Hierarchical Models for Quantifying Uncertainty in Human Health Risk/Safety Assessment

Ralph L. Kodell, Ph.D. Department of Biostatistics University of Arkansas for Medical Sciences Little Rock, AR

Risk/Safety Assessment: A Multi-step Process



Outline

- Background on Human Risk/Safety Assessment
- Exposure-to-Dose Response
 - PK/PD relationship via hierarchical model
 - Benchmark dose estimation (distributions)
 - How uncertainty can be reduced by PK information
- Dose Response-to-Risk/Safety Characterization
 - Inter-species and intra-species uncertainties
 - BMD conversion via hierarchical model
- Summary and Conclusions
- Challenges and Needs
 - Model uncertainty

Uncertainty Analysis

- <u>Issue</u>: There are many uncertainties in getting from Hazard and Dose-Response Assessment in experimental (animal) settings to Exposure and Risk/Safety Characterization for human settings
- <u>Challenge</u>: How to properly reflect these uncertainties
- <u>Today's Talk:</u> How Hierarchical Probabilistic Models can help to characterize and manage these uncertainties

Usual Approach to Exposure Setting: Two-Step Process

Human Exposure (Risk) =

<u>Animal-Derived Benchmark Dose (Risk)</u> Animal→Average Human→Sensitive Human

<u>Exposure→Dose-Response</u>

(Dose-Response→Risk/Safety Characterization)

Dose-Response Modeling for BMD Estimation: Illustration

D	n	#tumors	Observed	Predicted
0	50	5	0.10	0.096
10	50	7	0.14	0.157
20	50	13	0.26	0.239
40	50	20	0.40	0.407

- Weibull model: $P(D) = \alpha + (1-\alpha)[1-exp(-\beta D^{\gamma})]$
- P(D)=0.096 + 0.904 [1-exp(-0.0035D^{1.30})]
- Goodness-of-fit p-value = 0.61



Weibull Model with 0.95 Confidence Level

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$\mathsf{Exposure} \to \mathsf{Dose}\text{-}\mathsf{Response}$

- Context: Dose-response analysis for cancer
 - -Fit a mathematical model to D-R data: Prob(tumor|D) = F(D)
 - -D is administered (external) dose
- Generally acknowledged that PK information on *internal dose (d)* should be incorporated whenever possible

-e.g., d = mean AUC in tissue or blood

PK/PD Hidden Structure

- However, most often there is no formal attempt to separate the hidden Pharmacokinetic (PK) and Pharmacodynamic (PD) components of F that might explain the transformation of an external exposure into the development of a tumor
 - -e.g., F(D), F(d): multistage, probit, Weibull

Hierarchical Model

 The most natural way to link the PK and PD components of a dose-response model is via a hierarchical model

How to implement the model

- PK: Experiment, e.g., rats, n animals/D – Calculate mean and s.d. of d = AUC
 - Assume normal distribution for f(d|D)
 - Simple PK: variability in internal dose
 - Complex PK: variability + parameter uncertainty
- PD: Mechanism/Mode of Action?
 - e.g., two-stage clonal growth model for cancer
 OR, multistage, probit, Weibull
- Numerical integration to fit hierarchical model

Example

- PK analysis

 f(d|D) ~ Normal [μ=(2D/(10+D), σ=0.2μ]
 f(d|D)={1/[σ√(2π)]}exp{-½[(d-μ)/σ]²}
- PD model
 - g(tumor|d): Weibull model
 - $-g(tumor|d)=1-exp(-\beta d^k)$
- Fit hierarchical model using nonlinear least squares with numerical integration (e.g., SAS NLIN)

Results

D	n	#tumors	proportion	PK/PD fit
0	50	5	0.10	0.098
10	50	7	0.14	0.145
20	50	13	0.26	0.256
40	50	20	0.40	0.402

- μ =(2D/(10+D), σ =0.2 μ (from PK analysis)
- β =0.0406, k=4.65 (from fit to tumor data)

Benchmark Doses

- Can get BMD on scale of external (administered) dose
 - Fix the parameters at estimated values
 - Let the desired BMD, e.g., BMD₁₀, be the "parameter" of interest
 - Set BMR (0.10) = [P(tumor|D)-P₀]/[1-P₀]
- Estimated BMD₁₀ is 13.91 (SAS NLIN)

Uncertainty Analysis

- Can simulate a complete distribution of BMD_{100BMR} for any BMR using Monte Carlo bootstrap re-sampling of the tumor data.
- Similarly, can simulate a distribution of excess risks for any D







Use 5th percentile as 95% BMDL_{100BMR}

Useful for managing risk: BMDL₁₀ = 6.86BMDL₀₁ = 0.95

Reduced Uncertainty in BMDs

<u>PK (f)</u>	PD (g)	BMR	BMDL(05)
Mic-Men	Weibull	0.01	0.97
(mean only)		0.10	6.29
Mic-Men	Weibull	0.01	0.95
(distribution)		0.10	6.86
None	Weibull	0.01	0.09
		0.10	4.80

 Nonlinear PK info can reduce the spread of distributions of BMDs (reduce the data uncertainty). But, <u>mean</u> internal dose seems sufficient.

Why the Mean Seems Sufficient

$$P(tumor \mid D) = P_0 + (1 - P_0) \int_0^\infty g(tumor|x) f(x|D) dx$$
$$[P(tumor \mid D) - P_0] / (1 - P_0) = \int_0^\infty g(tumor|x) f(x|D) dx$$

$$E_{f} [g(tumor | d) | D] \cong g[tumor | E_{f}(d | D)]$$

Comparison of Variation from Hierarchical Model with Ordinary Binomial Variation

D	Ν	Mean	SD	Bin. SD
10	100	0.1432	0.0466	0.0495
20	100	0.2450	0.0620	0.0620
40	100	0.4066	0.0659	0.0695

- Model: Hierarchical model with P0=0.098, g: Weibull (0.0406, 4.65), f: N(2D/(10+D), 0.4D/(10+D))
- Mean: average of N generated tumor proportions
- SD: observed std dev of N generated tumor proportions
- Bin. SD: std dev calculated by [p(1-p)/50]^{1/2}, where p=observed mean and 50 is number of animals/group

Combining PK and PD Results OSHA: Methylene Chloride 1997

- Internal dose from PK analysis
- Mean d

- Risk estimate
 from PD model
- MLE excess risk
- UCL on excess risk

• UCL on d

- MLE excess risk
- UCL on excess risk

Usual Approach to Exposure Setting: Two-Step Process

• Human Exposure =

<u>Animal-Derived NOAEL or Benchmark Dose</u> Animal-Average Human-Sensitive Human

<u>Exposure→Dose-Response</u>

(Dose-Response→Risk/Safety Characterization)

Dose-Response \rightarrow

Risk Characterization

- Inter-species extrapolation:
 Animal → Human
 - Location extrapolation, from susceptibility of test animal to center (mean), μ_H , of human susceptibility distribution
 - Uncertainty is due to a lack of knowledge about $\mu_{\text{H}},$ because of the variability among

chemicals in their differential effects on test animals and humans

$\mathsf{Dose}\text{-}\mathsf{Response} \rightarrow$

Risk Characterization (cont.)

- Intra-species extrapolation: – Human \rightarrow Human
 - Scale extrapolation, from the center, μ_H , of the

human susceptibility distribution to an extreme tail area

 Uncertainty is due to the inherent interindividual variability in human sensitivity

BMD Conversion

- Suppose we have BMD or BMDL for animals, say, D_a
- Let T_a be a random variable representing the ratio of human-to-animal sensitivity over all chemicals
- Let T_h be a random variable representing the ratio of human-to-human sensitivity to the tested chemical
- Need to "convert" D_a to D_h to D_s

Conditional Distribution of Human Susceptibility

- Assume that T_a has a shifted lognormal distribution with pdf $-f_a(t_a|\mu_a, \sigma_a, \tau_a)$
- Assume that T_h has a *prior* shifted lognormal distribution with pdf $-f_h(t_h|\mu_h=c, \sigma_h, \tau_h)$
- Then, conditional on $T_a=t_a$, T_h has a shifted lognormal distribution - $f_h(t_h|\mu_h=log(t_a)+c$, σ_h , τ_h)

Unconditional Distribution of Human Susceptibility

• Hierarchical model for pdf of T_s:

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Human Extrapolated Dose

- Lower 100p% statistical confidence limit on human extrapolated dose:
- Instead of $D_a/(T_{a,100p}T_{h,100p})$ [$D_a/(10*10)$]
- Calculate by $D_a/T_{s,100p}$
 - where $T_{s,100p}$ is the 100pth percentile of the unconditional human susceptibility distribution
- In general, $T_{\rm ST100p}$ can be expected to be smaller than $T_{a,100p}^{\rm 100p}*T_{h,100p}$

Illustrations

- T_a(0, 0.58, 1):
- $T_h(0, 0.61, 0)$ $-T_{a,95}*T_{h,95} = 100$
 - $-T_{s,95} = 34$

 $T_{50}=2, T_{95}=10$ $T_{50}=1, T_{95}=10$

 $T_{s,99} = 100$

- T_a(0, 0.697, 1):
- $T_h(0, 0.715, 0)$ - $T_{a,95}*T_{h,95} = 225$ - $T_{s.95} = 60$

 $T_{50}=2, T_{95}=15$ $T_{50}=1, T_{95}=15$

 $T_{s,97} = 100$

$\mathsf{Exposure} \to \mathsf{Dose}\text{-}\mathsf{Response}$

Conclusions

- Information on internal dose though PK analysis can reduce uncertainty in BMD estimation (both data and model uncertainty) by improving the estimate of the mean risk
- But, the complete distribution of internal dose does not appear to affect the characterization of uncertainty...the *mean internal dose* seems sufficient
- The only measure of uncertainty in *risk* arises from the ultimate endpoint, presence or absence of an adverse effect

Dose-Response \rightarrow

Risk Characterization Conclusions

 Hierarchical probabilistic models can be useful for managing the uncertainties in the extrapolation process of converting animal-derived exposures into humanequivalent exposures for risk characterization by providing vehicles for proper quantification and propagation of the uncertainties

Overall Summary

Hierarchical models are useful for understanding and quantifying uncertainties in doing:

 $\frac{\text{Exposure} \rightarrow \text{Dose-Response}}{\text{Dose-Response}) \rightarrow \text{Risk Characterization}}$

$$D^{-1}\left\{BMR = \int_{0}^{\infty} g(tumor | x, \beta, k) f(x | D, \mu, \sigma) dx\right\}$$
$$T^{-1}\left\{100p = \int_{\tau_h}^{T} \int_{\tau_a}^{\infty} f_h(t_h | \mu_h = \log(t_a) + c, \sigma_h \tau_h) f_a(t_a | \mu_a, \sigma_a, \tau_a) dt_a dt_h\right\}$$

Challenges and Needs

- Correct propagation of uncertainty
 - Don't overstate or misstate
 - Hierarchical models
 - PK \rightarrow PD, A_{average} \rightarrow H_{average}, H_{average} \rightarrow H_{sensitive}
- Model uncertainty
 - Don't ignore
 - Model averaging
 - Which and how many?
 - Confidence limits on model-averaged BMDs
 - Should you average BMDLs?

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