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Appendix S1. Model statement, posterior distribution, and full-conditional distributions.

The model we propose is well-suited to a Bayesian analysis using Markov chain Monte Carlo methods. Such an approach estimates the joint posterior distribution by sampling iteratively from the full-conditional distributions. In the posterior and full-conditional distributions below, we use bracket notation to denote a probability distribution. For example, [x] indicates the probability distribution of x. Similarly, [x|y] indicates the probability distribution of x given the parameter y. The notation "·" represents the data and other parameters in the model.

In addition to the notation introduced in the main document, let c index Argos location quality class (i.e., $c \in \{3, 2, 1, 0, \text{A}, \text{and B}\}$).

Model Statement

$$
\begin{aligned}
\mathbf{s}_c(t) &\sim \begin{cases} \mathcal{N}(\boldsymbol{\mu}(t), \boldsymbol{\Sigma}_c), & \text{with prob. } p(t),\ y(t) = 1 \\ \mathcal{N}(\boldsymbol{\mu}(t), \widetilde{\boldsymbol{\Sigma}}_c), & \text{with prob. } 1 - p(t),\ y(t) = 1 \\ \mathcal{N}(\boldsymbol{\mu}(t), \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c), & \text{with prob. } p(t),\ y(t) = 0 \\ \mathcal{N}(\boldsymbol{\mu}(t), \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c), & \text{with prob. } 1 - p(t),\ y(t) = 0 \end{cases} \\
\boldsymbol{\Sigma}_c &= \sigma_c^2 \begin{bmatrix} 1 & \rho_c\sqrt{a_c} \\ \rho_c\sqrt{a_c} & a_c \end{bmatrix} \\
\widetilde{\boldsymbol{\Sigma}}_c &= \sigma_c^2 \begin{bmatrix} 1 & -\rho_c\sqrt{a_c} \\ -\rho_c\sqrt{a_c} & a_c \end{bmatrix} \\
\boldsymbol{\mu}(t) &\sim \sum_{j=1}^{J} \pi_j \delta_{\boldsymbol{\mu}_j} \\
\pi_j &= \eta_j \prod_{l<j} (1 - \eta_l) \\
\eta_j &\sim \text{Beta}(1, \theta) \\
y(t) &= \begin{cases} 0, & v(t) \leq 0 \\ 1, & v(t) > 0 \end{cases} \\
v(t) &\sim \mathcal{N}\left(\mathbf{x}(t)' \boldsymbol{\beta} + \mathbf{w}(t)' \boldsymbol{\alpha}, 1\right) \\
\boldsymbol{\mu}_j &\sim f_{\widetilde{\mathcal{S}}}(\mathbf{S}) \\
\theta &\sim \text{Gamma}(r_\theta, q_\theta) \\
\boldsymbol{\beta} &\sim \mathcal{N}\left(\boldsymbol{\mu}_\beta, \sigma_\beta^2 \mathbf{I}\right) \\
\boldsymbol{\alpha} &\sim \mathcal{N}\left(\mathbf{0}, \sigma_\alpha^2 \mathbf{I}\right) \\
\log(\sigma_\mu) &\sim \mathcal{N}\left(\mu_\sigma, \sigma_\sigma^2\right) \\
\sigma_\alpha^2 &\sim \text{IG}(r_\alpha, q_\alpha) \\
\sigma_c &\sim \text{Unif}(l_\sigma, u_\sigma) \\
a_c &\sim \text{Unif}(l_a, u_a) \\
\rho_c &\sim \text{Unif}(l_\rho, u_\rho)
\end{aligned}
$$

Note that $f_{\widetilde{\mathcal{S}}}(\mathbf{S})$ represents the kernel density estimate of the observed telemetry locations $\mathbf{S} \equiv \{\mathbf{s}_c(t) : t \in \mathcal{T}\}$ at location $\boldsymbol{\mu}_j$, where $f_{\widetilde{\mathcal{S}}}(\mathbf{S})$ is truncated and normalized over $\widetilde{\mathcal{S}}$.

Posterior Distribution

$$
\begin{aligned}
\left[\mathbf{M}_t, \boldsymbol{\eta}, \mathbf{v}, \boldsymbol{\alpha}, \mathbf{M}_j, \theta, \boldsymbol{\beta}, \sigma_\mu, \sigma_\alpha^2, \boldsymbol{\sigma}, \mathbf{a}, \boldsymbol{\rho} \mid \mathbf{S}, \mathbf{y}\right] \quad \propto \quad & \prod_{t\in\mathcal{T}}\prod_{j=1}^{J} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}(t), y(t), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right] \left[\boldsymbol{\mu}(t) \mid \boldsymbol{\mu}_j, \eta_j\right] \left[\eta_j \mid \theta\right] \\
& \times \left[y(t) \mid v(t)\right] \left[v(t) \mid \boldsymbol{\alpha}, \boldsymbol{\beta}\right] \left[\boldsymbol{\alpha} \mid \mathbf{0}, \sigma_\alpha^2\right] \\
& \times \left[\boldsymbol{\mu}_j\right] [\theta] [\boldsymbol{\beta}] [\sigma_\mu] \left[\sigma_\alpha^2\right] [\boldsymbol{\sigma}] [\mathbf{a}] [\boldsymbol{\rho}],
\end{aligned}
$$

where $\mathbf{M}_t \equiv \{\boldsymbol{\mu}(t) : t \in \mathcal{T}\}$ is a matrix of functional central places $\boldsymbol{\mu}(t)$ for all times $t \in \mathcal{T}$; $\boldsymbol{\eta} \equiv (\eta_1, \ldots, \eta_J)'$ is a vector of stick-breaking weights η_j for $j = 1, \ldots, J$; $\mathbf{v} \equiv \{v(t) : t \in \mathcal{T}\}$ is a vector of latent auxiliary variables $v(t)$ for all times $t \in \mathcal{T}$; $\mathbf{M}_j \equiv \left\{\boldsymbol{\mu}_j : j = 1, \ldots, J\right\}$ is a matrix of potential central places $\boldsymbol{\mu}_j$ for $j = 1, \ldots, J$; $\boldsymbol{\sigma} \equiv (\sigma_3, \sigma_2, \sigma_1, \sigma_0, \sigma_A, \sigma_B)'$, $\mathbf{a} \equiv (a_3, a_2, a_1, a_0, a_A, a_B)'$, and $\boldsymbol{\rho} \equiv (\rho_3, \rho_2, \rho_1, \rho_0, \rho_A, \rho_B)'$ are vectors of parameters describing telemetry measurement error for each Argos location quality class; $\mathbf{S} \equiv \{\mathbf{s}_c(t) : t \in \mathcal{T}\}$ is a matrix of observed telemetry locations $\mathbf{s}_c(t)$ for all times $t \in \mathcal{T}$; and $\mathbf{y} \equiv \{y(t) : t \in \mathcal{T}\}$ is a vector of ancillary behavioral data $y(t)$ for all times $t \in \mathcal{T}$.

Full-Conditional Distributions

Locations of functional central places ($\boldsymbol{\mu}(t)$):

$$
\begin{aligned}
[\boldsymbol{\mu}(t) \mid \cdot] \quad & \propto \quad \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}(t), y(t), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right] [\boldsymbol{\mu}(t) \mid \boldsymbol{\pi}] \\
& \propto \quad \sum_{j=1}^{J} \pi_j \delta_{\boldsymbol{\mu}_j} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, y(t), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right].
\end{aligned}
$$

Here, we introduce a variable for the latent class status, $h(t) \in \{1, \ldots, J\}$, that assigns each observed telemetry location $\mathbf{s}_c(t)$ to one of the central places $\boldsymbol{\mu}_j$, for $j = 1, \ldots, J$ (i.e., $\boldsymbol{\mu}(t) = \boldsymbol{\mu}_{h(t)}$). The update proceeds just as in multinomial sampling:

$$
\begin{aligned}
[h(t) \mid \cdot] \quad \sim \quad & \text{Cat}\left(\frac{\pi_1 \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_1, \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y(t)} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_1, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(t)}}{\sum_{j=1}^{J} \pi_j \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y(t)} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(t)}}, \cdots, \right. \\
& \left. \frac{\pi_J \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_J, \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y(t)} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_J, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(t)}}{\sum_{j=1}^{J} \pi_j \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y(t)} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(t)}} \right) \\
\sim \quad & \text{Cat}\left(\frac{a_1}{b}, \cdots, \frac{a_j}{b}\right),
\end{aligned}
$$

where $a_j = \pi_j \times \left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y(t)}$
$\times \left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y(t)}$
and $b = \sum_{j=1}^{J} \left\{\pi_j \times \left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y(t)}\right.$
$\left. \times \left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2 \mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y(t)}\right\}.$

Stick-breaking weights (η_j):

$$\begin{aligned}
[\eta_j \mid \cdot] &\propto \prod_{t\in\mathcal{T}} [\boldsymbol{\mu}(t) \mid \pi_j]^{1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}}} \prod_{i=j+1}^{J} \prod_{t\in\mathcal{T}} [\boldsymbol{\mu}(t) \mid \pi_i]^{1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_i\}}} [\eta_j \mid 1, \theta] \\
&\propto \prod_{t\in\mathcal{T}} \pi_j^{1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}}} \prod_{i=j+1}^{J} \prod_{t\in\mathcal{T}} \pi_i^{1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_i\}}} \mathrm{Beta}(\eta_j \mid 1, \theta) \\
&\propto \pi_j^{\sum_{t\in\mathcal{T}}\left(1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}}\right)} \prod_{i=j+1}^{J} \pi_i^{\sum_{t\in\mathcal{T}}\left(1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_i\}}\right)} \eta_j^{1-1} (1-\eta_j)^{\theta-1} \\
&\propto \left(\eta_j \prod_{l<j} (1-\eta_l)\right)^{m_j} \prod_{i=j+1}^{J} \left(\eta_i \prod_{l<i} (1-\eta_l)\right)^{m_i} (1-\eta_j)^{\theta-1} \\
&\propto \eta_j{}^{m_j} \prod_{i=j+1}^{J} \left(\prod_{l<i} (1-\eta_l)\right)^{m_i} (1-\eta_j)^{\theta-1} \\
&\propto \eta_j{}^{m_j} (1-\eta_j)^{\sum_{i=j+1}^{J} m_i} (1-\eta_j)^{\theta-1} \\
&\propto \eta_j{}^{m_j} (1-\eta_j)^{\sum_{i=j+1}^{J} m_i+\theta-1} \\
&= \mathrm{Beta}\left(m_j+1, \sum_{i=j+1}^{J} m_i + \theta\right),
\end{aligned}$$

where $m_j = \sum_{t\in\mathcal{T}}\left(1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}}\right)$, i.e., the number of observed telemetry locations ($\mathbf{s}_c(t)$) allocated to central place $\boldsymbol{\mu}_j$.

Auxiliary variable for temporal process model ($v(t)$):

$$\begin{aligned}
[v(t) \mid \cdot] &\propto [y(t) \mid v(t)]\,[v(t) \mid \boldsymbol{\alpha}, \boldsymbol{\beta}] \\
&\propto \left(1_{\{y(t)=0\}}1_{\{v(t)\leq 0\}} + 1_{\{y(t)=1\}}1_{\{v(t)>0\}}\right) \times \mathcal{N}\left(v(t) \mid \mathbf{x}(t)'\boldsymbol{\beta} + \mathbf{w}(t)'\boldsymbol{\alpha}, \mathbf{1}\right) \\
&= \begin{cases} \mathcal{TN}\left(\mathbf{x}(t)'\boldsymbol{\beta} + \mathbf{w}(t)'\boldsymbol{\alpha}, \mathbf{1}\right)_{-\infty}^{0}, & y(t)=0 \\ \mathcal{TN}\left(\mathbf{x}(t)'\boldsymbol{\beta} + \mathbf{w}(t)'\boldsymbol{\alpha}, \mathbf{1}\right)_{0}^{\infty}, & y(t)=1 \end{cases}.
\end{aligned}$$

Basis coefficients in temporal process model ($\boldsymbol{\alpha}$):

$$\begin{aligned}
[\boldsymbol{\alpha} \mid \cdot] &\propto [\mathbf{v} \mid \boldsymbol{\beta}, \boldsymbol{\alpha}]\,[\boldsymbol{\alpha} \mid \mathbf{0}, \sigma_\alpha^2] \\
&\propto \mathcal{N}(\mathbf{v} \mid \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha}, \mathbf{1})\,\mathcal{N}(\boldsymbol{\alpha} \mid \mathbf{0}, \sigma_\alpha^2\mathbf{I}) \\
&\propto \exp\left\{-\frac{1}{2}(\mathbf{v} - (\mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha}))'(\mathbf{v} - (\mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha}))\right\} \\
&\qquad \times \exp\left\{-\frac{1}{2}(\boldsymbol{\alpha} - \mathbf{0})'\left(\sigma_\alpha^2\mathbf{I}\right)^{-1}(\boldsymbol{\alpha} - \mathbf{0})\right\} \\
&\propto \exp\left\{-\frac{1}{2}((\mathbf{v} - \mathbf{X}\boldsymbol{\beta}) - \mathbf{W}\boldsymbol{\alpha})'((\mathbf{v} - \mathbf{X}\boldsymbol{\beta}) - \mathbf{W}\boldsymbol{\alpha})\right\} \\
&\qquad \times \exp\left\{-\frac{1}{2}\boldsymbol{\alpha}'\left(\sigma_\alpha^2\mathbf{I}\right)^{-1}\boldsymbol{\alpha}\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left(-2\left((\mathbf{v} - \mathbf{X}\boldsymbol{\beta})'\mathbf{W}\right)\boldsymbol{\alpha} + \boldsymbol{\alpha}'\left(\mathbf{W}'\mathbf{W} + \left(\sigma_\alpha^2\mathbf{I}\right)^{-1}\right)\boldsymbol{\alpha}\right)\right\} \\
&= \mathcal{N}(\mathbf{A}^{-1}\mathbf{b}, \mathbf{A}^{-1}),
\end{aligned}$$

where $\mathbf{A} = \mathbf{W}'\mathbf{W} + \left(\sigma_{\alpha}^{2}\mathbf{I}\right)^{-1}$ and $\mathbf{b}' = (\mathbf{v} - \mathbf{X}\boldsymbol{\beta})'\,\mathbf{W}$. Note that the matrix $\mathbf{X} \equiv \{\mathbf{x}(t) : t \in \mathcal{T}\}$ contains the vectors $\mathbf{x}(t)$ for all times $t \in \mathcal{T}$. Similarly, $\mathbf{W} \equiv \{\mathbf{w}(t) : t \in \mathcal{T}\}$ is a matrix containing the vectors $\mathbf{w}(t)$ for all times $t \in \mathcal{T}$.

Locations of potential central places $\left(\boldsymbol{\mu}_j\right)$:

$$\begin{aligned}
\left[\boldsymbol{\mu}_j \mid \cdot\right] &\propto \prod_{t \in \mathcal{T}} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}(t), y(t), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right]^{1_{\{\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}}} \left[\boldsymbol{\mu}_j\right] \\
&\propto \prod_{\{t:\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}} \left\{\left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y(t)} \left[\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(t)}\right\} \left[\boldsymbol{\mu}_j\right] \\
&\propto \prod_{\{t:\boldsymbol{\mu}(t)=\boldsymbol{\mu}_j\}} \left\{\left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y(t)}\right. \\
&\qquad \left. \times \left(p(t) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c\right) + (1 - p(t)) \times \mathcal{N}\left(\mathbf{s}_c(t) \mid \boldsymbol{\mu}_j, \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y(t)}\right\} \left[\boldsymbol{\mu}_j\right].
\end{aligned}$$

Note that the product is over all $t \in \mathcal{T}$ such that $\mathbf{s}_c(t)$ is allocated to central place $\boldsymbol{\mu}_j$ (i.e., instances where $\boldsymbol{\mu}(t) = \boldsymbol{\mu}_j$).

Dirichlet process concentration parameter (θ):

$$\begin{aligned}
[\theta|\cdot] &\propto \prod_{j=1}^{J-1} [\eta_j \mid 1, \theta] [\theta] \\
&\propto \prod_{j=1}^{J-1} \text{Beta} (\eta_j \mid 1, \theta) \, \text{Gamma} (\theta \mid r_\theta, q_\theta) \\
&\propto \prod_{j=1}^{J-1} \frac{\Gamma(1+\theta)}{\Gamma(1)\Gamma(\theta)} \eta_j^{1-1} (1-\eta_j)^{\theta-1} \theta^{r_\theta - 1} \exp\{-q_\theta \theta\} \\
&\propto \left(\frac{\theta \Gamma(\theta)}{\Gamma(1)\Gamma(\theta)} \right)^{J-1} \theta^{r_\theta - 1} \exp\left\{ -q_\theta \theta + \log \left(\prod_{j=1}^{J-1} (1-\eta_j)^{\theta-1} \right) \right\} \\
&\propto \left(\frac{\theta \Gamma(\theta)}{\Gamma(1)\Gamma(\theta)} \right)^{J-1} \theta^{r_\theta - 1} \exp\left\{ -q_\theta \theta + \log \left(\prod_{j=1}^{J-1} (1-\eta_j)^{\theta} (1-\eta_j)^{-1} \right) \right\} \\
&\propto \left(\frac{\theta \Gamma(\theta)}{\Gamma(1)\Gamma(\theta)} \right)^{J-1} \theta^{r_\theta - 1} \exp\left\{ -q_\theta \theta + \log \left(\prod_{j=1}^{J-1} (1-\eta_j)^{\theta} \right) \right\} \\
&\propto \theta^{J-1+r_\theta-1} \exp\left\{ -q_\theta \theta + \sum_{j=1}^{J-1} \log (1-\eta_j)^\theta \right\} \\
&\propto \theta^{J-1+r_\theta-1} \exp\left\{ -q_\theta \theta + \theta \sum_{j=1}^{J-1} \log (1-\eta_j) \right\} \\
&\propto \theta^{J-1+r_\theta-1} \exp\left\{ -\theta \left(q_\theta - \sum_{j=1}^{J-1} \log (1-\eta_j) \right) \right\} \\
&= \text{Gamma} \left(r_\theta + J - 1, q_\theta - \sum_{j=1}^{J-1} \log (1-\eta_j) \right).
\end{aligned}$$

Note that the product is over $j = 1, \ldots, J-1$ because $\eta_J = 1$ in the truncation approximation of a Dirichlet process.

Fixed effects in temporal process model ($\boldsymbol{\beta}$):

$$\begin{aligned}
[\boldsymbol{\beta} \mid \cdot] &\propto [\mathbf{v} \mid \boldsymbol{\beta}, \boldsymbol{\alpha}] [\boldsymbol{\beta}] \\
&\propto \mathcal{N} (\mathbf{v} \mid \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha}, \mathbf{1}) \mathcal{N}(\boldsymbol{\beta} \mid \boldsymbol{\mu}_\beta, \sigma_\beta^2 \mathbf{I}) \\
&\propto \exp\left\{ -\frac{1}{2} (\mathbf{v} - (\mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha}))' (\mathbf{v} - (\mathbf{X}\boldsymbol{\beta} + \mathbf{W}\boldsymbol{\alpha})) \right\} \\
&\qquad \times \exp\left\{ -\frac{1}{2} (\boldsymbol{\beta} - \boldsymbol{\mu}_\beta)' \left(\sigma_\beta^2 \mathbf{I}\right)^{-1} (\boldsymbol{\beta} - \boldsymbol{\mu}_\beta) \right\} \\
&\propto \exp\left\{ -\frac{1}{2} ((\mathbf{v} - \mathbf{W}\boldsymbol{\alpha}) - \mathbf{X}\boldsymbol{\beta})' ((\mathbf{v} - \mathbf{W}\boldsymbol{\alpha}) - \mathbf{X}\boldsymbol{\beta}) \right\} \\
&\qquad \times \exp\left\{ -\frac{1}{2} (\boldsymbol{\beta} - \boldsymbol{\mu}_\beta)' \left(\sigma_\beta^2 \mathbf{I}\right)^{-1} (\boldsymbol{\beta} - \boldsymbol{\mu}_\beta) \right\} \\
&\propto \exp\left\{ -\frac{1}{2} \left(-2 \left((\mathbf{v} - \mathbf{W}\boldsymbol{\alpha})' \mathbf{X} + \boldsymbol{\mu}_\beta' \left(\sigma_\beta^2 \mathbf{I}\right)^{-1} \right) \boldsymbol{\beta} + \boldsymbol{\beta}' \left(\mathbf{X}'\mathbf{X} + \left(\sigma_\beta^2 \mathbf{I}\right)^{-1} \right) \boldsymbol{\beta} \right) \right\} \\
&= \mathcal{N}(\mathbf{A}^{-1}\mathbf{b}, \mathbf{A}^{-1}),
\end{aligned}$$

where $\mathbf{A}=\mathbf{X}'\mathbf{X}+\left(\sigma_{\beta}^{2}\mathbf{I}\right)^{-1}$ and $\mathbf{b}'=(\mathbf{v}-\mathbf{W}\boldsymbol{\alpha})'\mathbf{X}+\boldsymbol{\mu}_{\beta}'\left(\sigma_{\beta}^{2}\mathbf{I}\right)^{-1}$. Note that the matrix $\mathbf{X}\equiv\{\mathbf{x}(t):t\in\mathcal{T}\}$ contains the vectors $\mathbf{x}(t)$ for all times $t\in\mathcal{T}$. Similarly, $\mathbf{W}\equiv\{\mathbf{w}(t):t\in\mathcal{T}\}$ is a matrix containing the vectors $\mathbf{w}(t)$ for all times $t\in\mathcal{T}$.

Animal movement parameter (σ_μ):

$$\begin{aligned}
[\sigma_\mu\mid\cdot] &\propto \prod_{t\in\mathcal{T}}\left[\mathbf{s}_c(t)\mid\boldsymbol{\mu}(t),y(t),\boldsymbol{\Sigma}_c,\widetilde{\boldsymbol{\Sigma}}_c,\sigma_\mu\right][\sigma_\mu]\\
&\propto \prod_{t\in\mathcal{T}}\left[\mathbf{s}_c(t)\mid\boldsymbol{\mu}(t),\boldsymbol{\Sigma}_c,\widetilde{\boldsymbol{\Sigma}}_c,\sigma_\mu^2\right]^{1-y(t)}[\sigma_\mu]\\
&\propto \prod_{\{t:y(t)=0\}}\left(p(t)\times\mathcal{N}\left(\mathbf{s}_c(t)\mid\boldsymbol{\mu}(t),\sigma_\mu^2\mathbf{I}+\boldsymbol{\Sigma}_c\right)+(1-p(t))\times\mathcal{N}\left(\mathbf{s}_c(t)\mid\boldsymbol{\mu}(t),\sigma_\mu^2\mathbf{I}+\widetilde{\boldsymbol{\Sigma}}_c\right)\right)\\
&\qquad\times\mathcal{N}\left(\log(\sigma_\mu)\mid\log(\mu_\sigma),\sigma_\sigma^2\right).
\end{aligned}$$

Note that the product is over all $t\in\mathcal{T}$ such that $y(t)=0$ (i.e., all observed telemetry locations ($\mathbf{s}_c(t)$) collected when the individual is not at the central place).

Variance of basis coefficients (σ_α^2):

$$\begin{aligned}
\left[\sigma_\alpha^2\mid\cdot\right] &\propto \left[\boldsymbol{\alpha}\mid\mathbf{0},\sigma_\alpha^2\right]\left[\sigma_\alpha^2\right]\\
&\propto \mathcal{N}\left(\boldsymbol{\alpha}\mid\mathbf{0},\sigma_\alpha^2\mathbf{I}\right)\mathrm{IG}\left(\sigma_\alpha^2\mid r_\alpha,q_\alpha\right)\\
&\propto \left|\sigma_\alpha^2\mathbf{I}\right|^{-1/2}\exp\left\{-\frac{1}{2}\left((\boldsymbol{\alpha}-\mathbf{0})'\left(\sigma_\alpha^2\mathbf{I}\right)^{-1}(\boldsymbol{\alpha}-\mathbf{0})\right)\right\}\left(\sigma_\alpha^2\right)^{-(q_\alpha+1)}\exp\left\{-\frac{1}{r_\alpha\sigma_\alpha^2}\right\}\\
&\propto \left(\sigma_\alpha^2\right)^{-M/2}\exp\left\{-\frac{1}{2\sigma_\alpha^2}\boldsymbol{\alpha}'\boldsymbol{\alpha}\right\}\left(\sigma_\alpha^2\right)^{-(q_\alpha+1)}\exp\left\{-\frac{1}{r_\alpha\sigma_\alpha^2}\right\}\\
&\propto \left(\sigma_\alpha^2\right)^{-(M/2+q_\alpha+1)}\exp\left\{-\frac{1}{\sigma_\alpha^2}\left(\frac{\boldsymbol{\alpha}'\boldsymbol{\alpha}}{2}+\frac{1}{r_\alpha}\right)\right\}\\
&= \mathrm{IG}\left(\left(\frac{\boldsymbol{\alpha}'\boldsymbol{\alpha}}{2}+\frac{1}{r_\alpha}\right)^{-1},\frac{M}{2}+q_\alpha\right),
\end{aligned}$$

where M is the length of $\boldsymbol{\alpha}$ (or column dimension of $\mathbf{W}$).

Longitudinal telemetry measurement error (σ_c):

$$\begin{aligned}
[\sigma_c\mid\cdot] &\propto \prod_{\tilde{t}\in\mathcal{T}}\left[\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),y(\tilde{t}),\boldsymbol{\Sigma}_c,\widetilde{\boldsymbol{\Sigma}}_c,\sigma_\mu\right][\sigma_c]\\
&\propto \prod_{\tilde{t}\in\mathcal{T}}\left\{\left[\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\boldsymbol{\Sigma}_c,\widetilde{\boldsymbol{\Sigma}}_c\right]^{y(\tilde{t})}\left[\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\sigma_\mu^2\mathbf{I}+\boldsymbol{\Sigma}_c,\sigma_\mu^2\mathbf{I}+\widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y(\tilde{t})}\right\}[\sigma_c]\\
&\propto \prod_{\tilde{t}\in\mathcal{T}}\left\{\left(p(\tilde{t})\times\mathcal{N}\left(\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\boldsymbol{\Sigma}_c\right)+\left(1-p(\tilde{t})\right)\times\mathcal{N}\left(\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y(\tilde{t})}\right.\\
&\qquad\left.\times\left(p(\tilde{t})\times\mathcal{N}\left(\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\sigma_\mu^2\mathbf{I}+\boldsymbol{\Sigma}_c\right)+\left(1-p(\tilde{t})\right)\times\mathcal{N}\left(\mathbf{s}_c(\tilde{t})\mid\boldsymbol{\mu}(\tilde{t}),\sigma_\mu^2\mathbf{I}+\widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y(\tilde{t})}\right\}\\
&\qquad\times\mathrm{Unif}\left(\sigma_c\mid l_\sigma,u_\sigma\right),
\end{aligned}$$

where $\tilde{t}\in\mathcal{T}$ is the subset of times for all observed telemetry locations ($\mathbf{s}_c(t)$) belonging to Argos location quality class c. In other words, the product is over all $t\in\mathcal{T}$ such that $\mathbf{s}_c(t)$ is allocated to location quality class c.

Adjustment for latitudinal telemetry measurement error (a_c):

$$\begin{aligned}
[a_c \mid \cdot] &\propto \prod_{\tilde{t}\in\mathcal{T}} \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), y\left(\tilde{t}\right), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right] [a_c] \\
&\propto \prod_{\tilde{t}\in\mathcal{T}} \left\{ \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y\left(\tilde{t}\right)} \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y\left(\tilde{t}\right)} \right\} [a_c] \\
&\propto \prod_{\tilde{t}\in\mathcal{T}} \left\{ \left(p\left(\tilde{t}\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \boldsymbol{\Sigma}_c\right) + \left(1 - p\left(\tilde{t}\right)\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y\left(\tilde{t}\right)} \right. \\
&\qquad \left. \times \left(p\left(\tilde{t}\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c\right) + \left(1 - p\left(\tilde{t}\right)\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y\left(\tilde{t}\right)} \right\} \\
&\qquad \times \text{Unif}\left(a_c \mid l_a, u_a\right).
\end{aligned}$$

where $\tilde{t} \in \mathcal{T}$ is the subset of times for all observed telemetry locations ($\mathbf{s}_c(t)$) belonging to Argos location quality class c. In other words, the product is over all $t \in \mathcal{T}$ such that $\mathbf{s}_c(t)$ is allocated to location quality class c.

Correlation between longitudinal and latitudinal telemetry measurement error (σ_c):

$$\begin{aligned}
[\rho_c \mid \cdot] &\propto \prod_{\tilde{t}\in\mathcal{T}} \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), y\left(\tilde{t}\right), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c, \sigma_\mu\right] [\rho_c] \\
&\propto \prod_{\tilde{t}\in\mathcal{T}} \left\{ \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \boldsymbol{\Sigma}_c, \widetilde{\boldsymbol{\Sigma}}_c\right]^{y\left(\tilde{t}\right)} \left[\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c, \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right]^{1-y\left(\tilde{t}\right)} \right\} [\rho_c] \\
&\propto \prod_{\tilde{t}\in\mathcal{T}} \left\{ \left(p\left(\tilde{t}\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \boldsymbol{\Sigma}_c\right) + \left(1 - p\left(\tilde{t}\right)\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{y\left(\tilde{t}\right)} \right. \\
&\qquad \left. \times \left(p\left(\tilde{t}\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \boldsymbol{\Sigma}_c\right) + \left(1 - p\left(\tilde{t}\right)\right) \times \mathcal{N}\left(\mathbf{s}_c\left(\tilde{t}\right) \mid \boldsymbol{\mu}\left(\tilde{t}\right), \sigma_\mu^2\mathbf{I} + \widetilde{\boldsymbol{\Sigma}}_c\right)\right)^{1-y\left(\tilde{t}\right)} \right\} \\
&\qquad \times \text{Unif}\left(\rho_c \mid l_\rho, u_\rho\right).
\end{aligned}$$

where $\tilde{t} \in \mathcal{T}$ is the subset of times for all observed telemetry locations ($\mathbf{s}_c(t)$) belonging to Argos location quality class c. In other words, the product is over all $t \in \mathcal{T}$ such that $\mathbf{s}_c(t)$ is allocated to location quality class c.