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APPENDIX A: Formulations for extensions of the models that include movement distance.

We consider move distance, D_i, in two ways. First, we develop a separate model for move distance. Second, we develop a joint model of move angle and distance. The formulation for both approaches parallels that of the move angle model, except that we model move distances as a mixture of Gamma distributions. For the kth subcomponent of component g, such that $k = 1, \ldots, s_g$, we model the ith move distance as a Gamma distribution:

$$h_{g,k}(D_i|\alpha_{g,k}, \lambda_{g,k}) = \lambda_{g,k}^{\alpha_{g,k}} \{\Gamma(\alpha_{g,k})\}^{-1} D_i^{\alpha_{g,k}-1} e^{-\lambda_{g,k} D_i}.$$

where $i = 1, \ldots, I$, $\alpha_{g,k} > 0$ is a shape parameter, and $\lambda_{g,k} > 0$ is an inverse scale parameter.

When we model move distance separately we simply replace the von Mises density with a Gamma density with component parameters $\boldsymbol{\zeta}_g = (\boldsymbol{\alpha}'_g, \boldsymbol{\lambda}'_g, \boldsymbol{\phi}'_g)'$, $\boldsymbol{\alpha}_g = (\alpha_{g,1}, \ldots, \alpha_{g,s_g})'$, $\boldsymbol{\lambda}_g = (\lambda_{g,1}, \ldots, \lambda_{s_g})'$, and $\boldsymbol{\phi}_g = (\phi_{g,1}, \ldots, \phi_{g,s_g})'$. Thus, our mixture model for move distance is

$$f(D_i|\mathbf{X}_i; \boldsymbol{\beta}, \boldsymbol{\zeta}) = \sum_{g=1}^{G} p_g(\mathbf{X}_i; \boldsymbol{\beta}) h_g(D_i|\boldsymbol{\zeta}_g), \tag{A.1}$$

with parameters $\boldsymbol{\zeta} = (\boldsymbol{\zeta}'_1, \ldots, \boldsymbol{\zeta}'_G)'$.

When we model the move angle and distance jointly, we replace the von Mises density in with the product of a von Mises distribution for move angles and a Gamma distribution for move distances. Thus, our mixture model for move angle and distance is:

$$f(Y_i, D_i|\mathbf{X}_i, A_i; \boldsymbol{\beta}, \boldsymbol{\eta}, \boldsymbol{\zeta}) = \sum_{g=1}^{G} p_g(\mathbf{X}_i; \boldsymbol{\beta}) f_g(Y_i|A_i; \boldsymbol{\eta}_g) h_g(D_i|\boldsymbol{\zeta}_g). \tag{A.2}$$

In this case, we can model both move angles and distances that are related by mixture components and reduce the number of parameters, compared to modeling move angle and distance with separate models, as there is only one set of parameters for the mixing proportion functions. This may be appropriate in some cases because increasing directionality in movement may lead to greater net displacement between observed locations. This means, *caeteris paribus*, that an increasing concentration parameter in the move angle distribution will be related to a larger mean in the corresponding move distance distribution over some discrete time interval. This relation, however, diminishes as the time interval between observed locations goes to zero. Thus, in (A.1) the model for selecting a move distance response is independent of the one for selecting a move angle response, whereas in (A.2) that same model is used for selecting a joint distribution for move distance and angle response.