N-mixture Model with Temporal Trend and Random Effect on Detection Probability Covariate

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Model implementation

The file N.mixture.trend.random.p.sim.R simulates data according to the model statement presented below, and N.mixture.trend.random.p.mcmc.R contains the MCMC algorithm for model fitting.

Model statement

Let y_{it} be the i^{th} count of individuals during time period t, for $i = 1, \ldots, m$ and $t = 1, \ldots, T$, and N_t be the true number of individuals at time t. Assuming the population is closed to mortality, recruitment, immigration, and emigration over the course of the m surveys conducted during any given time period,

$$
\begin{aligned}
y_{it} &\sim \text{Binom}(N_t, p_{it}) \\
N_1 &\sim \text{Pois}(\lambda_1) \\
N_t &\sim \text{Pois}(\lambda_t),\ t = 2, \ldots, T \\
\log(\lambda_t) &= \theta N_{t-1} \\
\text{logit}(p_{it}) &\sim \mathbf{W}_{it}\boldsymbol{\alpha}_t \\
\epsilon_{it} &\sim \text{N}(0, \zeta^2) \\
\lambda_1 &\sim \text{Gamma}(r, q) \\
\theta &\sim \text{N}(\boldsymbol{\mu}_\theta, \sigma^2) \\
\boldsymbol{\alpha}_t &\sim \text{N}(\boldsymbol{\mu}_\alpha, \tau^2\mathbf{I}) \\
\boldsymbol{\mu}_\alpha &\sim \text{N}(\mathbf{0}, \gamma^2\mathbf{I}) \\
\zeta &\sim \text{Unif}(a_\zeta, b_\zeta) \\
\tau &\sim \text{Unif}(a_\tau, b_\tau).
\end{aligned}
$$

Note that an identity link for the model on N_t could also be used, i.e., $N_t \sim \text{Pois}(\theta N_{t-1})$. The algorithm in N.mixture.trend.random.p.mcmc.R will also estimate the posterior predictive distribution for time periods in which no observations are available, i.e., $N_{\tilde{t}}$, $\tilde{t} = 2, \ldots, T-1$.

Posterior distribution

$$
[N_1, N_{\{t>2\}}, \boldsymbol{\alpha}, \lambda_1, \boldsymbol{\lambda}, \boldsymbol{\epsilon}, \zeta, \theta | \mathbf{Y}, \mathbf{W}] \propto \prod_{t=1}^{T}\prod_{i=1}^{m}[y_{it}|N_t, p_{it}][N_1|\lambda_1][N_{\{t>2\}}|\theta][\epsilon_{it}][\theta][\lambda_1][\boldsymbol{\alpha}][\zeta]
$$

Full conditional distributions

Coefficients describing the effect of covariates on detection probability ($\boldsymbol{\alpha}$):

$$
[\boldsymbol{\alpha}|\cdot] \propto \prod_{t=1}^{T}\prod_{i=1}^{m}[y_{it}|N_t, p_{it}][\boldsymbol{\alpha}].
$$

This full-conditional distribution does not have a known analytical form; therefore, sample $\mathbf{p}$ using Metropolis-Hastings.

The true number of individuals during $t = 1$ (N_1):

$$\begin{aligned}[N_1|\cdot] &\propto \prod_{i=1}^{m}[y_{i1}|N_1, p_{i1}][N_1|\lambda_1] \\ &\propto \prod_{i=1}^{m}\frac{(\lambda_1(1-p_{i1}))^{N_1-y_{i1}}}{(N_1-y_{i1})!}e^{-\lambda_1(1-p_{i1})}.\end{aligned}$$

This full-conditional is a little strange because $[N_1 - y_{i1}|\cdot] \propto \text{Pois}(\lambda_1(1-p_{i1}))$, which suggests there is one true abundance per replicate count during $t = 1$. This is in contrast to the case in which only one observation exists per site, i.e., $[N_i - y_i|\cdot] \propto \text{Pois}(\lambda_i(1-p_i))$. Given that $[N_1|\cdot]$ lacks a clear analytical solution, sample N_1 using Metropolis-Hastings.

The true number of individuals during $t = 2, \ldots, T-1$ (N_t):

$$[N_t|\cdot] \propto \prod_{i=1}^{m}[y_{it}|N_t, p_{it}][N_t|\theta, N_{t-1}][N_{t+1}|\theta, N_t]$$

This full-conditional lacks an analytical solution; therefore, sample N_t using Metropolis-Hastings. Note, for time periods $\tilde{t}$ in which observations are missing, the posterior predictive distribution for true abundance is:

$$[N_{\tilde{t}}|\cdot] \propto \prod_{i=1}^{m}[N_{\tilde{t}}|\theta, N_{\tilde{t}-1}][N_{\tilde{t}+1}|\theta, N_{\tilde{t}}].$$

The true number of individuals during $t = T$ (N_T):

$$[N_T|\cdot] \propto \prod_{i=1}^{m}[y_{iT}|N_T, p_{iT}][N_T|\theta, N_{T-1}]$$

This full-conditional lacks an analytical solution; therefore, sample N_T using Metropolis-Hastings.

Rate of the process model for N_1 (λ_1):

$$\begin{aligned}[\lambda_1|\cdot] &\propto [N_1|\lambda_1][\lambda_1] \\ &\propto \frac{\lambda_1^{N_1}e^{-\lambda_1}}{N_1!}\lambda_1^{r-1}e^{-\lambda_1 q} \\ &\propto \lambda_1^{N_1}e^{-\lambda_1}\lambda_1^{r-1}e^{-\lambda_1 q} \\ &\propto \lambda_1^{N_1+r-1}e^{-\lambda_1(1+q)} \\ &= \text{Gamma}\left(N_1 + r, 1 + q\right).\end{aligned}$$

Population growth rate (θ):

$$[\theta|\cdot] \propto [N_t|\theta, N_{t-1}][\theta]$$

This full-conditional lacks an analytical solution; therefore, sample θ using Metropolis-Hastings.

Random effect on detection probability ($\boldsymbol{\alpha}_t$):

$$[\epsilon_{it}|\cdot] \quad \propto \quad [y_{it}|N_t, p_{it}][\epsilon_{it}]$$

This full-conditional lacks an analytical solution; therefore, sample ϵ_{it} using Metropolis-Hastings.

Standard deviation of random effect (τ):

$$[\zeta|\cdot] \quad \propto \quad \prod_{t=1}^{T}\prod_{i=1}^{m}[\epsilon_{it}|\zeta][\zeta].$$

This full-conditional lacks an analytical solution; therefore, sample ζ using Metropolis-Hastings.