

A MORE INFORMATIVE STATISTICAL ANALYSIS

FOR PREDATOR-PREY STUDIES\*

by

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## INTRODUCTION

Statistical analyses in most predator-prey experiments is limited to determining whether a particular stress or toxicant affects prey vulnerability by either increasing or decreasing the probability that treated organisms will be differentially preyed upon. This paper proposes methods which (1) estimate how much a treatment increases or decreases prey vulnerability and (2) find significant differences between treatments. The additional calculations that are required more than double the information obtained from earlier analyses, yet remain a small fraction of the overall effort.

The typical predator-prey study, utilizing fish as the test organisms, exposes randomly selected members of a prey population to a sublethal level of a stress or toxicant. Following exposure, M members of the treated group and N members of the control group (usually  $M = N$ ) are placed in each of L experimental predator-prey chambers. After the prey fish have become acclimated to their surroundings a predator is added. When approximately half the prey have been consumed the number T of treated fish eaten and the number C of control fish eaten is recorded for each tank. The above process is repeated for as many treatment levels as the investigator wishes to test.

The predator-prey study on which the following techniques were first applied was undertaken by Jacquelyn F. Sullivan as part of her Ph.D. research for the Bionucleonics Department of Purdue University. This research was conducted in an innovative manner that recommends itself as a model for future predator-prey studies. Primary innovations

consisted of utilizing model ecosystems and sustained behavioral observations. Data from this experiment are used in examples throughout this paper; therefore, the essential results are provided in Table 1.

#### A STANDARD ANALYSIS

Predator-prey experiments provoke two main inquiries. The first inquiry concerns whether a particular treatment or level of treatment influences prey vulnerability. Normally, the investigator assumes that a treatment either will have no effect or will increase prey vulnerability. In such cases a one-sided hypothesis test is appropriate. An investigator, having knowledge of similar studies, may be fairly certain that a given treatment will double prey vulnerability; then a two-sided hypothesis test becomes appropriate. The latter section of this paper contains statistical procedures which test appropriate hypotheses and give point estimates and confidence intervals for the increase in prey vulnerability due to treatment. The second inquiry asks whether the treatments vary in their affect on prey vulnerability. Answering this inquiry is the purpose of this section.

The use of standard techniques to find significant differences between treatments will be illustrated with an example. In the Sullivan experiment, nine treatments were used. Common sense dictated that comparisons of interest be made among three subsets of the nine treatments: (1) acute exposure treatments; (2) chronic exposure treatments; and (3) the 0.05 mg Cd/liter treatments. The values of T/R (R equals the number of prey fish eaten during a subexperiment) for each treatment are listed in Table 2.

TABLE 1

Experimental results, maximum likelihood estimators of  $K$ ,  $\Sigma_1$  and  $\Sigma_1'$  confidence limits for  $K$ , and  $H_0: K=1$  versus  $H_1: K>1$  P values. Positions where an asterisk appears indicate that  $M=N=14$  for that subexperiment. Elsewhere,  $M=N=20$ . R denotes the number of fish eaten during the course of a subexperiment.

Mg Cd/ liter	Exposure Time	Tank	R	$T_{exp.}$	MLE(K)	90% C.I.(K)	$P(\Sigma_1 < \Sigma_1'_{1,exp}   K=1)$
.500	48 hr.	1	18	12	2.55	(1.8,6.7)	.000
	48 hr.	2	16	11			
	48 hr.	3	20	13			
.375	48 hr.	1	20	13	3.33	(2.1,6.9)	.000
	48 hr.	2	21	15			
	48 hr.	3	19	14			
.250	48 hr.	1	16	9	.77	(0.4,1.3)	.820
	48 hr.	2	19	8			
	48 hr.	3	16	6			
.050	48 hr.	1*	16	8	.49	(.4,.8)	.937
	48 hr.	2*	12	3			
	48 hr.	3	18	6			
.050	21 d.	1	24	14	1.84	(1.3,4.0)	.004
	21 d.	2	20	12			
	21 d.	3	21	13			
.025	21 d.	1	21	15	3.95	(1.7,5.2)	.000
	21 d.	2	20	12			
	21 d.	3	20	17			
.019	21 d.	1	21	11	1.36	(.8,1.9)	.214
	21 d.	2	24	11			
	21 d.	3	20	14			
.013	21 d.	1	20	8	.89	(0.5,1.4)	.614
	21 d.	2	17	11			
	21 d.	3	21	9			
.050 R	21 d.	1	22	13	2.02	(1.4,4.3)	.002
	21 d.	2	22	14			
	21 d.	3	21	13			

TABLE 2

Cd Conc. (mg/liter)	Exposure Time	T/R		
		Tank 1	Tank 2	Tank 3
0.500	48 hr	12/18	11/16	13/20
0.375	48 hr	13/20	15/21	14/19
0.250	48 hr	9/16	8/19	6/16
0.050	48 hr	8/16	3/12	6/18
0.050	21 day	14/24	12/20	13/21
0.025	21 day	15/21	12/20	17/20
0.019	21 day	11/21	11/24	14/20
0.013	21 day	8/20	11/17	9/21
0.050*	21 day	13/22	14/22	13/21

The proportion T/R or a variance stabilizing transformation of T/R is commonly used as the basic statistic for the analysis of variance of binomial type data. Although data from this experiment is not binomially distributed, the value T/R was chosen as the basic statistic for the following reasons. As prey vulnerability increases from treatment to treatment, the  $E[T/R|R]$  increases. A conservative estimate for the variance of  $(T/R|R)$  can easily be computed for each observation; subsequently, these variances can be used to estimate the residual mean square. Data from studies of this sort tends to become binomial as M and N ( $M = N$ ) are allowed to increase toward infinity while R is held below an upper bound. Finally, assumptions of homogeneity of variance and normality were met sufficiently well to ensure robustness for analysis of variance techniques.

Since  $T/R$  given  $R$  is discrete, it cannot have a normal distribution. But it is approximately normal for a wide range of prey vulnerability levels  $K$  in the sense that a normal approximation using the mean and variance of  $T/R|R, K$  yields a good estimate of the actual  $T/R$  probability density function (PDF). Table 3 compares the actual PDF of  $T/R$  for  $M = N = 20$ ,  $R = 20$  when  $K = 1.00$  and  $0.20$ . The value of  $K$  is  $1.00$  when a treatment has no effect;  $K = 0.20$  when a treatment decreases prey vulnerability five-fold.

TABLE 3.  $M = N = R = 20$ 

T/R	PDF	$K = 1.00$		T/R	PDF	$K = 0.20$	
			NORM. APP.				NORM. APP.
.25	.002		.002	.00	.000		.001
.30	.011		.012	.05	.004		.008
.35	.044		.045	.10	.034		.039
.40	.115		.115	.15	.126		.120
.45	.205		.204	.20	.245		.231
.50	.248		.244	.25	.275		.274
.55	.205		.204	.30	.193		.203
.60	.115		.115	.35	.089		.093
.65	.044		.045	.40	.027		.026
.70	.011		.012	.45	.006		.005
.75	.002		.002	.50	.001		.001

A tabular study of the influence of  $K$  and  $R$  on the variance of  $T/R$  [ $= P$ ],  $\arcsin P$  [ $= ASP$ ] and  $\arcsin (2P-1)$  [ $= A2P$ ] is presented in Tables 4 and 5. Table 4 examines the variance stabilizing effect of arcsine transformations when  $M = N = R$ . The function  $B$  is defined for argument  $X$  as follows:

$$B(X) = \frac{[\text{Max}_{K \in K \text{ interval}} \{\text{Var}(X) | K, M, N, R\}]}{[\text{Min}_{K \in K \text{ interval}} \{\text{Var}(X) | K, M, N, R\}]}$$

Values of  $B(X)$  near one indicate excellent homogeneity of variance.

Table 4 indicates a strong variance stabilizing effect for both arcsine transformations as  $M = N = R$  increases. Note, however, that variances remain nearly homogeneous as long as treatment effects  $K$  stay in a range from 0.20 to 5.00.

TABLE 4

M=N=R	K Interval	E(P) Interval	B(P)	B(ASP)	B(A2P)
5	0.10 - 10.0	.152 - .848	1.53	1.97	1.97
	0.20 - 5.0	.236 - .764	1.24	1.67	1.67
	0.30 - 3.3	.295 - .705	1.13	1.40	1.40
10	0.10 - 10.0	.160 - .840	1.60	1.74	1.74
	0.20 - 5.0	.241 - .759	1.27	1.24	1.24
	0.30 - 3.3	.299 - .701	1.14	1.10	1.10
15	0.10 - 10.0	.162 - .838	1.62	1.38	1.38
	0.20 - 5.0	.243 - .757	1.27	1.12	1.12
	0.30 - 3.3	.300 - .700	1.15	1.06	1.06
20	0.10 - 10.0	.163 - .837	1.63	1.23	1.23
	0.20 - 5.0	.243 - .757	1.28	1.09	1.09
	0.30 - 3.3	.300 - .700	1.15	1.05	1.05
25	0.10 - 10.0	.163 - .837	1.63	1.18	1.18
	0.20 - 5.0	.244 - .756	1.28	1.08	1.08
	0.30 - 3.3	.301 - .699	1.15	1.04	1.04

Table 5 examines the efficacy of arcsine transformations when  $M = N = 20$  for various  $K$  intervals and  $R$  ranges. Here the function  $B(X)$  is defined:

$$B(X) = \frac{\text{Max}_{K \in K \text{ interval, } R \in R \text{ values}} \{\text{Var}(X) | K, M=N=20, R\}}{\text{Min}_{K \in K \text{ interval, } R \in R \text{ values}} \{\text{Var}(X) | K, M=N=20, R\}}$$

This table indicates a general increase in heterogeneity of variance for P, ASP and A2P as R is permitted to fluctuate about twenty. The arcsine transformations also tend to lose their variance stabilizing effect under these circumstances, at least for the K intervals examined here.

TABLE 5

R Values	K int.	B(P)	B(ASP)	B(A2P)
20	1.00	1.00	1.00	1.00
	.5 - 2.0	1.05	1.02	1.02
	.2 - 5.0	1.28	1.09	1.09
19,20,21	1.00	1.22	1.23	1.23
	.5 - 2.0	1.28	1.25	1.25
	.2 - 5.0	1.58	1.39	1.39
18, ..., 22	1.00	1.49	1.51	1.51
	.5 - 2.0	1.57	1.55	1.55
	.2 - 5.0	1.97	1.78	1.78
17, ..., 23	1.00	1.83	1.86	1.86
	.5 - 2.0	1.93	1.93	1.93
	.2 - 5.0	2.50	2.42	2.42
16, ..., 24	1.00	2.25	2.30	2.30
	.5 - 2.0	2.39	2.42	2.42
	.2 - 5.0	3.24	3.35	3.35



The foregoing study implies that considerable heterogeneity of variance exists between T/R values from predator-prey experiments. In the most extreme case from Table 5, it was possible for variances to differ by a ratio of 3.24 to 1.00. Since analysis of variance techniques remain robust for variance heterogeneity of this size<sup>1</sup>, we are justified in proceeding with an analysis of variance on the Sullivan data for maximum likelihood estimators of K (next section) remain between 0.20 and 5.00 and R fluctuations about 20 remained between 16 and 24. The data, including the treatment cell where some tanks started with fourteen control and fourteen treated fish, easily passed Cochran's test for homogeneity of variance (P = .962).

A conservative estimate of the variance of each T/R value may be obtained by assuming that K = 1 (i.e. no treatment effect exists). Then the distribution of T is hypergeometric so that:

$$\begin{aligned} \text{Var}(T/R|K=1,R,M,N) &= \text{Var}(T|K=1,R,M,N)/R^2 \\ &= [MNR(M+N-R)] / [(M+N)^2(M+N-1)R^2] \end{aligned}$$

One may also generate these variances with the program of Appendix A. Variances for the example data are listed in Table 6.

An estimate of the residual mean square is calculated in the following manner:

$$\text{Residual MS} = \sum_{i=1}^{10} (F_i V_i) / \sum_{i=1}^{10} F_i = 0.006865$$

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<sup>1</sup>Anderson, p. 17.

Since this is a conservative (i.e. high) estimate of the average variance among observed results, the degrees of freedom for this residual mean square are assumed to be infinite.

TABLE 6

Variance estimates for tank-treatment results of the Sullivan experiment.

i	M=N	R	F (frequency)	V[Var(T/R K=1,R,M,N)]
1	14	12	1	.012346
2	14	16	1	.006944
3	20	16	3	.009615
4	20	17	1	.008673
5	20	18	2	.007835
6	20	19	2	.007085
7	20	20	7	.006410
8	20	21	6	.005800
9	20	22	2	.005245
10	20	24	2	.004274

The analysis of variance provided in Table 7 assumes that the three tanks as well as the nine treatments may influence the outcome of each subexperiment. As it turns out neither tanks nor the tank-treatment interaction is significant. Treatments, however, are significantly different.

TABLE 7

Analysis of variance for Sullivan experiment. The symbol \*\*\* denotes 0.001 significance.

DF	Source	Sum of Squares	Mean Square	F
2	Tank	.005	.0025	0.36
8	Trt	.348	.043	6.34***
16	Tank x Trt	.152	.010	1.38
Infinite	Residual		.006865	

A Newman Keuls multiple comparison test<sup>2</sup> produces the following treatment ranking:

TRT	50A	250A	13Ch	19Ch	50Ch	50Res	500A	375A	25Ch
Mean	.3611	.4529	.4919	<u>.5607</u>	<u>.6008</u>	<u>.6154</u>	<u>.6681</u>	<u>.7004</u>	<u>.7214</u>

This ranking may be subdivided into three meaningful subrankings:

- (1) 50A    50Ch    50Res
- (2) 50A    250A    500A    375A
- (3) 13Ch    19Ch    50Ch    25Ch

Treatments which are connected by the same line are not significantly different.

<sup>2</sup>Anderson, p. 10.

In summary, analysis of variance techniques utilizing T/R as the response variable seem appropriate when M equals N with both greater than nineteen (normality and homogeneity of variance assumptions were examined here chiefly for M=N=20) and when R values are kept near M. The residual mean square for the analysis of variance and multiple comparisons should be calculated in the manner discussed.

#### SPECIAL ANALYSIS

An important parameter in the following pages is the measure K of increased prey vulnerability due to treatment. If M treated and N control prey inhabit a tank with a predator, it is assumed that:

$$P_{t,1} = P_{t,2} \dots = P_{t,M} = P_t \quad \text{and}$$

$$P_{c,1} = P_{c,2} = \dots = P_{c,N} = P_c$$

where  $P_{t,i}$  ( $P_{c,i}$ ) is the probability that the predator will prey upon the  $i$ th treated (control) fish next. Parameter K can now be defined by the equation  $P_t = K \cdot P_c$ . Thus, when a treatment has no effect on prey vulnerability,  $K=1$ ; when it doubles prey vulnerability,  $K=2$ ; when it halves prey vulnerability  $K=0.5$ , etc.

Since  $MP_t + NP_c = 1$  and  $P_t = KP_c$ , we have  $P_t = K/(MK+N)$  and  $P_c = 1/(MK+N)$ . Note, however, that  $P_t$  and  $P_c$  change after each successful predatory attack.

The parameter K is closely related to the binomial parameters P and Q. To see this let  $M=N=R=1$ ; then  $P = P_t = \frac{K}{K+1}$  and  $Q = P_c = \frac{1}{K+1}$ . Recall that a binomial distribution with parameters n, P, and Q is equivalent to the distribution of the sum of N independent Beinoulli trials with parameters P and Q. The reader, however, is cautioned against designing

an experiment consisting of Bernoulli trials since there is evidence that learning is involved in the predator-prey process. Although treatment with a stress or toxicant strongly increases prey vulnerability, this effect may not be present until after the first strike.

A maximum likelihood estimator for  $K$  is easily obtained by using the program and instructions of Appendix B. The general procedure consists of finding a  $MLE(K)$  value such that the likelihood or probability of observing the experimental results for  $MLE(K)$  is greater than for any other  $K$  value. Algebraically,

$$MLE(K) = [K: \prod_{i=1}^L P(T=T_{i,exp} | M, N, R_i, K) \geq \prod_{i=1}^L P(T=T_{i,exp} | M, N, R_i, K')] \\ \text{for every } K' > 0]$$

The statistical procedures which follow are based on one-sided hypothesis tests like  $H_0: K=K_0$  vs  $H_1: K>K_0$  or  $H_0': K=K_0$  vs  $H_1': K>K_0$ . For most predator-prey studies  $K_0$  will equal one and the alternative hypothesis will be  $H_1: K>1$ . Nonetheless, the methods and programs that follow are versatile enough to handle a wide range of  $K_0$  values and both one-sided and two-sided hypothesis tests.

Consider an experiment where a treatment A is being examined for its effect on prey vulnerability. In each of  $L$  tanks,  $M$  treated and  $N$  control fish have been placed. The experiment is performed with results  $(T_i, R_i)$  for  $i=1, \dots, L$ . Suppose  $L$  equals one; then  $P_1 = P(T \geq T_1 | R_1, M, N, K_0)$  is the Type I error for testing  $H_0: K=K_0$  versus  $H_1: K>K_0$ . Thus,  $P_1$  by direct comparison with the  $\alpha$ -level for the above hypothesis determines whether we regard  $K_0$  as plausible or conclude  $K_0$  is too low to account for the experimental results. For

example, in an experiment where  $M=N=R_1=20$  and  $L=1$ , a result of  $T_1=15$  should be regarded as very strong evidence that  $K>1.00$  since the  $P(T \geq 15 | M=N=R_1=20, K=1) = 0.002$ .

When  $L$  is greater than one, this suggests that some function of  $P_i$  values should be used for testing  $H_0: K=K_0$  vs  $H_1: K>K_0$ . The random variable  $\Sigma_{K_0}$  where  $\Sigma_{K_0} = \Sigma_{i=1}^L P(T \geq T_i | K_0, M, N, R_i) = \Sigma_{i=1}^L P_i$  is preferred in this paper since it gives equal emphasis to each  $P_i$  value. Values which  $\Sigma_{K_0}$  may assume are finite and range from zero to  $L$ . Once  $K_0, M, N, R_1, \dots, R_L$  are given the true  $K$  value completely determines the probabilities assigned to values which  $\Sigma_{K_0}$  may assume; therefore we may make inferences about  $K$  by examining the experimental result  $\Sigma_{K_0, \text{exp}}$ . A computer program which calculates the  $\Sigma_{K_0}$  distribution for arbitrary  $K$  values is provided in Appendix C.

Recall the hypothesis test  $H_0: K=K_0$  vs  $H_1: K>K_0$ . The basic idea behind using the statistic  $\Sigma_{K_0}$  is that the experimental result  $\Sigma_{K_0, \text{exp}}$  will tend to be improbably low when  $K$  is substantially greater than  $K_0$ . Suppose an experimenter intended to conduct a predator-prey experiment where  $M=N=R_1=R_2=R_3=20$ , but was not sure whether the treatment would increase prey vulnerability. Then  $K_0=1$  and:

$$P(\Sigma_1 \leq 0.92 | K=1) = 0.043$$

$$P(\Sigma_1 \leq 0.92 | K=1.5) = 0.415$$

$$P(\Sigma_1 \leq 0.92 | K=2.0) = 0.795$$

If the investigator knew the treatment would at least double prey vulnerability,  $K_0=2.0$  would be hypothesized and:

$$P(\Sigma_2 \leq 0.94 | K=2) = 0.041$$

$$P(\Sigma_2 \leq 0.94 | K=3) = 0.375$$

$$P(\Sigma_2 \leq 0.94 | K=4) = 0.739$$

These probabilities indicate that  $H_0: K=K_0$  will be rejected roughly 75% of the time when the true  $K$  value is twice the hypothesized  $K$  value.

There are three possible hypothesis tests for predator-prey studies, and a different method applies to each. Test 1:  $H_0: K=K_0$  vs  $H_1: K>K_0$  is most common. If  $P(\Sigma_{K_0} \leq \Sigma_{K_0, \exp}^{K=K_0, M, N, R_1, \dots, R_L}) \leq \alpha$ , reject  $H_0$ ; otherwise accept  $H_0$ . Test 2 is  $H_0: K=K_0$  vs  $H_1: K<K_0$ . If  $P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \exp} |^{K=K_0, M, N, R_1, \dots, R_L}) \leq \alpha$ , reject  $H_0$ ; otherwise accept  $H_0$  ( $\Sigma'$  will be defined later). For test 3:  $H_0: K=K_0$  vs  $H_1: K \neq K_0$ , reject when  $P(\Sigma_{K_0} \leq \Sigma_{K_0, \exp} |^{K=K_0, M, N, R_1, \dots, R_L}) \leq \alpha/2$  or when  $P(\Sigma_{K_0} \geq \Sigma_{K_0, \exp} |^{K=K_0, M, N, R_1, \dots, R_L}) \leq \alpha/2$ ; otherwise accept  $H_0$ . Appendices A and C describe how to conduct these tests utilizing a computer.

The statistic  $\Sigma_{K_0}$  also provides a lower confidence limit for  $K$ .

If the one-sided test  $H_0: K=K_0$  vs.  $H_1: K>K_0$  is appropriate, find:

$$K_L = \max[K: P(\Sigma_{K_0} \leq \Sigma_{K_0, \exp} |^{K, M, N, R_1, \dots, R_L}) \leq \alpha]$$

For a two-sided test of  $H_0: K=K_0$  at level  $\alpha$ , find:

$$K_L = \max[K: P(\Sigma_{K_0} \leq \Sigma_{K_0, \exp} |^{K, M, N, R_1, \dots, R_L}) \leq \alpha/2]$$

The practical implementation of these procedures is described in Appendices A and C.

Obtaining upper confidence limits for  $K$  requires usage of the new random variable  $\Sigma'_{K_0}$  where  $\Sigma'_{K_0} = \Sigma_{i=1}^L P(T \leq T_i | K_0, M, N, R_i)$ . If the one-sided test  $H_0: K=K_0$  vs  $H_1: K < K_0$  is appropriate, then:

$$K_U = \min[K: P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \exp} | K, M, N, R_1, \dots, R_L) \leq \alpha]$$

For a two-sided test of  $H_0: K=K_0$  at level  $\alpha$ , find:

$$K_U = \min[K: P(\Sigma_{K_0} \leq \Sigma_{K_0, \exp} | K, M, N, R_1, \dots, R_L) \leq \alpha/2]$$

In the Sullivan experiment a one-sided test of  $H_0: K=1$  vs  $H_1: K > 1$  at level  $\alpha = 0.05$  seemed proper; therefore, to get a confidence interval for  $K$  consistent with the hypothesis test, two-sided methods with  $\alpha = 0.10$  were used. The  $\Sigma$  and  $\Sigma'$  methods are summarized in Table 8.

For some experimental designs  $\Sigma$  and  $\Sigma'$  methods for finding confidence intervals and testing hypotheses are too costly. In an experiment where  $M=N=20$  and  $R$  values are kept close to 20, determining confidence limits for  $L = 3$  on the Purdue CDC processor costs roughly \$1.00 per treatment. For  $L = 4$ , the cost would approach \$20.00 per treatment. A very rough formula for cost per treatment is:  $\text{COST} = M^L/8000$  dollars.

Fortunately, when  $\Sigma$  and  $\Sigma'$  methods become too expensive, maximum order statistics of  $P_i$  and  $P_i'$  can be used. Let  $P_{(1)}$  and  $P'_{(1)}$  denote these maximum order statistics. Then the following relations express the essential ideas upon which the  $P_{(1)}$  and  $P'_{(1)}$  methods are based:

- (1)  $P_{(1),K} = \max_{i=1, \dots, L} P(T \geq T_i | K, M, N, R_i)$
- (2)  $P'_{(1),K} = \max_{i=1, \dots, L} P(T \leq T_i | K, M, N, R_i)$



TABLE 8  
Summary of  $\Sigma$  and  $\Sigma'$  tests.

$H_0$	$H_1$	Test Rule
$K=K_0$	$K>K_0$	Reject $H_0$ if $P(\Sigma_{K_0} \leq \Sigma_{K_0, \text{exp}}   K=K_0, M, N, R_1, \dots, R_L) \leq \alpha$ . Otherwise, accept $H_0$ .
$K=K_0$	$K<K_0$	Reject $H_0$ if $P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \text{exp}}   K=K_0, M, N, R_1, \dots, R_L) \leq \alpha$ . Otherwise, accept $H_0$ .
$K=K_0$	$K=K_0$	Reject $H_0$ if $P(\Sigma_{K_0} \leq \Sigma_{K_0, \text{exp}}   K=K_0, M, N, R_1, \dots, R_L) \leq \alpha/2$ or $P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \text{exp}}   K=K_0, M, N, R_1, \dots, R_L) \leq \alpha/2$ . Otherwise, accept $H_0$ .

Two-sided confidence interval  $(K_L, K_U)$ :

$$K_L = \max [K: P(\Sigma_{K_0} \leq \Sigma_{K_0, \text{exp}} | K, M, N, R_1, \dots, R_L) \leq \alpha/2]$$

$$K_U = \min [K: P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \text{exp}} | K, M, N, R_1, \dots, R_L) \leq \alpha/2]$$

One-sided confidence interval  $(K_L, \infty)$ :

$$K_L = \max [K: P(\Sigma_{K_0} \leq \Sigma_{K_0, \text{exp}} | K, M, N, R_1, \dots, R_L) \leq \alpha]$$

One-sided confidence interval  $(0, K_U)$ :

$$K_U = \min [K: P(\Sigma'_{K_0} \leq \Sigma'_{K_0, \text{exp}} | K, M, N, R_1, \dots, R_L) \leq \alpha]$$

A one-sided confidence interval of the form  $(K_L, \infty)$  can be used if  $H_0$ :

$K=K_0$  vs  $H_1: K>K_0$  is the appropriate hypothesis test and if the investigator is not interested in setting an upper limit for  $K$ .

$$\begin{aligned}
(3) \quad & P(P_{(1),K} \leq P_{(1),K,\text{exp}}) \\
& = P(P_{1,K} \leq P_{(1),K,\text{exp}}; P_{2,K} \leq P_{(1),K,\text{exp}}; \dots; P_{L,K} \leq P_{(1),K,\text{exp}}) \\
& = P(P_{1,K} \leq P_{(1),K,\text{exp}})P(P_{2,K} \leq P_{(1),K,\text{exp}}) \dots P(P_{L,K} \leq P_{(1),K,\text{exp}}) \\
& \leq P_{(1),K,\text{exp}}^{**L} \text{ (Fortran notation)}
\end{aligned}$$

$$(4) \quad P_{(1),K,\text{exp}}^{**L} = \max_{i=1, \dots, L} (P_{i,K,\text{exp}}^{**L})$$

Since  $P_{(1)}$  and  $P'_{(1)}$  methods are included primarily for completeness, the test methods are presented in Table 9 without further explanation. Appendix D provides a computer program and practical procedures regarding  $P_{(1)}$  and  $P'_{(1)}$  tests.

TABLE 9.  $P_{(1)}$  and  $P'_{(1)}$  Tests

Hypothesis Testing:

$H_0$ :	$H_1$ :	Test Rule
$K=K_0$	$K>K_0$	Reject $H_0$ if $P_{(1),K_0}^{**L} \leq \alpha$ ; otherwise accept $H_0$ .
$K=K_0$	$K<K_0$	Reject $H_0$ if $P'_{(1),K_0}^{**L} \leq \alpha$ ; otherwise accept $H_0$ .
$K=K_0$	$K=K_0$	Reject $H_0$ if $P_{(1),K_0}^{**L} \leq \alpha/2$ or $P'_{(1),K_0}^{**L} \leq \alpha/2$ .

Two Sided Confidence Interval  $(K_L, K_U)$ :

$$K_L = \max[K: \max_{i=1 \dots L} (P\{T \geq T_i | K, M, N, R_i\}^{**L}) \leq \alpha/2]$$

$$K_U = \min[K: \max_{i=1 \dots L} (P\{T \leq T_i | K, M, N, R_i\}^{**L}) \leq \alpha/2]$$

One Sided Confidence Interval  $(K_L, \infty)$ :

$$K_L = \max[K: \max_{i=1 \dots L} (P\{T \geq T_i | K, M, N, R_i\}^{**L}) \leq \alpha]$$

One sided Confidence Interval  $(0, K_U)$ :

$$K_U = \min[K: \max_{i=1 \dots L} (P\{T \leq T_i | K, M, N, R_i\}^{**L}) \leq \alpha]$$

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## REFERENCES

Anderson, V. L. and McLean, R. A. (1974). Design of Experiments. Marcel Decker, NY.

Hogg, R. V. and Craig, A. T. (1970). Introduction to Mathematical Statistics. Macmillan, NY.

## Appendix A: Program PDE

Program PDE computes the probability density and cumulative distribution functions for random variable T given K, M, N and R. Included in the output are  $M, N, R, K, E(T/R|M, N, R, K)$  and  $\text{Var}(T/R|M, N, R, K)$ . The computations rely on the recursion formula:

$$\begin{aligned} P(T=i|R, M, N, K) &= P(T=i|(R-1), M, N, K)P(R^{\text{th}} \text{ fish eaten is a control fish}) \\ &\quad + P(T=i-1|(R-1), M, N, K)P(R^{\text{th}} \text{ fish eaten is a treated fish}) \\ &= P(T=i|(R-1), M, N, K) * (N-R+i+1) / [K(M-i) + (N-R+i+1)] \\ &\quad + P(T=i-1|(R-1), M, N, K) * K(M-i+1) / [K(M-i+1) + (N-R+i)] \end{aligned}$$

The important probabilities,  $P_{i,K} = P(T \geq T_i | K, M, N, R_i)$  and  $P'_{i,K} = P(T \leq T_i | K, M, N, R_i)$ , are easily extracted from the PDE output. Thus, using this program is a first step for  $\Sigma$  and  $\Sigma'$  methods since  $\Sigma_{K_0, \text{exp}} = \Sigma_{i=1}^L P_{i, K_0}$  and  $\Sigma'_{K_0, \text{exp}} = \Sigma_{i=1}^L P'_{i, K_0}$ .

Program PDE may require some modification before it can be used on your computer system. The Program PDE card may need to be removed, in which case Tape 5 and Tape 6 must be set as input and output on your control cards. The format statements which are non-Hollerith will cause no problems on most systems. Otherwise, Program PDE is written in standard Fortran. Note: Modifications which must be made for Program PDE will also need to be made for other programs in this paper.

Program input is provided by using the following data deck:

<u>Card</u>	<u>Information</u>	<u>Format</u>
1	RMIN, RMAX, NT, NC, K, KINC, KMAX	(2I2, X, 5F5.0)
...	...	...
LAST	Blank	

Fortran variables in the above list have the following meanings:

- (1) RMIN is the minimum R value for which a cumulative distribution table will be printed.
- (2) RMAX is the maximum R value for which a CDF table will be printed.
- (3) NT(NT=M) is the number of treated fish per tank at the beginning of an experiment.
- (4) NC(NC=N) is the number of control fish per tank at the beginning of an experiment.
- (5) K is an initial value for which a CDF table is desired.
- (6) KMAX is the maximum value for which a CDF table is desired.
- (7) KINC is the amount K is incremented until KMAX is reached.

Tables are printed for all combinations of (RMIN,RMIN+1,...,RMAX) and (K,K+KINC,K+(2\*KINC),...,KMAX).

Example: The experimental results for the Sullivan experiment for 0.025 mg. Cd/liter and 21 days exposure ( $M=N=20, K_0=1$ ) are:

Tank:	$\frac{1}{21}$	$\frac{2}{20}$	$\frac{3}{20}$
$R_i$	21	20	20
$T_i$	15	12	17

The data cards should be:

Card/Cols: 123456789012345678901234567890  
 1 2021 20.0 20.0 1.00 1.00 1.00  
 2 A blank card.

The resultant  $P_i$  and  $P_i'$  values are:

Tank:	$\frac{1}{21}$	$\frac{2}{20}$	$\frac{3}{20}$
$P_{i,K_0} = 1$	.005193	.171534	.000010
$P_i',K_0 = 1$	.999384	.943583	1.000000

Program Limitations:

1.  $2 \leq M, N, RMAX \leq 33$
2.  $RMAX \leq M+N$
3.  $K > 0.001$

4. In the programs that follow the three above restrictions must also be met; otherwise, the programs require modification. In addition, the programs of Appendices B, C and D require that the pair (M,N) for a given treatment remain the same for all L subexperiments. Thus, without serious changes, programs of these latter appendices cannot be used to analyze the 0.05 mg. Cd/l., 48 hr. treatment of Table 1. The reader is therefore advised to avoid such complications by designing experiments with all (M,N) pairs the same for the L subexperiments of each treatment.

An entire program deck will consist of the following:

- (1) Jobcard
- (2) Password card
- (3) Control card(s)
- (4) 7/8/9 multi-punch in column one
- (5) Program cards
- (6) 7/8/9 multi-punch in column one
- (7) Data cards
- (8) 6/7/8/9 multi-punch in column one

Program PDE follows on the next page.

```

PROGRAM PDE(INPUT,OUTPUT,TAPE5=INPUT,TAPE6=OUTPUT)
REAL P(35),REG(35),PDF(35),CDF(35)
REAL NT,NC,K,KINC,KMAX,FI,R,EP,EPSQ,VARP
INTEGER T(35),IM,RMAX,RMIN,R2,LO,HI
1000 READ(5,10) RMIN,RMAX,NT,NC,K,KINC,KMAX
10  FORMAT(2I2,X,5F5.0)
    IF(NT.GT.33.0) STOP
    IF(NC.GT.33.0) STOP
    IF(RMAX.GT.33) STOP
    IF(KINC.LT.0.001) STOP
    RMIN=RMIN+2
    RMAX=RMAX+2
    HI=IFIX(NT+2.1)
2000 CONTINUE
    DO 55 I=1,35
    REG(I)=0.0
    PDF(I)=0.0
    CDF(I)=0.0
55  CONTINUE
    PDF(2)=NC/(NT*K+NC)
    PDF(3)=NT*K/(NT*K+NC)
    DO 44 L=4,RMAX
    R2=L
    R=FLOAT(R2-2)
    LO=IFIX(R-NC+2.1)
    DO 11 I=2,R2
    FI=FLOAT(I)
    P(I)=(FI-2.0)/R
    T(I)=I-2
    REG(I)=0.0
    IF((I.LT.LO).OR.(I.GT.HI)) GO TO 12
    IM=I-1
    REG(I)=PDF(IM)*((NT-FI+3.0)*K/((NT-FI+3.0)*K+NC-R+FI-2.0))
    *   +PDF(I)*((NC-R+FI-1.0)/((NT-FI+2.0)*K+NC-R+FI-1.0))
12  CONTINUE
11  CONTINUE
    DO 66 I=2,R2
    PDF(I)=REG(I)
66  CONTINUE
    IF(R2.LT.RMIN) GO TO 45
    EP=0.0
    EPSQ=0.0
    DO 22 I=2,R2
    IM=I-1
    CDF(I)=CDF(IM)+PDF(I)
    EP=EP+PDF(I)*P(I)
    EPSQ=EPSQ+PDF(I)*P(I)*P(I)
22  CONTINUE
    VARP=EPSQ-EP*EP
    WRITE(6,33) NT,NC,R,K,EP,VARP,(P(I),PDF(I),CDF(I),T(I),I=2,R2)
33  FORMAT(///5X,≠TOTAL(T)=≠,F5.2,≠ TOTAL(C)=≠,F5.2,≠ R=≠,F5.2,
    *   ≠ K=≠,F6.3,≠ E(P)=≠,F8.6,≠ VAR(P)=≠,F8.6//5X,
    *   ≠N(T)/N(R)≠,7X,≠P(T.EQ.TEXP)≠,4X,≠P(T.LE.TEXP)≠,4X,≠TEXP≠//
    *   (5X,F9.6,7X,F9.6,6X,F9.6,7X,I2))
45  CONTINUE
44  CONTINUE
    K=K+KINC
    IF(K.GT.KMAX) GO TO 1000
    GO TO 2000
END

```



## Appendix B: Program MLE

Program MLE computes the likelihood of an experimental result for selected K values. Computer searching techniques can yield a maximum likelihood estimate of K which is accurate to two or three decimal places.

The data deck for this program should be as follows:

<u>Card</u>	<u>Information</u>	<u>Format</u>
1	TANKS (=L value)	(I1)
2	RMIN, RMAX, NT, NC, K, KINC, KMAX	(2I2, X, 5F5.0)
3	R <sub>1</sub> , T <sub>1</sub>	(2I2)
4	R <sub>2</sub> , T <sub>2</sub>	
...	...	...
L+2	R <sub>L</sub> , T <sub>L</sub>	
**	Cards 2 thru L+2 form a set which may be repeated if one wishes to conduct more than one search per program run. The TANKS value is listed only once.	
Last 10	Ten blank data cards.	

Explanation:

- (1) RMIN is set to  $\min_{i=1, \dots, L} R_i$
- (2) RMAX is set to  $\max_{i=1, \dots, L} R_i$
- (3) K, KINC, KMAX define K values for which the likelihood of the experimental result will be listed.

Example: The first step in getting a MLE of K is to guess roughly where the MLE(K) will be. A fair initial guess is  $G = \frac{\sum_{i=1}^L T_i}{\sum_{i=1}^L C_i}$ , which equals 2.59 in our example. We therefore search  $K = 2.5, 3.0, \dots, 5.0$  using the following data deck:

```
Card/Cols: 123456789012345678901234567890
1          3
2          2021 20.0 20.0 2.50 0.50 5.00
3          2115
4          2012
5          2017
6-15      Blank cards
```

We get output:

```
K = 2.500      Likelihood = .000312
K = 3.000      Likelihood = .000708
K = 3.500      Likelihood = .001019
K = 4.000      Likelihood = .001109
K = 4.500      Likelihood = .001008
K = 5.000      Likelihood = .000815
```

Since the zenith is near 4.00, we run  $K = 3.80, 3.85, \dots, 4.20$ .

The result is  $\text{MLE}(K) = 3.95$ .

Program MLE follows on the next page.

```

PROGRAM MLE(INPUT,OUTPUT,TAPE5=INPUT,TAPE6=OUTPUT)
REAL P(35),REG(35),PDF(35),CDF(35)
REAL NT,NC,K,KINC,KMAX,FI,R,EP,EPSQ,VARP
INTEGER T(35),IM,RMAX,RMIN,R2,LO,HI
REAL LIKE(3),LIKELY
INTEGER TANKS,RR(3),TT(3),RM,IR,TTJ2
READ(5,40) TANKS
40  FORMAT(I1)
1000 READ(5,10) RMIN,RMAX,NT,NC,K,KINC,KMAX
10  FORMAT(2I2,X,5F5.0)
    IF(NT.GT.33.0) STOP
    IF(NC.GT.33.0) STOP
    IF(RMAX.GT.33) STOP
    IF(KINC.LT.0.001) STOP
    READ(5,50) (RR(J),TT(J),J=1,TANKS)
50  FORMAT(2I2)
    DO 77 J1=1,TANKS
    TT(J1)=TT(J1)+2
77  CONTINUE
    RM=RMAX
    RMIN=RMIN+2
    RMAX=RMAX+2
    HI=IFIX(NT+2.1)
2000 CONTINUE
    DO 55 I=1,35
    REG(I)=0.0
    PDF(I)=0.0
    CDF(I)=0.0
55  CONTINUE
    PDF(2)=NC/(NT*K+NC)
    PDF(3)=NT*K/(NT*K+NC)
    DO 44 L=4,RMAX
    R2=L
    R=FLOAT(R2-2)
    LO=IFIX(R-NC+2.1)
    DO 11 I=2,R2
    FI=FLOAT(I)
    P(I)=(FI-2.0)/R
    T(I)=I-2
    REG(I)=0.0
    IF((I.LT.LO).OR.(I.GT.HI)) GO TO 12
    IM=I-1
    REG(I)=PDF(IM)*((NT-FI+3.0)*K/((NT-FI+3.0)*K+NC-R+FI-2.0))
    * +PDF(I)*((NC-R+FI-1.0)/((NT-FI+2.0)*K+NC-R+FI-1.0))
12  CONTINUE
11  CONTINUE
    DO 66 I=2,R2
    PDF(I)=REG(I)
66  CONTINUE
    IF(R2.LT.RMIN) GO TO 45
    IR=IFIX(R+0.1)
    DO 88 J2=1,TANKS

```

```
TTJ2=TT(J2)
IF(IR.EQ.RR(J2)) LIKE(J2)=PDF(TTJ2)
88 CONTINUE
IF(IR.EQ.RM) LIKELY=LIKE(1)*LIKE(2)*LIKE(3)
IF(IR.EQ.RM) WRITE(6,30) K,LIKELY
30 FORMAT(5X,#K=#,F6.3,5X,#LIKELIHOOD=#,F8.6)
45 CONTINUE
44 CONTINUE
K=K+KINC
IF(K.GT.KMAX) GO TO 1000
GO TO 2000
END
```

## Appendix C: Program SIGMAD

Program SIGMAD computes the cumulative distribution functions of  $\Sigma_{K_0}$  and  $\Sigma'_{K_0}$ . It may be used in conjunction with a computer search to find upper and/or lower confidence limits for K.

The data deck for SIGMAD should be as follows:

<u>Card</u>	<u>Information</u>	<u>Format</u>
1	$K_0, \Sigma_{K_0, \text{exp}}$ or $\Sigma'_{K_0, \text{exp}}$ (whichever is applicable)	(F5.0, F10.0)
2	Tanks, RMAX, NT, NC, $K_0, 1.00, K_0$	(I1, I2, 5F5.0)
3	SMIN, SMAX	(2F5.0)
4	$R_1$	(I2)
5	$R_2$	(I2)
...	...	...
L+3	$R_L$	(I2)
L+4	Tanks, RMAX, NT, NC, K, KINC, KMAX	(I2, I2, 5F5.0)
L+5	SMIN, SMAX	(2F5.0)
L+6	$R_1$	(I2)
L+7	$R_2$	(I2)
...	...	...
2L+5	$R_L$	(I2)
LAST 10	Ten blank cards	

## Explanation:

- (1)  $K_L$  and  $K_N$  for a given treatment must be sought after one at a time.

When seeking  $K_L$ , the  $\Sigma_{K_0, \text{exp}}$  value is listed on card 1. List

$\Sigma'_{K_0, \text{exp}}$  on card 1 when searching for  $K_U$ .

- (2)  $RMAX = \max_{i=1, \dots, L} R_i$

- (3) SMIN and SMAX specify the values of  $\Sigma_{K_0}$  or  $\Sigma'_{K_0}$  for which the CDF

values are desired. For example, setting SMIN = .58 and SMAX = .59

when  $\Sigma_{K_0, \text{exp}} = .586$  will cause  $P(\Sigma_{K_0} \leq .586 | K, M, N, R_1, \dots, R_L)$  and

$P(\Sigma'_{K_0} \leq .586 | K, M, N, R_1, \dots, R_L)$  to be printed.

Example (cont'd): From Appendix A we know  $\Sigma_{K_0=1, \text{exp}} = \Sigma_{i=1}^3 P_{i, K_0=1}$   
 $= .176737$  and that  $\Sigma'_{K_0=1, \text{exp}} = \Sigma_{i=1}^3 P'_{i, K_0=1} = 2.942967$ . Thus, for a  
 two-sided 90% confidence interval,

$$K_L = \max[K: P(\Sigma_{K_0} \leq 0.17674 | M=N=20, R_1=21, R_2=R_3=20, K) \leq .05]$$

and

$$K_U = \min[K: P(\Sigma'_{K_0} \leq 2.94297 | M=N=20, R_1=21, R_2=R_3=20, K) \leq .05]$$

The first step in finding  $K_L$  and  $K_U$  is to guess at a wide region for  
 their location. For  $K_L$  we search at  $K = 1.0, 1.5, \dots, 3.5$ ; for  $K_U$  we  
 search at  $K = 5.0, 6.0, 10.0$ . The correct data decks are (A) the  $K_L$  deck:

Card/Cols: 1234567890123456789012345678  
 1 1.00 0.176737  
 2 321 20.0 20.0 1.00 1.00 1.00  
 3 0.17 0.18  
 4 21  
 5 20  
 6 20  
 7 321 20.0 20.0 1.00 0.50 3.50  
 8 0.17 0.18  
 9 21  
 10 20  
 11 20  
 12-21 Ten blank cards

(B) the  $K_U$  deck:

Card/Cols: 123456789012345678901234567890  
 1 1.00 2.942967  
 2 321 20.0 20.0 1.00 1.00 1.00  
 3 2.94 2.95  
 4 21  
 5 20  
 6 20  
 7 321 20.0 20.0 5.00 1.00 10.0  
 8 2.94 2.95  
 9 21  
 10 20  
 11 20  
 12-21 Ten blank cards

These two decks must be run separately.

The output reveals that  $K_L$  is between 1.5 and 2.0 since  $P(\Sigma_{K_0} \leq .1767 | K=1.5) = .0169$  and  $P(\Sigma_{K_0} \leq .1767 | K=2.0) = .1252$ ; it also shows that  $K_U$  is between 5.0 and 6.0 since  $P(\Sigma'_{K_0} \leq 2.9430 | K=5) = .0574$  and  $P(\Sigma'_{K_0} \leq 2.9430 | K=6) = .0201$ . Therefore we continue our search by replacing data cards A7 and B7 by cards A and B, respectively:

```

Cards/Cols: 12345678901234567890123456789
A           321 20.0 20.0 1.60 0.10 1.90
B           321 20.0 20.0 5.10 0.10 5.90

```

After reviewing the output, we conclude that  $(K_L, K_U) \cong (1.7, 5.2)$  since the  $P(\Sigma_{K_0} \leq .1767 | K=1.7) = .0452$  and  $P(\Sigma'_{K_0} \leq 2.9430 | K=5.2) = .0464$ .

Bonuses from the output of data decks A and B are:

$$(1) P(\Sigma_{K_0} \leq 0.1767 | M=N=20, R_1=21, R_2=R_3=20, K=K_0=1) = .0002.$$

Since this probability is less than .05, we reject  $H_0: K=1$  in favor of  $H_1: K > 1$ .

$$(2) P(\Sigma'_{K_0} \leq 2.9430 | M=N=20, R_1=21, R_2=R_3=20, K=K_0=1) = .9996.$$

If we were testing  $H_0: K=1$  vs.  $H_1: K < 1$ , we would accept the null hypothesis.

The  $\Sigma$  and  $\Sigma'$  methods presented here are designed to ensure that 100(1- $\alpha$ )% confidence intervals are their given size or larger. This has been done by making the Fortran variable ADJUST 0.01 smaller than it should be if the computer calculations were arithmetically precise. But this protective measure can cause the confidence intervals to become overly large when  $\Sigma_{K_0, \text{exp}}$  or  $\Sigma'_{K_0, \text{exp}}$  are near zero or L. This problem, however, can be overcome by using the MLE(K) in place of  $K_0$ . Simply use

Program PDE to compute  $\Sigma_{MLE(K),exp}$  and  $\Sigma'_{MLE(K),exp}$ ; then find  
 $K_L = [K: P(\Sigma_{MLE(K)} \leq \Sigma_{MLE(K),exp} | K, M, N, R_1, \dots, R_L) \leq \alpha/2]$  and  
 $K_U = [K: P(\Sigma'_{MLE(K)} \leq \Sigma'_{MLE(K),exp} | K, M, N, R_1, \dots, R_L) \leq \alpha/2]$  using Program  
 SIGMAD.

At this point the  $\Sigma$  and  $\Sigma'$  methods offer an infinite number of procedures (one for every  $K_0 > 0$ ) for finding a confidence interval for  $K$ . This represents an uncomfortable situation since each procedure may yield somewhat different confidence intervals. Originally no such problem existed because  $K_0$  was postulated to equal one in all predator-prey experiments. When the authors decided to allow  $K_0$  to assume any value an experimenter believed to be appropriate, the problem of multiple confidence intervals arose. To resolve the multiple interval and computer accuracy problems simultaneously, the authors suggest that experimenters use exclusively the  $\Sigma_{MLE(K)}$  and  $\Sigma'_{MLE(K)}$  methods for calculating confidence intervals. The  $\Sigma_{K_0}$  and  $\Sigma'_{K_0}$  methods must still be used to get hypothesis test P values.

Program SIGMAD, as presented, works for experiments where the number of tanks per treatment is three. When the number of tanks is two or four (five tanks probably makes this program too expensive to use), amend this program as follows:

- (a) For  $L=TANKS=2$ , (1) replace the 3 in 3I4 of format statement 40 with a 2; (2) replace all statements between "DO 1 ... Big" and "1 Continue" by:



```

DO 1 I1 = Small, Big
DO 2 I2 = Small, Big
Sump = Ifix(100.0*(FF(I1,1) + FF(I2,2)) + Adjust)
Pdist(Sump) = Pdist(Sump) + (PP(I1,1)*PP(I2,2))
Spofg = Ifix(100.0*(GG(I1,1)+GG(I2,2)) + Adjust)
Pdofg(Spofg) = Pdofg(Spofg)+(PP(I1,1)*PP(I2,2))
2 Continue
1 Continue

```

- (b) For L=TANKS=4, (1) replace the 3 in 3I4 of format statement 40 with a 4; (2) replace all statements between "DO 1 ... Big" and

"1 Continue" by:

```

DO 1 I1= Small, Big
DO 2 I2= Small, Big
DO 3 I3= Small, Big
DO 4 I4= Small, Big
Sump = Ifix (100.0*[FF(I1,1) + FF(I2,2) + FF(I3,3) + FF(I4,4)] + ADJUST)
Pdist(Sump) = Pdist(Sump) + (PP(I1,1)*PP(I2,2)*PP(I3,3)*PP(I4,4))
Spofg = Ifix(100.0*[GG(I1,1) + GG(I2,2) + GG(I3,3) + GG(I4,4)] + ADJUST)
Pdofg(Spofg) = Pdofg(Spofg) + (PP(I1,1)*PP(I2,2)*PP(I3,3)*PP(I4,4))
4 Continue
3 Continue
2 Continue
1 Continue

```

Program SIGMAD starts on the next page.

```

PROGRAM SIGMAD(INPUT,OUTPUT,TAPE5=INPUT,TAPE6=OUTPUT)
REAL ADJUST,EXCESS,SIGEXP
REAL KZERO,KZEROL,KZEROH
REAL PP(35,5),FF(35,5),GG(35,5)
REAL POIST(502),COIST(502),V(502)
REAL NT,NC,K,KINC,KMAX,FI,R
REAL P(35),REG(35),PDF(35),CDF(35),G(35),CDOFG(502),PDOFG(502)
INTEGER RS(5),TANKS,LINDX
INTEGER SPOFG,SUMP,RR(5),RMAX,R2,IM,L,LO,HI
INTEGER BIG,SMALL,RMAX2
60 READ(5,60) KZERO,SIGEXP
   FORMAT(F5.0,F10.0)
   EXCESS=((100.0*SIGEXP)-FLOAT(IFIX(100.0*SIGEXP)))*0.01
   ADJUST=1.99-(100.0*EXCESS)
   KZEROL=KZERO-0.0001
   KZEROH=KZERO+0.0001
1000 READ(5,10) TANKS,RMAX,NT,NC,K,KINC,KMAX
10   FORMAT(I1,I2,5F5.0)
   IF(NT.GT.33.0) STOP
   IF(NC.GT.33.0) STOP
   IF(RMAX.GT.33) STOP
   IF(KINC.LT.0.001) STOP
   L=TANKS
   LINDX=(100*L)+1
   RMAX=RMAX+2
   HI=IFIX(NT+2.1)
797 READ(5,797) SMIN,SMAX
   FORMAT(2F5.0)
   DO 11 I=1,L
20   READ(5,20) RS(I)
   FORMAT(I2)
   RR(I)=RS(I)+2
11   CONTINUE
2000 CONTINUE
   DO 22 I=1,35
   REG(I)=0.0
   PDF(I)=0.0
   CDF(I)=0.0
22   CONTINUE
   PDF(2)=NC/(NT*K+NC)
   PDF(3)=(NT*K)/(NT*K+NC)
   DO 33 LL=4,RMAX
   R2=LL
   R=FLOAT(R2-2)
   LO=IFIX(R-NC+2.1)
   DO 44 I=2,R2
   FI=FLOAT(I)
   P(I)=(FI-2.0)/R
   REG(I)=0.0
   IF((I.LT.LO).OR.(I.GT.HI)) GO TO 12
   IM=I-1

```

```

REG(I)=PDF(IM)*((NT-FI+3.0)*K/((NT-FI+3.0)*K+NC-R+FI-2.0))
*   +PDF(I)*((NC-R+FI-1.0)/((NT-FI+2.0)*K+NC-R+FI-1.0))
12  CONTINUE
44  CONTINUE
    DO 55 I=2,R2
    PDF(I)=REG(I)
55  CONTINUE
    DO 780 JJ=1,L
    IF(R2.EQ.RR(JJ)) GO TO 35
780 CONTINUE
    GO TO 34
35  CONTINUE
    DO 66 I=2,R2
    IM=I-1
    CDF(I)=CDF(IM)+PDF(I)
    G(I)=1.0-CDF(IM)
66  CONTINUE
    DO 111 JA=1,L
    IF(R2.NE.RR(JA)) GO TO 333
    DO 222 JB=2,R2
    PP(JB,JA)=PDF(JB)
    IF(K.LT.KZEROL.OR.K.GT.KZEROH) GO TO 444
    FF(JB,JA)=CDF(JB)
    GG(JB,JA)=G(JB)
444 CONTINUE
222 CONTINUE
333 CONTINUE
111 CONTINUE
34  CONTINUE
33  CONTINUE
    DO 77 N=1,502
    PDIST(N)=0.0
    PDOFG(N)=0.0
77  CONTINUE
    DO 2222 J=2,RMAX
    SMALL=J
    DO 6666 JD=1,L
    IF(PP(J,JD).GT.0.0001) GO TO 3333
6666 CONTINUE
2222 CONTINUE
3333 CONTINUE
    RMAX2=RMAX+2
    DO 4444 J=2,RMAX2
    BIG=RMAX2-J
    DO 7777 JE=1,L
    IF(PP(BIG,JE).GT.0.0001) GO TO 5555
7777 CONTINUE
4444 CONTINUE
5555 CONTINUE
    DO 1 I1=SMALL,BIG
    DO 2 I2=SMALL,BIG
    DO 3 I3=SMALL,BIG

```

```

SUMP=IFIX(100.0*(FF(I1,1)+FF(I2,2)+FF(I3,3))+ADJUST)
PDIST(SUMP)=PDIST(SUMP)+(PP(I1,1)*PP(I2,2)*PP(I3,3))
SPOFG=IFIX(100.0*(GG(I1,1)+GG(I2,2)+GG(I3,3))+ADJUST)
PDOFG(SPOFG)=PDOFG(SPOFG)+(PP(I1,1)*PP(I2,2)*PP(I3,3))
3 CONTINUE
2 CONTINUE
1 CONTINUE
CDIST(1)=PDIST(1)
CDOFG(1)=PDOFG(1)
V(1)=EXCESS
DO 74 I=2,LINDX
IM=I-1
CDIST(I)=CDIST(IM)+PDIST(I)
CDOFG(I)=CDOFG(IM)+PDOFG(I)
V(I)=FLOAT(IM)*0.01+EXCESS
74 CONTINUE
WRITE(6,40) K, (RS(I),I=1,L),KZERO
40 FORMAT(/5X, #SIGMA+SIGMAPRIME P(SIGMAP.LE.SIGMAPEXP) #,
* #P(SIGMA.LE.SIGMAEXP) K=#,F6.3,3I4,# KZERO=#,F6.3)
DO 75 I=1,LINDX
IF(V(I).GT.SMIN.AND.V(I).LT.SMAX)
* WRITE(6,50) V(I),CDIST(I),CDOFG(I)
50 FORMAT(10X,F6.4,10X,F9.4,10X,F9.4)
75 CONTINUE
K=K+KINC
IF(K.GT.KMAX) GO TO 1000
GO TO 2000
END

```

## Appendix D: Program PITOL

Program PITOL computes  $P_{i,K}^{**L}$  and  $P'_{i,K}^{**L}$  values where  
 $P_{i,K} = P(T \geq T_i | K, M, N, R_i)$  and  $P'_{i,K} = P(T \leq T_i | K, M, N, R_i)$ . Used in  
 conjunction with Table 9, this program will aid in finding confidence  
 limits for K when SIGMAD is too expensive to use.

The data deck for PITOL must contain the following information:

<u>Card</u>	<u>Information</u>	<u>Format</u>
1	Tanks per treatment	(I1)
2	RMIN, RMAX, NT, NC, K, KINC, KMAX	(2I2, X, 5F5.0)
3	$R_1, T_1$	(2I2)
4	$R_2, T_2$	(2I2)
...	...	...
L+2	$R_L, T_L$	(2I2)
...	Searches for $(K_L, K_U)$ may be conducted for more than one treatment, provided the value for TANKS remains the same. Simply follow the format of cards 2 thru L+2.	
LAST 10	Ten blank cards	

Continuing our example we search for  $K_L$  below  $MLE(K) = 3.95$  and for  
 $K_U$  above 3.95. Since this program is fairly cheap to run, look at  
 $K = 1.0, 1.1, \dots, 3.0$  for  $K_L$  and at  $K = 5.0, 5.5, \dots, 20.0$  for  $K_U$ .  
 Conclude that the 90% confidence limits for K are  $K_L = 1.3$  and  $K_U = 18.5$   
 since the  $\max_{i=1,2,3} (P_{i,K=1.3}^{**3}) = .0454$ ,  
 the  $\max_{i=1,2,3} (P_{i,K=1.4}^{**3}) = 0.738$ ,  
 the  $\max_{i=1,2,3} (P_{i,K=18.0}^{**3}) = .0527$  and  
 the  $\max_{i=1,2,3} (P_{i,K=18.5}^{**3}) = .0467$ .

The data deck for this example is:

Card/Cols:	123456789012345678901234567890
1	3
2	2021 20.0 20.0 1.00 0.10 3.00
3	2115
4	2012
5	2017
6	2021 20.0 20.0 5.00 0.50 20.0
7	2115
8	2012
9	2017
10-19	Ten blank cards

Since  $\max_{i=1,2,3} (P_{i,K=1.0}^{**3}) = 0.0050$ , we reject  $H_0: K=1.0$  in favor of  $H_1: K > 1.00$ .

Program P1TOL follows on the next page.

```

PROGRAM P1TOL(INPUT,OUTPUT,TAPE5=INPUT,TAPE6=OUTPUT)
REAL P(35),REG(35),PDF(35),CDF(35)
REAL NT,NC,K,KINC,KMAX,FI,R,EP,EPSQ,VARP
INTEGER T(35),TANKS
INTEGER IM,RMAX,RMIN,R2,LO,HI
REAL PMAXPR,PPMXPR,PVALUE,PPRIME
INTEGER TT(3),RR(3),T1,T2,L,IR
READ(5,50) TANKS
50  FORMAT(I1)
    LL=TANKS
    WRITE(6,30) LL
30  FORMAT(6X,7 K      R      P**L  PP**L      L=7,I2//)
1000 READ(5,10) RMIN,RMAX,NT,NC,K,KINC,KMAX
10  FORMAT(2I2,X,5F5.0)
    IF(NT.GT.33.0) STOP
    IF(NC.GT.33.0) STOP
    IF(RMAX.GT.33) STOP
    IF(KINC.LT.0.001) STOP
    RMIN=RMIN+2
    RMAX=RMAX+2
    HI=IFIX(NT+2.1)
    READ(5,40) (RR(I),TT(I),I=1,LL)
40  FORMAT(2I2)
2000 CONTINUE
    DO 55 I=1,35
    REG(I)=0.0
    PDF(I)=0.0
    CDF(I)=0.0
55  CONTINUE
    PDF(2)=NC/(NT*K+NC)
    PDF(3)=NT*K/(NT*K+NC)
    DO 44 L=4,RMAX
    R2=L
    R=FLOAT(R2-2)
    LO=IFIX(R-NC+2.1)
    DO 11 I=2,R2
    FI=FLOAT(I)
    P(I)=(FI-2.0)/R
    T(I)=I-2
    REG(I)=0.0
    IF((I.LT.LO).OR.(I.GT.HI)) GO TO 12
    IM=I-1
    REG(I)=PDF(IM)*((NT-FI+3.0)*K/((NT-FI+3.0)*K+NC-R+FI-2.0))
    * PDF(I)*((NC-R+FI-1.0)/((NT-FI+2.0)*K+NC-R+FI-1.0))
12  CONTINUE
11  CONTINUE
    DO 66 I=2,R2
    PDF(I)=REG(I)
66  CONTINUE
    IF(R2.LT.RMIN) GO TO 45
    EP=0.0
    EPSQ=0.0

```

```
DO 22 I=2,R2
IM=I-1
CDF(I)=CDF(IM)+PDF(I)
EP=EP+PDF(I)*P(I)
EPSQ=EPSQ+PDF(I)*P(I)*P(I)
22 CONTINUE
PMAXPR=0.0
PPMXPR=0.0
IR=IFIX(R+0.1)
DO 77 I=1,LL
T1=TT(I)+1
T2=TT(I)+2
IF(IR.EQ.RR(I)) PVALUE=1.00-CDF(T1)
IF(IR.EQ.RR(I)) PPRIME=CDF(T2)
PMAXPR=PVALUE**LL
PPMXPR=PPRIME**LL
IF(IR.EQ.RR(I)) WRITE(6,20) K,IR,PMAXPR,PPMXPR
77 CONTINUE
20 FORMAT(5X,F6.3,I5,F8.4,F9.4)
45 CONTINUE
44 CONTINUE
K=K+KINC
IF(K.GT.KMAX) GO TO 1000
GO TO 2000
END
```