

Stevens, B. S., and B. Dennis. 2013. Wildlife mortality from infrastructure collisions: statistical modeling of count data from carcass surveys. Ecology 94:2087-2096.

Appendix A. Analytical maximum-likelihood estimators of θ from Eqs. 7 and 8.

Proof 1: Analytical maximum-likelihood estimator for θ assuming known ψ where the likelihood for all count observations assumes the stationary Poisson distribution for observations on the first sampling occasion ($k = 1$) and the transition density for all other observations ($k > 1$).

Let:

J = the number of sampling units

k = sampling occasion 1,..., K

$$\alpha_{jk} = \frac{1}{\psi} (1 - e^{-\psi t_{jk}})$$

t_{jk} = length of time since previous sampling event at sample unit j , or length of time since sampling event $k-1$ at sample unit j

Then the likelihood for all count observations is:

$$L(x_{11}, \dots, x_{jk} | \alpha_{12}, \dots, \alpha_{JK}, \theta) = \prod_{j=1}^J \left[\frac{\left(\frac{\theta}{\psi}\right)^{x_{j1}} e^{-\frac{\theta}{\psi}}}{x_{j1}!} \prod_{k=2}^K \frac{(\theta \alpha_{jk})^{x_{jk}} e^{-\theta \alpha_{jk}}}{x_{jk}!} \right] \quad (\text{A.1})$$

Simplifying the log-likelihood and solving for the MLE:

$$L(x_{11}, \dots, x_{jk} | \alpha_{12}, \dots, \alpha_{JK}, \theta) = \prod_{j=1}^J \frac{\left(\frac{\theta}{\psi}\right)^{x_{j1}} e^{-\frac{\theta}{\psi}}}{x_{j1}!} \prod_{j=1}^J \prod_{k=2}^K \frac{(\theta \alpha_{jk})^{x_{jk}} e^{-\theta \alpha_{jk}}}{x_{jk}!} \quad (\text{A.2})$$

Factoring the likelihood:

$$= \left(\frac{\theta}{\psi}\right)^{\sum_{j=1}^J x_{j1}} e^{-J \left(\frac{\theta}{\psi}\right)} \theta^{\sum_{j=1}^J \sum_{k=2}^K x_{jk}} e^{-\theta \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk}} \left[\prod_{j=1}^J \frac{1}{x_{j1}!} \right] \left[\prod_{j=1}^J \prod_{k=2}^K \frac{\alpha_{jk}^{x_{jk}}}{x_{jk}!} \right] \quad (\text{A.3})$$

Taking the natural logarithm:

$$\begin{aligned} \ln[L(x_{11}, \dots, x_{jk} | \alpha_{12}, \dots, \alpha_{JK}, \theta)] = \\ (\sum_{j=1}^J x_{j1}) \ln \theta - (\sum_{j=1}^J x_{j1}) \ln \psi - J \left(\frac{\theta}{\psi} \right) + (\sum_{j=1}^J \sum_{k=2}^K x_{jk}) \ln \theta - \theta \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk} + \\ \sum_{j=1}^J \ln \left(\frac{1}{x_{j1}!} \right) + \sum_{j=1}^J \sum_{k=2}^K \ln \left(\frac{\alpha_{jk}^{x_{jk}}}{x_{jk}!} \right) \end{aligned} \quad (\text{A.4})$$

Taking the derivative with respect to theta:

$$\frac{d}{d\theta} [\ln[L(x_{11}, \dots, x_{jk} | \alpha_{12}, \dots, \alpha_{JK}, \theta)]] = \frac{\sum_{j=1}^J x_{j1}}{\theta} - \frac{J}{\psi} + \frac{\sum_{j=1}^J \sum_{k=2}^K x_{jk}}{\theta} - \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk} \quad (\text{A.5})$$

Setting the derivative equal to zero and solving for the maximum-likelihood estimate of theta:

$$0 = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\hat{\theta}_{mle}} - \frac{J}{\psi} - \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk} \quad (\text{A.6})$$

$$\frac{J}{\psi} + \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk} = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\hat{\theta}_{mle}} \quad (\text{A.7})$$

$$\hat{\theta}_{mle} \left(\frac{J}{\psi} + \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk} \right) = \sum_{j=1}^J \sum_{k=1}^K x_{jk} \quad (\text{A.8})$$

$$\hat{\theta}_{mle} = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\frac{J}{\psi} + \sum_{j=1}^J \sum_{k=2}^K \alpha_{jk}} \quad (\text{A.9})$$

Proof 2: Analytical maximum-likelihood estimator for θ assuming known ψ and the stationary

Poisson distribution for all count observations.

Let:

$$X^* \sim \text{Poisson} \left(\lambda = \frac{\theta}{\psi} \right)$$

n = total number of count observations

Then the likelihood for all count observations is:

$$L(x_{11}, \dots, x_{JK} \mid \theta, \psi) = \prod_{j=1}^J \prod_{k=1}^K \frac{\left(\frac{\theta}{\psi}\right)^{x_{jk}} e^{-\frac{\theta}{\psi}}}{x_{jk}!} \quad (\text{A.10})$$

Factoring the likelihood:

$$\left(\frac{\theta}{\psi}\right)^{\sum_{j=1}^J \sum_{k=1}^K x_{jk}} e^{-n\left(\frac{\theta}{\psi}\right)} \left[\prod_{j=1}^J \prod_{k=1}^K \frac{1}{x_{jk}!} \right] \quad (\text{A.11})$$

Taking the natural logarithm:

$$\begin{aligned} \ln[L(x_{11}, \dots, x_{JK} \mid \theta, \psi)] &= (\sum_{j=1}^J \sum_{k=1}^K x_{jk}) \ln \theta - (\sum_{j=1}^J \sum_{k=1}^K x_{jk}) \ln \psi - n \left(\frac{\theta}{\psi}\right) + \\ &\sum_{j=1}^J \sum_{k=1}^K \ln \left(\frac{1}{x_{jk}!}\right) \end{aligned} \quad (\text{A.12})$$

Taking the derivative with respect to theta:

$$\frac{d}{d\theta} [\ln[L(x_{11}, \dots, x_{JK} \mid \theta, \psi)]] = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\theta} - \frac{n}{\psi} \quad (\text{A.13})$$

Setting the derivative equal to zero and solving for the maximum-likelihood estimate of theta:

$$0 = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\hat{\theta}_{mle}} - \frac{n}{\psi} \quad (\text{A.14})$$

$$\frac{n}{\psi} = \frac{\sum_{j=1}^J \sum_{k=1}^K x_{jk}}{\hat{\theta}_{mle}} \quad (\text{A.15})$$

$$\hat{\theta}_{mle} \frac{n}{\psi} = \sum_{j=1}^J \sum_{k=1}^K x_{jk} \quad (\text{A.16})$$

$$\hat{\theta}_{mle} = \frac{\psi}{n} \sum_{j=1}^J \sum_{k=1}^K x_{jk} \quad (\text{A.17})$$