

Advanced Statistical Tools For Estimating Wildlife Exposure

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Overview

- This presentation focuses on transfer of contaminants from prey to wildlife predators
- Two major issues:
 - Do the contaminant levels in the dataset represent the levels to which predators are exposed?
 - Is the dataset adequate to confidently estimate exposure?
- Briefly describe available techniques and present a case study

General Approach

- Identify and characterize wildlife at risk
 - diet, foraging range, preferred habitats
 - life history, migration patterns, etc
- Select exposure model, identify critical input variables
- Review available data, where possible, collect data to fill critical gaps
- Parameterize exposure model, run analyses

Parameterizing Exposure Models

- Representativeness of data
 - many data sets biased to more contaminated areas
 - may provide uneven coverage of wildlife foraging area
 - data need to be manipulated to account for spatial and temporal foraging patterns of wildlife focal species
- Adequacy of data
 - costly to obtain large data sets
 - need to account for variability in contaminant levels and uncertainty introduced by small data sets
 - probabilistic techniques account for variability and uncertainty

Representativeness of Data

- Various spatial weighting techniques available
 - inverse distance weighting
 - Thiessen polygons
 - kriging
- Habitat weighting techniques can be used to account for wildlife foraging patterns
- Random walk and other models can be used to account for wildlife foraging patterns over time and space

LEGEND:

 Total PCB above baseline

Natural Communities

-  Agricultural Field
-  Red maple swamp
-  White-bark-red maple-barren oak-sap. swamp
-  Northern hardwoods-basswood-white pine forest
-  Red oak-sugar maple transition forest
-  Successional northern hardwoods
-  Rich, grass forest
-  Low gradient stream
-  Medium-gradient stream
-  High-gradient stream
-  Moderately shallow herbaceous
-  Shallow peatbog and marsh
-  High-brown bog-pine forest
-  Transitional floodplain forest
-  Wet meadow
-  Shallow emergent marsh
-  Deep emergent marsh
-  Shrub swamp
-  Cultural grasslands

Elevation Contours

-  200
-  201
-  202
-  203
-  204
-  205
-  206
-  207
-  208

Total PCB

-  < 1
-  1 - 2
-  2 - 4
-  4 - 7
-  7 - 20
-  20 - 100
-  > 100



Scale in Feet



Types of Uncertainty in an Exposure Analysis

- Variability
- Incerititude
- Model uncertainty

Probabilistic Methods For Propagating Variability and Uncertainty

- Probability bounds
- Second-order Monte Carlo

Probability Bounds

How?

- specify what you are sure about
- establish bounds on probability distributions
- select dependencies (no assumption, independence, perfect, etc.)

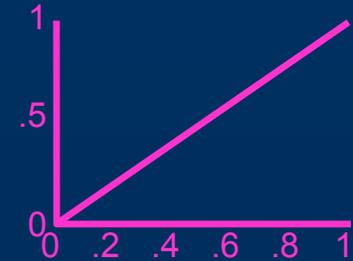
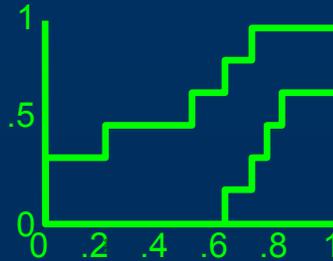
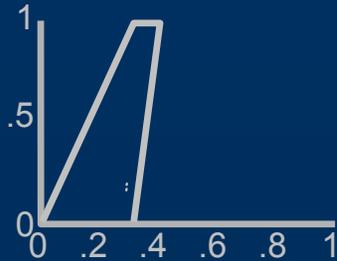
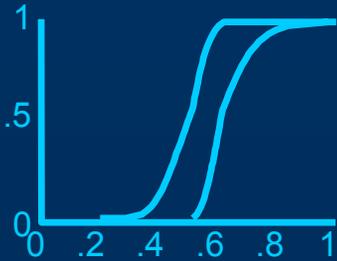
Why?

- accounts for uncertainty and variability
- puts bounds on Monte Carlo results
- bounds get narrower with better empirical information

Why not?

- cannot handle second-order probabilities
- may not be able to use subtle information to tighten bounds
- optimum bounds expensive to compute when variables repeated

Probability Bounds

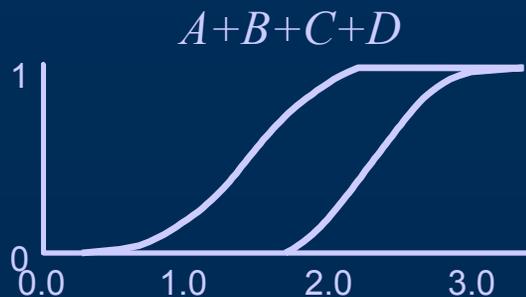


$A = \{\text{lognormal, mean}=[.5,.6], \text{variance}=[.001,.01]\}$

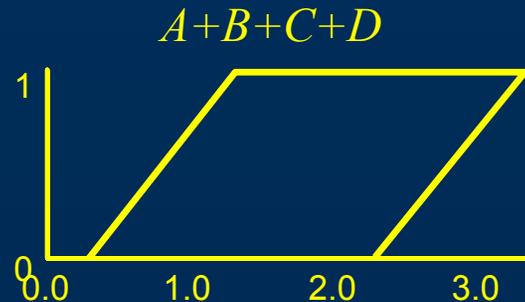
$B = \{\text{min}=0, \text{max}=.5, \text{mode}=.3\}$

$C = \{\text{data} = (.2, .5, .6, .7, .75, .8)\}$

$D = \{\text{shape} = \text{uniform, min}=0, \text{max}=1\}$



Under independence



Without independence

Second-order Monte Carlo

How?

- let parameters of input distributions be distributions too
- nest Monte Carlo analyses
- either summarize with distribution of distributions,
- or condense output into a single distribution

Why?

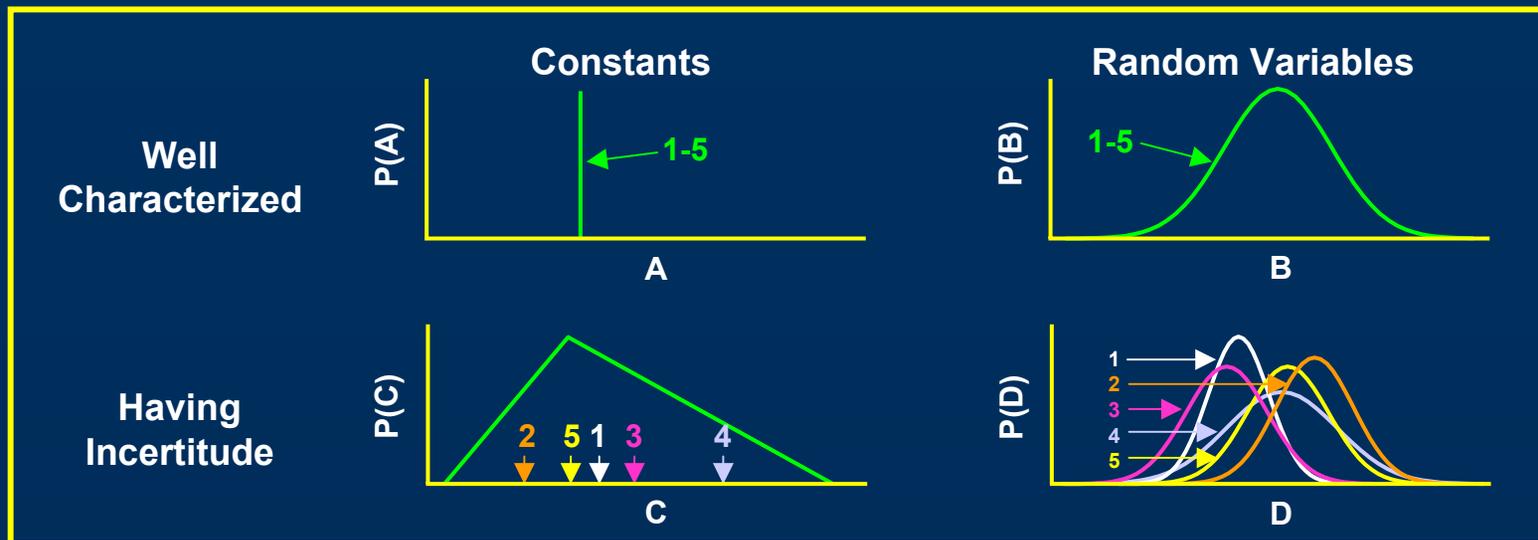
- acknowledges and accounts for the full extent of uncertainty

Why not?

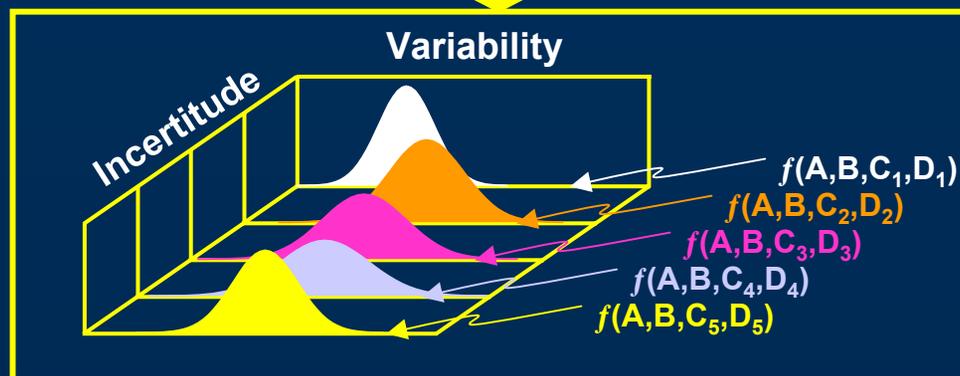
- squared computational expense
- parameterizations can be difficult
- either results are cumbersome to interpret and explain
- or results confound ignorance with variability

Second-order Monte Carlo

Inputs



Output



Case Study

- Hypothetical case study
- Scenario
 - birds exposed to persistent chemical
 - goal: estimate distribution for chronic exposure
 - local spatial scale
 - some input variables well known, others not

Exposure Model

$$TDI = \frac{F_c ([IR_w \times C_w] + \{IR_f [C_{sed} \times BSAF] + [C_{soil} \times 0.02]\})}{BW}$$

where

TDI = Total daily intake ($\mu\text{g}/\text{kg}$ bw/day)

F_c = Fraction of diet and drinking water that is contaminated (unitless)

IR_w = Intake rate for water (L/day)

IR_f = Intake rate for food (g/day)

C_w = Concentration in water ($\mu\text{g}/\text{L}$)

C_{sed} = Concentration in sediment ($\mu\text{g}/\text{g}$)

C_{soil} = Concentration in soil ($\mu\text{g}/\text{g}$)

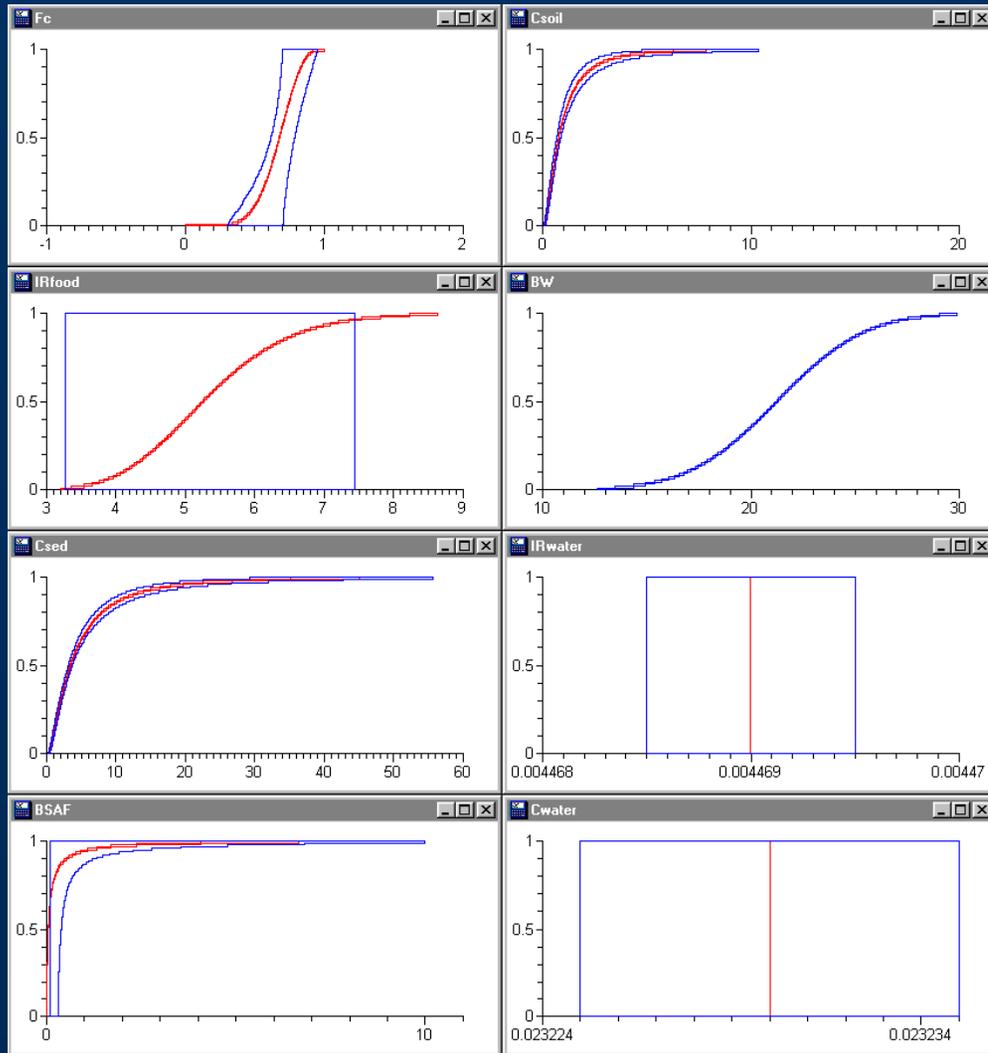
$BSAF$ = Biota-sediment accumulation factor (unitless)

BW = Body weight (kg)

Probability Bounds

- Several inputs have much uncertainty
 - biota-sediment accumulation factor
 - food intake rate
- Several inputs have mostly variability
 - body weight
 - concentrations in soil, sediment and water

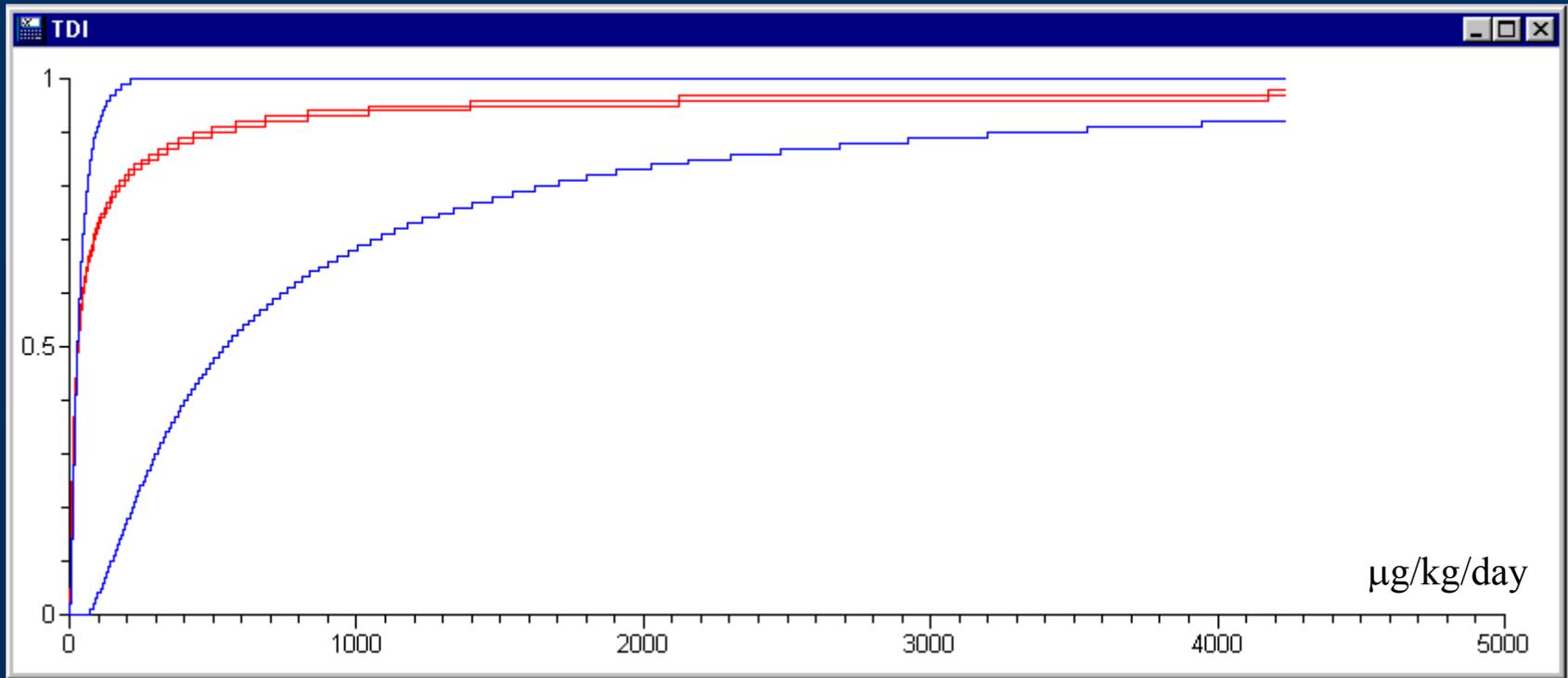
Inputs for Analysis



distributions used
in Monte Carlo
simulation shown
in red

probability bounds
shown in blue

Estimated Exposure



Estimated median

30

[27, 530]

90th percentile

450

[90, 3100]

Then What?

- Estimate risk by combining exposure distribution with effects information
- Risk curve is one line of evidence
- Also consider other lines of evidence (e.g., biological surveys, *in situ* toxicity studies)
- Where remediation required, probabilistic model can be used to help determine cleanup levels