

# **Data Fusion-based Human Health Risk Assessment Framework: Illustrative Examples**

**Workshop III: Alliance for Risk Assessment**

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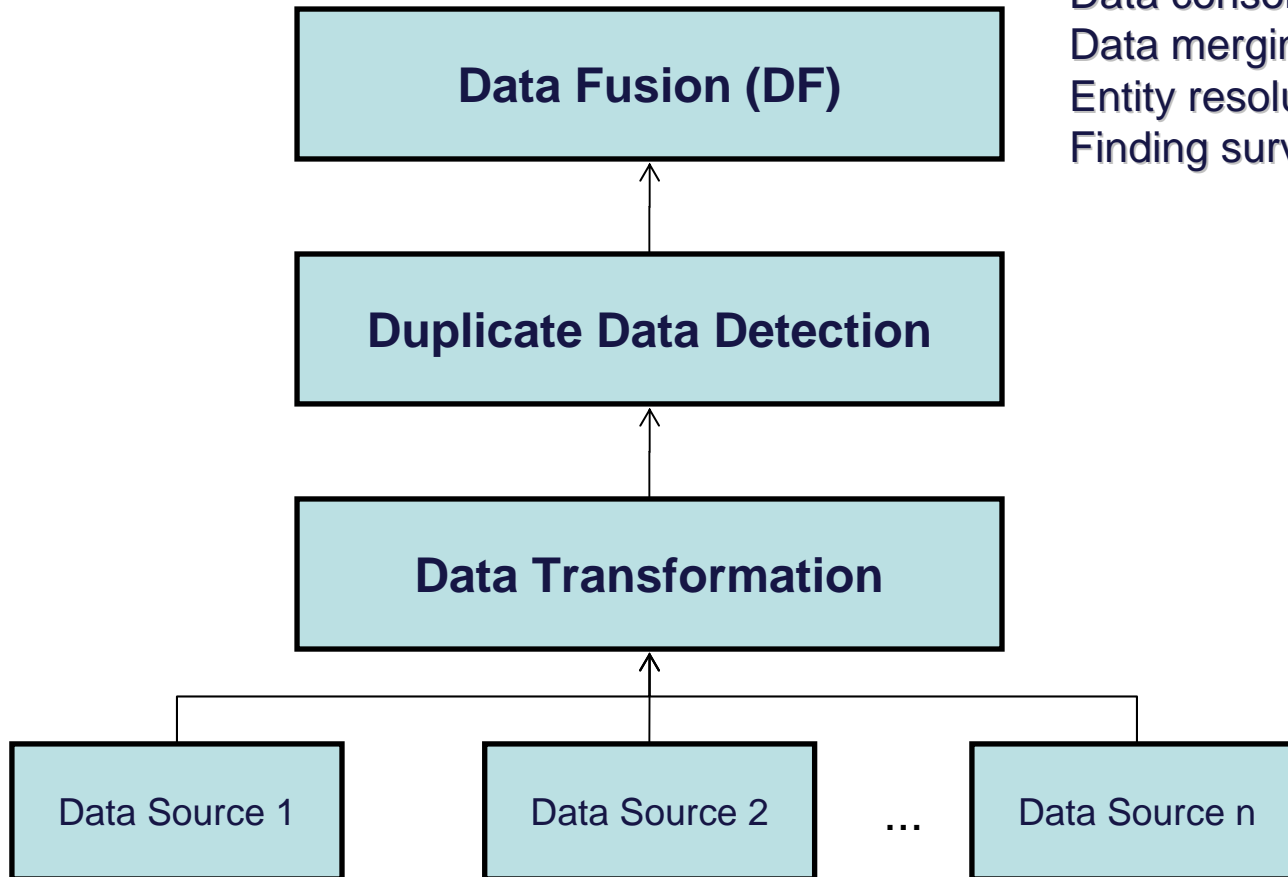
# Presentation Outline

- Data Fusion Human Health Risk Assessment Framework (DF – HHRA)
- Benzene
- F1

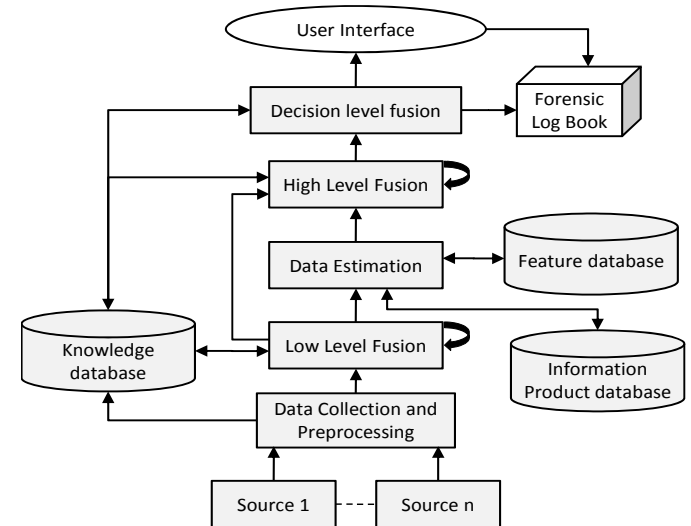
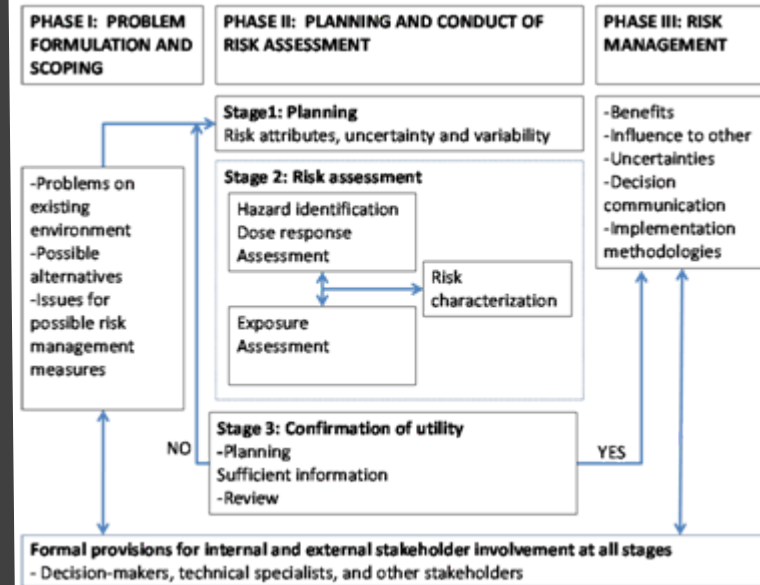
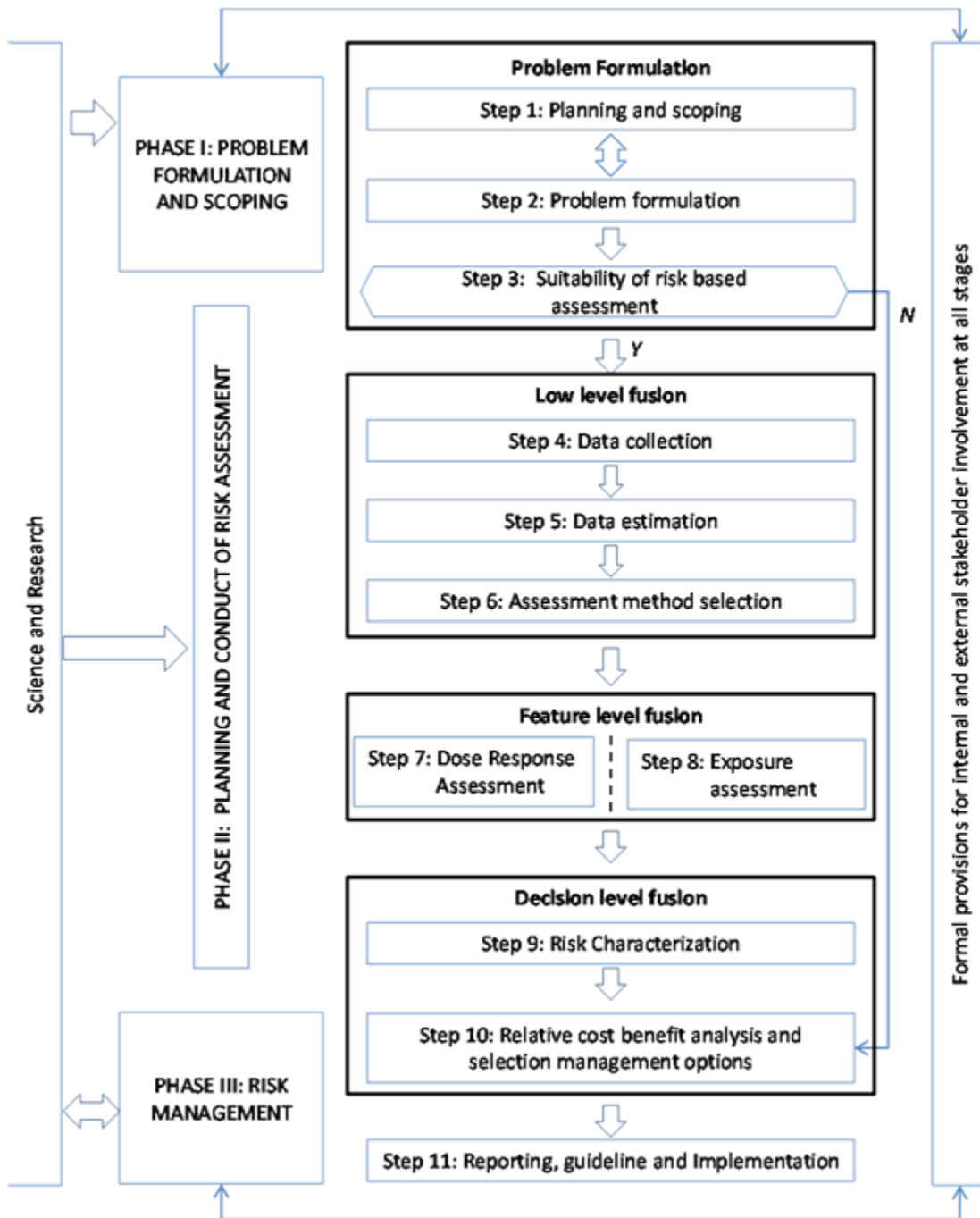
# Data Integration

Data refinement and improving data quality  
Additional inferences and increasing benefit from data  
Improving understanding and decision

Data consolidation  
Data merging  
Entity resolution  
Finding survivors ...



# Proposed DF Framework



# DF Techniques

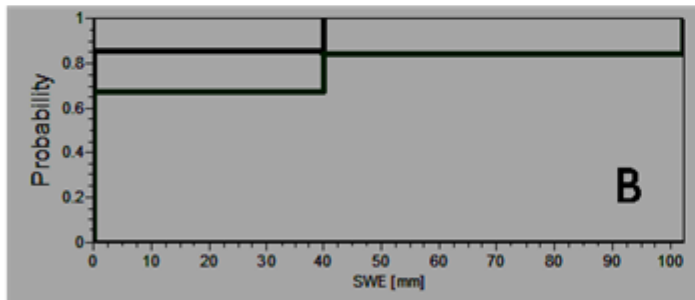
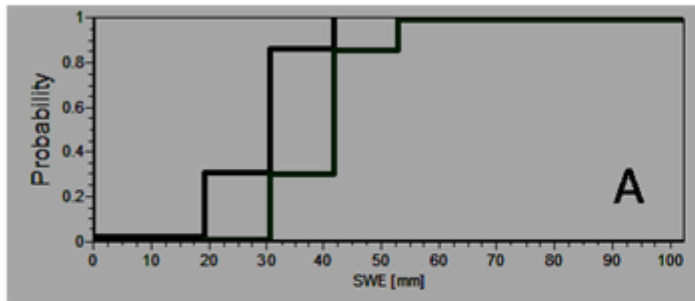
Fusion technique	Identity fusion	Feature-level fusion	Decision-level fusion
Cluster Analysis	X	X	
Classical Inference	X		X
Bayesian Inference	X	X	X
Dempster-Shafer Theory	X	X	X
Voting Strategies			X
Expert Systems	X	X	X
Logical Templates		X	X
(Adaptive) Neural Networks	X	X	X
Fuzzy Logic	X		X
Blackboard			X
Contextual Fusion			X
Syntactic Fusion			X
Estimation theory	X		
Entropy	X		
Figure of Merits	X		
Templates	X		
Generalized evidence processing theory			X

# DF in the Context of HHRA

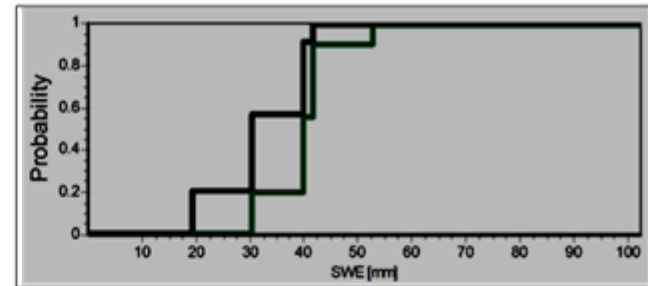
Data fusion technique	Application area(s)	Methods	HHRA area	Sources
Statistical and kernel inference	Genomic data fusion	Kernel-based statistical-learning; different data types/formats are transformed into kernels; to combine kernels, it uses semi-definite programming to minimize the statistical loss function	TA	(Lanckriet, <i>et al.</i> 2004a)
	Transcription factor target gene prediction	Statistical inference coupled with additional sources	TA	(Xiaofeng <i>et al.</i> 2010)
	Biomedical data fusion	Optimization of the $L_2$ -norm of multiple kernels	TA	( Yu <i>et al.</i> 2010)
Bayesian inference (BI)	Multi-study and multi-endpoint BMD	Combines mechanistically informed model results with empirical data to derive several endpoints; combines multi-endpoint BMDs to derive BMDL	TA	(Schmitt 2006)
	Wide-area assessment of UXO contamination	Generates PDFs of features extracted from survey maps, uses BI methods to combine features with auxiliary information and data quality features	EA	(Johnson <i>et al.</i> 2009)
	Syndrome surveillance	Uses Bayesian conditional autoregressive (CAR) models to combine symptom data collected from a network for early outbreaks detection	TA	(Banks <i>et al.</i> 2009)
Dempster-Shafer theory (DST)	Risk assessment of water treatment	Transferable belief models (TBM) input diverse data such as fuzzy, interval probabilities and statistical data to produce a belief network		(Demotier <i>et al.</i> 2006)
	Drinking water quality (WQ)	Uses disjunctive operator for the interpretation of overall WQ in the distribution system and the development of a WQ index	EA	(Sadiq and Rodriguez 2005)
	Microbial water quality in distribution network	Four DST fusion rules are applied to fuse weak information from two microbial water quality data sources, results in four p-boxes	EA	(Sadiq <i>et al.</i> 2006)
	Prediction of breast cancer tumours	Fuses the outputs of multiple classifiers from different diagnostic sources	TA	(Raza <i>et al.</i> 2006)
Artificial neural networks (ANN)	Surface WQ estimation	Combines optical data and microwave data to estimate surface WQ	EA	( Zhang <i>et al.</i> 2002)
Fuzzy sets theory	Analysis of gene expression data	Transforms gene expression values into qualitative descriptors that are then evaluated using a set of heuristic rules	TA	(Woolf and Wang 2000)

TA: toxicity assessment and EA: exposure assessment

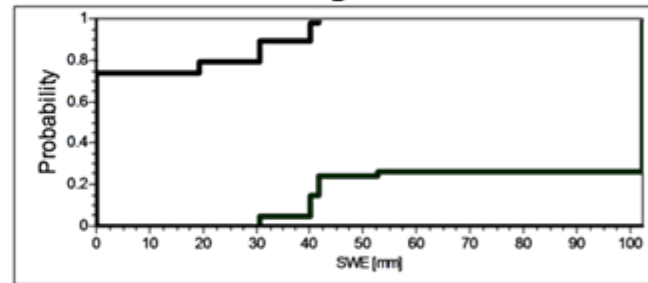
# DF Techniques



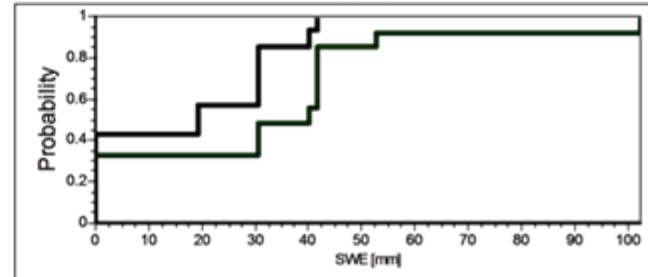
Dempster



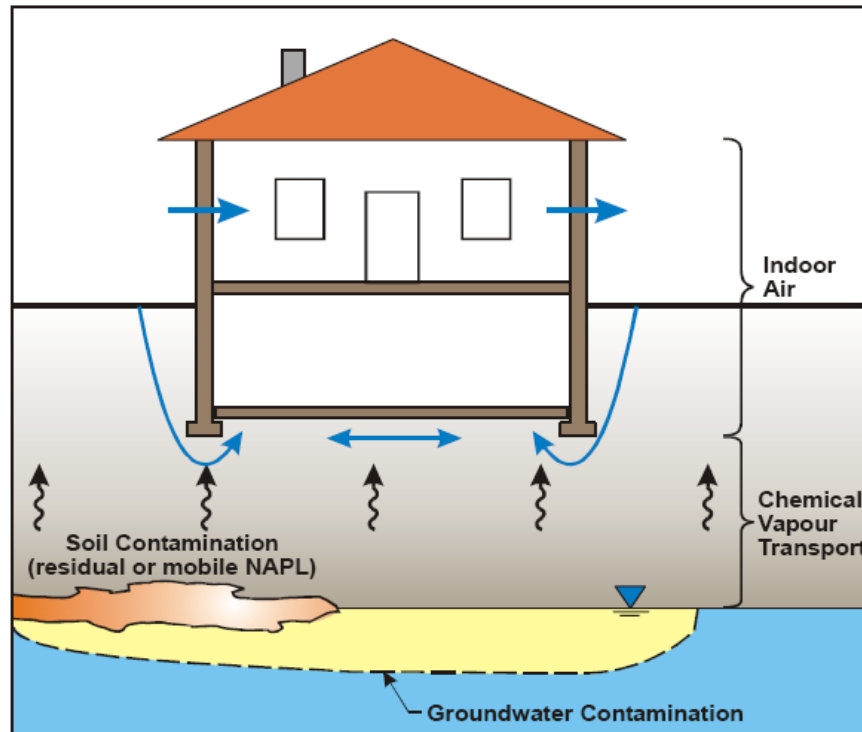
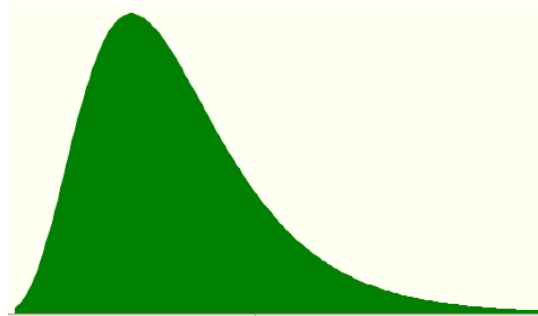
Yager



Mixture



# Exposure Scenarios





# Benzene Example

Standardized Mortality Ratios (SMRs) for leukemia among Pliofilm workers based on the estimated cumulative exposures

**Table 6.** Standardized mortality ratios for leukemia in Pliofilm workers<sup>a</sup> by cumulative exposure at all locations.

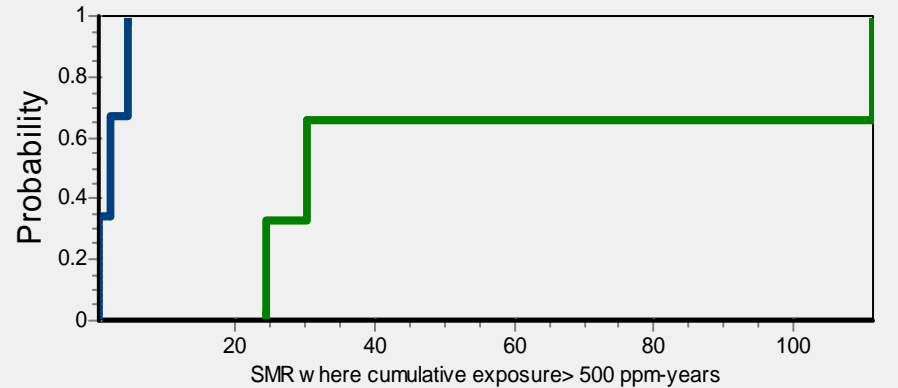
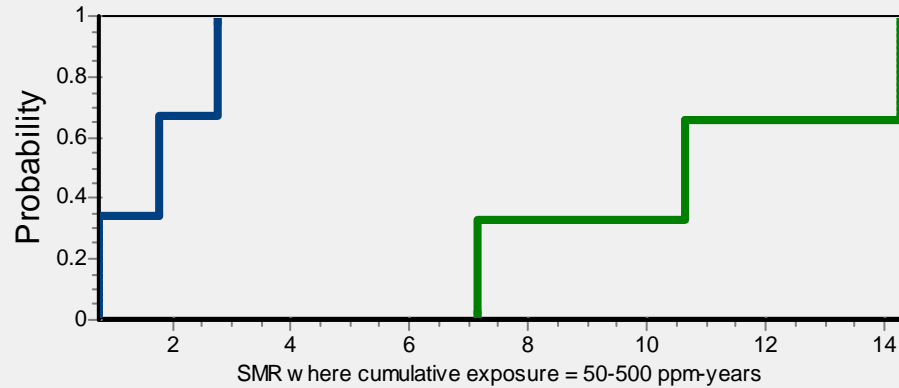
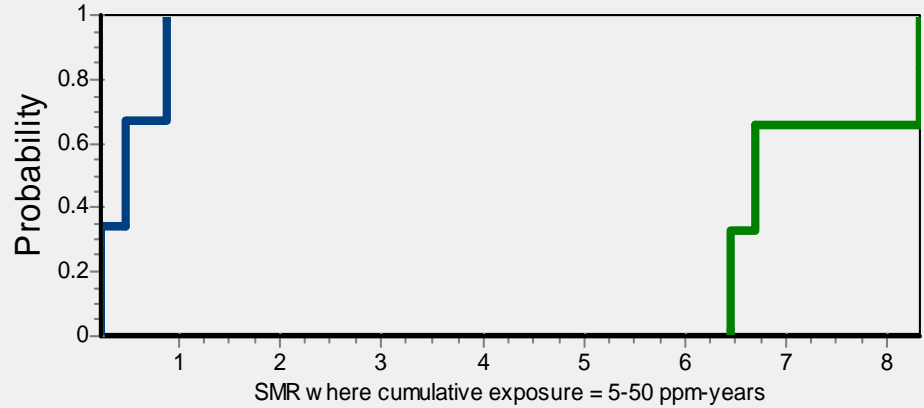
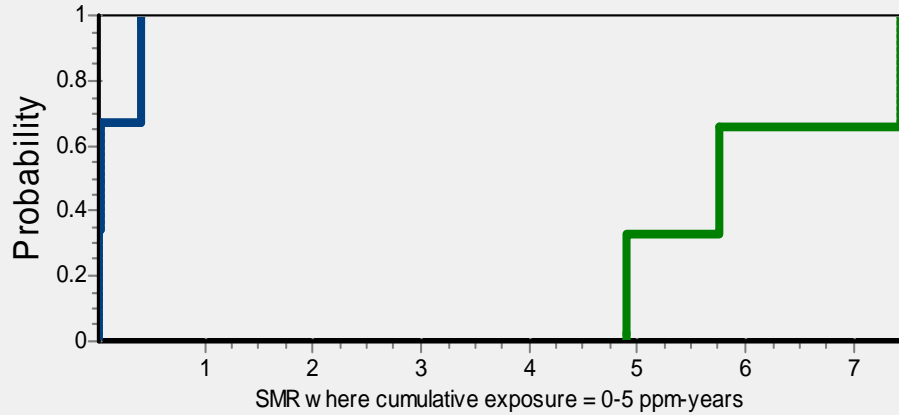
Exposure estimates	Cumulative exposure, ppm-years	Person-years	Observed	Expected	SMR <sup>b</sup>	95% CI
Rinsky	0-5	18,178	3	1.52	1.97	0.41-5.76
	>5-50	13,456	3	1.31	2.29	0.47-6.69
	>50-500	8,383	7	1.01	6.93**	2.78-14.28
	>500	328	1	0.05	20.00	0.51-111.4
Crump	0-5	12,974	1	1.14	0.88	0.02-4.89
	>5-50	13,951	4	1.23	3.25	0.88-8.33
	>50-500	11,448	6	1.23	4.87*	1.79-10.63
	>500	1,972	3	0.29	10.34**	2.13-30.21
Paustenbach	0-5	9,645	1	0.75	1.33	0.03-7.43
	>5-50	12,882	2	1.12	1.79	0.22-6.45
	>50-500	14,095	4	1.43	2.80	0.76-7.16
	>500	3,723	7	0.59	11.86**	4.76-24.44

<sup>a</sup>White male wetside workers. <sup>b</sup>p-Value by two-sided Poisson test: \*  $p < 0.05$ ; \*\*  $p < 0.01$ .

## Leukemia Risk Associated with Benzene Exposure in the Pliofilm Cohort

Mary Burr Paxton

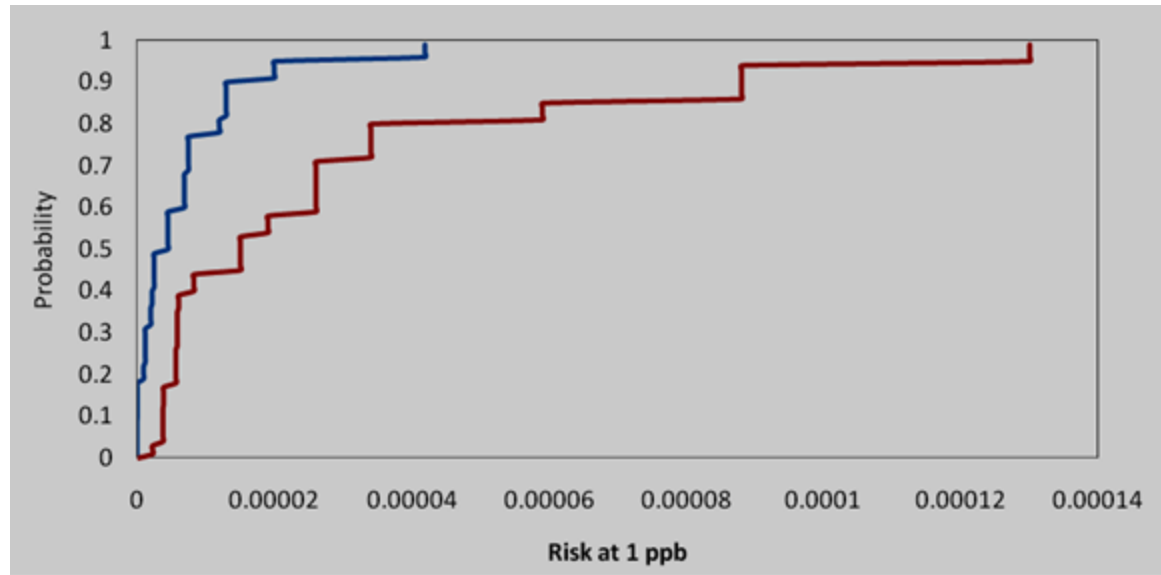
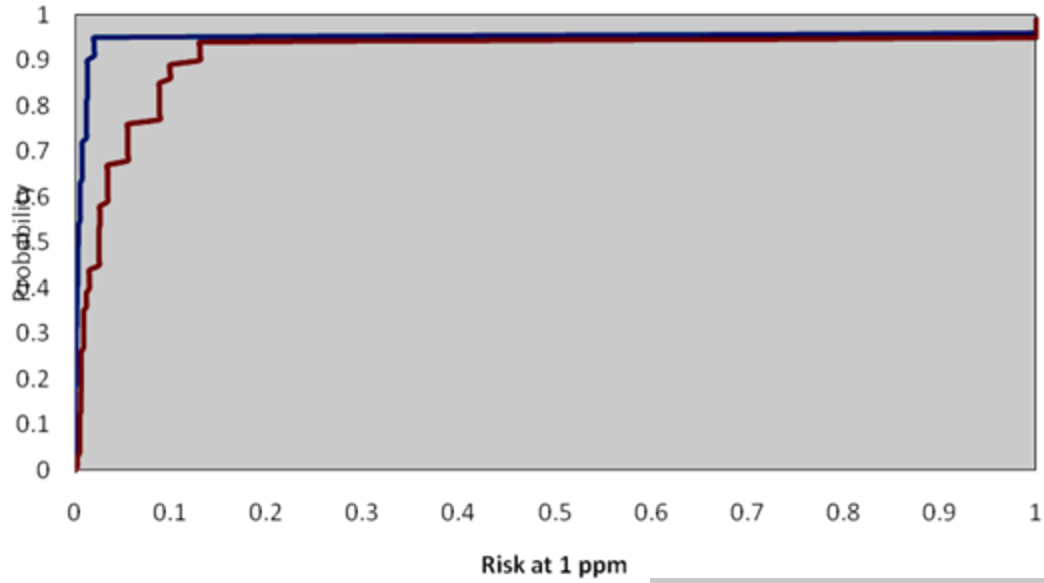
# Benzene Example



# Benzene Example

Source	Risk at 1 ppm	Risk at 1 ppb	Reference & model
US EPA (1985)	0.018 (7.5E-3, 3.4E-2)	0.000018 (7.5E-6, 3.4E-5)	Crump and Allen, additive risk
	0.041 (1.3E-2, 8.8E-2)	0.000041 (1.3E-5, 8.8E-5)	Crump and Allen, relative risk
Brett <i>et al.</i> (1989)	4.0E-3 (1.0E-3, 1.2E-2) to 2.5E-2 (2.5E-3, 9.9E-2)	3.6E-6 (9.5E-7, 6.9E-6) to 1.1E-5 (2.2E-6, 1.9E-5)	Crump and Allen, conditional logistic
	2.2E-1 (1.2E-2, 1.0) to 8.4E-1 (1.5E-2, 1.0)	2.4E-5 (6.9E-6, 4.2E-5) to 3.4E-5 (8.2E-6, 5.9E-5)	Rinsky, conditional logistic
Paxton (1992)	0.0022 (3.8E-5, 4.9E-3)	0.0000019 (3.7E-8, 3.7E-6)	Crump and Allen, proportional hazard
	0.0046 (1.3E-3, 9.0E-3)	0.0000035 (1.2E-6, 5.8E-6)	Paustenbach, proportional hazard
	0.018 (3.0E-3, 5.5E-2)	0.0000089 (2.5E-6, 1.5E-5)	Rinsky, proportional hazard
Crump (1992; 1994)	1.1E-2 (2.2E-3, 2.0E-2) to 2.5E-2 (6.0E-3, 1.3E-1)	1.1E-5 (2.2E-6, 2.0E-5) to 2.5E-5 (6.0E-6, 1.3E-4)	Crump and Allen, linear
	5.4E-3 to 2.5E-2	4.5E-6 to 2.6E-5	Crump and Allen, nonlinear
	7.1E-3 (2.0E-3, 1.2E-2) to 1.5E-2 (3.8E-3, 2.6E-2)	7.2E-6 (2.0E-6, 1.2E-5) to 1.6E-5 (3.8E-6, 2.6E-5)	Paustenbach, linear
	8.6E-5 to 6.5E-3	8.6E-11 to 5.6E-6	Paustenbach, nonlinear

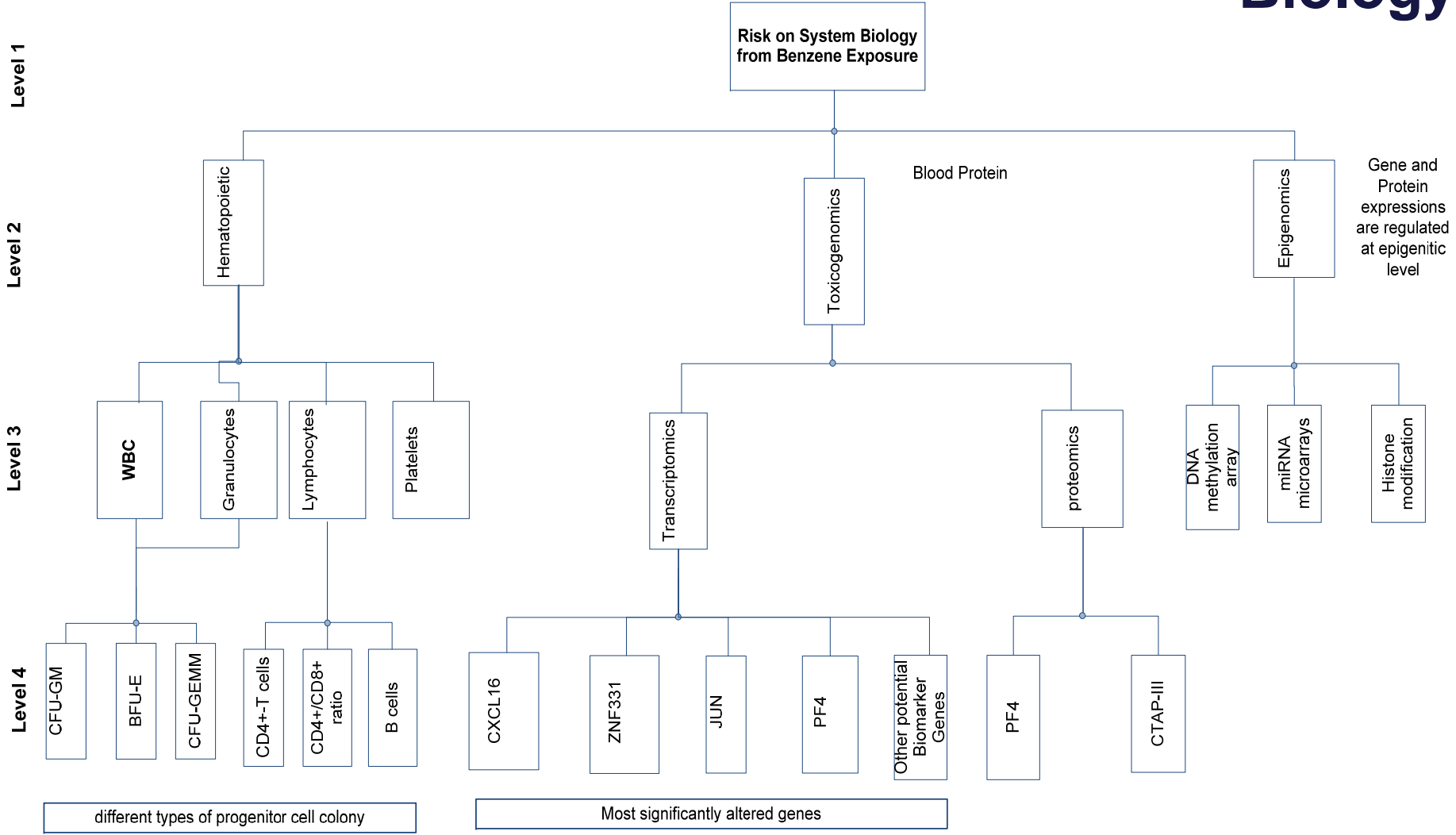
# Benzene Example



# Benzene: System Biology

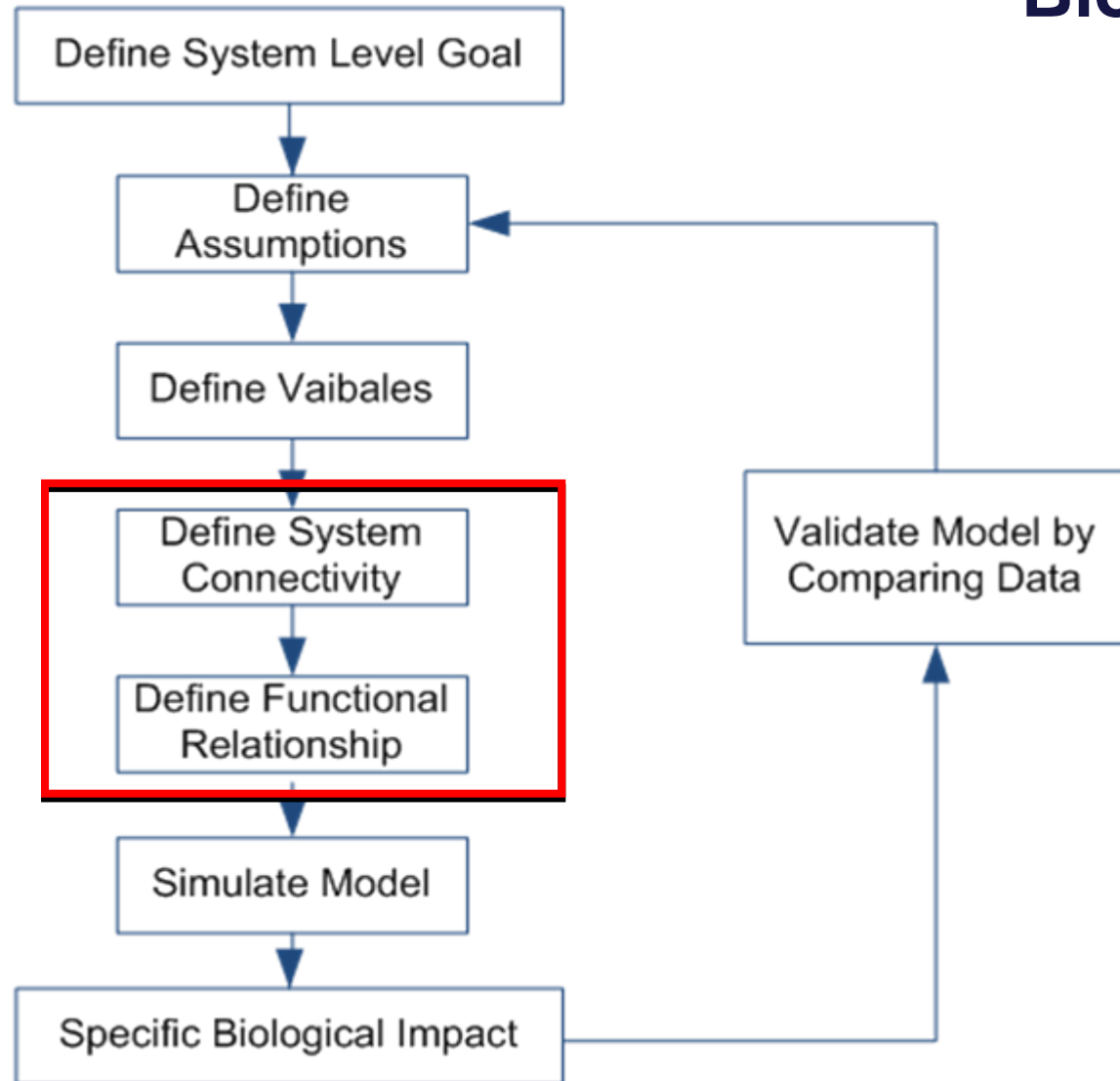
- Comparative Toxicogenomics Database
- 400 interacting genes - at least a dozen highly interacting genes
- Six most altered genes (based on Benzene (gene-cell-tissue-disease) Problem Formulation (with a disease focus – Leukaemia))
- Literature Extraction Process – 115 peer reviewed publications
- Overall objective: Probability of failure of biological systems identified in the Benzene System Biology flowchart (Overall impacts to Hematopoietic components).

# Benzene: System Biology



# Benzene: System Biology

## Mathematical Modelling of a Biological System



# Benzene: System Biology challenges

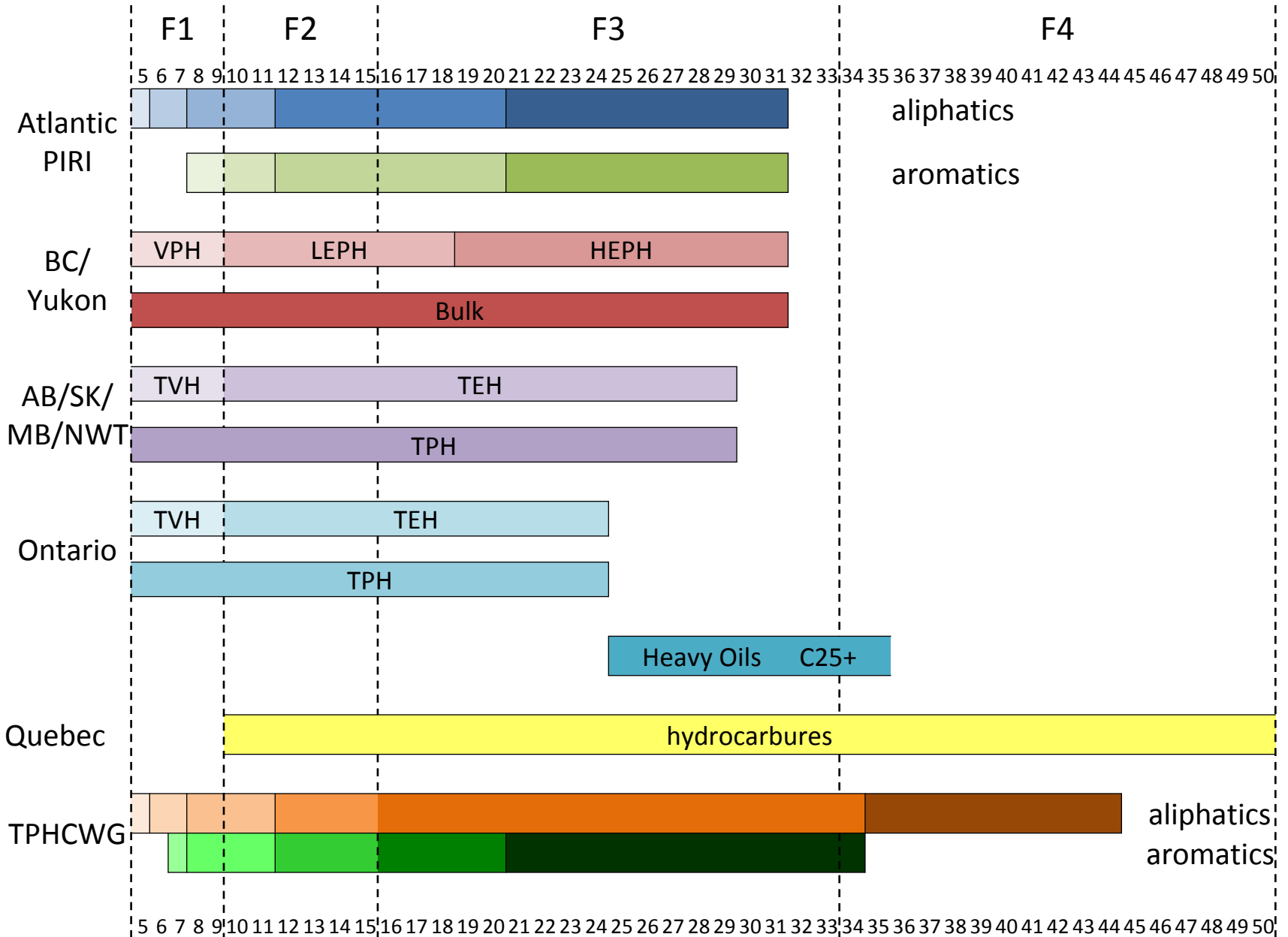
- Huge amount of sequence data
- Huge amount of genomics data
- Complex connectivity
- Understanding toxicological interactions
- Prediction of protein-coding genes
- Cell-cell interaction
- Cell-tissue-gene level interactions
- **Genome has a multi-dimensional structure**



# F1-Hydrocarbon Example

- F1 hydrocarbon mixture
  - **55% C6-C8 aliphatics**  
(n-hexane may vary between 3% to 12% or more?)
  - **36% C8-C10 aliphatics**
  - **9% C8-C10 aromatics**
- F1 PHC = [F1 –BTEX]
- n-hexane is used as a surrogate

# F1-Hydrocarbon Example



# F1-Hydrocarbon Example

Fraction	Equivalent Carbon #	Corresponding TPHCWG subfractions	TDI (mg/kg·d)	RfC (mg/m <sup>3</sup> )	Critical Effect used by TPHCWG to derive criteria
F1	C <sub>6</sub> to C <sub>10</sub>	aromatics C <sub>&gt;7</sub> -C <sub>8</sub>	- <sup>a</sup>	- <sup>a</sup>	- <sup>a</sup>
		C <sub>&gt;8</sub> -C <sub>10</sub>	0.04	0.2	hepatotoxicity, neurotoxicity
		aliphatics C <sub>6</sub> -C <sub>8</sub>	5.0	18.4	neurotoxicity
		C <sub>&gt;8</sub> -C <sub>10</sub>	0.1	1.0	Liver and blood changes
F2	C <sub>&gt;10</sub> to C <sub>16</sub>	aromatics C <sub>&gt;10</sub> -C <sub>12</sub>	0.04	0.2	decreased body weight
		C <sub>&gt;12</sub> -C <sub>16</sub>	0.04	0.2	decreased body weight
		aliphatics C <sub>&gt;10</sub> -C <sub>12</sub>	0.1	1.0	Liver and blood changes
		C <sub>&gt;12</sub> -C <sub>16</sub>	0.1	1.0	Liver and blood changes
		aliphatics C <sub>&gt;16</sub> -C <sub>21</sub>	0.03	NA <sup>b</sup>	nephrotoxicity
F3	C <sub>&gt;16</sub> to C <sub>34</sub>	aromatics C <sub>&gt;16</sub> -C <sub>21</sub>	0.03	NA <sup>b</sup>	nephrotoxicity
		C <sub>&gt;21</sub> -C <sub>34</sub>	0.1	1.0	hepatic granuloma
		aliphatics C <sub>&gt;16</sub> -C <sub>21</sub>	2.0	NA <sup>b</sup>	hepatic granuloma
		C <sub>&gt;21</sub> -C <sub>34</sub>	0.03	NA <sup>b</sup>	nephrotoxicity
F4	C <sub>&gt;34</sub> to C <sub>50</sub>	aromatics C <sub>&gt;34</sub>	20.0	NA <sup>b</sup>	hepatic granuloma
		aliphatics C <sub>&gt;34</sub>	<b>CCME (2008) &amp; Edwards (1997)</b>		

# F1-Hydrocarbon Example

## Review of neurotoxicity studies for F1

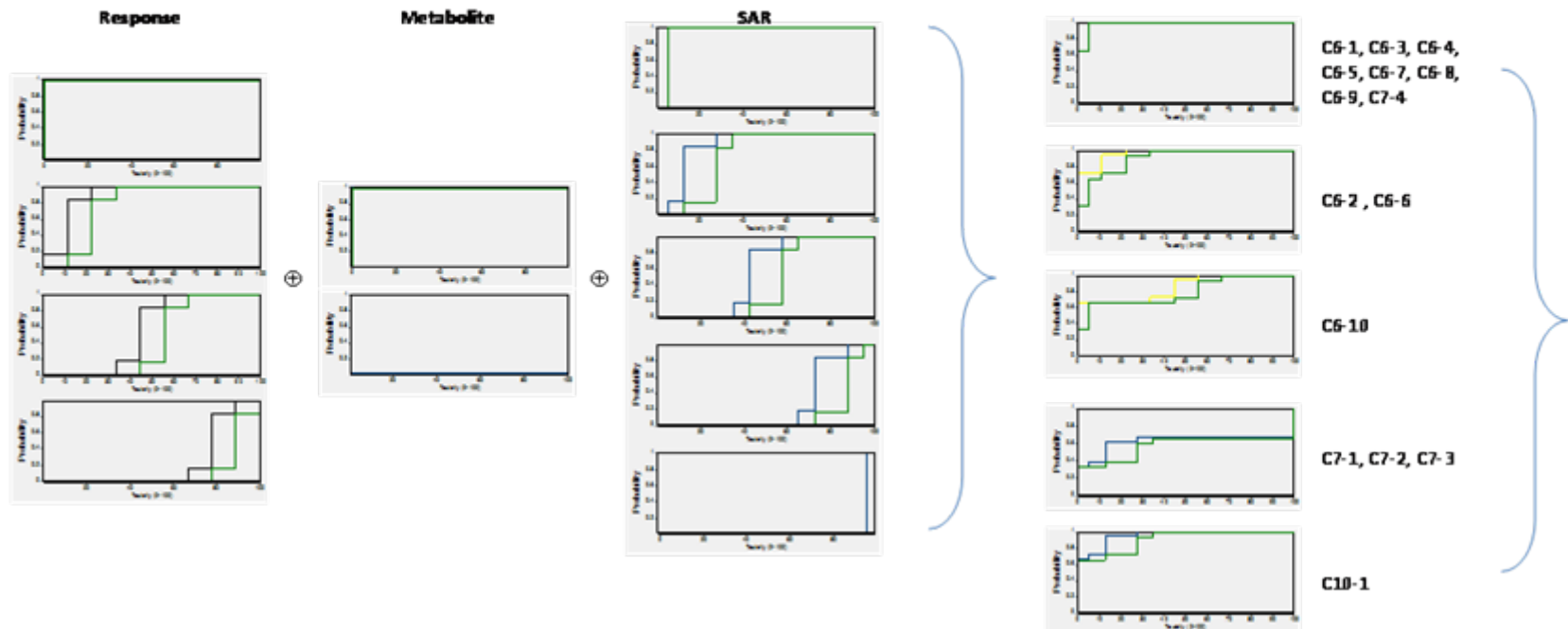
Compound	Author	Subjects	Duration	Delivery	Dose	Effects	Response	med
Heptane	(Takeuchi et al. 1981)	Rat		12h/d,7d/w, 16w		3000	no histopathological signs of neurotoxicity	no
	(Frontali et al. 1981)	Rat		9h/d,5d/w 30 wks		1500 ppm	no evidence of histopathological neurotoxicity	no
	(Bahima et al. 1984)	female rat		6h/d, 5d/w, 12 wks		2000 ppm	no clinical signs of neurotoxicity	no
2-methyl Hexane	(Perbellini et al. 1985; Sayre et al. 1986)	human/rat					neurotoxic metabolites detected	no
3-methyl hexane	(Valentini et al. 1994)	Human	8-10 hr		case study exposure	36ppm heptane 16ppm 3-methyl hexane	peripheral neuropathy, induced by MEK?	med*
Methyl cyclo hexane	(Parnell et al. 1988)	Rats	every second day for 14d		0.8g/kg by gavage		Histopathologic examination of the rat kidney slices indicated only very slight traces of nephropathy,	NA
C7 Mixtures	(MacEwen and Vernot 1985)	dogs, rats, mice, hamsters	.Year-long exposures			0, 400, 2000 ppm	mean body wt depression in hamsters and male rats. Only significant lesions noted was progressive renal nephropathy seen in virtually all of the male rats	NA

# F1-Hydrocarbon Example

Multi-study & multi-compound inference for F1 neuropathic toxicity using Dempster-Shafer mixture fusion (averaging)

① P-boxes for toxicity derived from 3 methods for different F1 compounds [45]

② Fused, single p-box for each study of different F1 compounds [15]



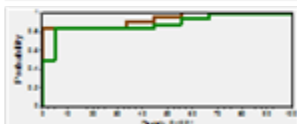
# F1-Hydrocarbon Example

③

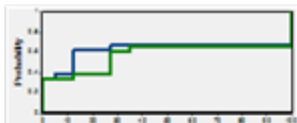
Fused p-boxes for 7 F1 compounds (various)



2-methylpentane,  
3-methylpentane



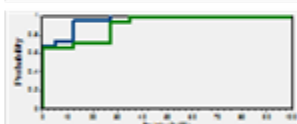
cyclohexane



heptane



2-methylhexane



n-decane



n-hexane

④

Assign weights as per 7-compound mass composition (percentage)

28.72%  
18.35%

6.19%

9.78%

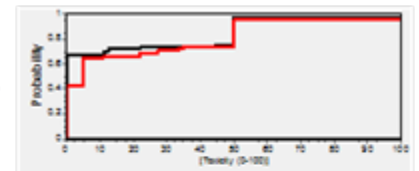
12.35%

2.23%

22.38%

⑤

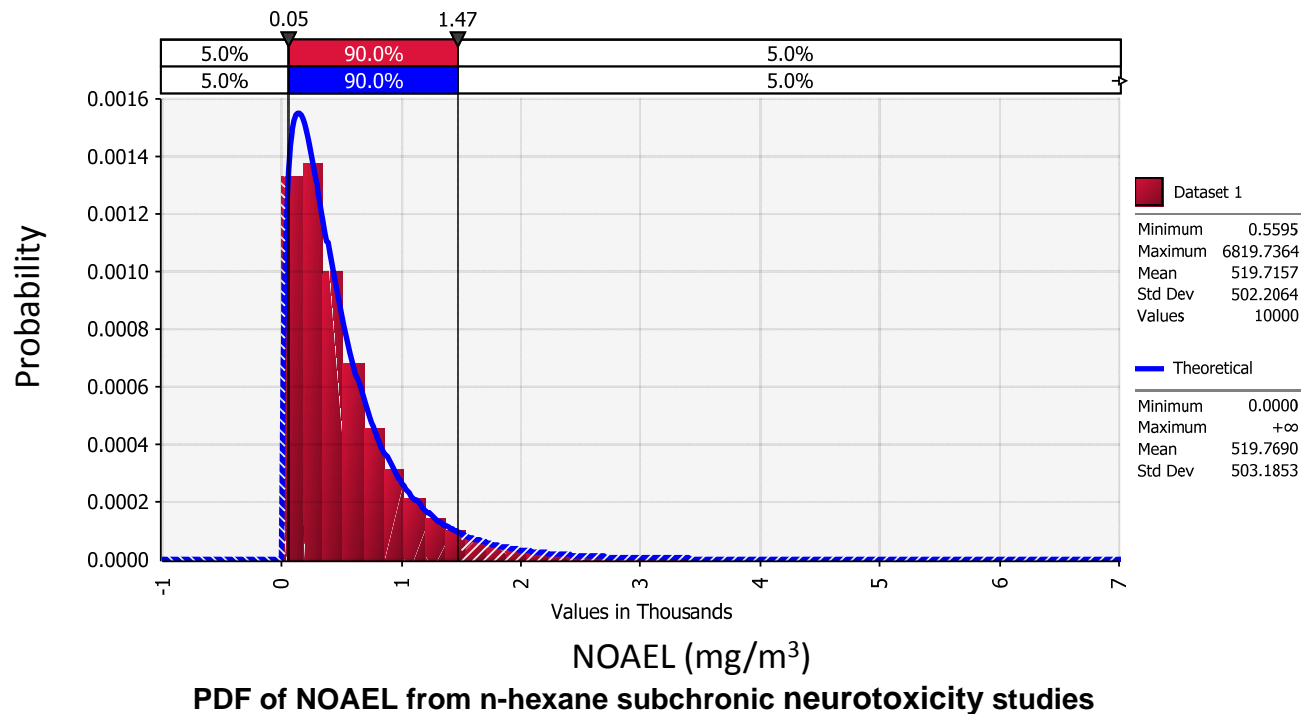
Fused p-box for F1



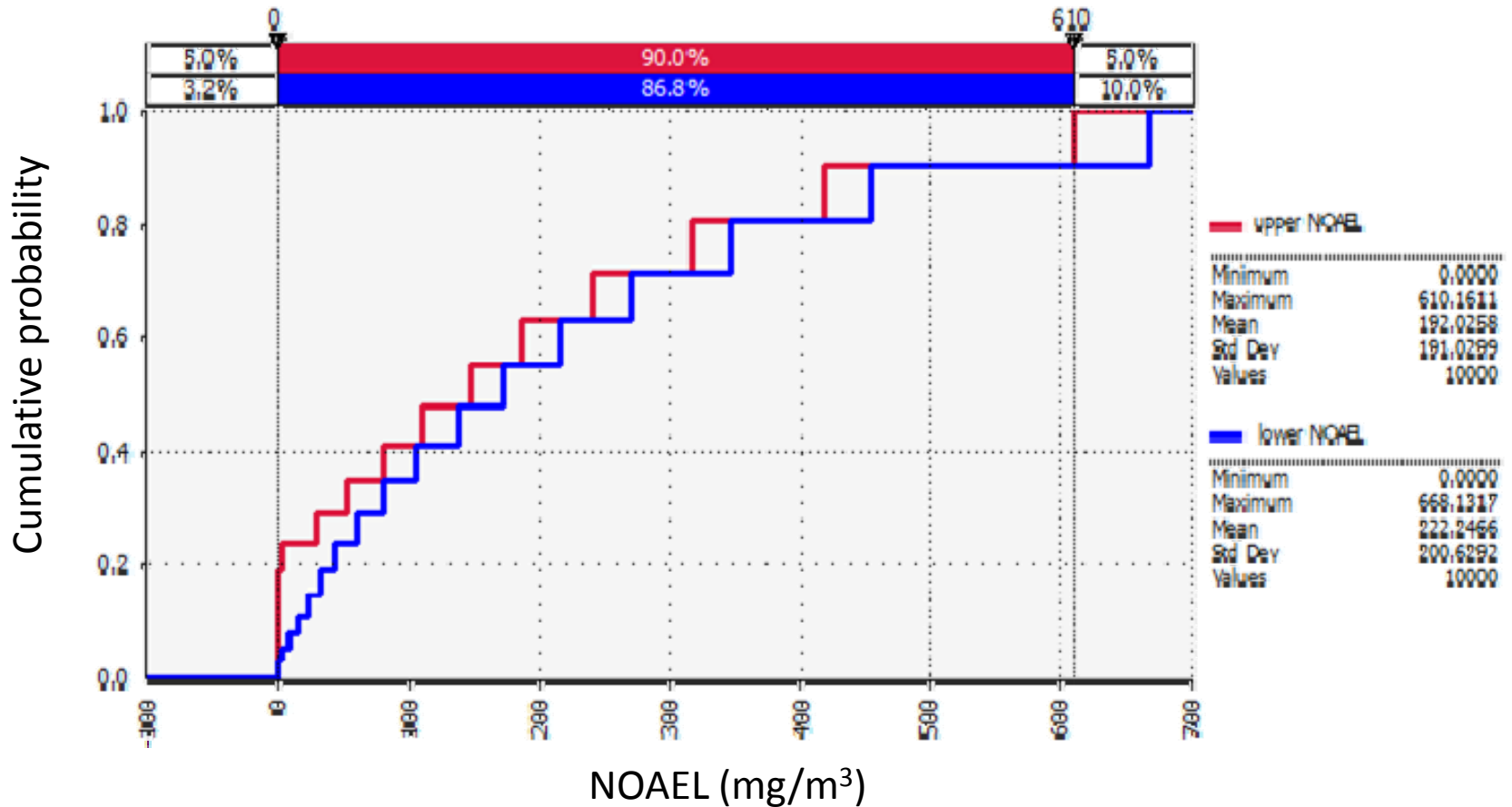
# F1-Hydrocarbon Example

Feature Level Data Fusion: Dose-Response assessment

The toxicity of each compound was applied to the probability density function of the NOAEL concentrations from studies on n-hexane, for which there was much more toxicity data.



# F1-Hydrocarbon Example



p-box for neurotoxicity NOAEL for all of F1



# F1-Hydrocarbon Example

## Decision Level Data Fusion: Risk Characterization

The NOAEL from the dose-response assessment applies for rats in a sub-chronic study. Where NOAEL values were not available, the LOAEL values were divided by an uncertainty factor of 10. Other uncertainty factors that can be applied include:

- 10 for inter-species differences
- 10 for intra-species differences
- 3 for deficiencies in the data set.

No uncertainty factor is being used for the severity of toxic effects: a factor was included in calculating the combined NOAEL for F1.

## Alternative Endpoints

Whether Current Inhalation Reference Concentrations are protective against irritancy for C<sub>6</sub>-C<sub>8</sub> aliphatics?

Is this the most sensitive end point? Other health effect endpoints are being evaluated

Limited preliminary analysis of system biology datasets

# Paradox of Risk Management

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“You always got to be prepared, but you never know for what”

*“Sugar Baby” Bob Dylan*