

Ecotoxicology is not normal.

A comparison of statistical approaches for analysis of count and proportion data in ecotoxicology.

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Abstract Counts and proportions from counts are data types of encountered by ecotoxicologists. However, such data is rare normally distributed. To meet the assumptions of normality and heteroscedasticity, the standard procedure has been to either transform the data or use non-parametric methods if this fails. Generalised Linear Models (GLM) allow to model directly distributions fitting to such data. Here, we compare the performance of analyses using transformed data, non-parametric methods and GLMs.

We simulated data mimicking ecotoxicological experiments of two common data types (counts and proportions from counts). We compare the performance of methods in terms of statistical power and type 1 error. In addition, we outlined differences and advantages of GLMs on a real world mesocosm data set.

We found that GLMs provide in most cases a gain in statistical power compared to analysis of transformed data or using non-parametric methods. We recommend that non-normal data should be analysed by GLMs and not by transformations or non-parametric methods. GLMs should become a standard method in ecotoxicology.

Keywords Generalized Linear Models · Transformations · Simulation · Power · Type 1 error

1 Introduction

Ecotoxicologists perform various kinds of experiments yielding different types of data. Examples are animal counts in

mesocosm experiments (non-negative, integer-valued data) or proportions of surviving animals (data bounded between 0 and 1, discrete). These data are typically not normally distributed. Nevertheless, they are usually analysed using methods assuming a normal distribution and variance homogeneity (Wang and Riffel 2011). To meet these assumptions, data are usually transformed. For example, ecotoxicological textbooks (Newman 2012) and guidelines (EPA 2002; OECD 2006) advise that survival data can be transformed using an arcsine square root transformation. For count data from mesocosm experiments a $\log(Ay + C)$ transformation is usually applied, where the constants A and C are either chosen arbitrarily or following general recommendations. For example, van den Brink et al (2000) suggest to set the term Ay to be 2 for the lowest abundance value (y) greater than zero and C to 1. Moreover, other transformations like the square root or fourth root are commonly applied in community ecology. Note that there has been little evaluation and advice for practitioners, which transformations to use. If the transformed data still do not meet the assumptions (i.e. normality and variance homogeneity), non-parametric tests are usually applied (Wang and Riffel 2011).

Generalised linear models (GLM) provide a method to analyse counts or proportions from counts in a statistically sound way (Nelder and Wedderburn 1972). GLMs can handle various types of data distributions, e.g. Poisson or negative binomial (for count data) or binomial (for proportions); the normal distribution being a special case of GLMs. Despite GLMs being available more than 40 years, ecotoxicologists do not regularly make use of them. Recent studies concluded that data transformations should be avoided and GLMs be used as they have better statistical properties (O'Hara and Kotze 2010 (counts), Warton and Hui 2011; Warton 2005 (proportions from counts)).

Ecotoxicological experiments often involve small sample sizes due to practical constraints. For example, extremely

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low samples sizes ($n < 5$) are common in many mesocosm studies (Sanderson 2002; Szöcs et al 2015). Small sample sizes lead to low power in statistical hypothesis testing, on which many ecotoxicological approaches (e.g. risk assessment for pesticides) rely. Such an endpoint are L/NOEC (Lowest / No observed effect concentration) values. Although their use has been heavily criticized in the past (Laskowski 1995), they are the predominant endpoint in mesocosm experiments (Brock et al 2015; EFSA PPR 2013).

We explore how GLMs may enhance inference in ecotoxicological studies and compared three types of statistical methods (transformation and normality assumption, GLM, non-parametric tests). We first illustrate differences between statistical methods using a data set from a mesocosm study. Then we further elaborate differences in detecting a general treatment effect and determining the LOEC using simulations of two common data types in ecotoxicology: counts and proportions from counts.

2 Methods

2.1 Models for count data

2.1.1 Linear model for transformed data

To meet the assumptions of the standard linear model, count data usually needs to be transformed. We followed the recommendations of van den Brink et al (2000) and used a $\log(Ay + 1)$ transformation (eqn. 1):

$$y_i^T = \log(Ay_i + 1) \quad (1)$$

, where y_i is the measured and y_i^T the transformed abundance of the i th observation. The factor A was chosen in such way that Ay equals 2 for the lowest non-zero abundance value (y).

Then we fitted the linear model to the transformed abundances (hereafter LM):

$$\begin{aligned} y_i^T &\sim N(\mu_i, \sigma^2) \\ E(y_i^T) &= \mu_i \text{ and } \text{var}(y_i^T) = \sigma^2 \\ \mu_i &= \beta \text{Treatment}_i \end{aligned} \quad (2)$$

This model assumes a normal distributed of the transformed abundances. The expected value for each observation i is given by its mean (μ_i) and the variance (σ^2) is constant between treatments. We allow this mean to vary between treatments and β are the coefficients related to these changes in transformed abundances between treatments (eqn. 2).

2.1.2 Generalised Linear Models

GLMs extend the normal model by modelling other distributions. Instead of transforming the response variable, the counts could be directly modelled by a Poisson GLM (GLM_p):

$$\begin{aligned} y_i &\sim P(\mu_i) \\ E(y_i) &= \text{var}(y_i) = \mu_i \\ \log(\mu_i) &= \beta \text{Treatment}_i \end{aligned} \quad (3)$$

This model assumes poisson distributed abundances with mean $\lambda_i \geq 0$. The expected value for each observation i is given by its mean. Moreover, this model assumes that mean and variance are equal. We are modelling the mean as a function of treatment membership. However, to avoid negative values of the mean this is done on a log scale. Therefore, β describes the differences between treatments also on a log scale (eqn. 3).

The assumption of equal mean and variance is rarely met with ecological data, which is typically characterized by greater variance than the mean (overdispersion). To overcome this problem a quasi-Poisson model (GLM_{qp}) could be used, which assumes that variance is a linear function of the mean (eqn. 4):

$$\text{var}(y_i) = \Theta \mu_i \quad (4)$$

Here, Θ is used to account for additional variation and is known as overdispersion parameter. The quasi-Poisson model is a post hoc method, meaning that first a Poisson model is estimated (eqn. 3) and then the standard errors are scaled by the degree of overdispersion.

Another possibility to deal with overdispersion is to fit a negative binomial distribution (GLM_{nb} , eqn. 5):

$$\begin{aligned} y_i &\sim NB(\mu_i, \kappa) \\ E(y_i) &= \mu_i \text{ and } \text{var}(y_i) = \mu_i + \mu_i^2 / \kappa \\ \log(\mu_i) &= \beta \text{Treatment}_i \end{aligned} \quad (5)$$

This models assumes that abundances are negative binomially distributed, with a mean of $\mu_i \geq 0$ and a variance $\mu_i + \mu_i^2 / \kappa$. Like in the Poisson model we use a log link between mean and treatments. Note, that the quasi-Poisson model assumes a linear mean-variance relationship (eqn. 4), whereas the negative binomial model assumes a quadratic relationship (eqn. 5).

The above described models are most commonly used in ecology (Ver Hoef and Boveng 2007), although other distributions for count data are possible, like the negative binomial model with a linear mean-variance relationship (also known as NB1) or the poisson inverse gaussian model (Hilbe 2014).

2.2 Models for binomial data

A binomial variable counts how often an event x occurs in a fixed number of independent trials N (e.g. "5 out of 10 fish survived"), with an equal probability of occurrence π between trials. The number of counts times an event occurs can also be calculated a proportion x/N .

2.2.1 Linear model for transformed data

To accommodate the assumptions for the standard linear model with such proportions, a special arcsine square root transformation (eqn. 6) is suggested (EPA 2002; Newman 2012):

$$y_i^T = \begin{cases} \arcsin(1) - \arcsin(\sqrt{\frac{1}{4n}}) & , \text{ if } y_i = 1 \\ \arcsin(\sqrt{\frac{1}{4n}}) & , \text{ if } y_i = 0 \\ \arcsin(\sqrt{y_i}) & , \text{ otherwise} \end{cases} \quad (6)$$

, where y_i^T are the transformed proportions and n is the total number of exposed animals per treatment. The transformed proportions are then analysed using the standard linear model (LM , eqn. 2). Note, that the parameters of the linear model are not directly interpretable due to transformation.

2.2.2 Generalised Linear Models

A more natural way to model such data is the binomial distribution with parameters N and π (GLM_{bin}):

$$\begin{aligned} y_i &\sim \text{Bin}(N, \pi_i) \\ E(y_i) &= \pi_i \times N \text{ and } \text{var}(y_i) = \pi_i(1 - \pi_i)/N \\ \text{logit}(\pi_i) &= \beta \text{Treatment}_i \end{aligned} \quad (7)$$

This model assumes that the number of occurrences are binomially distributed, where N = number of trials (e.g. exposed animals) and π_i is the probability of occurrences (fish survived), giving together the expected number of occurrences. The variance of the binomial distribution is a quadratic function of the mean. We are modelling the probability of occurrence as function of treatment membership and to ensure that $0 < \pi_i < 1$ we do this on a logit scale (eqn. 7). However, the parameters β of this model are directly interpretable as changes in log odds between treatments.

Similarly to counts, binomial data may also show exceeding variability. Methods to deal with overdispersed binomial data are either quasi methods (see above) or Generalized Linear Mixed models (GLMM). However, these are not further investigated in this paper (see Warton and Hui (2011) for a comparison).

2.3 Statistical Inference

After model fitting and parameter estimation the next step is statistical inference. Ecotoxicologists are generally interested in two hypotheses: (i) is there any treatment related effect? and (ii) which treatments show a treatment effect (to determine the LOEC)?

Following general recommendations (Bolker et al 2009; Faraway 2006), we used F-tests (LM and GLM_{qp}) and Likelihood-Ratio (LR) tests (GLM_p , GLM_{nb} and GLM_{bin}) to test the first hypothesis. However, it is well known that LR test are unreliable with small sample sizes (Wilks 1938). Therefore, we additionally explored the parametric bootstrap (Faraway 2006) to assess the significance of the LR. Bootstrapping is computationally very intensive and for this reason we applied it only for the negative binomial models (using 500 bootstrap samples, denoted as GLM_{npb}).

To assess the LOEC we used Dunnett contrasts (Dunnett 1955) with one-sided Wald t tests (normal and quasi-Poisson models) and one-sided Wald Z tests (Poisson, negative binomial and binomial models). Beside these parametric methods we also applied two, in ecotoxicology commonly used, non-parametric methods: The Kruskal-Wallis test (KW) to test for a general treatment effect and a pairwise Wilcoxon test (WT) to determine the LOEC. We adjusted for multiple testing using the method of Holm (1979).

2.4 Case study

Brock et al (2015) presents a typical example of data from mesocosm studies, which we use to demonstrate differences between methods. The data are mayfly larvae counts on artificial substrate samplers were at one sampling date. A total of 18 mesocosm have been sampled from 6 treatments (Control ($n = 4$), 0.1, 0.3, 1, 3 mg/L ($n = 3$) and 10 mg/L ($n = 2$)) (Figure 1).

2.5 Simulations

2.5.1 Count data

To further scrutinise the differences between methods we simulated data sets with known properties. We simulated count data that mimics the data of the case study with five treatments (T1 - T5) and one control group (C). Counts were drawn from a negative binomial distribution with overdispersion at all treatments ($\kappa = 4$, eqn. 5). We simulated data sets with different number of replicates ($N = \{3, 6, 9\}$) and different abundances in control treatments ($\mu_c = \{2, 4, 8, 16, 32, 64, 128\}$). For power estimation, mean abundance in treatments T2 - T5 was reduced to half of control and T1

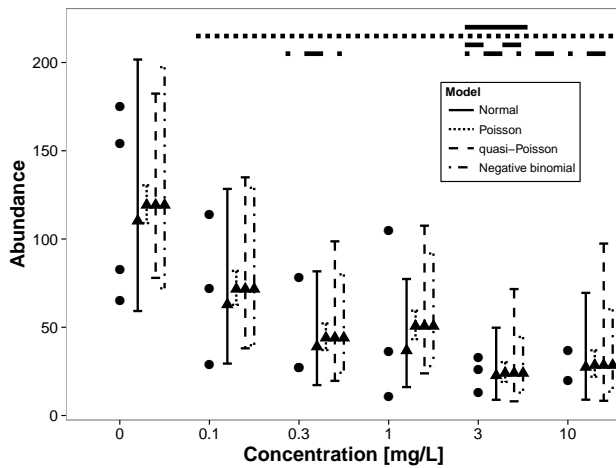


Fig. 1 Data from Brock et al (2015) (dots). Predicted values (triangles) and 95% Wald Z or t confidence intervals from the fitted models (vertical lines) are given beside. Horizontal bars above indicate treatments statistically significant different from the control group (Dunnett contrasts). The data showed overdispersion ($\kappa = 4$) and therefore, the Poisson model underestimates the width of confidence intervals.

($\mu_{T2} = \dots = \mu_{T5} = 0.5 \mu_C = 0.5 \mu_{T1}$), resulting in a theoretical LOEC at T2. Mean abundance was kept equal between all groups in Type 1 error simulations. We generated 1000 data sets for each combination of N and μ_C and analysed these using the models outlined in section 2.1.

2.5.2 Binomial data

We simulated data from a commonly used design as described in Weber et al (1989), with 5 treated (T1 - T5) and a control group (C). Proportions were drawn from a $\text{Bin}(10, \pi)$ distribution, with varying probability of survival ($\pi = \{0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90, 0.95\}$) and varying number of replicates ($N = \{3, 6, 9\}$). For Type 1 error estimation, π was held constant between groups. For power estimation π in C and T1 was fixed at 0.95 and was set to values between 0.6 and 0.95 for the treatments T2 - T5. For each combination we simulated 1000 data sets and analysed these using the models outlined in section 2.2.

2.6 Data Analysis

We analysed the case study and the simulated data using the outlined methods. We compared the methods and models in terms of Type 1 error (detection of an effect when there is none) and power (ability to detect an effect when it is present).

All simulations were done in R (Version 3.1.2) (R Core Team 2014) on an Amazon EC2 virtual Linux server (64bit, 15GB RAM, 8 cores, 2.8 GHz). Source code to reproduce the simulations and paper is available online at <https://github.com/EDiLD/usetheglm>. Moreover, Supplement 2

provides worked examples of the data of Brock et al (2015) and Weber et al (1989).

3 Results

3.1 Case study

The data set showed considerable overdispersion ($\Theta = 22.41$, eqn. 4). Therefore, the Poisson model did not fit to this data and lead to underestimated standard errors and confidence intervals, as well as overestimated statistical significance (Figure 1). In this case, inferences on the Poisson model are not valid and we do not further discuss its results. The normal ($F = 2.57$, $p = 0.084$) and quasi-Poisson model ($F = 2.90$, $p = 0.061$), as well as the Kruskal test ($p = 0.145$) did not show a statistically significant treatment effects. By contrast, the LR test and parametric bootstrap of the negative binomial model indicated a treatment-related effect (LR = 13.99, $p = 0.016$, bootstrap: $p = 0.042$).

All methods predicted similar values, except the normal model predicting always lower abundances (Figure 1). 95% confidence intervals (CI) were most narrow for the negative binomial model and widest for the quasi-Poisson model - especially at lower estimated abundances. Consequently, the LOECs differed (Normal and quasi-Poisson: 3 mg/L, negative binomial: 0.3 mg/L). The pairwise Wilcoxon test did not detect any treatment different from control.

3.2 Simulations

3.2.1 Count data

For detecting a general treatment effect GLM_{nb} and GLM_p showed inflated type 1 error rates, whereas KW was conservative at low sample sizes. However, using parametric bootstrap for the negative binomial model (GLM_{npb}) resulted in an appropriate type 1 error rates. For detecting a treatment effect GLM_{npb} and GLM_{qp} exhibited higher power than LM and KW , the latter having least power (Figure 2). For our simulation design (reduction in abundance by 50%) a sample size per treatment of $n = 9$ was needed to achieve a power greater than 80%. At small sample sizes ($n = 3, 6$) and low abundances ($\mu_C = 2, 4$) many of the negative binomial models (GLM_{nb} and GLM_{npb}) did not converge to a solution (convergence rate $< 85\%$ of the simulations, Supplement 1).

For LOEC determination GLM_{nb} and GLM_p showed an increased Type 1 error and all other methods being slightly conservative. The inferences on LOEC generally showed less power. LM showed a mean reduction of 20.7% and GLM_{qp} of 24.3%. Power to detect the LOEC was highest for GLM_{qp} . LM and WT showed less power, with WT having no power to detect the LOEC at low sample sizes (Figure 3).

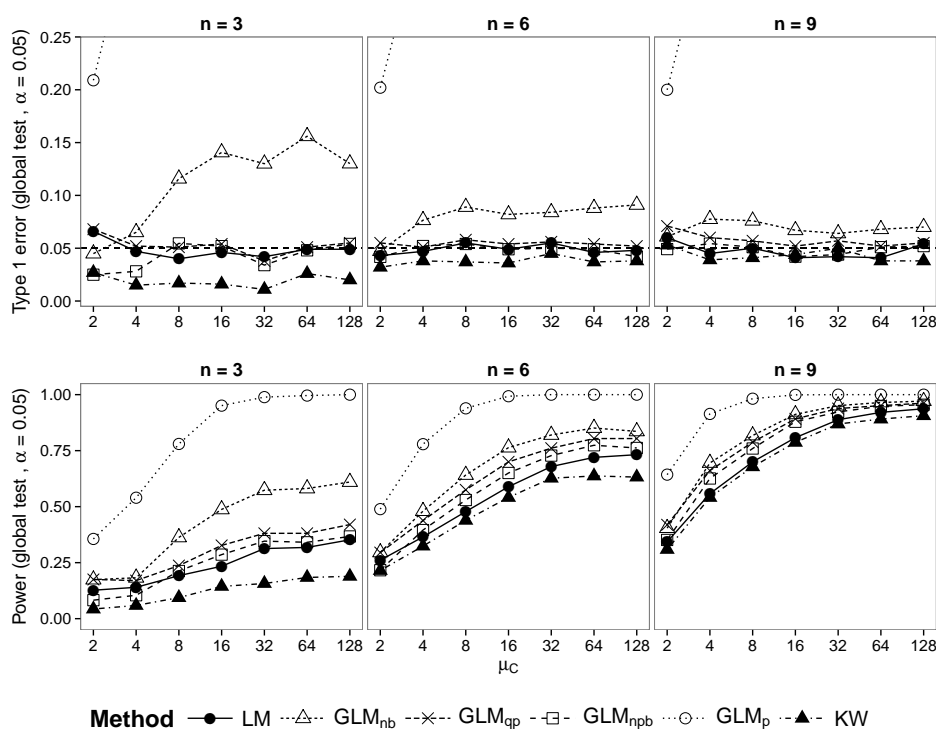


Fig. 2 Count data simulations: Type 1 error (top) and Power (bottom) for the test of a treatment effect. Only type 1 errors $< 25\%$ are displayed. GLM_p showed type 1 errors $> 20\%$ in all simulation scenarios. Power levels for models with inflated type I error are shown for completeness. For $n = \{3, 6\}$ and $\mu_C = \{2, 4\}$ less than 85% of GLM_{nb} and GLM_{npb} models did converge. Dashed horizontal line denotes the nominal Type 1 error rate at $\alpha = 0.05$.

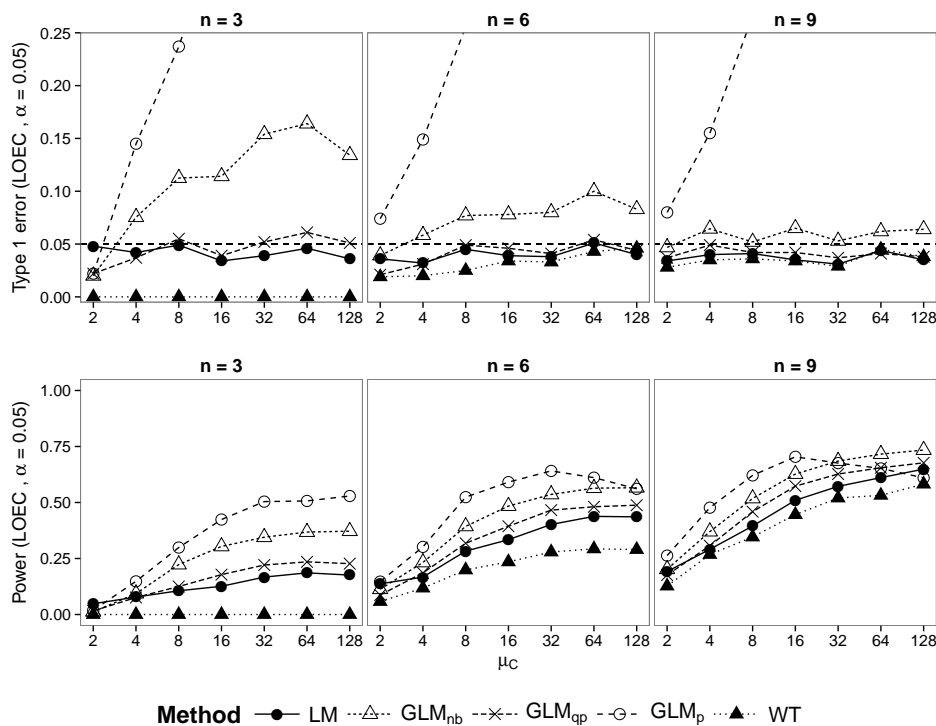


Fig. 3 Count data simulations: Type 1 error (top) and Power (bottom) for determination of LOEC. For clarity only type 1 errors $< 25\%$ are displayed. Power levels for models with inflated type I error are shown for completeness. For $n = \{3, 6\}$ and $\mu_C = \{2, 4\}$ less than 85% of GLM_{nb} models did converge. Dashed horizontal line denotes the nominal Type 1 error rate at $\alpha = 0.05$.

3.2.2 Binomial data

GLM_{bin} showed slightly increased type 1 error rates at low sample sizes and small effect sizes. KW was more conservative than LM and GLM_{bin} . GLM_{bin} showed the greatest power for testing the treatment effect. This was especially apparent at low sample sizes ($n = 3$), with up to 27% higher power compared to LM . However, the differences between methods quickly vanished with increasing samples sizes (Figure 4).

For inference on LOEC we found that all methods were slightly conservative. WT was generally more conservative and GLM_{bin} especially at low effect sizes ($p_E > 0.7$). Inference on LOEC was not as powerful as inference on the general treatment effect. Contrary to the general treatment effect, LM showed the higher power than GLM_{bin} at small sample sizes ($n = 3, 6$). WT had no power for $n = 3$ and showed less power in the other simulation runs (Figure 5).

4 Discussion

4.1 Case study

The outlined case study demonstrates that the choice of the statistical model and procedure can have substantial impact on ecotoxicological inferences and endpoints like the LOEC. Therefore, ecotoxicologists should not base their inferences solely on statistical significance tests, but also on parameter estimates, their uncertainty and importance (Gelman and Stern 2006). Nevertheless, O'Hara and Kotze (2010) showed that LM using a log transformation gave unreliable and biased parameter estimates, whereas GLMs performed well with little bias.

This is further highlighted by the fact that for the same model (linear model of transformed data), Brock et al (2015) reported a 10-fold lower LOEC (0.3 mg/L) then found in our study (3 mg/L, Figure 1). The reasons are manifold: (Brock et al 2015) used a $\log(2y + 1)$ transformation, whereas we used a $\log(Ay + 1)$ transformation, where $A = 2 / 11 = 0.182$ (van den Brink et al 2000). Furthermore, Brock et al (2015) used a one-sided Williams test which assumes a monotonic dose-response relationship. In contrast, we used one-sided comparisons to the control (Dunnett contrasts), which does not assume monotonicity and allows individual comparisons between treatment groups and the control, but has under monotonicity less power (Jaki and Hothorn 2013).

Moreover, the case study illustrates the potential effects of overdispersion that is not accounted for: standard errors will be underestimated and significance overestimated (Figures 1). This is also shown by our simulations (Figures 2, 3) where GLM_p showed increased type 1 error rates because of overdispersed simulated data. However, in factorial designs the mean-variance relationship can be easily checked

by plotting mean versus variance of the treatment groups (see Supplement 2). In the introduction we pointed out that there is little advice how to choose between the plenty of possible transformations - how do GLMs simplify this problem? The distribution modelled can be chosen by the nature of the data giving a statistically sound model reflecting its properties (e.g. bounds, integer or continuous data etc.). Knowing what type of data is modelled (see Methods section), the model selection process can be completely guided by the data and diagnostic plots. Therefore, choosing an appropriate model is more sound and straightforward than choosing between possible transformations.

4.2 Simulations

Our simulations showed that generally GLMs have greater power than data transformations. However, the simulations also suggest that the power at the population level in common mesocosm experiments is low. For common samples sizes and a reduction in abundance of 50% we found a low power to detect any treatment-related effect (<50% for methods with appropriate Type 1 error, Figure 2). Statistical power to detect the correct LOEC was even lower (less than 30%). This suggests that population level NOECs reported from mesocosm experiments should be interpreted with caution and underpins the criticism of NOEC (Laskowski 1995; Landis and Chapman 2011).

Mesocosm studies allow also inferences on community level. For community analyses *GLM for multivariate data* (Warton et al 2012) have been proposed as alternative to Principal Response Curves (PRC) and yielded to similar inferences, but better indication of responsive taxa (Szöcs et al 2015). However, ter Braak and Šmilauer (2014) argue to use data transformations with community data because of their easy- and robustness. Although our simulations covered only simple experimental designs at the population level, findings may also extend to more complex situations. Nested or repeated designs with non-normal data could be analysed using Generalised Linear Mixed Models (GLMM) and may have advantages with respect to power (Stroup 2014).

To counteract the problems with low power at the population level Brock et al (2015) proposed to take the Minimum Detectable Difference (MDD), a method to assess statistical power *a posteriori*, for inference into account. However, *a priori* power analyses can be performed easily using simulations, even for complex experimental designs (Johnson et al 2014), and might help to design, interpret and evaluate ecotoxicological studies. Moreover, Brock et al (2015) proposed that statistical power of mesocosm experiments can be increased by reducing sampling variability through improved sampling techniques and quantification methods, though they also caution against depleting populations through

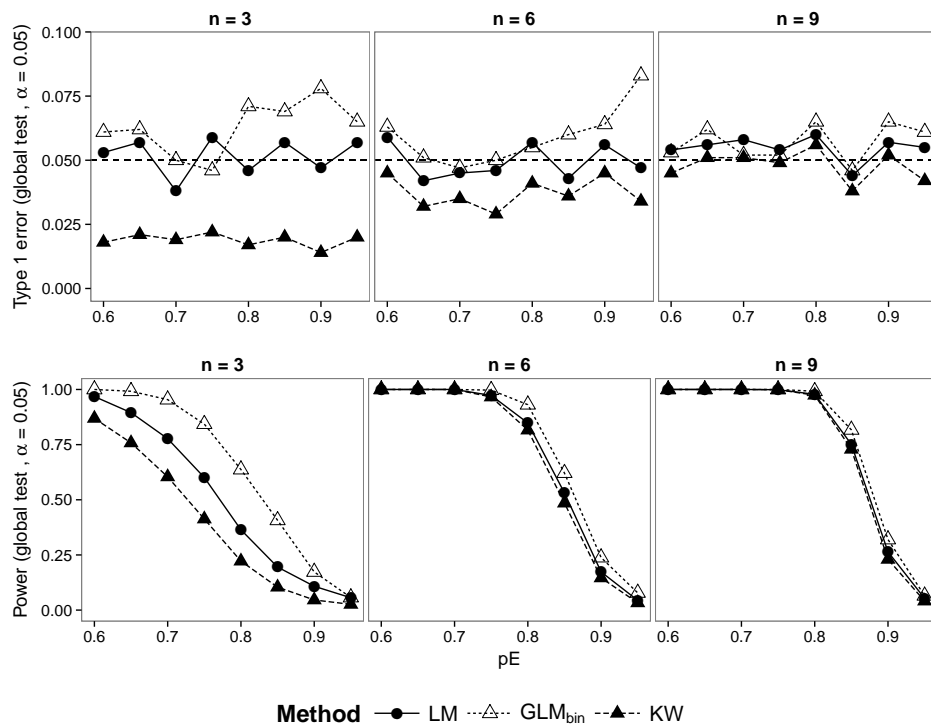


Fig. 4 Binomial data simulations: Power (top) and Type 1 error (bottom) for the test of a treatment effect. Dashed horizontal line denotes the nominal Type 1 error rate at $\alpha = 0.05$.

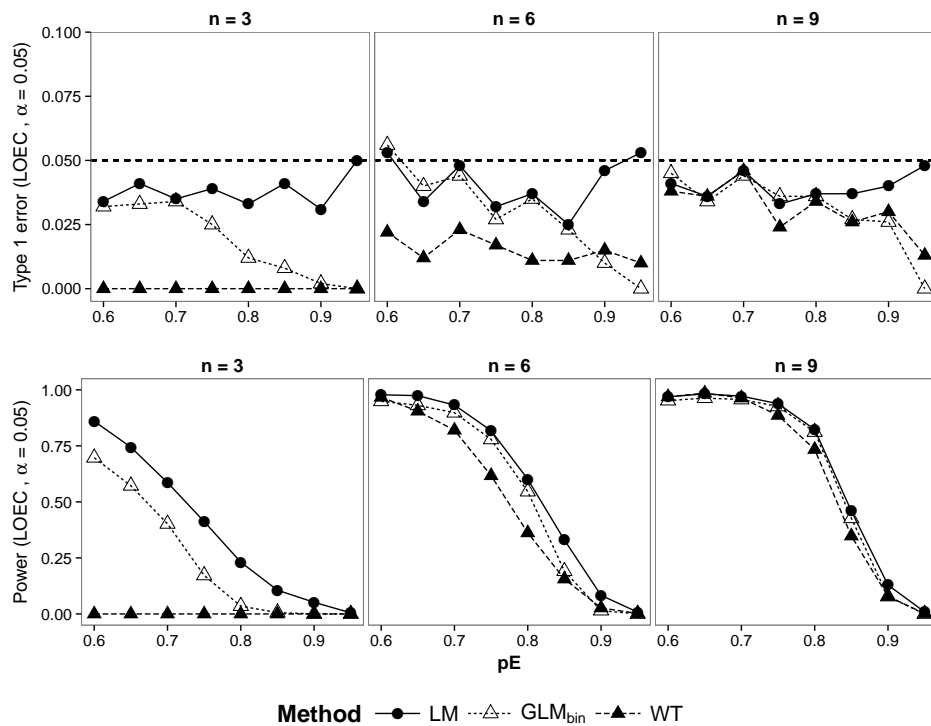


Fig. 5 Binomial data simulations: Power (top) and Type 1 error (bottom) for the test for determination of LOEC. Dashed horizontal line denotes the nominal Type 1 error rate at $\alpha = 0.05$.

more exhaustive sampling. As we showed, using appropriate statistical methods (like GLMs) can enhance the power at no extra costs.

Wang and Riffel (2011) advocated that in the typical case of small sample sizes ($n < 20$) and non-normal data, non-parametric tests perform better than parametric tests assuming normality. In contrast, our results showed that the often applied *KW* and *WT* have less power compared to *LM*. Moreover, *GLMs* always performed better than non-parametric tests. Though more powerful non-parametric tests may be available (Konietschke et al 2012), these are focused on hypothesis testing and do not provide estimation of effect sizes. Additionally to testing, GLMs allow the estimation and interpretation of effects that might not be statistically significant, but ecologically relevant. Therefore, we advise using GLMs instead of non-parametric tests for non-normal data.

At small sample sizes and low abundances a significant amount of negative binomial models did not converge. We used an iterative algorithm to fit these models (Venables and Ripley 2002) and other methods assessing the likelihood directly may perform better. Moreover, the Likelihood-Ratio test gave an increased Type-I error for these models, where the non reliability of the LR statistic for small sample sizes has long been reported (Bolker et al 2009; Wilks 1938). We found that parametric bootstrap (*GLM_{npb}*) provides a valuable alternative in such situations (Figure 2). At small samples sizes, low abundances or few treatment groups it is difficult to determine the mean-variance relationship. *GLM_{qp}* assumes a simpler, linear mean-variance relationship, which might explain the higher power compared to *GLM_{npb}* at small sample sizes (Figure 2, top).

Binomial data are often collected in lab trials, where increasing the sample size is easy to accomplish. We found notable differences in power to detect a treatment effect for all simulated sample sizes. Similarly, Warton and Hui (2011) also found that GLMs have higher power than arcsine transformed linear models. Though we did not simulated overdispersed binomial data, this should be checked and accounted for. In such situations a GLMM may offer an appealing alternative (Warton and Hui 2011). Nevertheless, for deriving LOECs the *LM* performed better at low sample sizes ($n = 3$) (Figure 5).

GLMs can be fitted with many statistical software packages and a lot of textbooks are available to introduce ecotoxicologists to these models (e.g. Zuur 2013 or Quinn and Keough 2009). We recommend that counts or proportions from counts in ecotoxicological experiments should be analysed by GLMs and not by transformations or non-parametric methods. To improve the power to detect effects, GLMs should become a standard method in ecotoxicology and incorporated into respective guidelines.

5 Compliance with Ethical Standards

Conflict of Interest: The authors declare that they have no conflict of interest.

References

- Bolker B, Brooks M, Clark C, Geange S, Poulsen J, Stevens M, White J (2009) Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology & Evolution* 24(3):127–135
- ter Braak CJF, Šmilauer P (2014) Topics in constrained and unconstrained ordination. *Plant Ecology* DOI 10.1007/s11258-014-0356-5, URL <http://link.springer.com/10.1007/s11258-014-0356-5>
- van den Brink PJ, Hattink J, Brock TCM, Bransen F, van Donk E (2000) Impact of the fungicide carbendazim in freshwater microcosms. II. Zooplankton, primary producers and final conclusions. *Aquatic Toxicology* 48(2-3):251–264
- Brock TCM, Hammers-Wirtz M, Hommen U, Preuss TG, Ratte HT, Roessink I, Strauss T, Van den Brink PJ (2015) The minimum detectable difference (MDD) and the interpretation of treatment-related effects of pesticides in experimental ecosystems. *Environmental Science and Pollution Research* 22(2):1160–1174
- Dunnett CW (1955) A Multiple Comparison Procedure for Comparing Several Treatments with a Control. *Journal of the American Statistical Association* 50(272):1096–1121
- EFSA PPR (2013) Guidance on tiered risk assessment for plant protection products for aquatic organisms in edge-of-field surface waters. *EFSA Journal* 11(7):3290
- EPA (2002) Methods for Measuring the Acute Toxicity of Effluents and Receiving Waters to Freshwater and Marine Organisms. U.S. Environmental Protection Agency
- Faraway JJ (2006) Extending the linear model with R: Generalized linear, mixed effects and nonparametric regression models. Chapman / & Hall/CRC texts in statistical science series, Chapman / & Hall/CRC, Boca Raton
- Gelman A, Stern H (2006) The difference between “significant” and “not significant” is not itself statistically significant. *The American Statistician* 60(4):328–331, URL <http://pubs.amstat.org/doi/abs/10.1198/000313006X152649>
- Hilbe JM (2014) Modeling Count Data. Cambridge University Press, New York, NY
- Holm S (1979) A simple sequentially rejective multiple test procedure. *Scandinavian journal of statistics* 6(2):65–70
- Jaki T, Hothorn LA (2013) Statistical evaluation of toxicological assays: Dunnett or Williams test—take both. *Archives of Toxicology* 87(11):1901–1910
- Johnson PCD, Barry SJE, Ferguson HM, Müller P (2014) Power analysis for generalized linear mixed models in ecology and evolution. *Methods in Ecology and Evolution* DOI 10.1111/2041-210X.12306
- Konietschke F, Hothorn LA, Brunner E (2012) Rank-based multiple test procedures and simultaneous confidence intervals. *Electronic Journal of Statistics* 6:738–759
- Landis WG, Chapman PM (2011) Well past time to stop using NOELs and LOELs. *Integrated Environmental Assessment and Management* 7(4):vi–viii
- Laskowski R (1995) Some good reasons to ban the use of NOEC, LOEC and related concepts in ecotoxicology. *Oikos* 73(1):140–144, times Cited: 35
- Nelder JA, Wedderburn RWM (1972) Generalized Linear Models. *Journal of the Royal Statistical Society Series A (General)* 135(3):370–384

- Newman MC (2012) Quantitative ecotoxicology. Taylor & Francis, Boca Raton, FL
- OECD (2006) Current Approaches in the Statistical Analysis of Ecotoxicity Data: A Guidance to Application. No. 54 in Series on Testing and Assessment, OECD, Paris
- O'Hara RB, Kotze DJ (2010) Do not log-transform count data. *Methods in Ecology and Evolution* 1(2):118–122
- Quinn GP, Keough MJ (2009) Experimental design and data analysis for biologists. Cambridge Univ. Press, Cambridge
- R Core Team (2014) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL <http://www.R-project.org/>
- Sanderson H (2002) Pesticide studies. *Environmental Science and Pollution Research* 9(6):429–435
- Stroup WW (2014) Rethinking the Analysis of Non-Normal Data in Plant and Soil Science. *Agronomy Journal* DOI 10.2134/ agronj2013.0342
- Szöcs E, Van Den Brink PJ, Lagadic L, Caquet T, Roucaute M, Auber A, Bayona Y, Liess M, Ebke P, Ippolito A, Ter Braak CJ, Brock CM, Schäfer RB (2015) Analysing chemical-induced changes in macroinvertebrate communities in aquatic mesocosm experiments: A comparison of methods. *Ecotoxicology* DOI 10.1007/s10646-015-1421-0
- Venables WN, Ripley BD (2002) Modern Applied Statistics with S, 4th edn. Springer, New York
- Ver Hoef JM, Boveng PL (2007) Quasi-Poisson vs. negative binomial regression: how should we model overdispersed count data? *Ecology* 88(11):2766–2772
- Wang M, Riffel M (2011) Making the right conclusions based on wrong results and small sample sizes: interpretation of statistical tests in ecotoxicology. *Ecotoxicology and Environmental Safety* 74(4):684–92
- Warton DI (2005) Many zeros does not mean zero inflation: comparing the goodness-of-fit of parametric models to multivariate abundance data. *Environmetrics* 16(3):275–289
- Warton DI, Hui FKC (2011) The arcsine is asinine: the analysis of proportions in ecology. *Ecology* 92(1):3–10
- Warton DI, Wright ST, Wang Y (2012) Distance-based multivariate analyses confound location and dispersion effects. *Methods in Ecology and Evolution* 3(1):89–101
- Weber CI, Peltier WH, Norbert-King TJ, Horning WB, Kessler F, Menkedick JR, Neiheisel TW, Lewis PA, Klemm DJ, Pickering Q, Robinson EL, Lazorchak JM, Wymer L, Freyberg RW (1989) Short-term methods for estimating the chronic toxicity of effluents and receiving waters to fresh- water organisms. Tech. Rep. EPA/600/4-89/001, Environmental Protection Agency, Cincinnati, OH: Environmental Monitoring Systems Laboratory
- Wilks SS (1938) The large-sample distribution of the likelihood ratio for testing composite hypotheses. *The Annals of Mathematical Statistics* 9(1):60–62
- Zuur AF (2013) A beginner's guide to GLM and GLMM with R: a frequentist and Bayesian perspective for ecologists. Highland Statistics, Newburgh