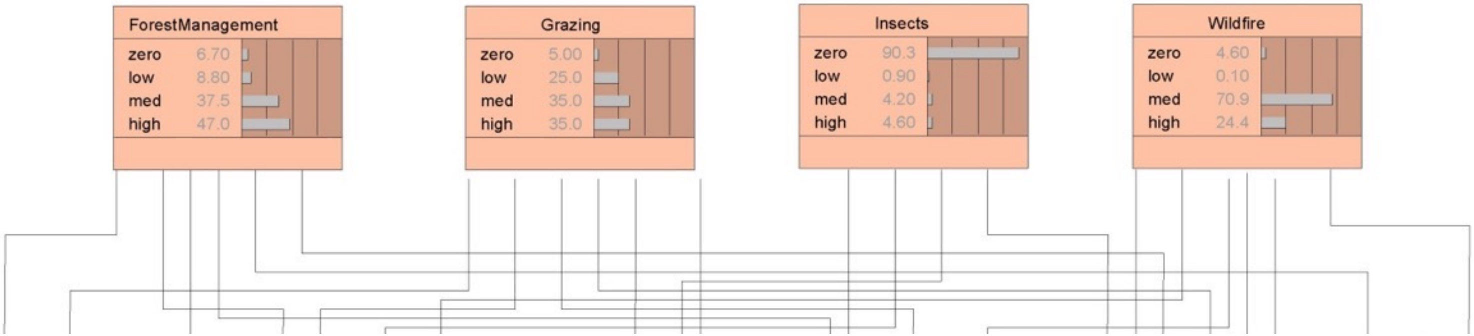

Disturbances

Habitats

Endpoints

# The Bayesian network in Netica for UGR watershed of INLAS

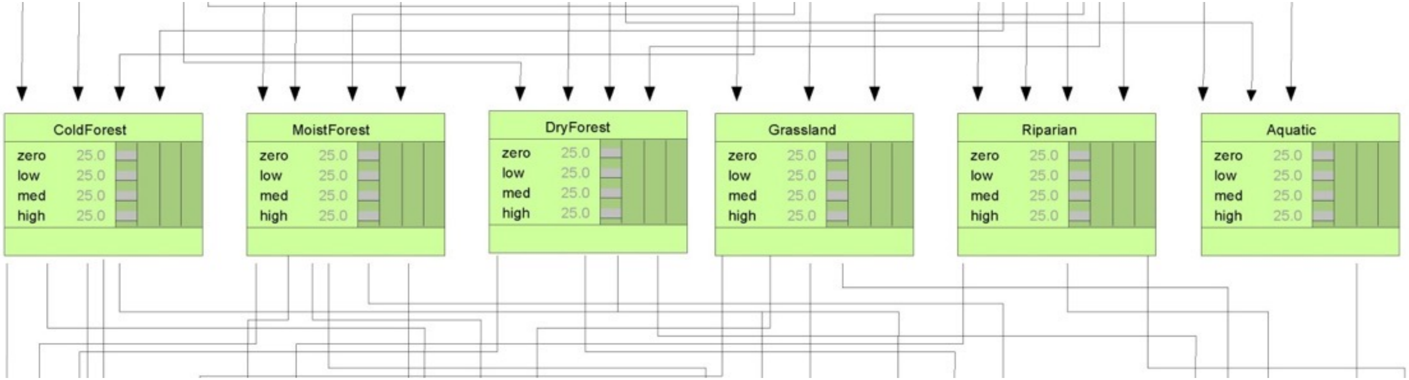
Disturbances




Note the distributions….the inputs have been incorporated into the Parent Nodes

# The Bayesian network in Netica for UGR watershed of INLAS

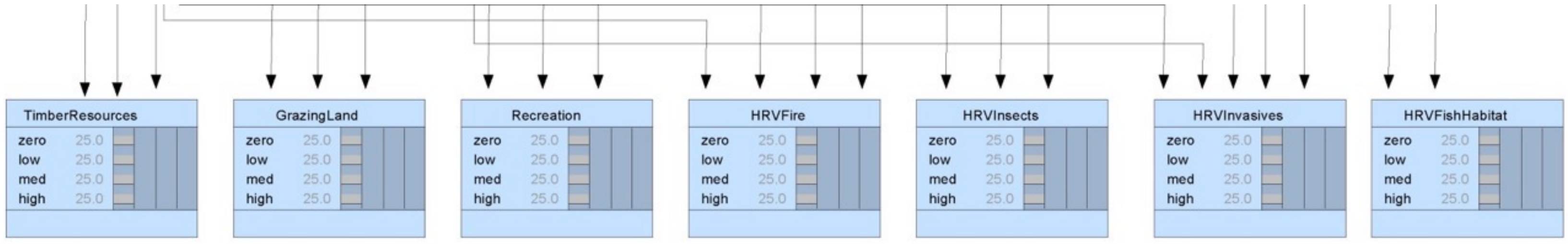
Habitats/Locations




Note the even distributions….model is not yet compiled. Left out in the examples to come.

# The Bayesian network in Netica for UGR watershed of INLAS

Endpoints-to be managed




Note the even distributions….model is not yet compiled.

HRV-Historic Range of Variation
Interesting criterion in the time of climate change

# GIS Data Used to Develop CPTs

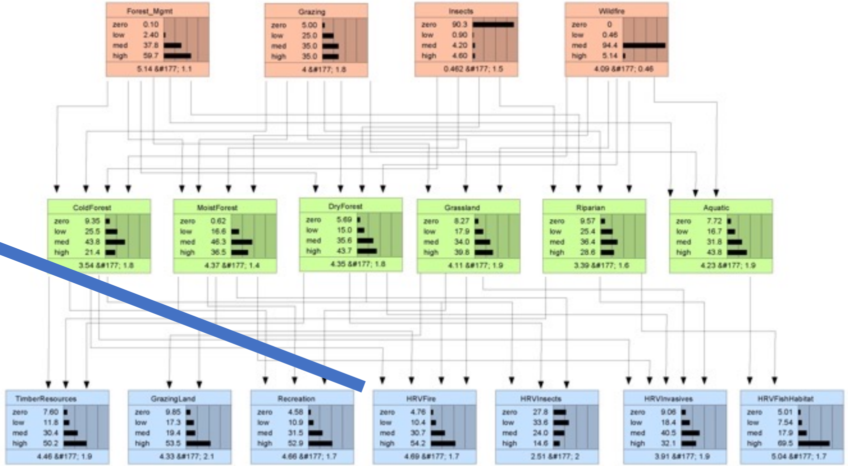
| **Variable** | **Data Source** |
|---|---|
| Forest Management | Land Management Plan Allocations for W-W NF online at http://www.fs.fed.us/r6 /data-library/gis/wallowa-whitman/mas.zip |
| Grazing | Range Allotments - Blue Mtn. Province online at http://www.fs.fed.us/r6/data-library/umatilla/data/rmu.zip |
| Insect Outbreaks | 2007 Insect & Disease Aerial Survey Data online at http://www.fs.fed.us/r6 /nr/fid/as/r6id2007e00.zip |
| Wildfire | Consequences of Wildfires on the W-W NF online at http://www.fs.fed.us/r6/data-library/gis/wallowa-whitman/data/cons.zip |

# Conditional Probability Table

Node: HRVFire | Apply | Okay

Chance | % Probability | Reset | Close

| Grassland | DryForest | MoistForest | ColdForest | zero | low | med | high |
|---|---|---|---|---|---|---|---|
| zero | zero | zero | zero | 100.00 | 0.000 | 0.000 | 0.000 |
| zero | zero | zero | low | 60.000 | 30.000 | 8.000 | 2.000 |
| zero | zero | zero | med | 30.000 | 50.000 | 15.000 | 5.000 |
| zero | zero | zero | high | 15.000 | 25.000 | 50.000 | 10.000 |
| zero | zero | low | zero | 60.000 | 25.000 | 10.000 | 5.000 |
| zero | zero | low | low | 30.000 | 45.000 | 15.000 | 10.000 |
| zero | zero | low | med | 15.000 | 30.000 | 40.000 | 15.000 |
| zero | zero | low | high | 5.000 | 35.000 | 35.000 | 25.000 |
| zero | zero | med | zero | 30.000 | 45.000 | 20.000 | 5.000 |
| zero | zero | med | low | 15.000 | 35.000 | 35.000 | 15.000 |
| zero | zero | med | med | 10.000 | 20.000 | 50.000 | 20.000 |
| zero | zero | med | high | 5.000 | 15.000 | 45.000 | 35.000 |
| zero | zero | high | zero | 10.000 | 20.000 | 50.000 | 20.000 |
| zero | zero | high | low | 5.000 | 15.000 | 50.000 | 30.000 |
| zero | zero | high | med | 2.000 | 13.000 | 40.000 | 45.000 |
| zero | zero | high | high | 1.000 | 4.000 | 35.000 | 60.000 |
| zero | low | zero | zero | 60.000 | 30.000 | 8.000 | 2.000 |
| zero | low | zero | low | 30.000 | 50.000 | 15.000 | 5.000 |
| zero | low | zero | med | 15.000 | 25.000 | 50.000 | 10.000 |
| zero | low | zero | high | 5.000 | 30.000 | 45.000 | 20.000 |
| zero | low | low | zero | 30.000 | 50.000 | 15.000 | 5.000 |
| zero | low | low | low | 15.000 | 25.000 | 50.000 | 10.000 |
| zero | low | low | med | 5.000 | 15.000 | 40.000 | 40.000 |
| zero | low | low | high | 1.000 | 4.000 | 45.000 | 50.000 |

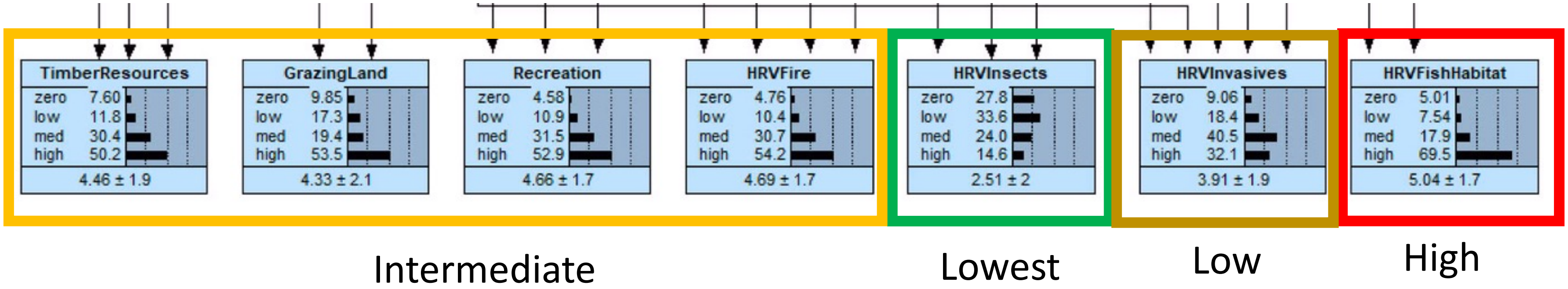



Real distributions….model is compiled.

# Risk Ranks

- Risk rankings calculated as the mean state of the probability distribution
- Expressed ± standard deviation for the probability distribution-but note that they do not look like Gaussian distributions, but many seem to like seeing them.
- Output represents the likely range of risk ranks

# Risk Ranks initial risk assessment

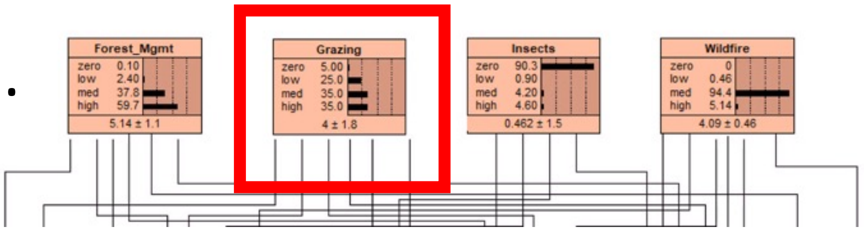



Range of risk values-note the distributions

# Solving the Model "Backwards"

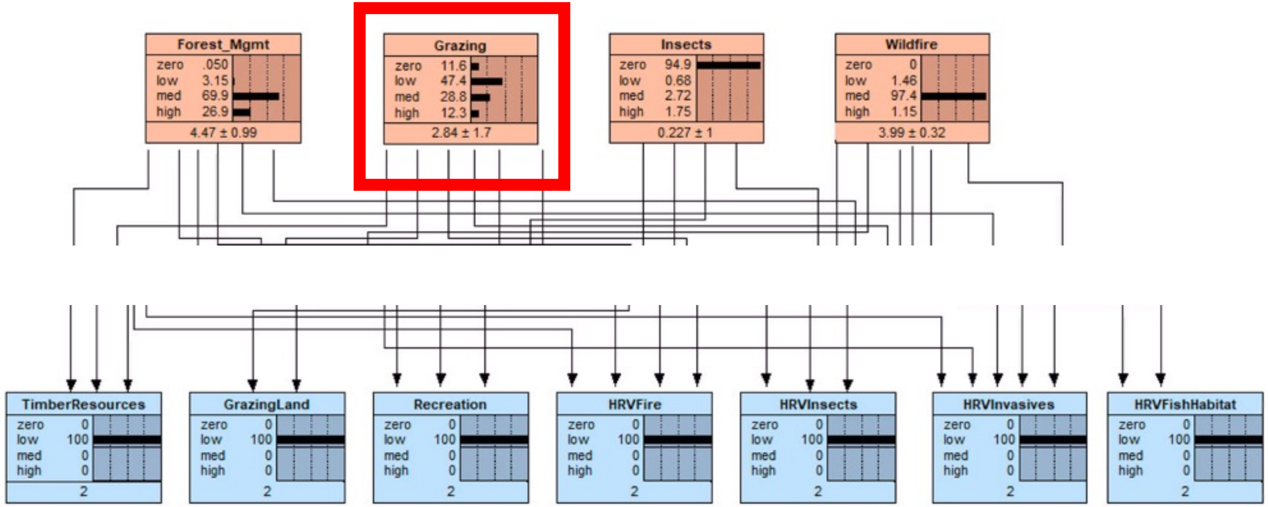
- Set endpoint risk values to desired risk level
- Model automatically updates values of parent parameters need to achieve desired risk level
- Can the parameters be managed in such a pattern?
- Which endpoint has a priority, what if questions.

# Low Risk for each endpoint....



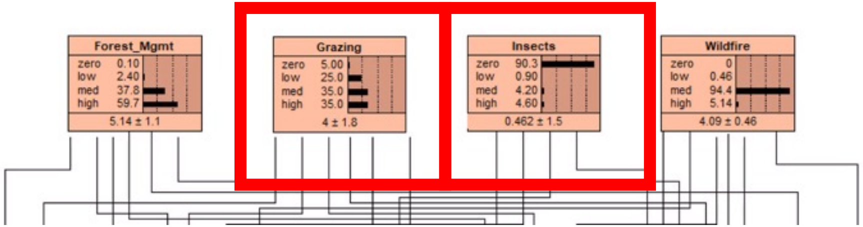

Initial conditions

## Low risk each endpoint



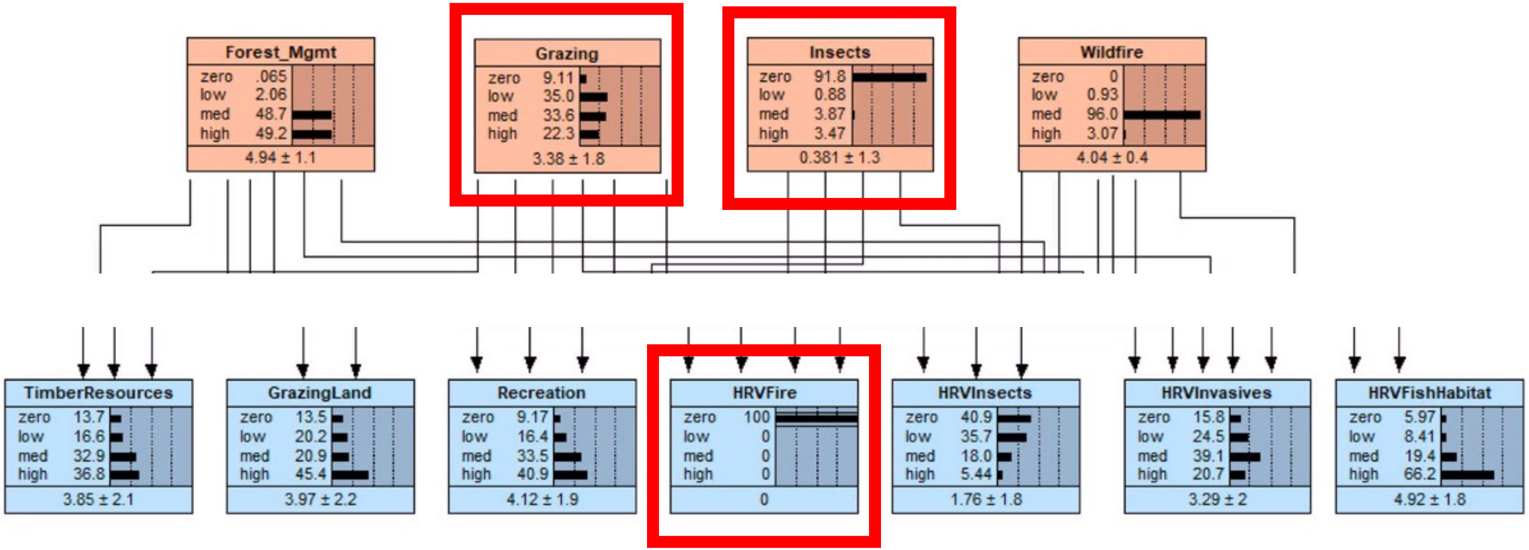

Low risk each endpoint-Grazing has the largest change

# Zero Risk for HRV fire….

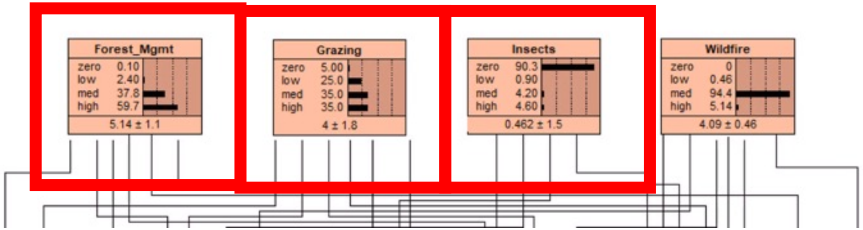



Initial conditions

## Zero risk Fire

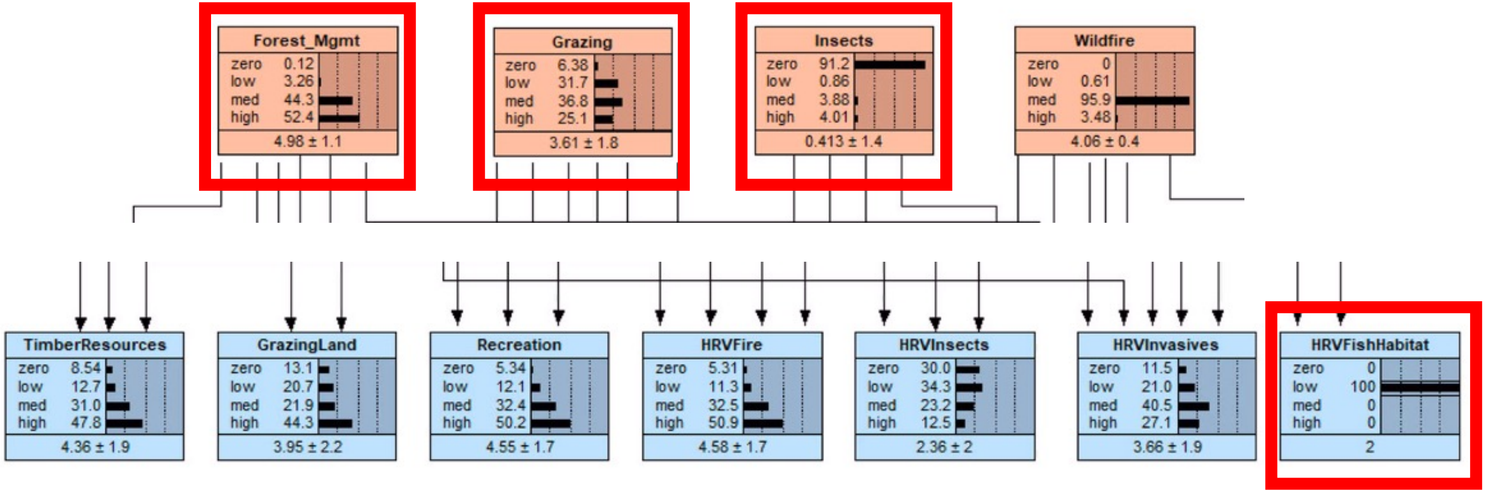


# Zero Risk for HRV Fish….



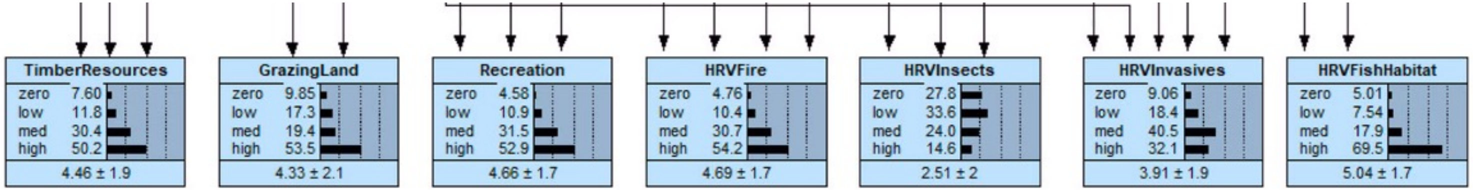

Initial conditions

## Low risk Fish

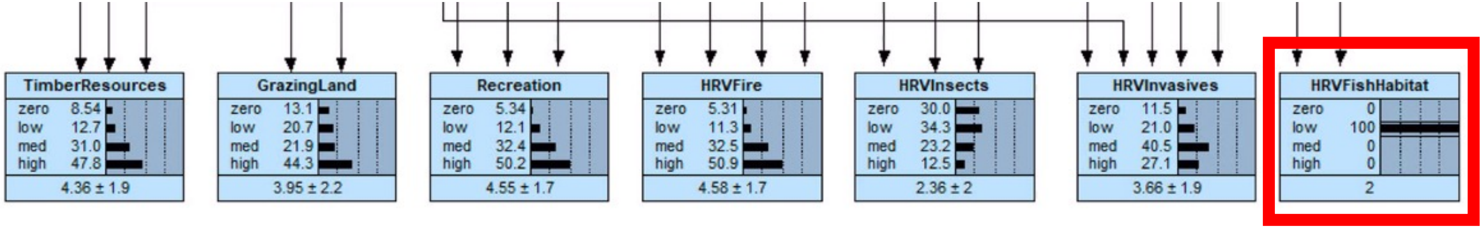


# Comparison of Scenarios

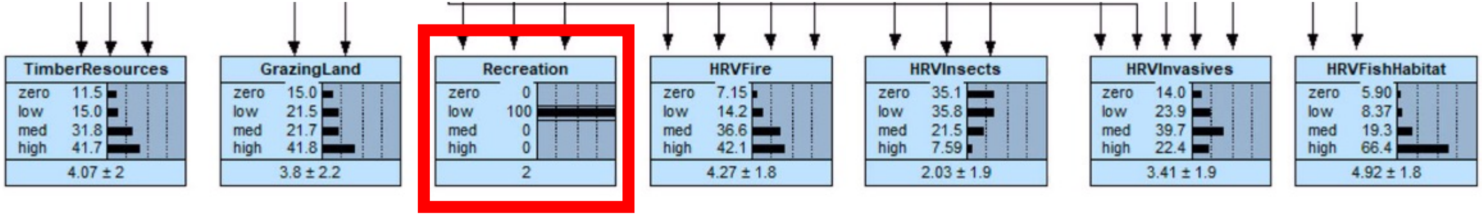
## Initial conditions-state as of 2012




## Low risk Fish-all other risks are also reduced…..

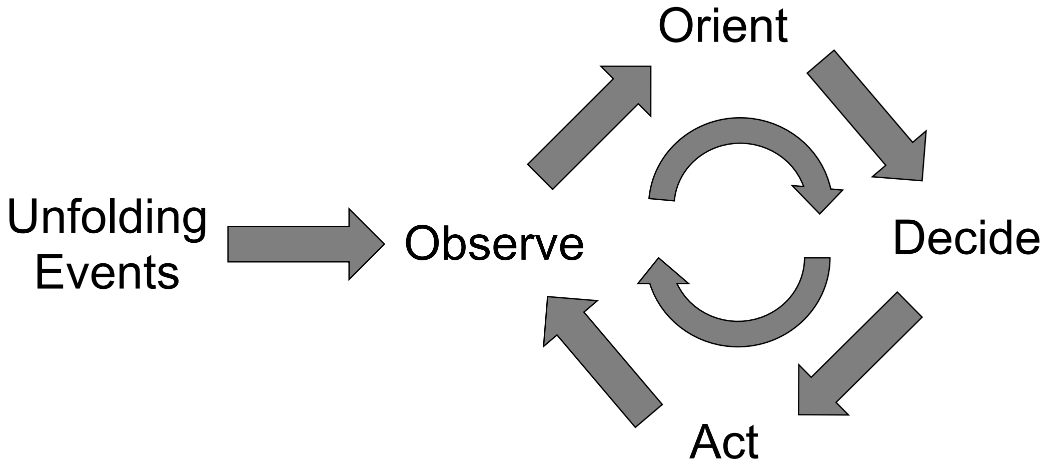



## Low risk Recreation-all other risks reduced to even lower than focusing on fish…

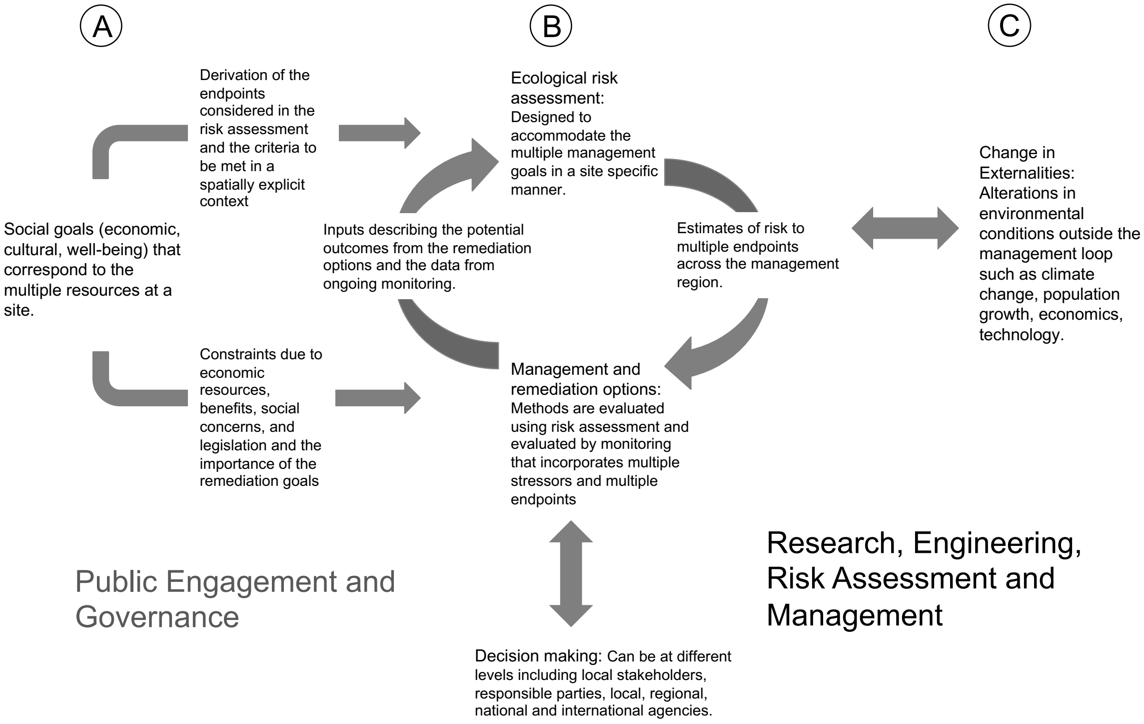


# Why  do all this analysis? OODA Loops

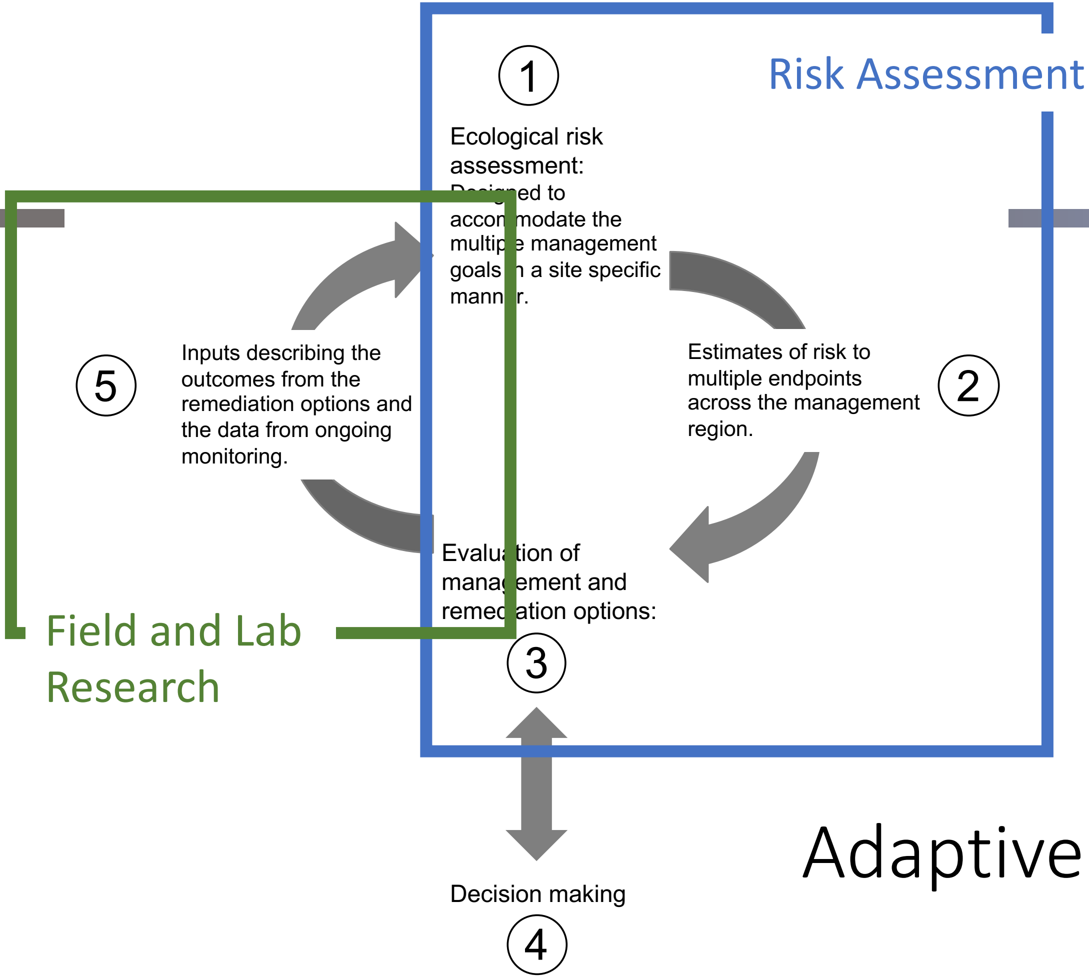
Observe, Orient, Decide and Act—Loop



# Adaptive management-Landis 2017




Just another OODA loop with the externalities included.




Just another OODA loop with the externalities included.

# Adaptive management

# Why Bayesian networks?....

- Adaptable—Fire and lots more
- Multiple stressors are normal and can be calculated
- Interactions of management methods can be evaluated
- Pictures and numbers…
- Warning—risks do not always go down together like in this example.


Thanks for your time…..