An Introduction to Bayesian Networks for Environmental Risk Assessment and Management

Wayne G. Landis
Western Washington University
Institute of Environmental Toxicology

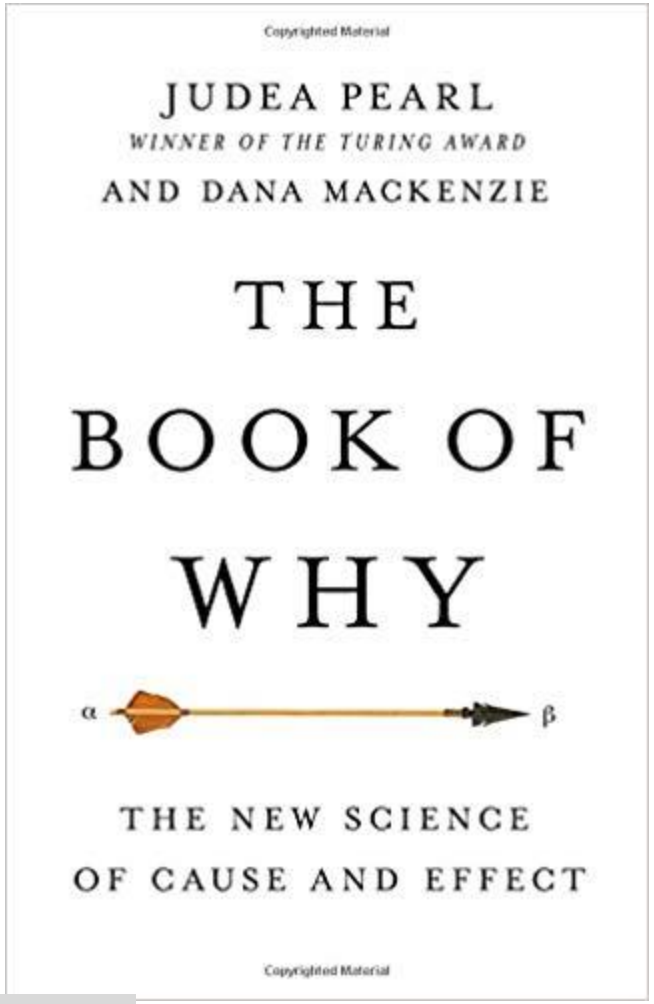
John F. Carriger, Jr.
U.S. EPA
National Risk Management Research Laboratory

the EPA Disclaimer

- The views expressed in this presentation are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency.

So who uses Bayesian Networks?—You do!

Bayesian networks, the machine-reasoning tool that underlies the Bonaparte software, affect our lives in many ways that most people are not aware of. They are used in speech recognition software, in spam filters, in weather forecasting, in the evaluation of potential oil wells, and in the Food and Drug Administration's approval process for medical devices. If you play video games on a Microsoft Xbox, a Bayesian network ranks your skill. If you own a cell phone, the codes that your phone uses to pick your call out of thousands of others are decoded by belief propagation, an algorithm devised for Bayesian networks. Vint Cerf, the chief Internet evangelist at another company you might have heard of, Google, puts it this way: "We're huge consumers of Bayesian methods."



Read pages 108-133

Outline of the presentation

- Definition of a Bayesian network
- The Pioneers
- The workings of a Bayesian network
- The papers of the session
- What to look for

The Pioneers-Google their papers

Bruce Marcot-Wildlife Management

Barry Hart and Carmel Pollino-Ecological Risk Assessment

Peter Bayliss-Ecological Risk Assessment

Sakari Kuikka-Fisheries Management

Laura Uusitalo-Management and Uncertainty

John Carriger-Management and responses

David Barton-Environmental Management

Landis and colleagues-Ecological Risk Assessment

The Pioneers-Google their papers

Bruce Marcot-Wildlife Management

Barry Hart and Carmel Pollino-Ecologica

Peter Bayliss-Ecological Risk Asses

Sakari Kuikka-Fisheries Mana

Laura Uusitalo-Manage y

John Carriger-Ma nses

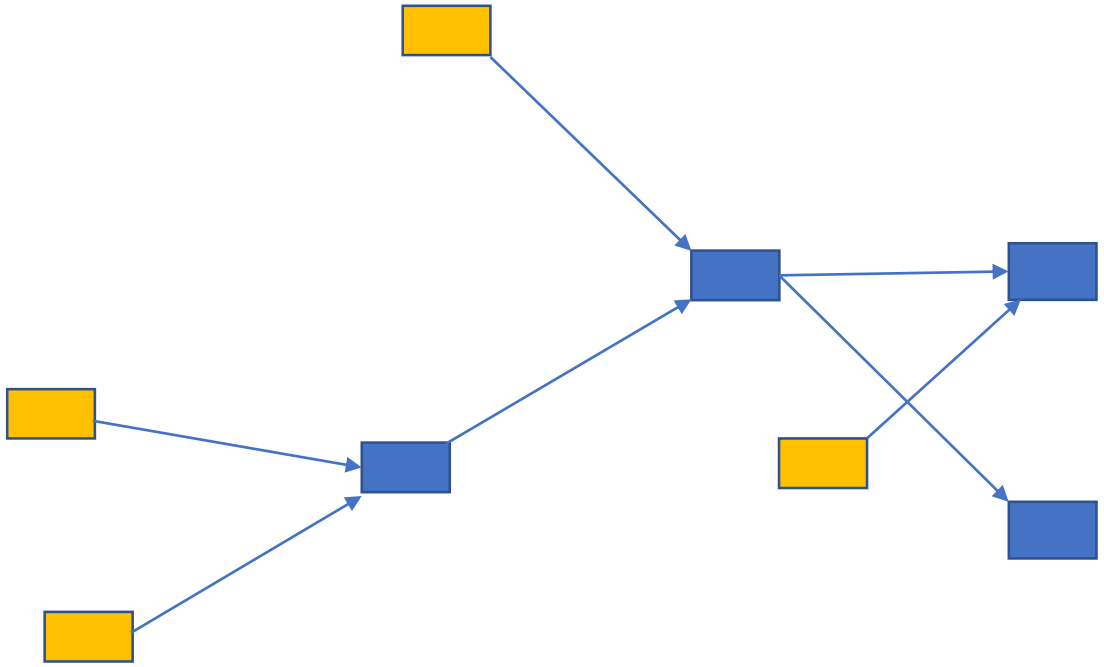
David Barto nagement

Landis ogical Risk Assessment

Now to make it the new normal with sessions at SETAC NA and next at SETAC EU in Helsinki

Definition of a Bayesian network

Bayesian networks: Graphically depicted web of nodes that link cause and effect relationships using conditional probability to describe the interactions and to generate the probability outcome or outcomes.

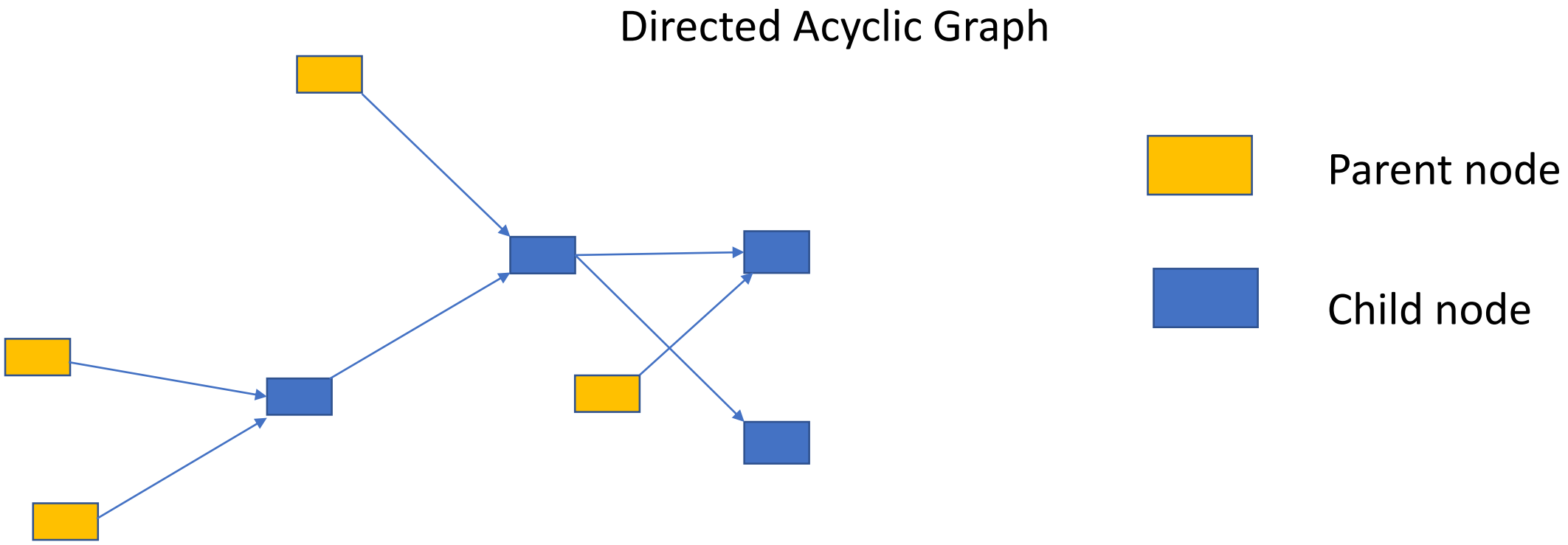


Directed Acyclic Graph

Marcot, B.G., J.D. Steventon, G.D. Sutherland, and R.K. McCann. 2006. Guidelines for development and updating Bayesian belief networks applied to ecological modeling and conservation. Can. J. Forest Res. 36(12):3063-3074.

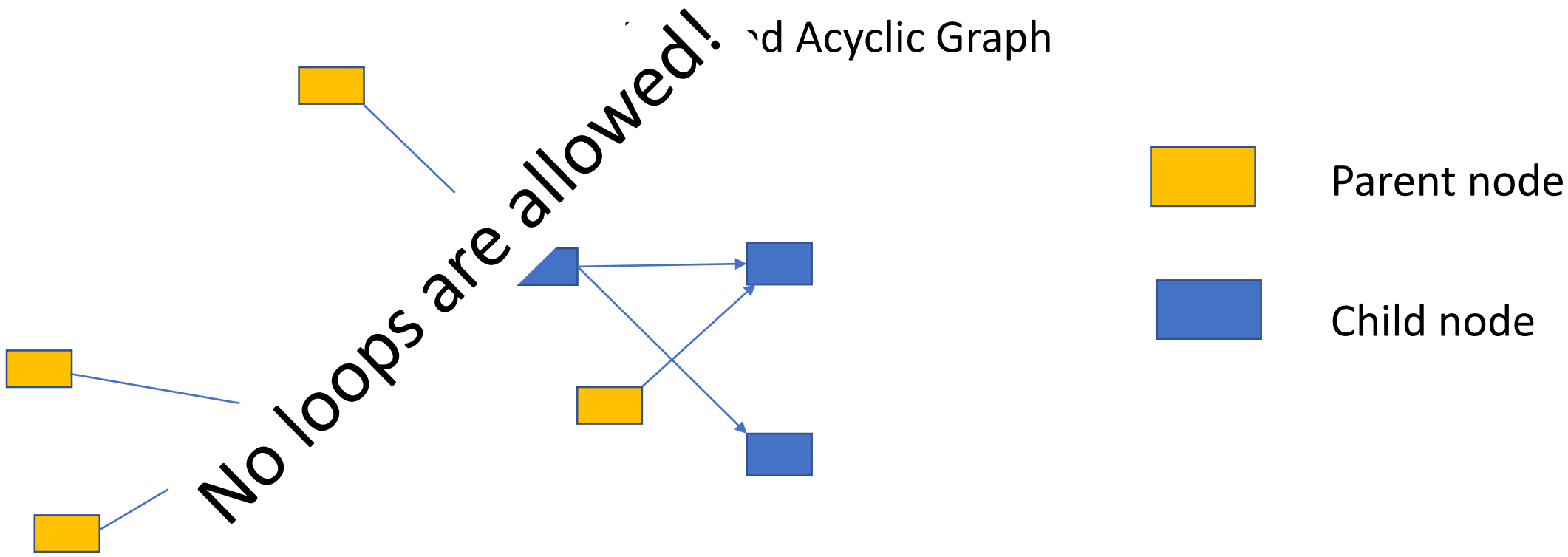
Definition of a Bayesian network

A directed acyclic graph where the interactions between nodes are described by conditional probabilities.



Definition of a Bayesian network

A directed acyclic graph where the interactions between nodes are described by conditional probabilities.



Definition of a Bayesian network

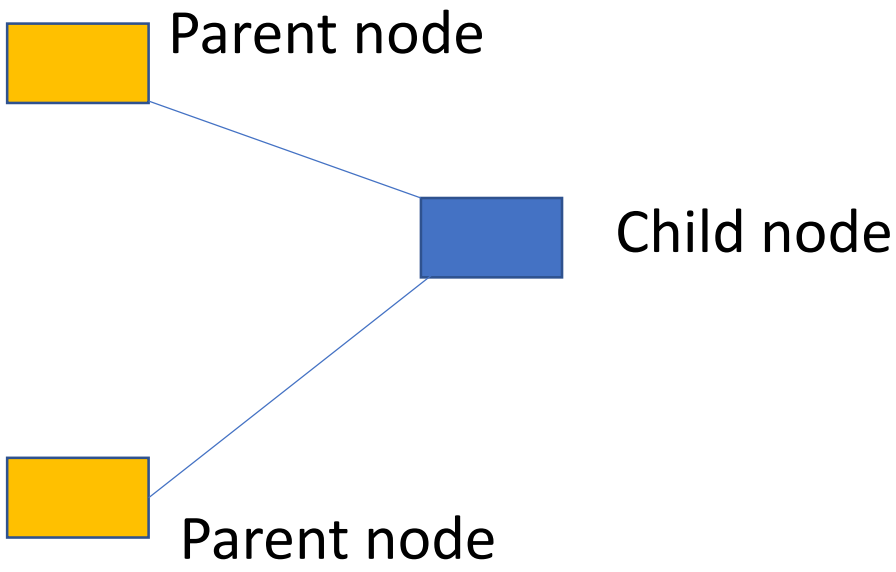
Nodes are variables describe as a set of discrete states with a specified probability.

Variable -Temperature	
State	Probability
-5 to 10	0.1
11 to 20	0.5
20 to 30	0.3
> 30	0.1

There are two types of Nodes - Parent Nodes and Child Nodes

Definition of a Bayesian network-simpler

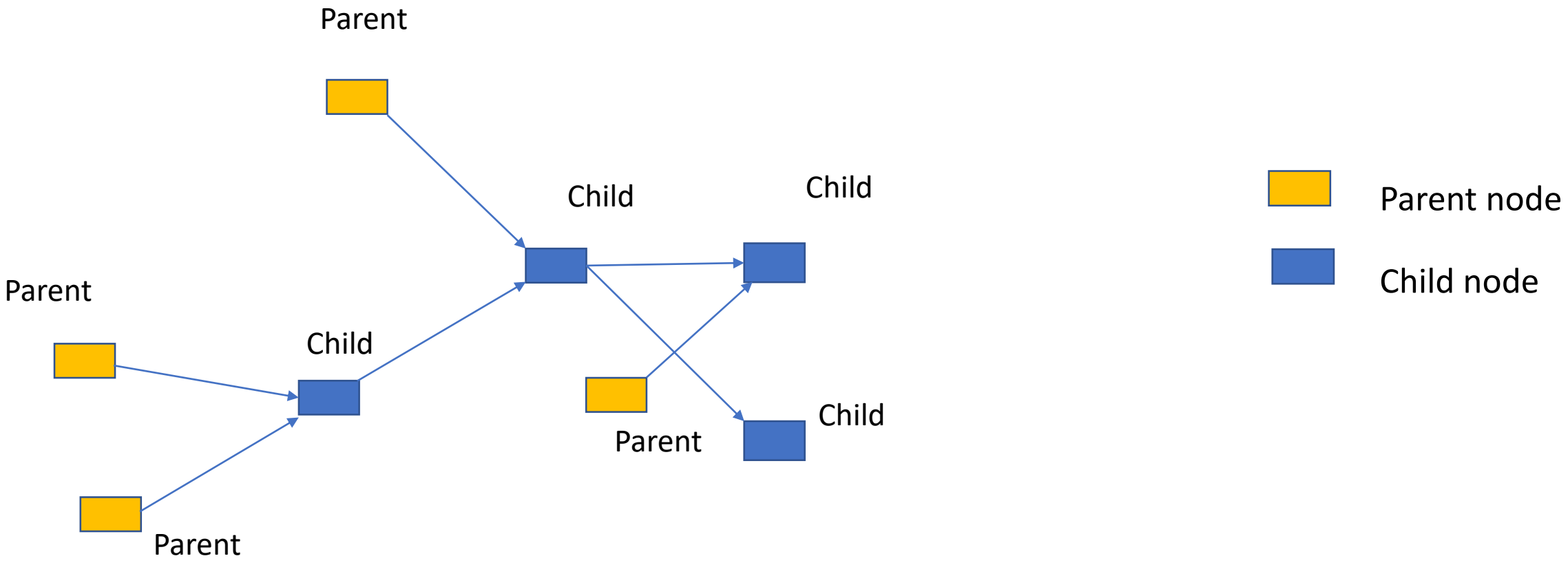
A directed acyclic graph where the interactions between nodes are described by conditional probabilities.



A Conditional Probability Table Describes the interactions

Definition of a Bayesian network

Parent Nodes define the original states and are the inputs. The Child Nodes are derived by two or more parent nodes and the interaction is determined by the conditional probability table.

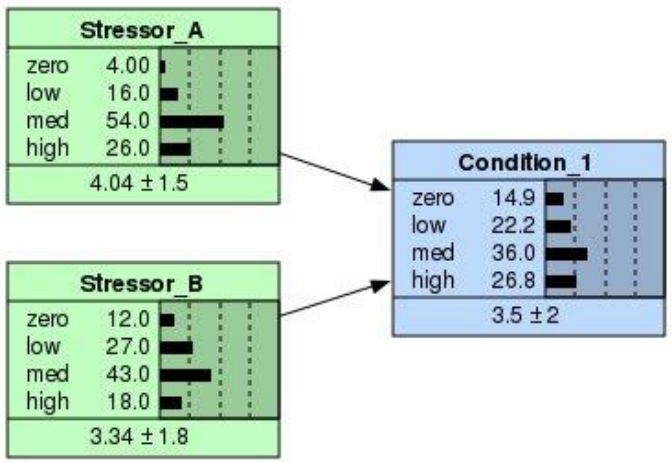


Conditional probability tables (CPTs)

A conditional probability table describes the interactions between two or more nodes.

Parents

Child



CPT

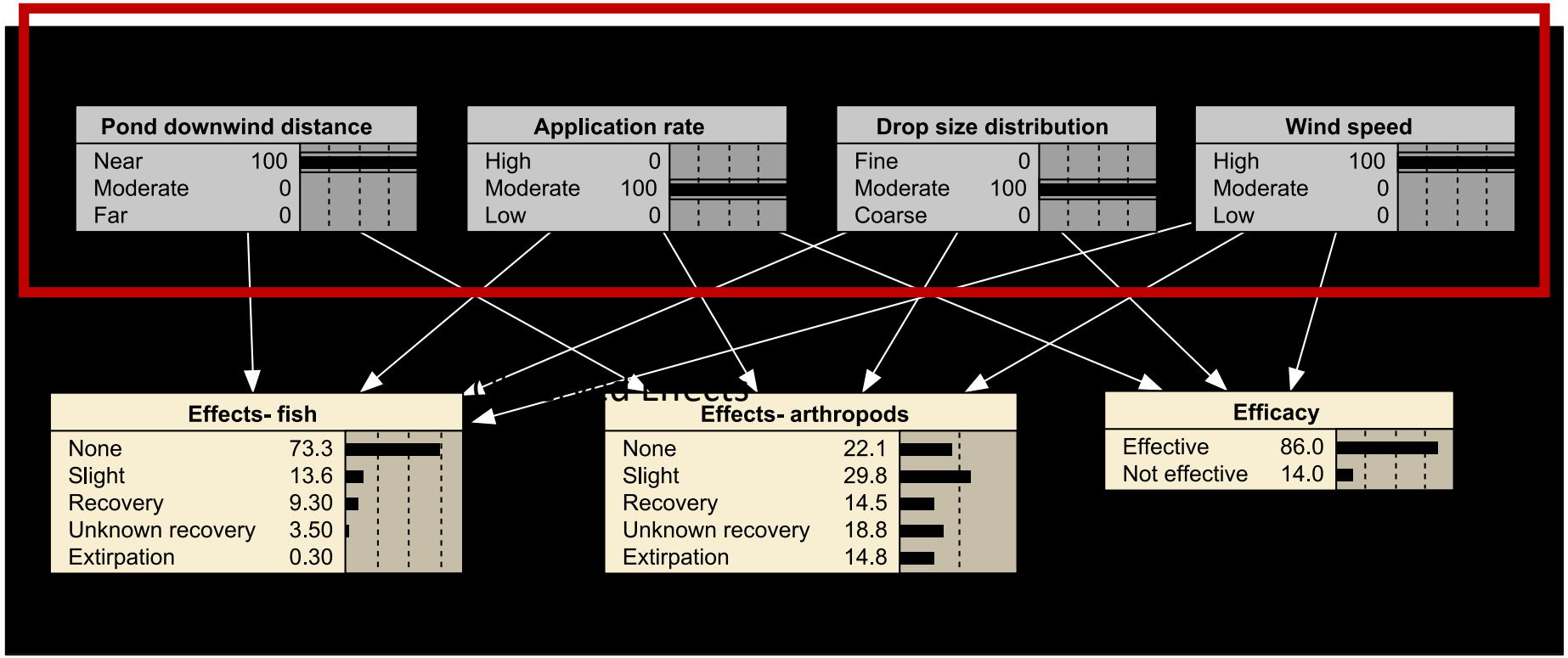
Stressor_A	Stressor_B	zero	low	med	high
zero	zero	100.00	0.000	0.000	0.000
zero	low	90.000	8.000	1.500	0.500
zero	med	75.000	20.000	4.000	1.000
zero	high	60.000	25.000	10.000	5.000
low	zero	75.000	20.000	4.000	1.000
low	low	50.000	35.000	10.000	5.000
low	med	25.000	35.000	30.000	10.000
low	high	10.000	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

The probabilities of the outputs of all the possible combinations of inputs are described in the conditional probability table

Example of a simple BN-Cause to Effect

Takes measurements and estimates effects

Observed Conditions

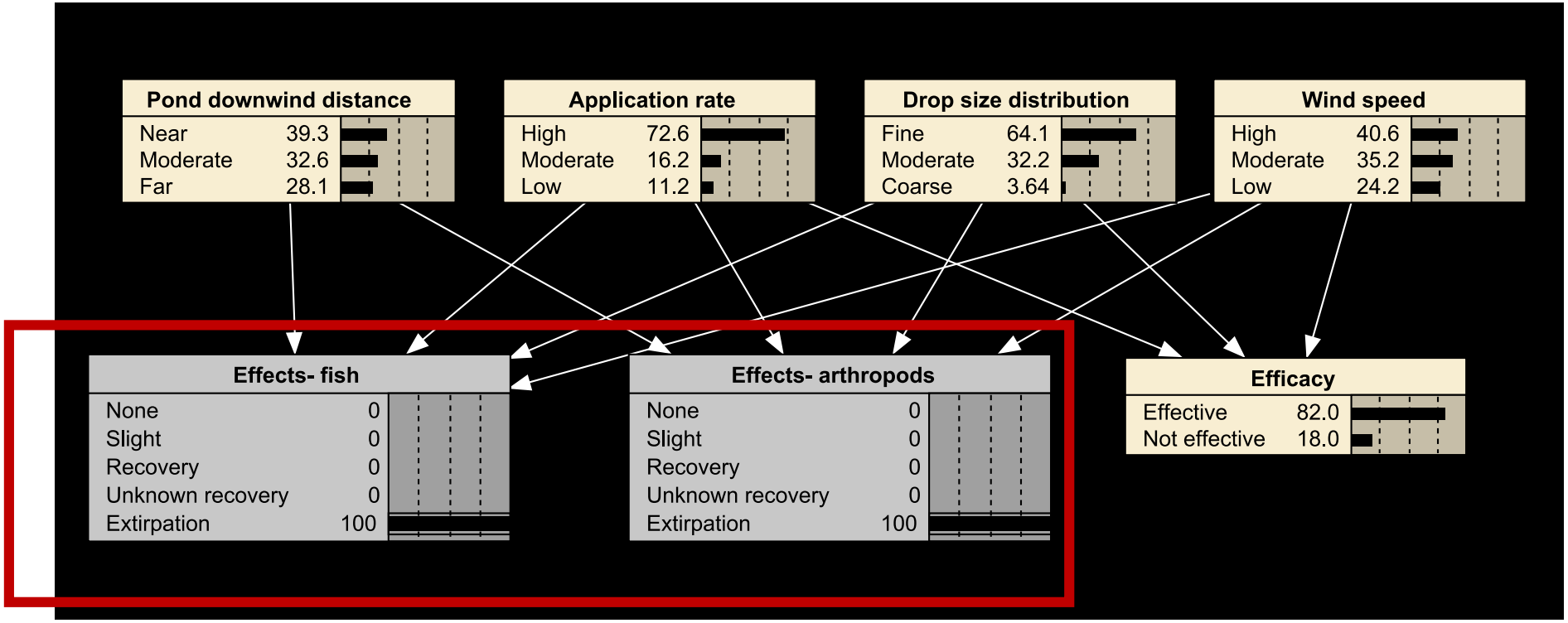


Predicted Outcomes

Example of a simple BN-Effect to cause (diagnostic)

Can take effects and estimate likely causes

Predicted Causes



Observed Effects

Presentations

Mariana Cains

Data-informed city-level adaptive management: a Bayesian approach for quantifying climate change risk and resilience in Charleston, SC.

Jannicke Moe

Quantification of AOPs by Bayesian network modelling: linking chemical exposure to adverse outcomes in *Lemna minor* populations

Presentations

Eric Lawrence

Integrating climate change stressors and human health and well-being endpoints into a Bayesian network relative risk model

Gordon C. O'Brien

A regional scale ecological risk framework for environmental flow evaluations.

Presentations

I. Govender

Multiple Stressor Ecological Risk Assessment of a Highly Regulated Water Catchment in the Context of South African Legislation

John F. Carriger, Jr.

Combining Bayesian networks and conceptual models for Superfund remediation support

Presentations

Sagar Thakali

Relative Risk Models Using Bayesian Networks: Application, Communication and Regulatory Use

What to look for…..

Diverse set of applications-from QSAR to resilience to climate change

All are probabilistic, deal with diverse datasets and types of data, and quantify uncertainty

All deal with establishing causality and making decisions