

A Bayesian network approach for probabilistic risk assessment of pesticides: expanding the binary risk outcome

Highlights

- Bayesian Networks (BNs) can act as an intermediate step between traditional and fully probabilistic Risk Assessment.
- A BN can predict the probability of several risk levels
- BNs can facilitate the communication of risk estimates and uncertainties

Background

The common practice for the environmental risk assessment of pesticides is based on a calculated **risk quotient (RQ)**, representing the ratio of exposure to effects, in combination with assessment factors to account for uncertainty. However, the traditional use of a single value (RQ) to quantify the risk does not communicate the uncertainty associated with this value (Verdonck et al., 2002). Moreover, a binary outcome (RQ above/below 1) does not communicate the **level of the risk**. We propose using **Bayesian networks** to calculate a **probabilistic RQ**, based on **probability distribution for exposure and effects** (Carriger & Barron, 2020).

Approach

BNs are causal models implementing **Bayes' rule** for updating probability distributions based on evidence (Pollino & Hart, 2008). The nodes (variables) have discrete states (e.g. intervals), quantified by discrete probability distributions (Fig. 1). The causal links (arrows) represent **conditional probability tables (CPTs)**, which can be based on equations.

The approach used in this study accounts for variability and/or uncertainty in both exposure and effects, and can also include a safety factor (Fig. 2).

Our BN approach had the following main steps:

- Discretise the exposure and effects concentrations into intervals (Fig. 1)
- Fit a log-normal distribution to the exposure and effects data (Fig. 1)
- Calculate the area under the curve for each interval, to obtain probabilities for the BN nodes (Fig. 3)
- Calculate the Exposure/Effect ratio distribution by Equation 1 (Fig. 2)
- Select a safety factor and calculate the Risk Quotient distribution

Figure 1. Frequency distributions of observations (bars) and fitted log-normal model (curves) for the exposure concentrations (a) and effect concentrations (b) for the selected pesticide, Azoxystrobin (CAS: 131860-33-8).

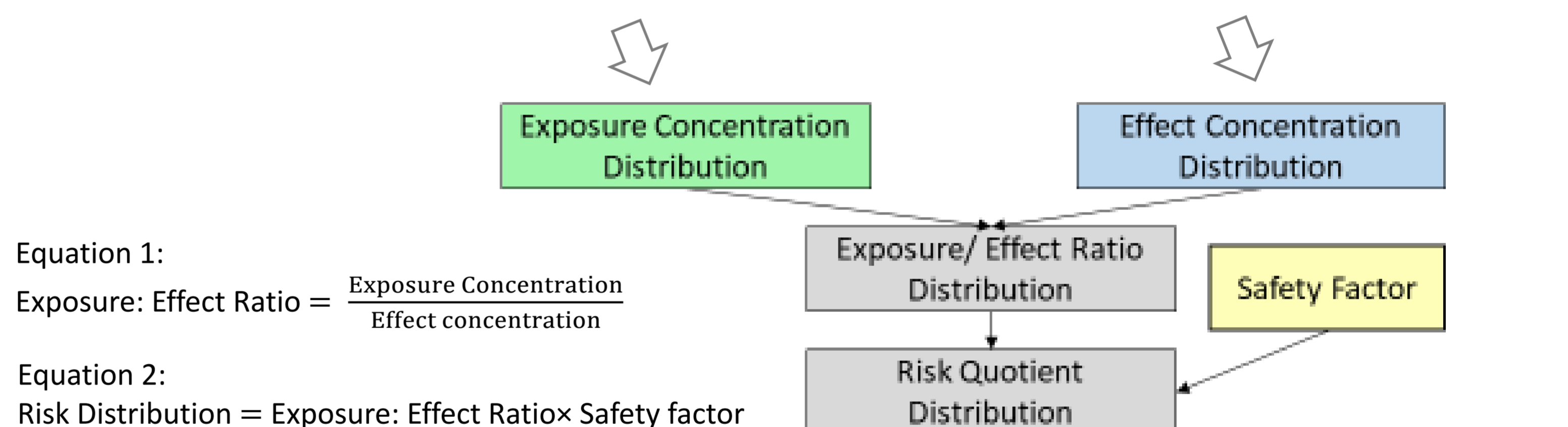
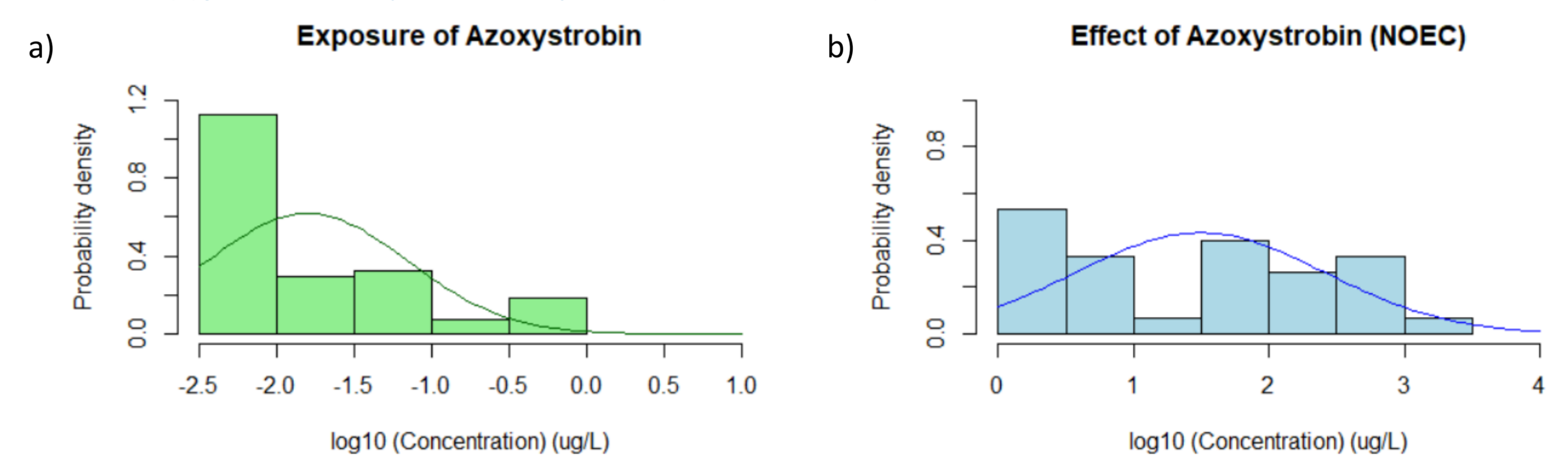


Figure 2. Conceptual model showing the variables, structure and equations used in the Bayesian network for calculating a probabilistic Risk Quotient

Results

The calculated probability distribution of RQ for the selected pesticide, is shown for three scenarios representing the range of observed exposure values and a range of safety factors (Fig. 3):

- Low exposure and low safety factor: probability of RQ>1 is less than 1%
- High exposure and low safety factor: probability of RQ>1 is 65%; probability of RQ>5 is 18%
- High exposure and high safety factor: probability of RQ>1 is 74%; probability of RQ>5 is 47%

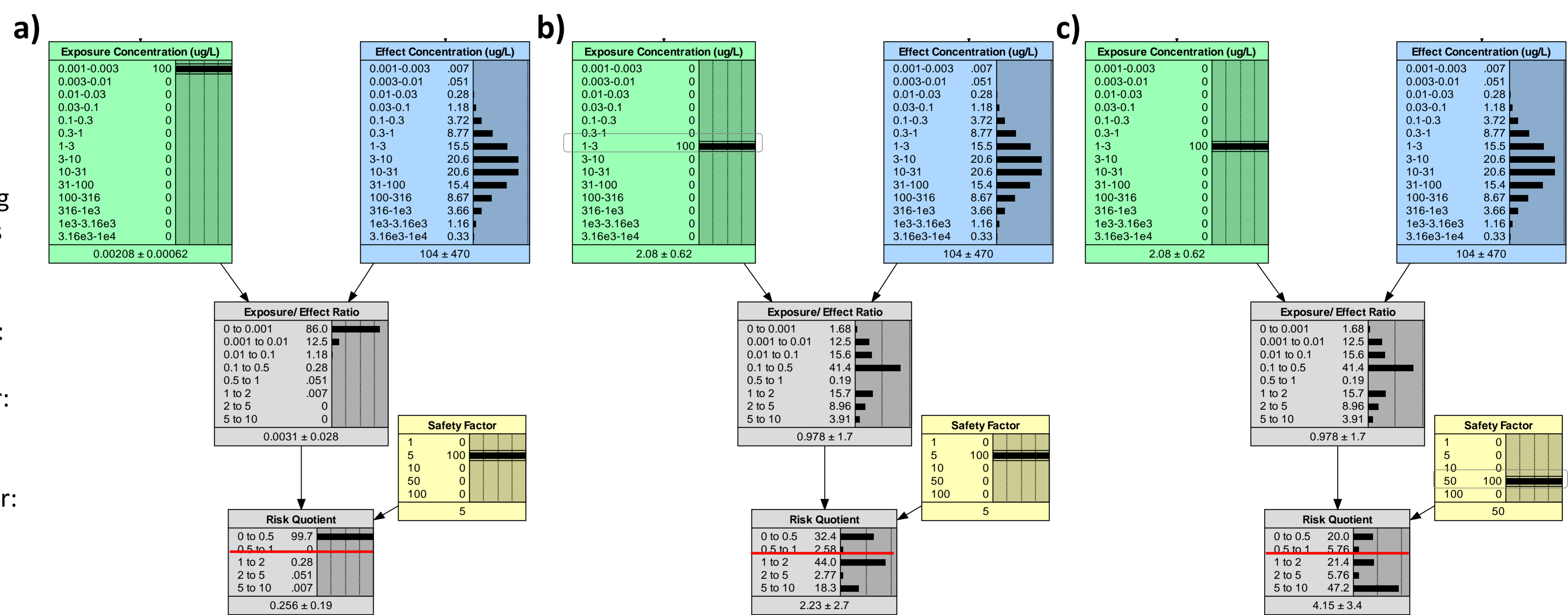


Figure 3. Bayesian network model with calculation of a probabilistic Risk Quotient (RQ) from the effect and exposure concentration distributions of Azoxystrobin, with application of a safety factors, for three scenarios (a,b,c). To facilitate comparison with the traditional binary outcome, the red horizontal line marks the intervals of the RQ above vs. below 1. The network was built in Netica (Norsys Software Corp., www.norsys.com)

Discussion and future perspectives

These examples demonstrate that BN modelling is a promising tool for calculating the RQ as a full probability distribution instead of a single value to be interpreted as a binary outcome.

This approach provides the probability of the RQ exceeding not only 1, but also other specified threshold values. The BN approach is comparable to the traditional risk assessment and can still apply safety factors. Thus, BNs can offer a transparent way of evaluating the required characterization of uncertainty for pesticide risk assessment as well as for ecological risk assessment in general (Carriger & Newman, 2011).

The current BN model can be improved in several ways, e.g.

- Obtaining more effect data (toxicity data), representing more species and especially native species
- Model the values below detection limit, to fit the distribution better
- Better modelling of the exposure concentrations below the detection limit
- Better fitting of curves to exposure and effect data by alternative distribution models (Fig. 1)

For related topics see also Poster 2.12P.2 (Mixture Toxicity), 4.06P.8 (Uncertainty & Risk), 7.03PC.1 (ECORISK2050), and 7.03PC.3 (Future Scenario & BN)

References

- Verdonck, F. A. M., Janssen, C. & Vanrolleghem, P. A., 2002. Probabilistic Ecological Risk Assessment Framework for Chemical Substances. Environmental Toxicology and Chemistry. Environmental Toxicology and Chemistry.
- Pollino, C. & Hart, B., 2008. Developing Bayesian network models within a Risk Assessment framework. Environmental Modelling & Software.
- Carriger, J. F. & Newman, M. C., 2011. Influence Diagrams as decision-making tools for pesticide risk management. Integrated Environmental Assessment and Management.
- Carriger, J.F. & Barron, M. G., 2020. A Bayesian network approach to refining ecological risk assessments: Mercury and the Florida panther (*Puma concolor coryi*). Ecological Modelling.

Acknowledgements

This research was funded by ECORISK2050, with funding from European Union's Horizon 2020 research and innovation program, grant agreement No. 813124 (H2020-MSCA-ITN-2018).

Knut Erik Tollefsen was funded by NIVAs Computational Toxicology Program (NCTP)

