

Improving Study Designs for Quantifying Biological Potency with Genomics Data

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Genomic Dose-Response Modeling
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- What comprises “Design”
- Special features of genomic concentration/dose – response (DR henceforth), and constraints on design
- Tools for evaluating an experimental design
- Classical toxicological design: BMD changed all that
- Classical Optimal Design for DR
- Injecting Realism
- Conclusions

What Do I Mean by Design?

- Number of dose (concentration) groups
- What concentrations to use (e.g., control + 1, 10, 100 mg/kg in *in vivo* study)?
- How to distribute replicates among doses?

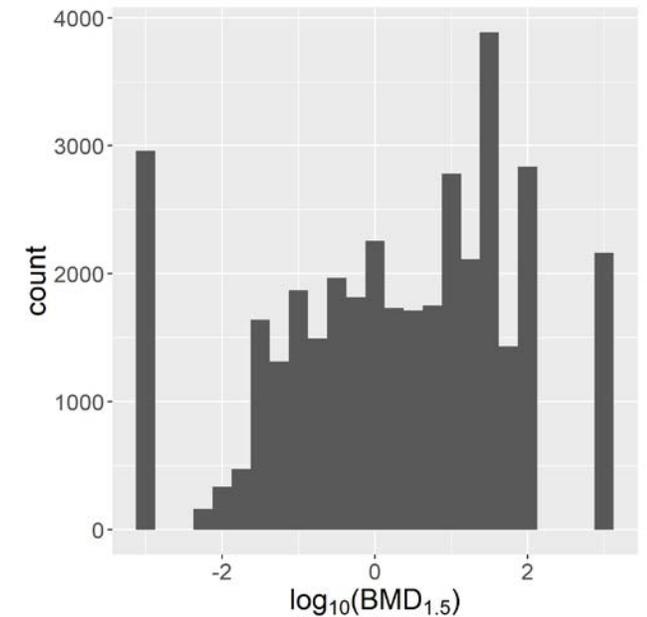
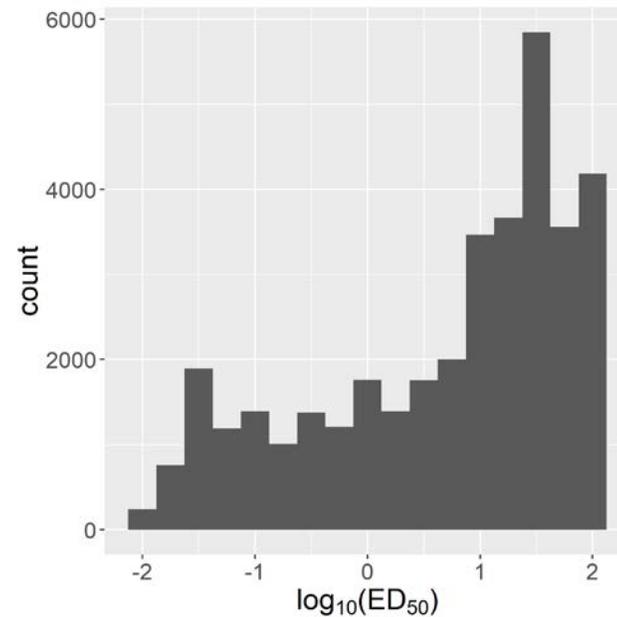
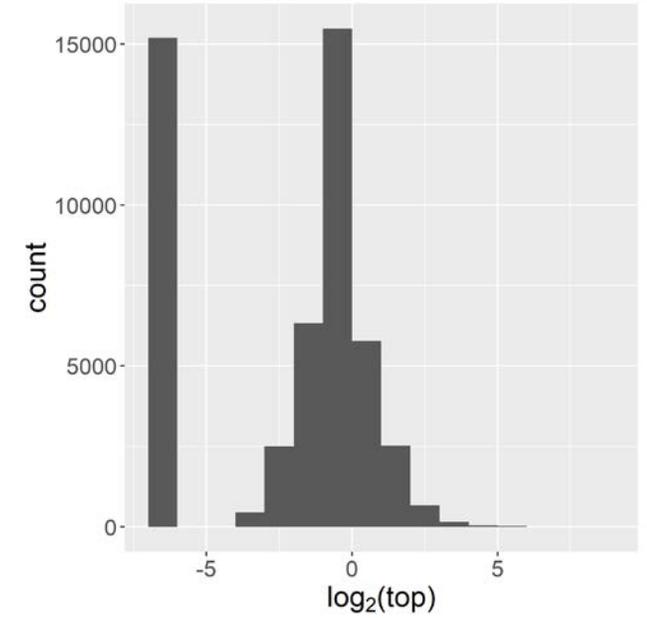
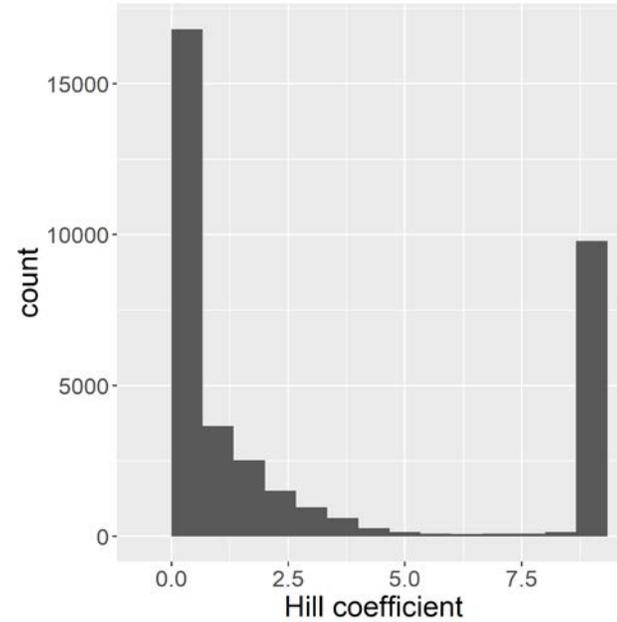
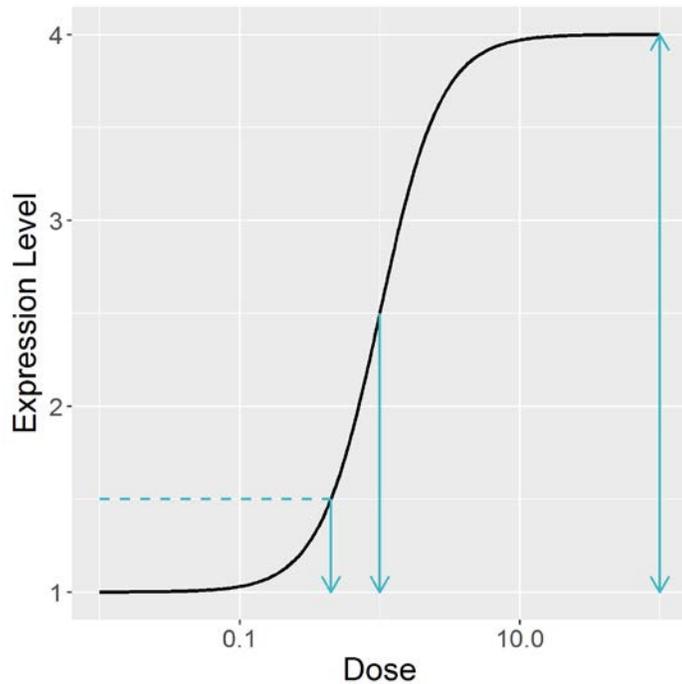
Resource and structural constraints will limit some or all of these.

E.g., it may not be feasible in a high throughput *in vitro* study to have unequal replication.

Design Considerations of Features of Genomic Dose Response

- Most curves are likely to be sigmoid (approximated by a Hill model), but can be nonmonotonic, mainly at high doses.
- Thousands of endpoints (genes) – much worse than chronic bioassay!
- For a chemical, the design should function well over the full range of:
 - gene-specific potencies (*e.g.*, BMDs).
 - gene-specific DR shapes (*e.g.* power parameter, limiting fold-change).

- 44 chemicals, TempO-Seq whole genome, gene expression in MCF7 cells.
- DR: 8 half-log doses, 0.03 - 100 μM + vehicle control
- 3 biological reps – separate cultures, 1/plate
- Hill model fits

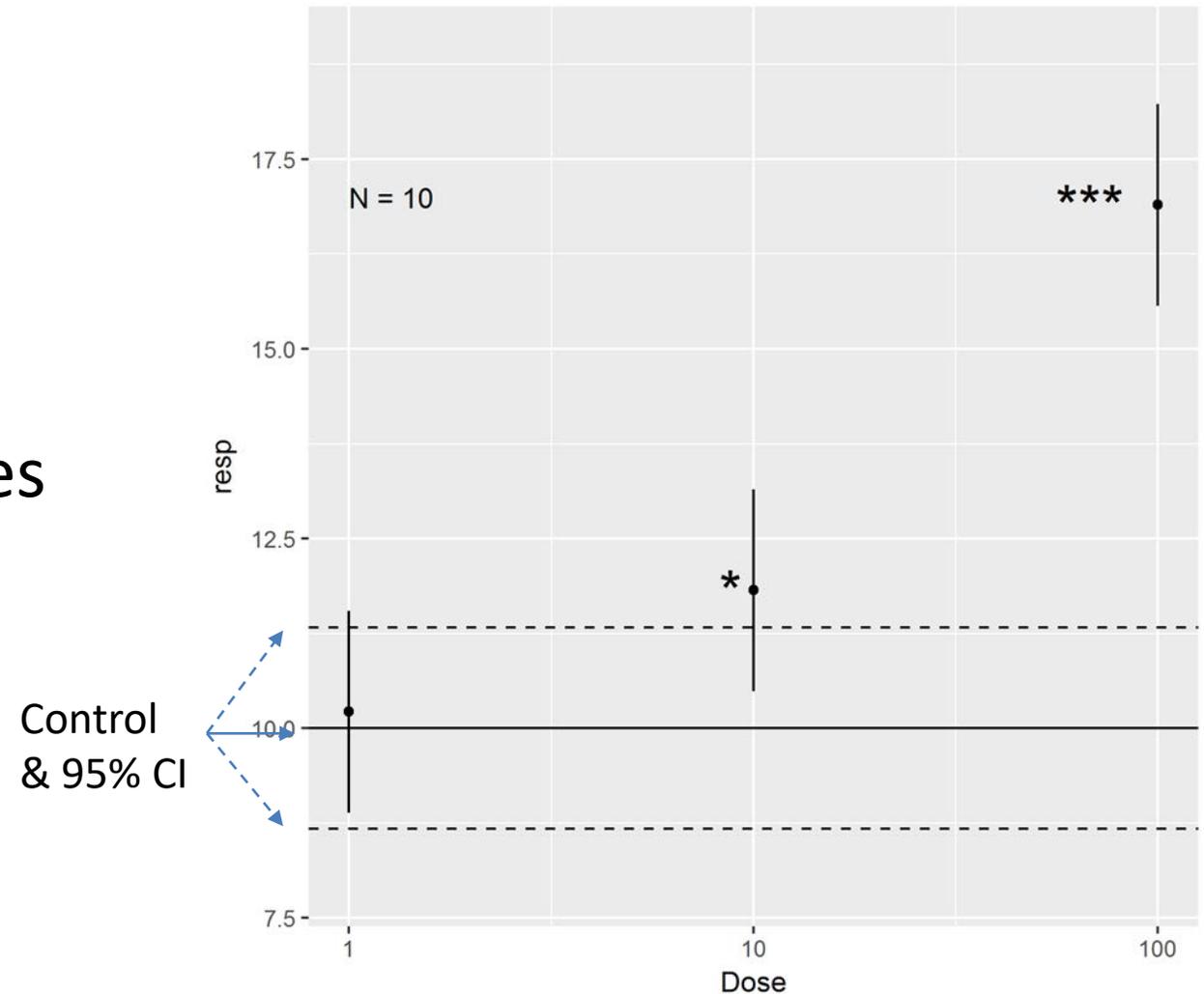


Conceptual Tools for Evaluating Experimental Design

- From Statistical Theory:
 - Requires a statistical model:
 - specific (though maybe very flexible) DR model (*e.g.*, Hill (or Emax), spline) +
 - error model (*e.g.*, data are normal, lognormal, negative binomial, *etc.*)
 - usually assumes the true model up to parameter values is known.
 - Select a criterion to characterize the design:
 - The general variance of all model parameters: the determinant of the asymptotic covariance matrix of the parameter estimates
 - variance of a function of model parameters, *e.g.*, the asymptotic variance of the log BMD.
 - ...
 - Explore the effect of different designs on the selected criteria.
 - Computationally (relatively) straightforward
 - Relies on asymptotic results
- Simulation
 - Simulate replicate data sets using different designs, and estimate model parameters for the simulated data
 - Use variances among replicate fits to characterize the performance of different designs
 - Computationally challenging for large scale evaluations
 - Captures the effects of finite, small sample sizes

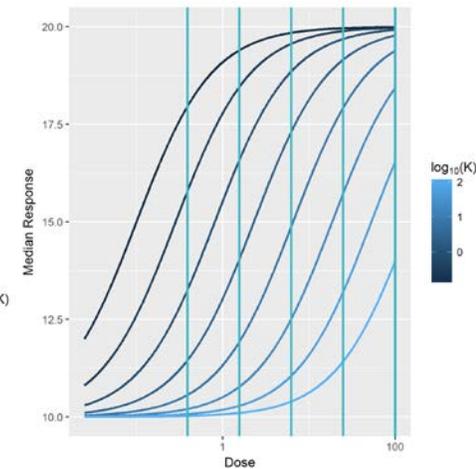
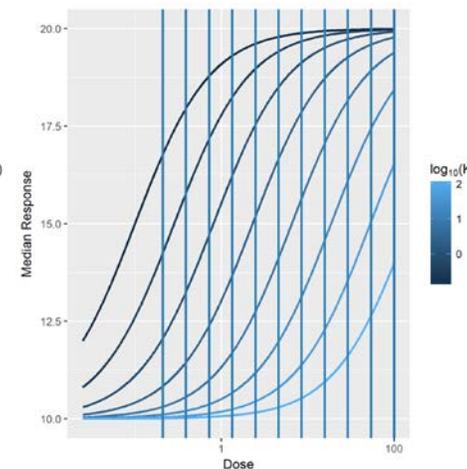
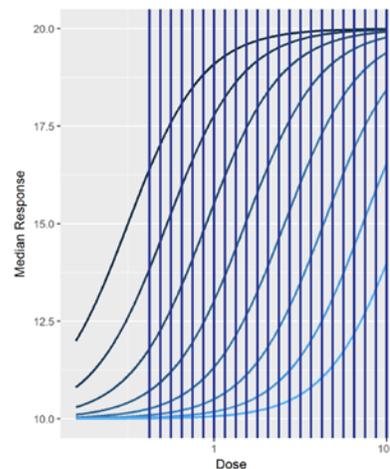
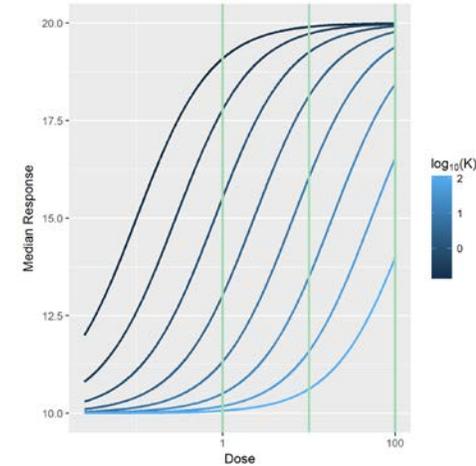
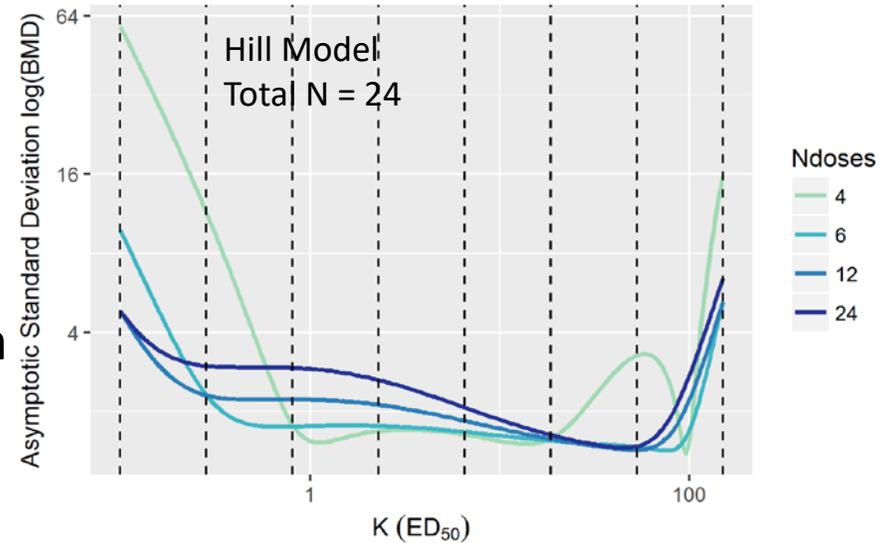
Classical Toxicology Design

- Goal: provide sufficient power to identify a dose where the response was “different enough” from background - POD
- Few doses, multiple replicates per dose.
- Analyzed with sequential tests against control
- Later, analyzed with BMD



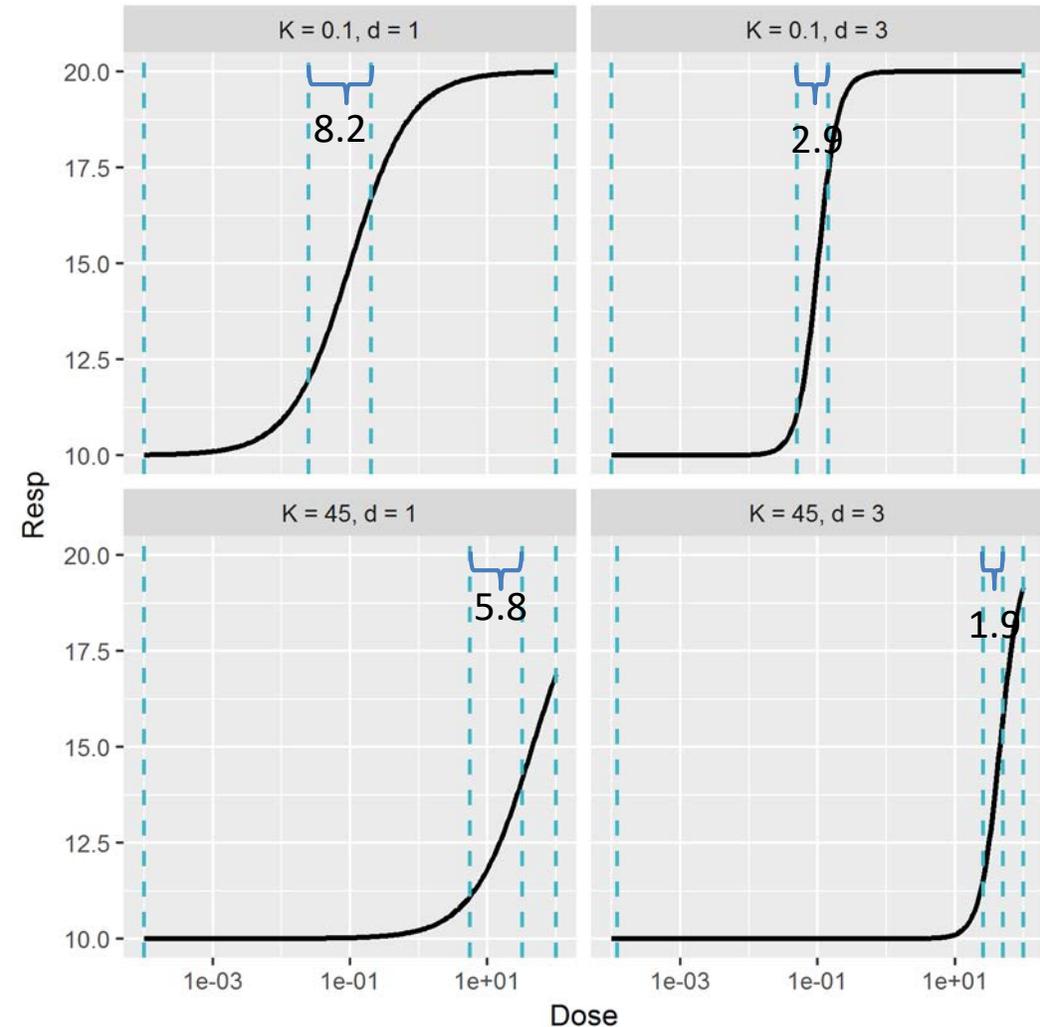
Modifications for Dose-Response and BMD Estimation

- Kavlock et al (1996): For BMD estimation, it does not hurt to decrease reps per dose and increase doses, and the increased number of doses help. Disposition of doses matters.
- Slob et al (2005): Performance of design depends on total number of subjects, regardless of number of doses. Dose placement is crucial – including more doses improves the chances of good dose placement.
- Why Increase number of doses?
 - Robustness against range of DR curves
 - Robustness against extra, dose-group level ‘noise’ (e.g., Slob & Setzer, 2014)



Optimal Design for Hill Dose-Response

- “Optimal Design” – design that minimizes the performance criterion, *e.g.*:
 - D-optimal design: minimizes the determinant of the asymptotic parameter covariance matrix
 - c-optimal design: minimizes the variance of a function of model parameters, *e.g.* the variance of the log(BMD).
- Optimal design depends on model parameter values: You have to know the truth to see it.
- For Hill w/lognormal error, D-optimal design has:
 - 4 doses: control, max dose, 2 bracketing the ED_{50} .
 - Equal weights
 - The spacing between the 2 bracketing doses decreases as the power (“hill coefficient”) increases.
- There has been a lot of literature on this recently (see *References*).



Adding Realism

- In reality, we have to design to be able to estimate models over a pretty wide range of DRs. No single optimal design will do.

Theoretical Alternatives:

- Multi-stage design – alternate experiment and optimization to close in on the best parameter estimates. –*not practical for genomics DR*
- Find the design that minimizes the maximum variance over the range of uncertain parameters: make a design in which the worst-fit DR is fit well enough
- Find the design that minimizes the criterion *on average* over a prior distribution of parameter values – Bayesian optimal design: make a design that does pretty well on average.
 - Both tend to add dose levels to the design.
- Determinants of practical designs:
 - the top and bottom doses
 - the dose spacing required to cover the range of DR steepnesses (steeper curves require closer spacing) (may not be regular!)
 - Replication both reduces variance, also protects against ‘outliers’
 - Consider alternative DR models (including splines)
 - Incorporate noise, and use simulation to evaluate proposed designs

Conclusions

- Switching from the classical tox approach to DR to benchmark dose-like considerations leads to designs with more dose levels and fewer replicates per dose
- Classical optimal design considerations: “To see the truth, you have to know it first” – a design is optimal only for a single DR curve. Still, provides useful information about DR shape and dose spacing.
- Practical designs will have multiple dose levels, log-spaced, evenly weighted.
- Dose spacing should depend on the range of steepnesses of the curves.
- The lower end of the dose-range is probably the most interesting – there will be tension between dose spacing, achieving low enough doses, and cost.
- Both simulation and theory jointly should inform designs used.

References and Additional Reading

Chernoff, H. 1953. Locally optimal design for estimating parameters. *The Annals of Mathematical Statistics* **24**: 586-602.

Dette, & al. 2009. Optimal designs for estimating critical effective dose under model uncertainty in a dose response study. *Statistics and Its Interface*. **2**: 27-36.

Dette, & al. 2013. Optimal design for smoothing splines. *Annals of the Institute of Statistical Mathematics* **63**: 981-1003.

Holland-Letz & al. 2015. Optimal experimental designs for dose-response studies with continuous endpoints. *Archives of Toxicology* **89**: 2059-2068.

Hyun & Wong. 2015. Multiple-objective optimal designs for studying the dose response function and interesting dose levels. *International Journal of Biostatistics* **11**: 253-271.

Kavlock, Schmid, & Setzer. 1996. A simulation study of the influence of study design on the estimation of benchmark doses for developmental toxicity. *Risk Analysis* **16**: 399-410.

Li & Majumdar. 2008. D-optimal designs for logistic models with three and four parameters. *Journal of Statistical Planning and Inference* **138**: 1950-1959.

Slob & al. 2005. A statistical evaluation of toxicity study designs for the estimation of the benchmark dose in continuous endpoints. *Toxicological Sciences* **84**: 167-185.

Slob & Setzer. 2014. Shape and steepness of toxicological dose-response relationships of continuous endpoints. *Critical Reviews in Toxicology* **44**: 270-297.

Wang & al. 2013. Two-stage experimental design for dose-response modeling in

toxicology studies. *ACS Sustainable Chemistry and Engineering* **9**: 1119-1128.

Zhai & Fang. 2017. Locally optimal designs for some dose response models with continuous endpoints. *Communications in Statistics – Theory and Methods*. in press. DOI: [10.1080/03610926.2017.1361996](https://doi.org/10.1080/03610926.2017.1361996)