Appendix S3. Posterior distributions of dynamic occupancy models

Below are the posterior distributions of dynamic occupancy models for a species potentially located at k in 1,2,…,K sites across t in 1,2,…,T time steps. While the colonization (γ) parameterization differed between periodic time models, stochastic time models, and homogeneous time models, initial occupancy (ψ), persistence (ϕ), and detection probability (p) remained the same throughout. Further, let x_k be the measured level of URB at site k.

Therefore, for all models let

$$logit(\Phi_{k,t}) = d_0 + d_1 x_k + g_t$$
$$logit(p_{k,t}) = f_0 + f_1 x_k + \omega_t + \varepsilon_k$$

where g_t and ω_t are random effects that respectively allow ϕ and p to vary each time step. Similar to ω_t, ε_k is a random effect that allows p to vary at each site. As empirical Bayes methods were used to specify the Beta prior for Ψ, we used the shape parameters in Table S1 for each species.

Table S1. Shape parameters of beta priors used for the probability of initial occupancy calculated from the mean and standard deviation of sites a species was detected at each time step such that Ψ ~ Beta(a, b) for each species.

Species	a	b
Coyote	24.35	31.08
Red fox	2.13	26.69
Striped skunk	5.70	30.78
Raccoon	24.35	31.08
Virginia opossum	36.03	29.78

Periodic time model: single season pulse (Coyote, red fox, and striped skunk)

The colonization function that includes a single season pulse is

$$logit(\gamma_{k,t}) = m_0 + m_1 x_k + \sum_{n=1}^{P} \beta_{1,n} c_{t,n} + \beta_2 s_{t,n}$$

where

$$\beta_{1,n} = A\cos\left(\frac{2\pi n}{P}\delta\right), \qquad \text{for } n = 1, 2, \dots, P$$

$$\beta_{2,n} = A\sin\left(\frac{2\pi n}{P}\delta\right), \qquad \text{for } n = 1, 2, \dots, P$$

and

$$\boldsymbol{C} = \cos\left(\frac{2\pi n}{P}t\right)\sin\left(\frac{\pi n}{P}\right)\frac{2}{\pi n}, \text{for } n = 1, 2, \dots, P \text{ and } t = 1,2, \dots, T$$

$$\boldsymbol{S} = \sin\left(\frac{2\pi n}{P}t\right)\sin\left(\frac{\pi n}{P}\right)\frac{2}{\pi n}, \text{for } n = 1, 2, \dots, P \text{ and } t = 1,2, \dots, T.$$

Using this particular parametrization for colonization, the posterior distribution is then

$$[\boldsymbol{m}, \boldsymbol{d}, \boldsymbol{f}, \psi, \boldsymbol{Z}, A, \delta, g, \omega, \varepsilon\, |\boldsymbol{Y}] \propto \prod_{k=1}^{95}\prod_{t=1}^{9} \text{Bin}\left(y_{k,t}\middle|j_{k,t}, z_{k,t}p_{k,t}\right)\text{Bern}\left(z_{k,t=1}\middle|\psi\right)$$
$$* \text{Bern}\left(z_{k,t+1}\middle|(1 - z_{k,t})\gamma_{k,t} + z_{k,t}\phi_{k,t}\right) \text{Beta}(\psi|a, b)\, \text{N}(\boldsymbol{m}|0, 1.83)$$
$$* \text{N}(\boldsymbol{d}|0, 1.83)\, \text{N}(\boldsymbol{f}|0,1.83)\text{Gamma}(A|1,1)\text{Categorical}(\delta|\rho_1, \dots, \rho_P)$$
$$* \text{N}\left(g_t\middle|0, \sigma_g\right)\text{half} - \text{Cauchy}\left(\sigma_g\middle|0,25\right)\text{N}(\omega_t|0, \sigma_\omega)\text{half} - \text{Cauchy}(\sigma_\omega|0,25)$$
$$* \text{N}(\epsilon_k|0, \sigma_\varepsilon)\text{half} - \text{Cauchy}(\sigma_\varepsilon|0,25)$$

where the categorical values that δ can take are ϵ (0,…,P-1), P = 4, and $\boldsymbol{\rho}$ = 1/P. The probability that a pulse occurs at a particular time step is then the proportion of times a categorical value was chosen over all samples from the posterior distribution.

Periodic time model: boom-bust pattern (Raccoon and Virginia opossum)

A colonization parameterization that includes multiple pulses per year is

$$logit\left(\gamma_{k,t}\right) = m_0 + m_1x_k + + \beta_1c_t + \beta_2s_t$$

where

$$\beta_1 = A\cos\left(\frac{2\pi}{P}\delta\right)$$

$$\beta_2 = A \sin\left(\frac{2\pi}{P}\delta\right)$$

and

$$\boldsymbol{c} = \cos\left(\frac{2\pi}{P}t\right), \text{for } t = 1,2, \dots, T$$

$$\boldsymbol{s} = \sin\left(\frac{2\pi}{P}t\right), \text{for } t = 1,2, \dots, T.$$

Using this colonization parameterization, the posterior distribution is then

$$\begin{aligned}[\boldsymbol{m}, \boldsymbol{d}, \boldsymbol{f}, \psi, \boldsymbol{Z}, A, \delta, g, \omega, \varepsilon \,|\boldsymbol{Y}] \propto \prod_{k=1}^{95}\prod_{t=1}^{9} &\text{Bin}\left(y_{k,t}\middle|j_{k,t}, z_{k,t}p_{k,t}\right)\text{Bern}\left(z_{k,t=1}\middle|\psi\right) \\ &* \text{Bern}\left(z_{k,t+1}\middle|\left(1- z_{k,t}\right)\gamma_{k,t} + z_{k,t}\phi_{k,t}\right) \text{Beta}(\psi|a,b)\ \text{N}(\boldsymbol{m}|0, 1.83) \\ &* \text{N}(\boldsymbol{d}|0, 1.83)\ \text{N}(\boldsymbol{f}|0,1.83)\text{Gamma}(A|1,1)\text{Categorical}(\delta|\rho_1, \dots, \rho_P) \\ &* \text{N}\left(g\middle|0, \sigma_g\right)\text{half} - \text{Cauchy}\left(\sigma_g\middle|0,25\right)\text{N}(\omega_t|0, \sigma_\omega)\text{half} - \text{Cauchy}(\sigma_\omega|0,25) \\ &* \text{N}(\epsilon_k|0, \sigma_\varepsilon)\text{half} - \text{Cauchy}(\sigma_\varepsilon|0,25)\end{aligned}$$

where the categorical values that δ can take are ϵ (0,…,P-1), P = 2, and $\boldsymbol{\rho}$ = 1/P.

Stochastic time model

A colonization parameterization that varies each time step can be represented as

$$logit\left(\gamma_{k,t}\right) = m_0 + m_1x_k + u_t.$$

Using this, the posterior distribution can then be written as

$$\begin{aligned}[\boldsymbol{m}, \boldsymbol{d}, \boldsymbol{f}, \psi, \boldsymbol{Z}, A, \delta, g, \omega, \varepsilon \,|\boldsymbol{Y}] \propto \prod_{k=1}^{95}\prod_{t=1}^{9} &\text{Bin}\left(y_{k,t}\middle|j_{k,t}, z_{k,t}p_{k,t}\right)\text{Bern}\left(z_{k,t=1}\middle|\psi\right) \\ &* \text{Bern}\left(z_{k,t+1}\middle|\left(1- z_{k,t}\right)\gamma_{k,t} + z_{k,t}\phi_{k,t}\right) \text{Beta}(\psi|a,b)\ \text{N}(\boldsymbol{m}|0, 1.83) \\ &* \text{N}(\boldsymbol{d}|0, 1.83)\ \text{N}(\boldsymbol{f}|0,1.83)\text{N}(u_t|0, \sigma_u)\text{half} - \text{Cauchy}(\sigma_u|0,25) \\ &* \text{N}\left(g_t\middle|0, \sigma_g\right)\text{half} - \text{Cauchy}\left(\sigma_g\middle|0,25\right)\text{N}(\omega_t|0, \sigma_\omega)\text{half} - \text{Cauchy}(\sigma_\omega|0,25) \\ &* \text{N}(\epsilon_k|0, \sigma_\varepsilon)\text{half} - \text{Cauchy}(\sigma_\varepsilon|0,25)\end{aligned}$$

Homogeneous time model

A colonization parameterization that does not change through time can be represented as

$$logit(\gamma_{k,t}) = m_0 + m_1 x_k$$

and the posterior distribution can then be written as

$$[\boldsymbol{m}, \boldsymbol{d}, \boldsymbol{f}, \psi, \boldsymbol{Z}, A, \delta, g, \omega, \varepsilon \,|\boldsymbol{Y}] \propto \prod_{k=1}^{95} \prod_{t=1}^{9} \mathrm{Bin}\left(y_{k,t} \middle| j_{k,t}, z_{k,t} p_{k,t}\right) \mathrm{Bern}\left(z_{k,t=1} \middle| \psi\right)$$

$$* \, \mathrm{Bern}\left(z_{k,t+1} \middle| (1 - z_{k,t})\gamma_{k,t} + z_{k,t}\phi_{k,t}\right) \mathrm{Beta}(\psi|a, b) \; \mathrm{N}(\boldsymbol{m}|0, 1.83)$$

$$* \, \mathrm{N}(\boldsymbol{d}|0, 1.83)\mathrm{N}(\boldsymbol{f}|0, 1.83) \; \mathrm{N}\left(g_t \middle| 0, \sigma_g\right) \mathrm{half-Cauchy}\left(\sigma_g \middle| 0{,}25\right)$$

$$* \, \mathrm{N}(\omega_t|0, \sigma_\omega) \mathrm{half-Cauchy}(\sigma_\omega|0{,}25)$$

$$* \, \mathrm{N}(\epsilon_k|0, \sigma_\varepsilon) \mathrm{half-Cauchy}(\sigma_\varepsilon|0{,}25)$$