Before a Decision-Making Committee
Of the Environmental Protection Authority

APP203660

Under	the Hazardous Substances and New Organisms Act 1996
In the matter of	the modified reassessment of methyl bromide
By	**Stakeholders in Methyl Bromide Reduction Inc**
	Applicant

STATEMENT OF EVIDENCE OF DAVID JAMES FLETCHER

27 JULY 2020

Counsel Acting
M J Slyfield
Stout Street Chambers

(04) 915 9277
morgan.slyfield@stoutstreet.co.nz
PO Box 117, Wellington

INTRODUCTION

1. My full name is David James Fletcher.

Qualifications and Experience

2. I am a Statistical Consultant specializing in providing advice on data analysis, primarily in the fields of ecology and conservation. I am a member of the New Zealand Statistical Association.

3. I have a BSc in Mathematics (1980), an MSc in Applied Statistics (1982), and a PhD in Statistics (1985) from Southampton University in the UK.

4. From 1984 to 2019 I worked in Universities in the USA, UK, Australia and New Zealand. I have published over 90 peer-reviewed papers in international science journals, primarily in applied statistics. Much of my research has been in ecology and conservation, including developing methods to allow for the uncertainty associated with estimates obtained from skewed data, like those in the air-dispersion simulations.

5. My most recent appointment was at the University of Otago, where I was Lecturer/Senior Lecturer/Associate Professor from 1991 to 2019. In 1993 I initiated a series of international conferences on "Statistics in Ecology and Environmental Monitoring"; the most recent one took place at Victoria University, Wellington in 2019.

6. I have taught many courses on statistics to undergraduate and postgraduates, in both mathematics and the sciences, including a specialist course for environmental scientists. In addition to my academic work I have been providing statistical consulting advice since 1990 to a range of organisations such as the Sydney Water Board, the Ministry of Fisheries, and the Department of Conservation.

Scope of Evidence

7. I have been engaged by Stakeholders in Methyl Bromide Reduction Incorporated (**STIMBR**) to comment on aspects of data analysis that may be relevant to the assessment of air dispersion modelling that forms part of this reassessment.

8. I have no experience in air dispersion modelling or fumigants. My role is to provide a statistician's perspective on the limitations inherent in using percentiles in regulatory standards.

9. For this purpose I have reviewed:

   (a) "Modeling Report for Methyl Bromide Exposures for Timber Fumigation at the Port of Tauranga, New Zealand" by Sullivan Environmental Consulting (6/22/2020)

   (b) "Addendum to Air Concentration Dispersion Modeling Assessment of Methyl Bromide Concentrations in Tauranga Port, New Zealand" by Sullivan Environmental Consulting (3/20/2019)

   (c) "Review of an Air Concentration Dispersion Modelling Assessment of Methyl Bromide Concentrations in Tauranga Port, New Zealand" Jennifer Barclay, Atmospheric Science Global (August 2019)

   (d) "Air Quality Review Dispersion Modelling Assessment Of Methyl Bromide" by Todoroski Air Sciences (16 September 2019)

   (e) "Air Dispersion Modelling Methyl Bromide" by Todoroski Air Sciences (4 November 2019)

   (f) "Review of Air Dispersion Modelling of Methyl Bromide Fumigation Events" Prepared for New Zealand Environmental Protection Authority by Pattle Delamore Partners (13 November 2019)

   (g) "Good Practice Guide for Atmospheric Dispersion Modelling" by NIWA, Aurora Pacific and Earth Tech for the Ministry for the Environment (June 2004)

   (h) Expert Conferencing Joint Witness Statement on Air Concentration Dispersion Modelling. Participants: Bruce Graham, Dennis Hlinka (15 October 2018)

   (i) "Percentile Limits Currently used by the USEPA in their NAAQS and Risk Assessment Guidelines: Summary prepared by Dennis Hlinka (pdf dated October 2018)

(j) "Advice To The EPA Following Expert Conferencing on EDN Air Concentration Dispersion Modelling" by Bruce W Graham (2 November 2018)

(k) Joint Statement of Experts in the Field of Air Dispersion Modelling. Participants: David Sullivan, Aleks Todoroski, Jennifer Barclay, Cathy Nieuwenhuijsen (30 January 2020)

(l) Joint Statement of Experts in the Field of Air Dispersion Modelling. Participants: David Sullivan, Aleks Todoroski, Jennifer Barclay, Cathy Nieuwenhuijsen (19 March 2020)

(m) Statement of Evidence of David Sullivan (27 July 2020)

10. This statement will cover the statistical issues that arise when estimating percentiles in air dispersion modelling, in particular the degree to which the estimated percentiles become much less reliable at the upper extremes.

Code of Conduct

11. I understand this reassessment is to be determined by a Decision-making Committee of the Environmental Protection Authority. However, I have read the Code of Conduct for expert witnesses in the Environment Court Practice Note 2014 and I have complied with it when preparing this evidence. Other than when I state that I am relying on the advice of another person, this evidence is within my area of expertise. I have not omitted to consider material facts known to me that might alter or detract from the opinions that I express.

ESTIMATING PERCENTILES IN SKEWED DATA

12. It is important to realise that the percentiles produced by the simulation results obtained from air dispersion modelling are estimates of the percentiles that will be observed in practice. For example, in practice the 98th percentile of the distribution of concentrations of a methyl bromide over the next 24 years at a particular location might be 0.042 ppm. The 98th percentile from a simulation over 24 years at that location might be 0.033 ppm or 0.039 ppm or 0.047 ppm. The hope is that the simulations will provide a reliable estimate of the percentiles that will occur in practice.

13. The reliability of a percentile estimate will be affected by a number of factors (Rao 2005), including the degree to which the modelling reflects the process by which methyl bromide will disperse in a particular location in the future. I am not an expert in air dispersion modelling, so cannot comment on this aspect.

14. Even if the modelling provides a perfect representation of the dispersion process there will be uncertainty, as the data produced by the simulation can only provide a sample of possible future concentrations. There is an underlying "population" of concentrations that would be observed if the simulations were repeated infinitely often. Thus the simulation results can be thought of as a sample from a population, in the same way that the results from an opinion poll provides a sample from a human population. The "margin of error" associated with such a poll provides an idea of its reliability.

15. I will now provide an illustration of the difficulty in estimating the highest upper percentiles of a population of concentrations.

16. Summaries of the percentiles obtained from some of the simulations performed by Sullivan Environmental Consulting were recently provided to me. These indicated the shape of the distribution of a sample of simulated methyl bromide concentrations at a single location. Figure 1 provides a visual summary of such a distribution. The area under the curve to the left of 0.00005 is 96.7% of the total area under the curve, so this is the 96.7th percentile. Likewise 0.0001 is the 99.9th percentile, and so on. The distribution is positively skewed, which means that it has a long "tail" to the right, where there are few relatively high concentrations. In fact the summaries of the simulations that I was given suggest that the distribution of concentrations is often more skewed than shown in this diagram, which makes it difficult to plot, as the right-hand tail is so long.

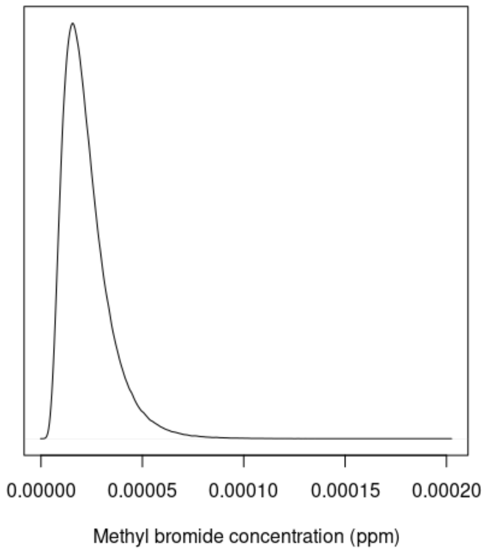


Figure 1. Illustration of the positive skewness in the distribution of methyl bromide concentration.

17. In what follows I have used a well known skewed distribution, the lognormal, to represent the underlying population of concentrations that would have been observed over a very large number of simulations (Rao 2005). This allowed me to replicate what might have been recorded in each of 100,000 identical air dispersion modelling simulations. Note that this hypothetical population is not meant to represent the true population, which can never be precisely known. The idea is simply to assess the degree to which the percentile estimates would vary over many repetitions of the modelling, when the underlying population of concentrations has a shape similar to a lognormal distribution.

18. Figure 2 shows how the 95th, 98th, 99.9th, and 99.99th percentiles varied over the 100,000 repetitions of a 24-year simulation, where we focus on the 8-hour average for all hours of fumigation. Thus each percentile estimate is based on a sample of 24 x 365 = 8,760 concentrations.

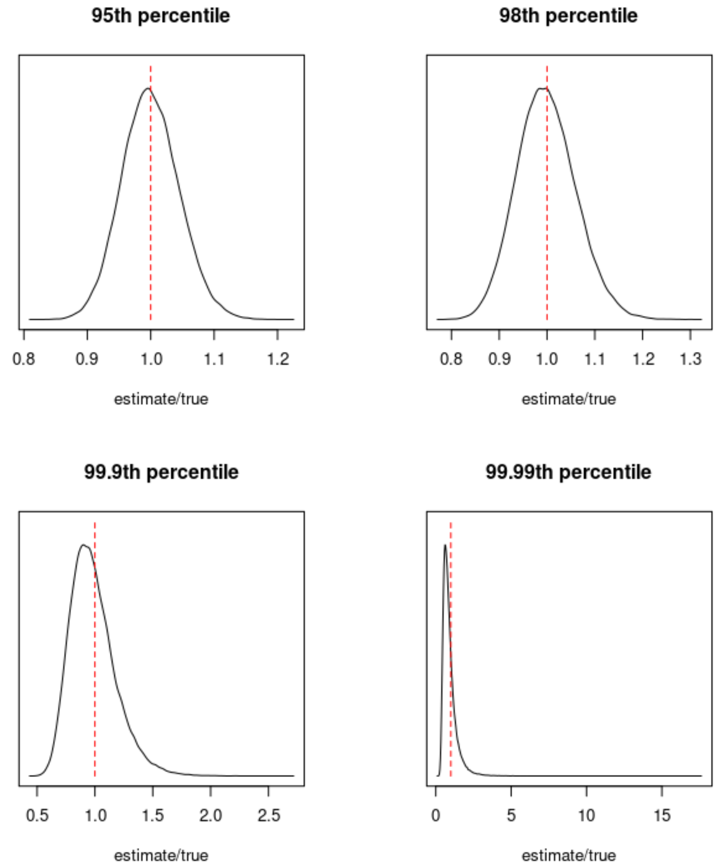


Figure 2. Distributions showing the variation in the 95th, 98th, 99.9th, and 99.99th percentiles in 100,000 repetitions of a simulation over 24 years in which we record the 8-hour average for all hours of fumigation.

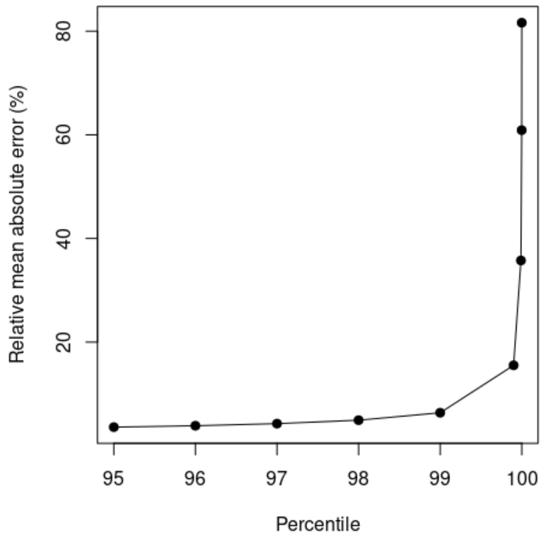
19. The horizontal axis in Figure 2 shows the ratio of the percentile estimate to the true (population) percentile. If this ratio is 1, the estimate is perfect and we have no error in the estimation. If it is 1.1, the estimate is 10% too high and if it is 0.8, the estimate is 20% too low. The narrower the distribution, and the closer the centre of the distribution is to 1, the better the percentile estimate.

20. Consider first the 95th percentile. Almost all of the 100,000 repetitions led to this percentile being between 0.8 and 1.2 of the true percentile, giving an error of at most 20% in both directions. For the 98th percentile there is a bit more variation, and for the 99.9th percentile there is even more, with the estimate sometimes being 2.5 times the true percentile, an error of +150%. The most extreme variation occurs for the 99.99th percentile, which can be as much as 15 times the value of the true percentile, an error of +1500%.

21. Figure 3 shows the relative mean absolute error associated with each of a range of percentiles from the 95th upwards. This is the average error expressed as a percentage of the true percentile (ignoring the direction of

the error). For the 95th percentile this average error is 4%. This gradually increases to 5% for the 98th percentile and then rapidly to 16% for the 99.9th percentile, 36% for the 99.99th percentile, and as high as 82% for the 99.9999th percentile. It is important to emphasise that this is an average error, and for the very highest percentiles the error can be much higher, as shown in Figure 2 for the 99.99th percentile.

Figure 3. Relative mean absolute error a percentile estimate, for each of a number



of percentiles, based on 100,000 repetitions of a simulation over 24 years in which we record the 8-hour average for all hours of fumigation.

22. In summary, Figure 3 shows the degree to which the reliability of a percentile estimate rapidly worsens as we approach the highest percentiles.

23. The results for 1-hour and 24-hour averages lead to a similar pattern, in terms of the difficulty in estimating the very highest percentiles. Likewise, this pattern also arises when we record concentrations for all hours of the day, or for just the first hour of fumigation. For brevity I have not included these results in my statement but can supply them on request.

24. This issue with estimating the very highest percentiles is well known to statisticians, and applies even when the distribution of measurements in the population is not skewed (Chakraborti and Li 2007).

25. I note from David Sullivan's evidence that an American Meteorological Society workshop on air dispersion modelling came to similar conclusions and recommended that standards make use of the 95th to 98th percentiles, rather than anything more extreme.

CONCLUSIONS

26. The very highest percentile concentrations obtained from air dispersion modelling simulations will be prone to a high degree of estimation error. In particular, the 95th and 98th percentiles will be estimated much more reliably than the 99.9th or 99.99th percentiles.

27. From Section 2 of the Sullivan addendum report[1] I note that the 98th percentile is used in some of the standards applied by the EPA in the US.

28. From David Sullivan's evidence I note that use of the 100th percentile estimate (the maximum) is known to be unreliable as an estimate of the maximum in the population distribution. Despite this, in Section 3.5 of the Todoroski review,[2] the authors assert that 100th percentiles should be reported. I consider such percentiles to be almost worthless, as they are so poorly estimated.

29. The NIWA Good Practice Guide[3] at 6.2.4 recommends that 100th percentiles not be used, and suggests that the 99.9th percentile is more reliable. I agree, but note that for the results I have presented in Figure 3, this percentile estimate has more than three times the average error of that for the 98th percentile.

David James Fletcher
27 July 2020

References

Chakraborti and Li. 2007. Confidence interval estimation of a normal percentile. The American Statistician 61: 331-336

Rao. 2005. Uncertainty analysis in atmospheric dispersion modeling. Pure and Applied Geophysics 162: 1893-1917

[1] Paragraph 9(b) above.

[2] Paragraph 9(d) above.

[3] Paragraph 9(g) above.