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Discussion of Data on the Killing by Cold of Fruit Fly Larvae in Mangosteens

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ABSTRACT

Burikam *et al.* have recently quantified the relationship between exposure to cold and death of fruit fly larvae infesting mangosteens. It is shown here that the results are robust with respect to a number of minor changes that could have been made in the statistical analysis. But the results are very sensitive to the choice of statistical model assumed (probit or logit).

Key words : guarantine policy (fresh fruit), logit model, statistical robustness

INTRODUCTION

Experiments using cold (5, 6, or 7°C) to kill oriental fruit fly larvae infesting mangosteens were reported by Burikam *et al* (1991). No doubt the practical implications of this work will be of great interest to the fresh fruit industry. But *I* would like to comment on the statistical treatment of the data: an attention was caught by Burikam *et al* attempting to draw conclusions about what length of treatment leads to 99.9968% mortality (probit 9), when the total number of insects exposed to each of the cold temperatures was only some 3000. Burikam *et al* were extrapolating their regression lines well beyond the region in which they had data; how robust are their results to changes in the statistical analysis performed? The conclusions will be:

Minor variations in statistical analysis, relating to exactly what data was analysed at one time, in most cases make little difference to the numerical results.

But the choice of which basic statistical model is assumed to be true (the probit or the logit) has a very big effect on the numerical results.

In Section 1, will be described the statistical analyses and carried out using the data in Table 1 of Burikam *et al.* (1991). Then in Section 2, some more general (and perhaps controversial) comments on the function of probit analysis and related statistical methods will be offered.

STATISTICAL ANALYSES

Factors investigated

Burikam *et al* .(1991) reported on the percentage mortality of fruit fly larvae in festing mangosteens, after 10 periods of exposure (6, 12, 24, 48, 96, 192, 264, 336, 384, and 480 hours) to each of three temperatures (5, 6 and 7°C). In the statistical analysis of any data of this type, a number of decisions have to be made. The sensitivity of the results obtained to the following factors have been investigated.

Inclusion vs. exclusion of exposures for which there was 100% mortality. (At all three temperatures, there was 100% mortality observed for exposures of 264 hours and more. It appears that Burikam *et al* did not include the data for 336, 384, and 480 hours in fitting their model to the data, but there seems no compelling reason for this.)

Inclusion vs. exclusion of data for low exposure times. The natural thing to do is to include all the data in the analysis. But it could be argued that the data for low exposure times in only relevant to estimated mortality at high exposure times if one believes that the assumed model (equation (1) below) holds exactly; and that, otherwise, one would prefer to place relatively greater weight on data for the high exposure times. An additional point, this one of a more technical nature, is that when mortality is close to the baseline level, the corrected mortality has appreciable

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sampling variability arising from the baseline mortality as well as from the experimental mortality.

Handling of the temperature variable. Three alternatives may be suggested: (a) The data for the three temperatures could be analysed separately. (b) But at some exposure times, mortality was not observed to increase with decreasing temperature. Presumably this is merely the result of chance. A common strategy in such cases is to modify the data if the mortality is lower at a lower temperature than at a higher, change both figures to their average. (c) Alternatively, over the (narrow) range of temperatures considered, the temperature colud be assumed to contribute linearly to the probit of mortality.

Choice of statistical model. The basic assumption of Burikam *et al* was that

$$\text{probit}(y) = a + b.\log(x), \quad (1)$$

where y = proportion killed and x = hours of exposure. However, there was no justification given for this choice. (This is not a criticism of Burikam *et al*: both the use of the model and the failure to justify it are common) Clearly, a vast range of alternative models could be proposed, with various functions of y on the left hand side of the equation, and various function of x on the right hand side. I will only investigate one,

$$\text{logit}(y) = a + b.\log(x). \quad (2)$$

In view of the similarity of the normal and logistic distributions, this model is as close to the standard one as any alternative is likely to be.

RESULTS

Burikam *et al.* report their data in sufficient detail that it is possible to reproduce their equations quite closely. Estimates of the parameters a and b in equation (1), together with the corresponding estimated times to attain probit 9, using the *glim* procedure in the software package *S-PLUS*, are compared with the results of Burikam *et al* in Table 1. The discrepancy for the data obtained at 5°C is appreciable, and I do not know the reason for this, but the other differences are negligible (and no doubt arise from minor variations in the computations performed).

The main results of this paper are given in Table 2.

Comparing lines b, c, d and e in that Table with line a, showing that these minor variations in analysis have only small effects on the estimated time corresponding to probit 9.

Comparing line f with line a, the choice of the logit versus the probit model has an enormous effect on the conclusions drawn.

Table 1 Comparison of results with those of Burikam *et al.*

	Burikam *et al*			Hatchinson		
	a	*b*	P9	*a*	*b*	P9
5°C	−1.01	3.75	466	−0.23	3.32	607
6°C	−0.29	3.34	600	−0.30	3.35	595
7°C	−0.08	3.27	600	−0.23	3.35	569

P9 means the time corresponding to probit 9.

Table 2 The estimated hours of exposure needed to attain probit 9.

	5°C	6°C	7°C
(a) Standard	607	595	569
(b) All exposures	595	585	561
(c) Low exposures omitted	498	641	644
(d) Averaging of data across temperatures	590	574	605
(e) Two independent variables	602	591	580
(f) Logit model	1987	2044	1923

Comment

It is often said in the statistical literature that the probit and logit models are very similar. This is confirmed by the present results, in that the estimated exposures corresponding to 50% mortality were similar (Table 3(a)), as was the goodness-of -fit of the models. However, in the disinfestation of fruit, it is necessary to achieve a very high mortality, and the fact that the normal and logistic distributions behave differently in the tails means that the estimated exposures are very different. As examples of previous work supporting this, the following three references will suffice:

Morgan (1985, Table 3) compared the levels of stimulus necessary to achieve a defined proportion of response, as estimated by three models (which included the logit, but not the probit, model); for 50% response, the three models gave very similar results, but as to 99% response, the resluts were more heavily dependent on the model used.

In the Discussion of Brown (1970), C.I. Bliss remarked (p. 141) that "Sometimes an extreme percentage is important. For example, in sterilization tests for fruit flies the quarantine officials desired 0% survival. It took some arguments to convince them that it is impossible to measure 0% or 100%." To this, Brown replied (pp. 141-142) that the situation where interest is in the tails, rather than the centre, of the stimulus-response curve, requires either very large samples sizes at the extreme doses or extrapolation that depends critically on the chosen mathematical form for the dose-response function. It is a very difficult situation — maybe hopeless!

Schmoyer (1984) remarked that estimators of the stimulus-response curve, can be wildly biased and variable when the specified model is incorrect.

Table 3 Demonstration that the probit and logit models give similar estimates of the times corresponding to 0 and 4 s.d.'s above the mean.

	5°C	6°C	7°C
(a) Hours of exposure for 50% mortality			
Probit	38	38	36
Logit	38	38	36
(b) Hours of exposure for 4 s.d. above the mean.			
Probit	607	595	569
Logit	608	620	585

It is difficult to imagine convincing reasons for preferring either the probit or the logit model to the other. So, what purpose is a statistical analysis truly serving in this context? This question is taken up in Section 2.

(a) Standard analysis: data for exposures of 6, 12, 24, 48, 96, 192, and 264 hours was included, with each temperature considered separately, and the probit model fitted. (b) As standard, except that exposures of 336, 384, and 480 hours were also included. (c) As standard, except that exposures of 6 and 12 hours were omitted. (d) As standard, except that data was aveaged across temperatures when it violated the assumption that mortality increases with lower temperature. (e) As standard, except that data for all temperatures was analysed to gether, with both log (hours) and temperature appearing in the equation. (f) As standard, except logit (y) replaced probit (y).

LIMITATIONS OF PROBIT ANALYSIS

On the face of it, Burikam *et al* were using statistical methods (specifically, probit analysis) to establish what length of exposure to cold is necessary in order to kill 99.9968% of insect larvae. The first point, however, is that the wording of pp. 253-254 indicates that Burikam *et al* did not take their own results seriously, it seems that the estimated exposures were unexpectedly large, and that instead of adopting these, Burikam *et al* envisage conducting an experiment in which 100% mortality is actually achieved with a sample of 30,000 insects.

The second point is that Burikam *et al* were probably right to consign probit analysis to a less formal role than it apparently is designed to play.

A. One argument in favour of this is the sensitivity (Section 1) of the results to the choice of the probit vs. the logit model. Expressing this sensitivity in another way, whereas .0032% of observations lie more than 4 standard deviations above the mean of a normal distribution, about 20 times that number (.071%) lie more than 4 standard deviations above the mean of a logistic distribution. It seems that if statisticians take the results of probit analysis seriously, what they are serious about is the figure of 4 standard deviations above the mean as being an impressive figure to convince the decision-makers with, not the survival probability. The time corresponding to 4 s.d.'s above the mean is indeed robust to choice of model (Table 3b).

B. Another is the choice of a mortality of

99.9968% as being the criterion. According to Burikam *et al*, it is the accepted security level and they give no further justification. Conceivably, one might attempt a justification along the following lines. Let $p1$ = average number of insects per fruit (before treatment), $p2$ = proportion of insects surviving disinfestation, $p3$ = probability of an insect surviving the journey to the customer, N = number of fruits exported per year. Then the expected number of insects reaching the customer per year = $N\,p1p2p3$. Suppose one requires that this be less than n. If we know, or are prepared to make guesstimates of, n, N, $p1$, and $p3$, then $p2$ can be determine to achieve. Incidentally, it is clear from this that there is little point in reducing $p2$ much below the fraction of fruits that (through technical failure, administrative mistake, criminality, or otherwise) escape being treated. Similarly, with m being the number of insects reaching the customer per year by other routes (e.g., carried by tourists), there is little point in reducing $p2$ much below $m/(Np1p3)$. Hoewever, it is plain that 99.9968% is chosen because it corresponds to probit 9, which is a nice round number, and it has become commonly used in this context.

Notice how easily results very different from the probit model were obtained. I did not hvae to search among unusual distributions, and even retained the logarithm as being the transformation of exposure time.

Finally, three commonsense suggestions are recommended for further research.

(1) *Disinfestation* within the wider processing system. Critically examine whether a survival probability as low as .0032% is really necessary. Reasoning such as that in paragraph B above may be helpful. Attention should also be given to the *process of decision* on a quarantine strategy: it is not clear that the usual tools one might expect to employ, including the calculation of the expectations of the utilities of the options considered, are truly relevant when what is of concern is an event (the import of the fruit fly) of very low probability and very high cost.

(2) *Experiment.* Carry out large-scale experiments involving the exposure to long periods of cold of tens or hundreds of thousands of insects. Until adequate theoretical development has taken place (see (3) below), statistical methods cannot be expected to make up for inadequate sample sizes. Naturally, large-scale experiments would not be possible without the experience and expertise developed in the course of smaller-scale studies.

(3) *How the cold work.* Develop greater understanding of the mechanism by which cold kills insects. Any model of this mechanism will necessarily have an important random component. In particular, it would be very helpful if deductions could be made about the tail-behaviour of exposure tolerances — that is, whether the mortality curve approaches 1 to be quickly or slowly. For example, it is plausible that a true limit of exposure exists, such that no insect survives longer than this.

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