

# Some Advances in the Estimation and Use of Pesticide Dissipation Kinetics

J S Dyson, Syngenta Crop Protection AG, CH-4002 Basel, Switzerland;  
I A J Hardy, Battelle UK Ltd, Ongar, Essex CM5 0GZ, UK

## ABSTRACT

Reducing uncertainty in the estimation and use of pesticide dissipation kinetics remains critical to risk assessment. An exploratory simulation exercise was thus conducted with 10 data sets to get a better understanding of this uncertainty and examine options for reduction in practice. The exercise demonstrated two advances, by deriving more effective constraints for fitting kinetics, and by relating estimated kinetics to actual kinetics in order to derive, e.g. realistic worst-case half-lives for use in risk assessment.

## INTRODUCTION

Many advances have been made in pesticide dissipation kinetics in recent years. These advances have generally improved our ability to represent the kinetics of dissipation more accurately. However, these advances also highlight that fitting kinetics to data often leads to imprecise estimates. It is essential, therefore, to make further advances in how estimation procedures are applied in practice.

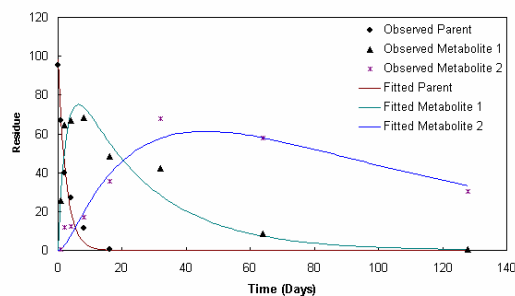
Hence, we wanted to conduct an exploratory exercise to see if more effective constraints could be derived in fitting kinetics to data, since unconstrained fitting can lead to both large over- and under-estimates of pesticide half-lives. Furthermore, we also wanted this exercise to relate estimated kinetics to actual kinetics, because this is crucial for helping to decide which estimates are most appropriate to use in risk assessments, e.g. for representing realistic worst-case half-lives.

## METHODS

We simulated 10 field data sets to examine the above areas of uncertainty. The simulations were based on a parent molecule degrading quantitatively to form a single metabolite, of which 90±9% degraded to form a second metabolite. The average first-order half-lives were: 2, 10 and 50 days for parent, metabolite 1 and metabolite 2, respectively, each with a CV of 35%. A sample population was then created by sampling randomly from underlying formation fractions and degradation rates; and the data sets were created from this sample population by adding random noise. A graph of one of the data sets and the kinetics fitted to the data is shown below.

Three types of fitting were conducted to estimate the kinetics:

- Completely unconstrained fits;
- Simple mechanistic fits constraining metabolite formation to <100%; and
- Statistico-mechanistic fits using both mechanistic and statistical criteria.



## RESULTS

The completely unconstrained fits showed the classic correlation between the estimated application / formation fraction and the estimated half-life: the estimated half-lives got shorter as the estimated application/formation fraction increased and vice versa, as shown on Figure 1, giving a "see-saw" correlation effect through the metabolism pathway.

When the simple mechanistic constraint was used, it dampened the "see-saw" correlation effect. However, because the average formation was 100% (metabolite 1) or close to 100% (metabolite 2), it is possible that the constraints biased the estimates, since they were one-sided rather than two-sided. Hence, we set metabolite 1 formation to 100% from "mechanistic" considerations, as an extreme two-sided constraint, e.g. in the case of esters degrading to form acids. The situation was more complex for metabolite 2. Given that the upper constraint on formation could be set as 100% on mechanistic grounds, we set the lower constraint on statistico-mechanistic considerations in three different ways:

**Percentile Method:** If the upper X% are not used because they are >100%, then the lower X% should also not be used, as equally unlikely to be realistic;

**Min-Max Method:** If the average formation was  $\mu$  and <100%, then the upper and lower X% can be set as  $\mu \pm (100-\mu)$ ; and

**Hybrid Method:** Set the lower X% as the average of the two above methods.

The second option minimised the correlation between application/formation fractions and half-lives, marginally improving the estimates of the means (see Figure 1), and thus has the potential to reduce uncertainty further than simple mechanistic constraints.

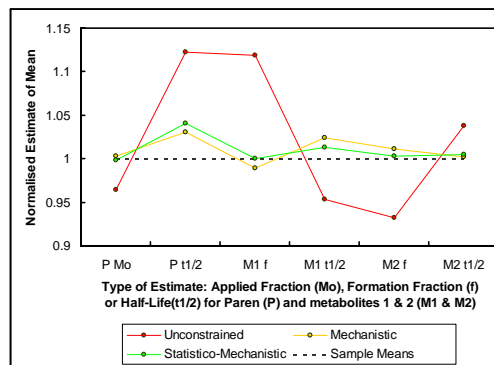


Figure 1 : Precision of means of various types of kinetics estimates down the metabolic pathway (The means were normalised to enable all the estimates to be plotted on a single graph)

For some environmental risk assessments, realistic worst-case estimates of half-lives are required. Little or no analysis appears to be published about how to interpret such a requirement. We therefore decided to plot the distribution of all the estimated half-lives as normalised half-lives and compare them to the sample population. The sample population was plotted using the non-parametric formula:

$$\text{Percentile} = 100 \times [m / (N + 1)]$$

where  $m$  is the rank order and  $N$  is the number of observations. This plotting formula seems to have the best theoretical justification (Bras, 1990), as demonstrated by Thomas (1948). This formula assumes that the *whole* population is not covered. However, due to uncertainties in kinetics estimates, it is possible that the *estimated* population may cover the whole population, so we also used a formula that does:

$$\text{Percentile} = 100 \times [(m - 1) / (N - 1)]$$

In addition, if the distribution is known, then a parametric formula may be used. The sample population is normally distributed, so it can be plotted using the formula:

$$\text{Half-life} = \mu + z\sigma$$

where  $\mu$  is the mean of distribution,  $z$  is the multiplier for the standard deviation ( $\sigma$ ) for a given percentile.

Figures 2 and 3 both show that the upper percentile half-lives are over-estimated, and vice versa for the lower percentile half-lives, compared to the sample population, particularly for the first non-parametric formula and the unconstrained fits. This is due to the correlation between half-lives and application/formation fractions, also skewing the estimated population away from a normal distribution. Thus, if realistic worst-case half-life is defined as the 90th percentile of the sample population, we recommend estimating it from the 90th percentile of the estimated half-lives with the second non-parametric formula, since it is unlikely to underestimate it and using the longest estimated half-life clearly over-estimates it.

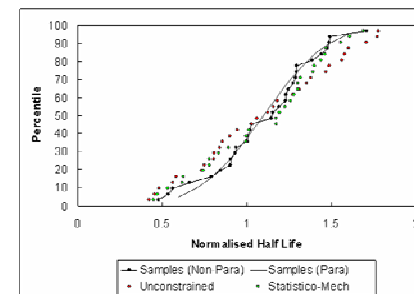


Figure 2 : Percentile plots of normalised half-lives for parent and metabolites, assuming that kinetics estimates covered only part of the underlying total population

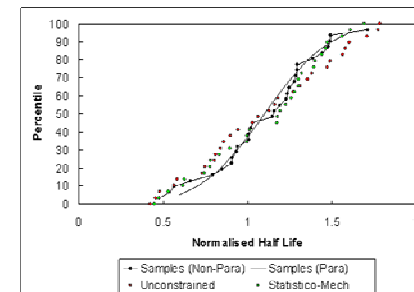


Figure 3 : Percentile plots of normalised half-lives for parent and metabolites, assuming that kinetics estimates covered the whole underlying total population.

## CONCLUSIONS

- The use of constraints reduces the uncertainty in kinetics estimates from *individual* data sets.
- Uncertainty in kinetics estimates is reduced considerably by the process of averaging across *multiple* data sets.
- There is a sound basis for using the 90th percentile half-life as a "realistic worst-case" in environmental risk assessments.
- The methods used here should be applied generally to understand further how to reduce uncertainty in the estimation and use of kinetics estimates.

## References

1. Bras RL, 1990. *Hydrology: An Introduction to Hydrologic Science*. Addison-Wesley, p.543
2. Thomas HR, 1948. Frequency of minor floods. *Boston Soc. Civil Eng.* 34: 425-442.

For questions, comments or reprints, please e-mail [jeremy.dyson@syngenta.com](mailto:jeremy.dyson@syngenta.com) or [i.hardy@battelleuk.com](mailto:i.hardy@battelleuk.com)