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# Modeling Joint Effects of Mixtures of Chemicals on Microorganisms Using Quantitative Structure Activity Relationships

Grant Nº AFOSR-91-0394

Interim Progress Report Phase I September 1991- August 1992

By N. Nirmalakhandan M. Mohsin, V. Arulgnanendran S Bangxin, and F. Cadena



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# Toxicity of Mixtures of Organic Contaminants to Microorganisms - Phase I: Study Using Polytox Cultures-

# N. N. Khandan', M. Moshin<sup>2</sup>, V. Arulgnanendran<sup>2</sup>, S. Bangxin<sup>2</sup> and, F. Cadena<sup>a</sup>.

## Abstract

Toxicity of 50 organic chemicals to microorganisms was determined using the respirometeric approach. Using this experimental database, models for predicting toxicity ( $IC_{50}$  values) were developed using QSAR techniques. Toxicity measurements were also made for ten binary mixtures, and sixteen multi-component mixtures. The joint effects of organic chemicals in mixtures were analyzed by three different approaches. Using the QSAR model developed from single chemical studies, an approach was developed to analyze and predict joint effects of chemicals in mixtures. The results of this study indicate that the joint effects could be considered simply additive for the different classes of chemicals tested.

### Introduction

Acute and chronic toxicity testing is a major component in the NPDES permitting process. The concept of whole effluent toxicity testing has been introduced into this program due to the realization that a mixture of several chemicals may exhibit greater toxicity than they would individually. While current Water Quality Standards are based on single chemical toxicity assays, in future, controls may be set based on the joint effects of mixtures of two or more chemicals. Non-point sources, industrial effluents, leachates and contaminated groundwaters are all known to contain several chemicals in mixtures. Thus an ability to analyze and predict joint effects of mixtures of chemicals on microorganisms and other aquatic life forms will be of considerable benefit in managing the environmental hazards of synthetic chemicals.

Several ecological researchers, notably from Europe, have studied the effects of mixtures of chemicals on fish (Ref 1 - 20). Hardly any studies have been reported on the joint effects of several chemicals on microorganisms. As microorganisms are employed in municipal waste treatment by environmental engineers, and are also present in the natural environment, it would be of interest to be able predict such effects on microorganisms. A study is underway in our laboratories to determine and predict joint effects of binary and multiple chemical mixtures on three classes of organisms of interest to environmental engineers. This interim report covers the results of the Phase I study during the first year.

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## Objectives of Phase I Study

The ultimate objective of this 3-year research is to develop an approach to predict the joint toxic effects of mixtures of organic chemicals to microorganisms. Towards this end, the following tasks were identified for the first year:

- a) measure single chemical toxicity to a surrogate culture of microorganisms;
- b) develop a QSAR model to predict single chemical toxicity to the surrogate organisms;
- c) measure and analyze toxicity of binary mixtures to surrogate organisms and verify simple additivity;
- d) measure and analyze toxicity of multi-component mixtures to surrogate organisms and verify simple additivity;
- e) develop an approach to predict joint effects of mixtures of organic chemicals to the surrogate culture based purely on the molecular structures of the components of the mixtures.

Work during the second and third years will focus on the effects of mixtures on activated sludge and anaerobic cultures with a view to predict joint effects on them using molecular structures of the components and the surrogate culture results.

Several techniques and approaches in toxicity modeling reported in the literature as individual studies are integrated in this study. Some of the features of this study are use of a 20-reactor, computer integrated respirometer for toxicity determination; use of the probit transformation method to determine  $IC_{50}$ ; and use of QSAR approach to predict joint effects of binary mixtures and multi-component mixtures.

This interim report covers the work done in Phase I during the first year. Results reported below include:

- a) developing an experimental procedure for IC<sub>50</sub> determination using the respirometeric approach;
- b) evaluation of the use of Polytox (polbac Corp.) cultures as surrogate microorganisms in rapid toxicity determination;
- c) development of QSAR model for single chemical toxicity;
- d) testing the hypothesis that joint effects of the chosen chemicals are simply additive in binary and multi-component mixtures;
- e) establishment of a methodology to analyze joint effects in binary mixtures and multi-component mixtures;
- f) development and validation of a QSAR-based approach to predict the concentrations of the components in mixture that would cause 50% inhibition.

#### Experimental Approach

All tests were conducted using research grade chemicals as supplied by the manufacturers without any further purification. The toxicity tests were run on a 20-reactor computer interfaced N-Con Respirometer Model as detailed in Appendix I. The test procedure is detailed in Appendix II. The percent inhibition caused by a toxicant at a given concentration was determined by comparing the oxygen uptake rate of a toxicant-free control reactor against the rates of eight other reactors spiked with different concentrations of the toxicant. This rate was in turn obtained from the slopes of the linear portion of the oxygen uptake curves generated by the respirometer for each reactor. The % inhibition values were then transformed to probit values were then determined [IC<sub>50</sub> is the concentration of the toxicant at which a 50% inhibition is caused]. The above procedure is illustrated schematically in Fig 1.



Figure 1. Schematic Illustration of Procedure to Find IC<sub>50</sub>

In the single chemical studies, 50 chemicals belonging to several different congeneric classes with a diversity of molecular structures were chosen for testing. These chemicals spanned a wide range of aqueous solubility, Henry's Constant and octanol-water partition coefficient. Such a variety of chemicals would enhance the robustness and the utility of the QSAR models.

In the binary mixture tests, n-octanol was chosen as one of the toxicants and the following chemicals as the second component: chlorobenzene, 2,4 dimethyl phenol, 1,1,1 trichloroethane, cyclohexane, n-butyl amine, n-amyl acetate, ethanol, chlorodibromomethane, cyclohexanone and ethanolamine. For each combination of the two components, a matrix of four octanol concentrations by four second contaminant concentrations was assayed. The four test concentrations were chosen as 0.4, 0.6, 0.8 and 0.9 of the individual IC<sub>50</sub> concentrations.

In the multi-component mixture tests, ten mixtures each containing 10 different chemicals mixed in equitoxic proportions were assayed. For each mixture, one control reactor and six spiked reactors were run. The six reactors received 0.04, 0.06, 0.08, 0.1, 0.12 and 0.14 Toxic Units of each of the ten components. Additional six testing mixtures, each containing 8 different chemicals, were also assayed. In this case, the six spiked reactors received 0.05, 0.075, 0.1, 0.125, 0.150 and 0.175 Toxic Units of each of the components.

### **Modeling Approach**

The single chemical toxicity results from the 50 chemicals were used to develop a QSAR model. Molecular connectivity indexes were calculated for the 50 chemicals following the algorithms developed by Kier and Hall and modified by Nirmalakhandan (1988). Simple and multiple step-wise regression analysis procedures were used to derive the QSAR model with  $IC_{50}$  values as the dependent variable. The  $IC_{50}$  values calculated from the QSAR models were then compared with the experimentally measured values.

In the binary mixture studies, isobolograms were first constructed to test the hypothesis that the joint effects were according to the simple additivity model. Then, the QSAR models developed from single chemical was used to predict the joint toxicity caused by the second chemical in the presence of n-octanol. The predicted values were compared with the experimental results.

In the multi-component mixture studies, the joint effects were analyzed using three concepts: Toxic Unit, Additivity Index, and Mixture Toxicity Index. The validity of these concepts was further verified using the results of the 8-component testing set. Finally, the QSAR models developed from single chemical tests were used to predict the concentrations of the components in the 8-component mixture that would cause 50% inhibition. These predicted concentrations were then compared with the experimentally measured concentrations.

## **Results and Discussion**

a) Single chemical results-

The 50 chemicals used in this study are listed in Table I. This Table also contains the respective  $IC_{50}$  values and the corresponding  $r^2$  found from the probit vs. concentration plots from which the  $IC_{50}$  values were determined. These  $r^2$  values range from 0.7 to 0.98, indicating a reasonably good database. The distribution of  $r^2$  is shown in Fig 2. On preliminary evaluation, the following four chemicals were found to be "outliers": 1,4 dichlorobenzene, 1,2 dichloroethylene, triethanolamine and bromodichloromethane. At this point, no explanation could be postulated for the outlying tendency of these chemicals. Other researchers have found similar peculiarities too. These chemicals were therefore excluded from the analysis and the remaining 46 were used in the QSAR model development.

The first order molecular connectivity index,  ${}^{1}\chi^{v}$ , was found to fit the individual IC<sub>50</sub> values (in mM/L) for the alkanes, aromatic compounds, alcohols, esters, ketones, amines:

Alcohols, ketones and esters:

$$\begin{split} &\log |C_{50} = 3.690 - 0.896\ {}^1\chi^{v} \\ &n = 14; \ r = 0.954; \ r^2 = 0.910; \ \text{RMS residual} = 0.246. \\ &\text{Alkanes:} \\ &\log |C_{50} = 1.851 - 0.765\ {}^1\chi^{v} \\ &n = 5; \ r = 0.999; \ r^2 = 0.999; \ \text{RMS residual} = 0.018. \\ &\text{Amines and acids:} \\ &\log |C_{50} = 1.045 - 0.470\ {}^1\chi^{v} \\ &n = 6; \ r = 0.957; \ r^2 = 0.915; \ \text{RMS residual} = 0.101. \\ &\text{Aromatics:} \\ &\log |C_{50} = 3.258 - 1.133\ {}^1\chi^{v} \\ &n = 9; \ r = 0.852; \ r^2 = 0.726; \ \text{RMS residual} = 0.311. \end{split}$$

In the case of halogenated aliphatics, the zero order molecular connectivity index,  ${}^{0}\chi^{v}$ , fitted the data set more closely:

Halogenated aliphatics: log IC<sub>50</sub> = 2.670 - 0.448  ${}^{0}\chi^{v}$ n = 12; r = 0.942; r<sup>2</sup> = 0.887; RMS residual = 0.141.

ĪD	Chemical	Туре	IC50	r^2	Log IC50 [mM/L]		WL]
#			[mg/L]	-	Exp.	Calc.	Error
1.	Benzene	ARO	685	0.898	0.94	0.99	-0.05
2.	Toluene	ARO	207	0.870	0.35	0.53	-0.18
3.	Xylene	ARO	140	0.851	0.12	0.06	0.06
4.	Ethylbenzene	ARO	220	0.950	0.32	-0.11	0.43 **
5.	Chlorobenzene	ARO	350	0.966	0.50	0.46	0.04
6.	1,2 Dichlorobenzene	ARO	135	0.939	-0.04	-0.10	0.06
7.	1,3 Dichlorobenzene	ARO	40	0.903	-0.57	-0.09	-0.48 **
8.	1,4 Dichlorobenzene	ARO	6	0.908	-1.39		?
9.	1,2,4 Trichlorobenzene	ARO	23	0.810	-0.90	-0.63	-0.27 *
10.	2,4 Dimethyl phenol	ARO	240	0.953	0.29	-0.10	0.39 **
11.	Methylene chloride	HAL	1,750	0.845	1.31	1.34	-0.03
12.	Dibromomethane	HAL	1,110	0.848	0.81	0.60	0.21 *
13.	Carbon tetrachloride	HAL	325	0.701	0.32	0.42	-0.09
14.	1,2 Dichloroethane	HAL	685	0.979	0.84	1.02	-0.18
15.	1,1,1 Trichloroethane	HAL	415	0.850	0.49	0.48	0.02
16.	1,1,2,2 Tetrachloroethane	HAL	180	0.949	0.03	0.13	-0.10
17.	1,2 Dichloropropane	HAL	500	0.954	0.65	0.63	0.01
18.	Bromochloromethane	HAL	1,800	0.948	1.15	0.97	0.18
19.	Bromodichloromethane	HAL	90	0.916	-0.26		?
20.	Chlorodibromomethane	HAL	425	0.959	0.31	0.15	0.17
21.	Ethylene dibromide	HAL	520	0.939	0.45	0.37	0.08
22.	1,2 Dichloroethylene	HAL	350	0.783	0.56		?
23.	Trichloroethylene	HAL	500	0.979	0.58	0.67	-0.09
24.	Tetrachloroethylene	HAL	175	0.923	0.02	0.19	-0.17
25.	Cyclohexane	ALK	74	0.964	-0.06	-0.06	0.01
26.	Pentane	ALK	70	0.793	-0.01	0.01	-0.02
27.	Hexane	ALK	38	0.751	-0.36	-0.38	0.02 ·
28.	Heptane	ALK	18	0.739	-0.75	-0.76	0.01
29.	Octane	ALK	8	0.857	-1.15	-1.14	-0.01
30.	Bis (2-chloroethyl) ether	AKE	1,600	0.886	1.05	0.84	0.21 *
31.	Ethanol	AKE	40,000	0.964	2.94	2.79	0.15
32.	Propanol	AKE	7,200	0.942	2.08	2.33	-0.25 *
33.	Pentanol	AKE	2,325	0.821	1.42	1.41	0.01
34.	Octanol	AKE	126	0.968	-0.01	0.04	-0.05
<u>35.</u>	n-Butyl acetate	AKE	3,750	0.923	1.51	1.07	0.44 **

Table I. Chemicals Assayed and Single Chemical Results

Code for type: ARO- aromatics; HAL- halogenated aliphatics; ALK- alkanes; AKE- alcohols,ketones and esters; AMI- amines. Note: \* error >1 std. dev.; \*\* error > 2 std. dev.; ? excluded from analysis.

Table I (contd.)

ID Chemical	Гуре	IC50	r^2 _	Log	IC50 [mN	1/L]
#		[mg/L]		Exp.	Calc.	Error
36. Isobutyl acetate	AKE	1,600	0.955	1.14	1.20	-0.06
37. n-Amyl acetate	AKE	440	0.980	0.53	0.61	-0.08
38. Ethyl acetate	AKE	5,400	0.916	1.79	1.98	-0.19
39. Acetone	AKE	48,000	0.864	2.92	2.62	0.30 *
40. Methyl ethyl ketone	AKE	1,900	0.885	1.41	1.90	-0.49 **
41. Methyl isobutyl ketone	AKE	2,600	0.905	1.42	1.32	0.09
42. Methyl n-propyl ketone	AKE	4,500	0.883	1.72	1.65	0.07
43. Cyclohexanone	AKE	3,750	0.964	1.58	1.51	0.07
44. n-Butyl amine	AMI	90	0.952	0.09	0.05	0.04
45. t-Butyl amine	AMI	85	0.919	0.07	0.21	-0.14
46. Diethylamine	AMI	104	0.769	0.15	0.05	0.11
47. Acetic acid	AMI	287	0.744	0.68	0.61	0.07
48. Cyclohexylamine	AMI	60	0.885	-0.22	-0.20	-0.02
49. Ethanolamine	AMI	160	0.955	0.42	0.47	-0.05
50. Triethanolamine	AMI	900	0.829	0.78		?
Average	Э		0.893			

Code for type: ARO- aromatics; HAL- halogenated aliphatics; ALK- alkanes; AKE- alcohols,ketones and esters; AMI- amines. Note: \* error >1 std. dev.; \*\* error > 2 std. dev.; ? excluded from analysis.





Detailed statistical parameters of these equations are included in Appendix III. These models explain about 90% of the variance in the experimental data for alcohols, ketones, esters, alkanes, amines and aromatics and over 70% in the case of the halogenated aliphatics. The average RMS residuals of 0.163 suggests that these equations can predict  $IC_{50}$  within a factor of 1.5. Except in the case of the aromatic compounds, this degree of precision is comparable to the uncertainty of the experimental  $IC_{50}$  values. The  $IC_{50}$  values calculated by these equations are tabulated in Table I and compared against the respective experimental values in Fig 3, from which the overall quality of the agreement between the two can be seen to be comparable to the experimental uncertainty in the  $IC_{50}$  values, with  $r^2 = 0.954$ . The distribution of the predictive error is shown in Fig 2.



Figure 3. Comparison Between Experimental and Calculated log IC<sub>50</sub> Values [mM/L].

b) Binary mixture results-

The isobologram developed from the experimental  $IC_{50}$  of the binary mixtures is shown in Fig 4. The experimental data points for the six toxicants falling on or around the diagonal confirms the hypothesis of simple additivity. Additional tests are being done now to check these results and include more chemicals.



Figure 4. Isobologram- Octanol vs. Six Other Chemicals

c) Multi-component mixture results-

The results of the multi-component tests are presented in graphical form in Appendix IV-a for the 10-component mixtures and in Appendix IV-b for the 8-component mixtures. The  $r^2$  in these plots range from 0.860 to 0.995, indicating a satisfactory database. The IC<sub>50</sub> values obtained from these plots were used to analyze the joint effects by the Toxic Units, Additivity Index and Mixture Toxicity Index concepts as summarized in Table III.

Mixture	Mixture Chemicals in Mixture			Joint Effects Analyzed by			
N⁰	ID # of components	Total	Toxic Units	Additivity Index	Toxicity Index		
		n_	$M = \Sigma TU$	<u>Al = M - 1</u>	MTI = 1 - logM/logn		
10C-1	4,5,10,36,32,33,12,18,1,2	10	1.10	0.10	0.96		
10C-2	4,5,10,36,32,33,12,18,22,23	10	1.00	0.00	1.00		
10C-3	40,41,35,36,32,33,4,5,10,17	10	1.14	0.14	0.94		
10C-4	40,41,35,36,32,33,4,5,10,2	10	1.05	0.05	0.98		
10C-5	40,41,35,36,32,33,31,43,34,17	10	1.31	0.31	0.88		
10C-6	40,41,35,36,31,43,12,18,1,2	10	1.10	0.10	0.96		
10C-7	40,41,43,31,32,33,12,18,22,23	10	1.15	0.15	0.94		
10C-8	40,41,35,36,4,5,17,43,34,17	10	0.90	-0.10	1.05		
10C-9	40,41,35,36,4,5,17,18,1,2	10	0.90	-0.10	1.05		
10C-10	40,41,43,4,5,17,12,18,22,23	10	0.90	-0.10	1.05		
8C-1	40,41,35,36,32,33,12,30	8	1.19	0.19	0.92		
8C-2	40,41,35,36,12,18,1,2	8	1.02	0.02	0.99		
8C-3	40,41,35,36,32,33,22,23	8	1.07	0.07	0.97		
8C-4	4,36,32,33,12,18,34,17	8	1.02	0.02	0.99		
8C-5	4,10,36,32,33,18,22,23	8	0.92	-0.08	1.04		
8C-6	40,35,21,15,4,5,10,2	8	0.93	-0.07	1.03		
	Average 1.04 0.04 0.98						

Table III. Analysis of Joint Effects of Multi-component Mixtures

Note: ID # refer to chemicals listed in Table I; Simple additivity implied by M = 1, AI = 0 and MTI = 1.

The results of these analyses presented in Table III support the hypothesis of simple additivity for the chemicals assayed, with average values of  $\Sigma TU = 1.04\pm0.12$ , AI = 0.04±0.12, and MTI = 0.98±0.05.

The results from the 8-component multi-mixture studies were used to test the hypothesis that the concentrations of the components of a mixture causing 50% inhibition could be predicted from single chemical results. Two different approaches were used to predict the concentrations of the components at which 50% inhibition would be caused:

- in one approach, perfect simple additivity (i.e  $\Sigma TU = 1.0$ ) was assumed and the corresponding concentrations of the components in the mixtures were determined from *experimentally measured single chemical IC*<sub>50</sub> values.
- in the second approach, perfect simple additivity (i.e  $\Sigma TU = 1.0$ )was assumed and the corresponding concentrations of the components in the mixtures were determined from *QSAR models for single chemical IC*<sub>50</sub> values.

Results of these calculations and comparisons are presented in detail in Appendix V. The concentrations predicted by these two approaches are compared against the actual experimental concentrations in Fig 5 for the 48 sets of data points for each approach (six different mixtures, each containing 8 components). The concentrations calculated by the first approach is in near perfect agreement ( $r^2 = 0.995$ ) with the experimentally measured concentrations. This confirms that the joint action is according to simple additivity mechanism for the components tested.

In the second approach, the agreement appears to be "poor" ( $r^2$ = 0.799). This deviation stems mainly from the inadequacy of the QSAR models and partly from the slight deviation from simple additivity. In addition, two of these mixtures, Mixture N<sup>o</sup> 3 and 5, contain 1,2 dichloroethylene which was found to be an "outlier" in the single chemical studies and excluded in the QSAR model development. Thus the single chemical IC<sub>50</sub> predicted by the QSAR model for this chemical results in a higher error.

Nevertheless, it must be appreciated that the second approach does not require any experimental inputs whatsoever and the predictive errors are within a factor of 3, and the predictions are practically of the same order of magnitude as the experimental values, in the span of 2 log units of  $IC_{50}$  concentrations. This degree of precision is comparable to the work reported in the literature for single chemical studies, and can be considered sufficiently adequate for predicting toxicity of multi-component mixtures.



Figure 5. Comparison Between Experimental and Predicted Concentrations

#### Conclusions

The respirometeric technique for determining toxicity data has been demonstrated to be an efficient and reliable one. Joint effects of the range of chemicals assayed can be adequately quantified by the simple additivty concept using toxic units. The results of the above studies show clearly that QSAR approaches can be used to predict joint toxic effects of multiple chemicals on microorganisms. The quality of the predictions by the QSAR models for the range of chemicals tested in this study are comparable to the experimental uncertainty in the IC<sub>50</sub> data.

Additional chemicals belonging to a wider range of molecular structures need to be assayed and used for checking the validity and utility value of these models. In addition, similar studies on activated sludge and anaerobic cultures need to be done to establish correlation between the Polytox surrogate cultures so that far reaching predictions can be made to maximize the benefits of this research.

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### Bibliography

- 1. Abernathy et al (1986); Aquatic Toxic, 8, 163-172.
- 2 Anderson P D and Webber L J (1975); Proc. Int Conf. on Heavy Metals, Ontario, Canada.
- 3. Ashford J R (1958); *Biometrika*; 45, 74-88.
- 4. Ashford J R and Smith C S (1964); Biometrika; 51, 413-428.
- 5. Ashford J R and Smith C S (1965); *Biometrics*; 21, 182-189.
- 6 Hall, L H and Kier, B K (1984); Bull. Environ. Contam. Toxicol., 32, 354-362.
- 7. Hermens et al (1985); Aquatic Toxicology, 6, 209-217.
- 8. Hermens et al (1985); Ecotoxicology and Env Safety; 9, 17-25.
- 9. Hermens et al (1985); Env Toxicology and Chem.; 4, 273-279.
- 10. Konemann H (1981); *Toxicology*; 19, 209-221.
- 11. Konemann H (1981); Toxicology, 19, 223-228.
- 12. Konemann H (1981); Toxicology, 19, 229-238.
- 13. Marking L L (1977); ASTM STP Publication 634, 99-108.
- 14. Plackett R L and Hewlett P S (1948); Ann Appl. Biol.; 35, 347-358.
- 15. Plackett R L and Hewlett P S (1952); J. R. Statis. Sco.; B 14, 141-154.
- 16. Plackett R L and Hewlett P S (1963); Biometrics; 19, 517-531.
- 17. Plackett R L and Hewlett P S (1967); Biometrics; 23, 27-44.
- 18. Sprague J B (1964); J Fish Res Ca.; 21, 17-26.
- 19. Sprague J B and Ramsay, B A (1965); J. Fish. Res. Bd Can.; 22, 425-432.
- 20. Sprague J B (1970); Water Res; 4, 3-32.
- 21. Finney, D J; Probit Analysis, Cambridge University Press, 1964.
- 22. Nirmalakhandan N; PhD Dissertation, Drexel University, PA, 1988.

# Appendix I: Details of Respirometer System

The respirometer being used in our research was developed here at New Mexico State University, and is commercially marketed by N-CON Corporation, Inc., NY. The system has been recently modified in our laboratory to work either in the aerobic or anaerobic mode. The reactors in this system are maintained at constant temperature and pressure. Changes in headspace pressure, due to gas production (or consumption), are sensed by a pressure (or vacuum) switch and are converted to gas volume using Ideal Gas Laws, reactor volume, temperature and type of gas being exchanged, and, monitored on a real time basis. These volumes can then be easily related to biological activity in the reactor. A brief description of the system in the aerobic mode is as follows.

In this mode, the  $CO_2$  produced is absorbed by KOH pellets placed in the headspace. Thus, consumption of  $O_2$  results in a vacuum in the headspace. A vacuum switch has its vacuum side connected to the headspace. The pressure side of the switch is connected to a closed, constant pressure tank, thus providing a steady reference pressure, eliminating any fluctuations due to barometric/atmospheric variations. When the pressure differential across the switch exceeds 2.5 mm H<sub>2</sub>O, a signal is sent through the data acquisition system to the computer and, a precise pulse of oxygen from an oxygen cylinder is injected into the headspace. The computer keeps track of the number of pulses (or the amount) of oxygen supply as a function of time. From this data, oxygen utilization rate can then be established. A schematic arrangement of this system is shown below:



# Appendix II: Details of the Test Procedures

In this study, a commercial culture- Polytox, was used to determine  $IC_{50}$  values of 50 organic chemicals. One vial of 8 gr of Polytox freeze dried cultures was dispersed in 250 mL of buffered dilution water, prepared according to Standard Methods. This medium was mixed for 30 minutes and then allowed to settle for 5 minutes. The supernatant was then separated for placement in eight 123 mL-reactors. Each of the eight reactors was fed with 6 mL of the supernatant and topped with buffered dilution water to bring up the final volume to 60 mL. The control reactor was topped up to 62 mL. All the reactors were then capped with potassium hydroxide pellets in the holders attached to the caps.

The capped reactors were then placed in the respirometer water bath, and oxygen was supplied to each reactor for a period of 4 hours. During this period the temperature of the water bath was maintained constant at 25°C, and the contents of the reactors were kept well-mixed by magnetic stirrer bars. At the end of the 4-hr period, each reactor, except the control, was administered with different volumes of the toxicant being assayed. Each toxicant dose was prepared by dissolving the toxicant in 2 mL of acetone. The dosed reactors and the control reactor were then placed in the respirometer, with continued supply of oxygen. The data acquisition system was then re-initiated to monitor the oxygen uptake of each reactor for the next 6 hour period.

For each toxicant, a trial run was first made to establish the range of concentrations to bring about 50% inhibition. Once this range was determined by trial and error, a final run was made with appropriate volumes of the toxicant to cover inhibitions in the range of about 30 to 80%. The oxygen uptake as a function of time as recorded by the data acquisition system was then used to determine the  $IC_{50}$  values as described in the main text.

Appendix III

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Detailed Statitics of QSAR Models

# Regression Summary log Y-RM vs. 1XV

Count	14	
Num. Missing	0	
R	.954	
R Squared	.910	
Adjusted R Squared	.903	
RMS Residual	.246	

# Residual Statistics log Y-RM vs. 1XV

# >= 0	7
#<0	7
SS[e(i) - e(i-1)]	1.665
Durbin-Watson	2.288
Serial Autocorrelation	236

# ANOVA Table log Y-RM vs. 1XV

•	DF	Sum of Squares	Mean Square	F-Value	P-Value
Regression	1	7.398	7.398	122.014	<.0001
Residual	12	.728	.061		
Total	13	8.126			

#### **Regression Coefficients** 1

	Coefficient	Std. Error	Std. Coeff.	t-Value	P-Value
Intercept	3.690	.206	3.690	17.920	<.0001
1XV	896	.081	954	-11.046	<.0001

# Confidence Intervals log Y-RM vs. 1XV

	Coefficient	95% Lower	95% Upper
Intercept	3.690	3.241	4.138
1XV	896	-1.072	719



#### Regression Summary log Y-RM vs. 1XV Split By: Type Cell: Alkane

Count	5	
Num. Missing	0	
R	.999	
R Squared	.999	
Adjusted R Squared	.999	
RMS Residual	.018	

#### Residual Statistics log Y-RM vs. 1XV Split By: Type Cell: Alkane # >= 0 # < 0 SS[e(i) - e(i-1)]

SS[e(i) - e(i-1)]	.003
Durbin-Watson	2.578
Serial Autocorrelation	403

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#### ANOVA Table log Y-RM vs. 1XV Split By: Type Cell: Alkane

	DF	Sum of Squares	Mean Square	F-Value	P-Value
Regression	1	.936	.936	2823.077	<.0001
Residual	3	.001	3.314E-4		
Total	4	.937			

#### Regression Coefficients log Y-RM vs. 1XV Split By: Type Cell: Aikane

	Coefficient	Std. Error	Std. Coeff.	t-Value	P-Value
Intercept	1.851	.044	1.851	41.741	<.0001
1XV	765	.014	999	-53.133	<.0001

# Confidence Intervals

log Y-RM vs. 1XV Split By: Type Cell: Alkane



**Regression Summary Residual Statistics** log Y-RM vs. 1XV log Y-RM vs. 1XV Spilt By: Type Cell: Amine Split By: Type Cell: Amine Count 6 #>=0 3 0 Num. Missing 3 # < 0 .957 R SS[e(i) - e(i-1)] .104 .915 **R** Squared **Durbin-Watson** 2.549 Adjusted R Squared .894 Serial Autocorrelation -.326 **RMS Residual** .101 **ANOVA Table** log Y-RM vs. 1XV Split By: Type Cell: Amine Mean Square DF Sum of Squares **F-Value** P-Value Regression 1 .443 .443 43.327 .0028 Residual 4 .041 .010 5 484 Total

**Regression Coefficients** log Y-RM vs. 1XV Split By: Type Cell: Amine

	Coefficient	Std. Error	Std. Coeff.	t-Value	P-Value
Intercept	1.045	.135	1.045	7.738	.0015
1XV	470	.071	957	-6.582	.0028

**Confidence Intervals** log Y-RM vs. 1XV Split By: Type

Cell: Amine

	Coefficient	95% Lower	95% Upper
Intercept	1.045	.670	1.420
1XV	470	669	272





#### ANOVA Table log Y-RM vs. 1XV Split By: Type Cell: Aromatic

	DF	Sum of Squares	Mean Square	F-Value	P-Value
Regression	1	1.792	1.792	18.566	.0035
Residual	7	.676	.097		
Total	8	2.468			

Regression Coefficients log Y-RM vs. 1XV Split By: Type Cell: Aromatic

	Coefficient	Std. Error	Std. Coeff.	t-Value	P-Value
Intercept	3.258	.737	3.258	4.420	.0031
1XV	-1.133	.263	852	-4.309	.0035

Confidence Intervals log Y-RM vs. 1XV Split By: Type Cell: Aromatic



# Regression Summary log Y-RM 2 vs. 0XV

Count	12	Residual Statistics
Num. Missing	39	10g Y-HM 2 VS. UXV # >= 0
R	.942	# - 0
R Squared	.887	SSIe(i) - e(i-1)]
Adjusted R Squared	.876	Durbin-Watson
rms residual	.141	Serial Autocorrelation

Dg Y-HM 2 VS. UXV	
#>=0	6
#<0	6
SS[e(i) - e(i-1)]	.394
Durbin-Watson	1.990
Serial Autocorrelation	066

# ANOVA Table log Y-RM 2 vs. 0XV

-	DF	Sum of Squares	Mean Square	F-Value	P-Value
Regression	1	1.558	1.558	78.803	<.0001
Residual	10	.198	.020		
Total	11	1.756			

# **Regression Coefficients**

log	Y-RM	2 vs.	0XV
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	Coefficient	Std. Error	Std. Coeff.	t-Value	P-Value
Intercept	2.670	.239	2.670	11.178	<.0001
0XV	448	.050	942	-8.877	<.0001

# Confidence Intervals log Y-RM 2 vs. 0XV

	Coefficient	95% Lower	95% Upper
Intercept	2.670	2.137	3.202
0XV	448	560	335



Appendix IV a

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Results of 10-Component Mixtures





















Appendix IV b

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Results of 8-Component Mixtures













Appendix V

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Results of 8-Component Mixtures

Comparison of Experimental Results vs. Predictions

Appendix V- Results of 8-Component Mixture Studies Comparison of Experimental vs. Predicted Concentrations Causing 50% Inhibition

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Mixture N <sup>®</sup>	Components	Individua	I IC50 From	Conc. of Com	ponent in Mixture	causing IC50
		Experiment	<b>QSAR Model</b>	Measured	Predicted Usi	ng IC50 From
Results				in Experiment	Experiemnt	<b>QSAR Model</b>
		[mg/L]	[mg/L]	[mg/L]	[mg/L]	[mg/L]
Ŧ	Methyl ethyl ketone	1,900	5,865	283	238	733
	Methyl isobutyl ketone	2,600	2,099	387	325	262
r^2 = 0.889	h-Butyl acetate	3,750	1,350	559	469	169
ΣTU = 1.19	Isobutyl acetate	1,600	1,851	238	200	231
AI = 0.19	Propanol	7,200	12,798	1,073	006	1,600
MTI = 0.916	Pentanol	2,325	2,283	346	231	285
	Dibromomethane	1,110	684	165	139	86
	<b>Bis2-chloroethyl ether</b>	1,600	992	238	200	124
3	Methyl ethyl ketone	1,900	5,865	243	238	733
	Methył isobutył ketone	2,600	2,099	333	325	262
r^2 = 0.946	n-Butyl acetate	3,750	1,350	480	469	169
ΣTU = 1.02	Isobutyl acetate	1,600	1,851	205	200	231
AI = 0.02	Dibromomethane	1,110	684	142	139	86
MTI = 0.990	Bromochloromethane	1,800	1,201	230	225	150
	Benzene	685	766	88	86	96
	Toluene	207	310	26	26	39
0	Methyl ethyl ketone	1,900	5,865	255	238	733
	Methyl isobutyl ketone	2,600	2,099	348	325	262
r^2 = 0.916	n-Butyl acetate	3,750	1,350	503	469	169
<b>ZTU = 1.07</b>	Isobutyl acetate	1,600	1,851	214	200	231
AI = 0.07	Propanol	7,200	12,798	965	006	1,600
MTI = 0.967	Pentanol	2,325	2,283	312	291	285
	1,2 Dichloroethylene	350	1,332	47	44	167
	Trichloroethylene	500	611	67	8	76

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Appendix V- Results of 8-Component Mixture Studies (contd.)

Niverso	Companye	Individual				
						causing 1000
°.		Experiment	QSAR Model	Measured	Predicted Usi	ng IC50 From
				in Experiment	Experiemnt	<b>OSAR Model</b>
		[mg/L]	[mg/L]	[mg/L]	[mg/L]	[mg/L]
4	Ethyl benzene	220	83	87	28	10
	Isobutyl acetate	1,600	1,851	205	200	231
r^2 = 0.995	Propanol	7,200	12,798	922	006	1,600
ΣTU = 1.02	Pentanol	2,325	2,283	298	291	285
AI = 0.02	Dibromomethane	1,110	684	142	139	86
060.0 = ITM	Bromochloromethane	1,800	1,201	230	225	150
	Octanol	126	143	16	16	18
	1,2 Dichloropropane	500	485	64	63	61
5	Ethyl benzene	220	8	25	28	10
	2,4 Dimethyl phenol	240	86	28	30	12
r^2 = 0.860	Isobutyl acetate	1,600	1,851	184	200	231
ΣTU = 0.92	Propanol	7,200	12,798	828	006	1,600
Al = -0.08	Pentanol	2,325	2,283	267	291	285
MTI = 1.040	Bromochloromethane	1,800	1,201	207	225	150
	1,2 Dichloroethylene	350	1,332	40	44	167
	Trichloroethylene	500	611	58	63	76
9	Methyl ethyl ketone	1,900	5,865	220	238	733
	n-Butyl acetate	3,750	1,350	435	469	169
r^2 = 0.976	Ethylenedibromide	520	437	60	65	55
ΣTU = 0.93	1,1,1,Trichloroethane	415	398	48	52	50
AI = -0.07	Ethyl benzene	220	83	26	28	10
MTI = 1.035	Chlorobenzene	350	322	41	44	40
	2,4 Dimethyl phenol	240	86	28	30	12
	Toluene	207	310	24	26	39