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Zero-Inflated Regression Methods for Insecticides

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1. Introduction

The numerical abundance of many species sharing the same ecosystem very different levels of the organism and are in constant change, depending on many factors. Due to the heterogeneous strucspeciese of the life cycles of organisms and abiotic resources in the environment based on census population densities derived from overdispersion (variance is higher than means in Poisson distribution) (Cox, 1983; Cameron and Trivedi, 1998) and a large number of zero values (zero-inflated data) is observed (Yeşilova et al, 2011). In such a case, zero-inflated Poisson (ZIP) regression model is a appropriate approach for analyzing a dependent variable having excess zero observations (Lambert, 1992; Böhning, 1998; Böhning et al, 1999; Yau and Lee, 2001; Lee et al, 2001; Khoshgoftaar et al, 2005; Yeşilova et al, 2010).
Zero-inflation is also likely in data sets, excess zero observations. In such cases, a zero-inflated negative binominal (ZINB) regression model is an alternative method (Ridout et al, 2001; Yau, 2001; Cheung, 2002; Jansakul, 2005; Long and Frese, 2006; Hilbe, 2007; Yeşilova et al, 2009; Yeşilova et al, 2010). Morever, The Poisson hurdle model and negative binomial hurdle model (Rose and Martin, 2006; Long and Frese, 2006; Hilbe, 2007; Yeşilova et al, 2009; Yeşilova et al, 2010), and zero-inflated generalized Poisson (ZIGP) model (Consul, 1989, Consul and Famoye, 1992; Czado et al., 2007) are widely used in the analysis of zero-inflated data.
In this part, the analysis of data with many zeros for *Notonecta viridis* Delcourt (Heteroptera: Notonectidae) and Chironomidae species (Diptera) were carried out by means of using the models of Poisson Regression (PR), negative binomial (NB) regression, zero-inflated Poisson (ZIP) regression, zero-inflated negative binomial (ZINB) regression and negative binomial hurdle (NBH) model.

Samplings

The study was based on periodical samplings of the coastal band of Van Lake, conducted between July-September 2005 and May-September 2006. Samples were taken at totally twenty sampling points as streams entrance (6 points), settlement coastlines (7 points) and naspeciesal coastlines (7 points). Samples were taken according to Hansen et al. (2000). The

invertebrates were collected with a standard sweep net (30 cm width, 1 mm mesh) (Southwood, 1978; Rosenberg, 1997; Hansen et. al, 2000; Yeşilova et al., 2011).
Notonectid identification was made by Dmitry A. Gapon (Zoological Institute RAS, Universitetskaya nab., 1, St. Petersburg, Russia).

2. Methods

2.1 Poisson regression

The logarithm of mean of Poisson distribution (μ) is supposed to be a linear function of independent variables (x_i) is,

$$\log(\mu_i) = \left(x_i^{'}\beta\right)$$

Poisson Regression Model can be written as

$$\Pr(y_i / \mu_i, x_i) = \exp(-\mu_i)\mu_i^{y_i} / y_i! \text{ ,yi=0,1,...} \tag{1}$$

In equation 1, y_i denotes dependent variable having Poisson distribution. Likelihood function for PR model is, (Böhning, 1998)

$$LL\left(\beta / y_i, x_i\right) = \sum_{i=1}^{n}\left[y_i x_i^{'}\beta - \exp\left(x_i^{'}\beta\right) - \ln y_i!\right] \tag{2}$$

In equation 2, β are unknown parameters. β can be estimated by maximizing log likelihood function according to ML (Khoshgoftaar et al, 2005;Yau, 2006).

2.2 Negative binomial regression

NB regression model is,

$$\Pr(Y = y_i / x_i) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)} \frac{(\alpha\mu_i)^{y_i}}{(1+\alpha\mu_i)^{y_i + \frac{1}{\alpha}}} \quad \alpha > 0 \tag{3}$$

In equation 3, α is a arbitrary parameter and indicates overdispersion level. Log likelihood function for NB regression model is (Hilbe, 2007; Yau, 2006),

$$LL\left(\beta, \alpha, y\right) = \sum_{i=1}^{n}\left[\begin{array}{l}\frac{1}{\alpha}\log\left(1+\alpha\mu_i\right) - y_i\log\left(1+\frac{1}{\alpha\mu_i}\right) \\ +\log\Gamma\left(y_i+\frac{1}{\alpha}\right) - \log\Gamma\left(\frac{1}{\alpha}\right) - \log y_i!\end{array}\right]$$

2.3 Zero inflated poisson regression

ZIP regression is [13],

$$\Pr(y_i/x_i)=\begin{cases}\pi_i+(1-\pi_i)\exp(-\mu_i), & y_i=0\\ (1-\pi_i)\exp(-\mu_i)\mu_i^{y_i}\big/y_i!, & y_i>0\end{cases} \tag{4}$$

In equation (4), π_i represents the possibility of extra zeros' existence. Log likelihood function for ZIP model is (Yau, 2006),

$$LL=\sum_{i=1}^{n}\left(\begin{array}{l} I_{y_i=0}\log\left(\pi_i+\left(1-\pi_i\right)e^{-\mu_i}\right)\\ +I_{y_i>0}\log\left(\left(1-\pi_i\right)\dfrac{\mu_i^{y_i}e^{-\mu_i}}{y_i!}\right)\end{array}\right)$$

$$LL=\sum_{i=1}^{n}\left(\begin{array}{l} I_{y_i=0}\log\left(\pi_i+\left(1-\pi_i\right)e^{-\mu_i}\right)\\ +I_{y_i>0}\left(\begin{array}{l}\log\left(1-\pi_i\right)\\ +y_i\log\mu_i-\mu_i-\log y_i!\end{array}\right)\end{array}\right) \tag{5}$$

$I(.)$, given in equation (5) is the indicator function for the specified event. Then μ_i and π_i parameters can be obtained following link functions,

$$\log(\mu)=B\beta \tag{6}$$

and

$$\log\left(\frac{\pi}{1-\pi}\right)=G\gamma \tag{7}$$

In equations 6 and 7, B(nxp) and G(nxq) are covariate matrixes. β and γ are respectively unknown parameter vectors with px1 and qx1 dimension (Yau, 2006).

2.4 Zero inflated negative binomial regression

ZINB regression model is [18],

$$\Pr(y_i/x_i)=\begin{cases}\pi_i+\left(1-\pi_i\right)\left(1+\alpha\mu_i\right)^{-\alpha^{-1}}, & y_i=0\\ (1-\pi_i)\dfrac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)}\dfrac{(\alpha\mu_i)^{y_i}}{(1+\alpha\mu_i)^{y_i+\frac{1}{\alpha}}}, & y_i>0\end{cases} \tag{8}$$

In equation (8), $(\alpha \geq 0)$ indicates an overdispersion parameter. Log likelihood function for ZINB model is (Yau, 2006),

$$LL(\mu,\alpha,\pi;y) = \sum_i \begin{pmatrix} I_{y_i=0} \log(\pi_i \\ +(1-\pi_i)(1+\alpha\mu_i)^{-\alpha^{-1}} \end{pmatrix}$$

$$+I_{y_i>0} \log\left((1-\pi_i) \frac{\Gamma\left(y_i+\frac{1}{\alpha}\right)}{y_i!\Gamma\left(\frac{1}{\alpha}\right)} \frac{(\alpha\mu_i)^{y_i}}{(1+\alpha\mu_i)^{y_i+\frac{1}{\alpha}}} \right)\Bigg)$$

$$= \sum_i \Bigg(I_{y_i=0} \log(\pi_i + (1-\pi_i)(1+\alpha\mu_i)^{-\alpha^{-1}}$$

$$+I_{y_i>0}\Bigg(\log(1-\pi_i) - \frac{1}{\alpha}\log(1+\alpha\mu_i)$$

$$-y_i \log\left(1+\frac{1}{\alpha\mu_i}\right) + \log\Gamma\left(y_i+\frac{1}{k}\right)$$

$$-\log\Gamma\left(\frac{1}{\alpha}\right) - \log y_i! \Bigg)\Bigg) \tag{9}$$

$I(.)$, given in equation 9 is the indicator function for the specified event. The model descripted by Lambert (1992) can be given as,

$$\log(\mu) = X\beta \quad \text{and} \quad \log\left(\frac{\pi}{1-\pi}\right) = G\gamma$$

Here, X(nxp) and G(nxq) covariate matrixes, β and γ are respectively unknown parameter vectors with px1 and qx1 dimension. Maximum likelihood estimations for β, α and γ can be obtained by using EM algorithm.

2.5 Negative binomial hurdle model

Log-likelihood for negative binomial hurdle model (Hilbe, 2007),

$$L = \ln(f(0)) + \{\ln[1-f(0)] + \ln P(j)\} \tag{10}$$

In equation (10), $f(0)$ indicates the probability of the binary part and $p(j)$ indicates the probability of positive count. The probability of zero for logit model is,

$$f(0) = P(y=0;x) = 1/(1+\exp(xb1))$$

and
1- $f(0)$ is,

$$\exp(xb1)/(1+\exp(xb1))$$

The log likelihood function for both parts of negative binomial Hurdle Model is,

$$\text{L=cond}\{y == 0, \ln(1/1-\exp(xb1)),$$

$$\ln(\exp(xb1)/(1+\exp(xb1)))$$

$$+y * \ln(\exp(xb)/(1+\exp(xb)))$$

$$-\ln(1+\exp(xb))/\alpha + \ln\Gamma(y+1/\alpha)$$

$$-\ln\Gamma(y+1) - \ln\Gamma(1/\alpha)$$

$$-\ln(1-(1+\exp(xb))(-1/\alpha))\}$$

2.6 Model selection

Akaiki Information Criteria (AIC) is goodness of criteria used for model selection. AIC,

$$AIC = -2LL + 2r \tag{11}$$

In equations, LL indicates log likelihood, r indicates parameter number and n indicates sample size.

3. Results

In this study, R statistical software program was used. Insect densities were included to the model as dependent variable. Besides years, months, species and station are included as independent variables to the model. The 66 (20.63%) of the 320 dependent variable were zero valued. The distribution of the insect densities was skewed to right because of excess zeros.

Model	AIC
PR	57846.00
ZIP	47791.71
NB	3176.40
ZINB	2819.800
PH	47791.71
NBH	**2803.206**

Table 1. Model selection criteria for PR, NB, ZIP, ZINB, PH and NBH.

In PR analyses, deviance and Pearson Chi-square goodness of statistics higher than one (831.417 and 650.213, respectively). Thus, goodness of statistics represents that there is an overdispersion in insect densities. AIC model selection criteria for the models of PR, NB, ZIP, ZINB, PH, and NBH were given in Table 1. The model with the smallest AIC was NBH regression.
Maximum likelihood (ML) parameter estimations and standard errors for PR were given in Table 2.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	6.179499	0.054470	113.449	<2e-16 ***	482.992
year	0.118847	0.013069	9.094	<2e-16 ***	1.125244
month	0.175298	0.005066	34.604	<2e-16 ***	1.191246
Station	-0.081353	0.001124	-72.357	<2e-16 ***	0.921917
species	-1.943212	0.018356 -	105.863	<2e-16 ***	0.1432735

*p<0.05, **p<0.01, ***p<0.001

Table 2. Parameter estimations and standard errors for Poisson regression.

ML parameter estimations and standard errors for negative binomial regression were given in Table 2.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	8.52318	0.99249	8.588	4.16e-16 ***	5029.119
year	-0.15794	0.24824	-0.636	0.525	0.853901
month	-0.08205	0.09168	-0.895	0.372	0.9212259
Station	-0.08031	0.01949	-4.121	4.82e-05 ***	0.9228302
species	-1.92518	0.22452	-8.575	4.56e-16 ***	0.1458495

*p<0.05, **p<0.01, ***p<0.001

Table 3. Parameter estimations and standard errors for negative binomial regression.

ML parameter estimations and standard errors for zero-inflated Poisson regression both count model and logit model were given in Table 4 and Table 5, respectively.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	6.017745	0.056073	107.32	<2e-16 ***	410.6515
year	0.271101	0.013047	20.78	<2e-16 ***	1.311408
month	0.162333	0.005271	30.80	<2e-16 ***	1.176252
station	-0.046859	0.001122	-41.76	<2e-16 ***	0.954222
species	-2.002676	0.018382	-108.94	<2e-16 ***	0.1349736

*p<0.05, **p<0.01, ***p<0.001

Table 4. Parameter estimations and standard errors for ZIP count model.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	-3.92991	1.33906	-2.935	0.00334 **	0.01964544
year	0.50266	0.33705	1.491	0.13587	1.653113
month	0.04405	0.11930	0.369	0.71197	1.045035
station	0.17250	0.02994	5.761	8.36e-09 ***	1.188272
species	-0.44380	0.30013	-1.479	0.13923	0.6415937

*p<0.05, **p<0.01, ***p<0.001

Table 5. Parameter estimations and standard errors for ZIP logit model.

ML parameter estimations and standard errors for zero-inflated negative binomial regression both count model and logit model were given in Table 6 and Table 7, respectively.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	9.47226	1.04897	9.030	< 2e-16 ***	12994.22
year	-0.13254	0.20609	-0.643	0.520132	0.8758679
month	-0.16895	0.09356	-1.806	0.070957	0.8445511
station	-0.06233	0.01806	-3.452	0.000557 ***	0.9395728
species	-2.21006	0.20855	-10.597	< 2e-16 ***	0.1096941

*p<0.05, **p<0.01, ***p<0.001

Table 6. Parameter estimations and standard errors for ZINB count model.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	-1.21687	4.61145	-0.264	0.791872	0.2961557
year	1.64137	0.88380	1.857	0.063288	5.162237
month	-0.23791	0.22636	-1.051	0.293246	0.7882736
station	0.18398	0.05485	3.354	0.000795 ***	1.201992
species	-3.69139	3.88424	-0.950	0.341934	0.02493732

*p<0.05, **p<0.01, ***p<0.001

Table 7. Parameter estimations and standard errors for ZINB logit model.

ML parameter estimations and standard errors for Poisson hurdle both count model and logit model were given in Table 8 and Table 9, respectively.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	6.017745	0.056073	107.32	<2e-16 ***	410.6515
year	0.271101	0.013047	20.78	<2e-16 ***	1.311408
month	0.162333	0.005271	30.80	<2e-16 ***	1.176252
station	-0.046859	0.001122	-41.76	<2e-16 ***	0.954222
species	-2.002676	0.018382	-108.94	<2e-16 ***	0.1349736

*p<0.05, **p<0.01, ***p<0.001

Table 8. Parameter estimations and standard errors for PH count model.

ML parameter estimations and standard errors obtained for the NBH count model was given in Table 8. While stations and species were significant on the insect densities, the effect of years and the effect of months were not significant on the insect densities.
ML parameter estimations and standard errors obtained for the NBH logit model was given in Table 9. The effects months, years and species were not significant on the insect densities. However, the effect of station was significant on the insect densities.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	3.92991	1.33906	2.935	0.00334 **	50.9024
year	-0.50266	0.33705	-1.491	0.13587	0.6049194
month	-0.04405	0.11930	-0.369	0.71197	0.9569061
station	0.17250	0.02994	-5.761	8.36e-09 ***	1.188272
species	0.44380	0.30013	1.479	0.13923	1.558619

*p<0.05, **p<0.01, ***p<0.001

Table 9. Parameter estimations and standard errors for PH logit model.

ML parameter estimations and standard errors obtained for negative binomial hurdle both count model and logit model were given in Table 10 and Table 11, respectively.
ML parameter estimations and standard errors obtained for the NBH count model was given in Table 10. While stations and species were significant on the insect densities, the effect of years and the effect of months were not significant on the insect densities.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	9.43372	1.26292	7.470	8.03e-14 ***	12502.95
year	-0.19128	0.24381	-0.785	0.4327	0.8259013
month	-0.17020	0.11124	-1.530	0.1260	0.8434961
station	-0.04587	0.02096	-2.188	0.0287 *	0.9551661
species	-2.33333	0.25071	-9.307	< 2e-16 ***	0.0969723

*p<0.05, **p<0.01, ***p<0.001

Table 10. Parameter estimations and standard errors for NBH count model.

ML parameter estimations and standard errors obtained for the NBH logit model was given in Table 11. The effects months, years and species were not significant on the insect densities. However, the effect of station was significant on the insect densities.

	Estimate	Std. Error	z value	Pr(>|z|)	e^{β}
(Intercept)	3.92991	1.33906	2.935	0.00334 **	50.9024
year	-0.50266	0.33705	-1.491	0.13587	0.6049194
month	-0.04405	0.11930	-0.369	0.71197	0.9569061
station	-0.17250	0.02994	-5.761	8.36e-09 ***	0.8415583
species	0.44380	0.30013	1.479	0.13923	1.558619

*p<0.05, **p<0.01, ***p<0.001

Table 11. Parameter estimations and standard errors for NBH logit model.

Average insect density observed in the year 2005 has shown 17% decrease in reference to the year 2006. Insect densities observed at monthly sampling ranges depending on water temperaspeciese were increased with the rise of temperaspeciese, but specifically after the month of July such intensity was decreased at the rate of 16% ($e^{-0.19128} \sim 0.8434961$) towards the month of September within the both years. It has been determined that insect intensities observed at different stations have shown differentiation at the rate of 5%. Chironomid larvae which are included in prey of notonectidae fed by different sources of food at aquatic environment have been found at rather lower density in reference to notonectid density. However, it is hard to guess that such decrement has been formed under the impact of notonectidae. Nevertheless notonectidae do not depend on a single host, their sources of food are rather wide range of variety. Small arthropods on the water surface, small crustaceans living in water, larvae of aquatic insects, snails, small fish or larvae of frog are among their preys (Bruce et al., 1990).

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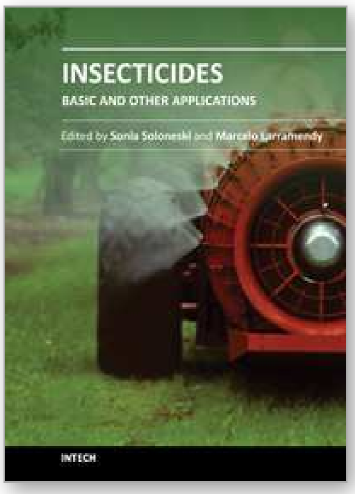

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It is our hope that this book will be of interest and use not only to scientists, but also to the food-producing industry, governments, politicians and consumers as well. If we are able to stimulate this interest, albeit in a small way, we have achieved our goal.