

1 APPENDIX

A Identifying boundaries

The figures below illustrate the algorithm for identifying boundary location using the “not-quite MCP” algorithm, followed by wolf-specific boundary identifications.

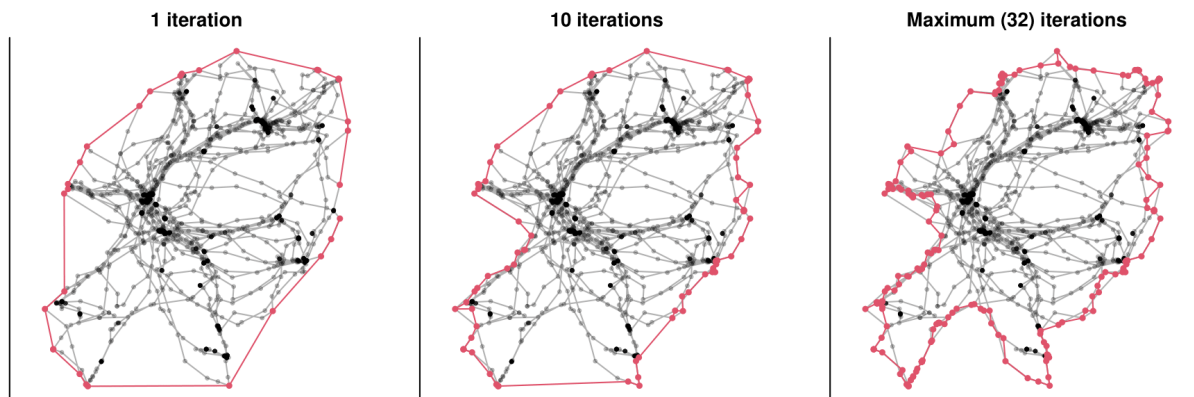
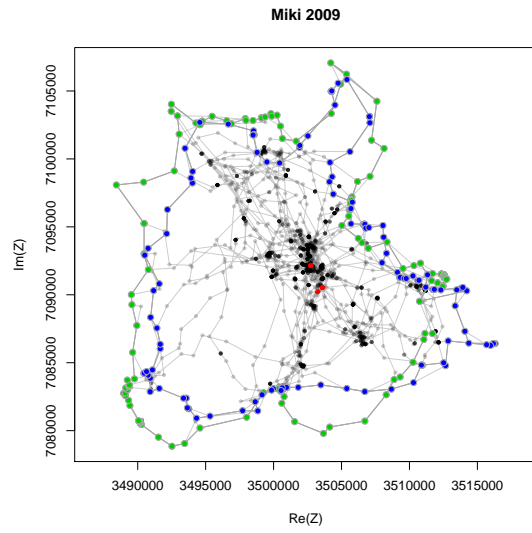
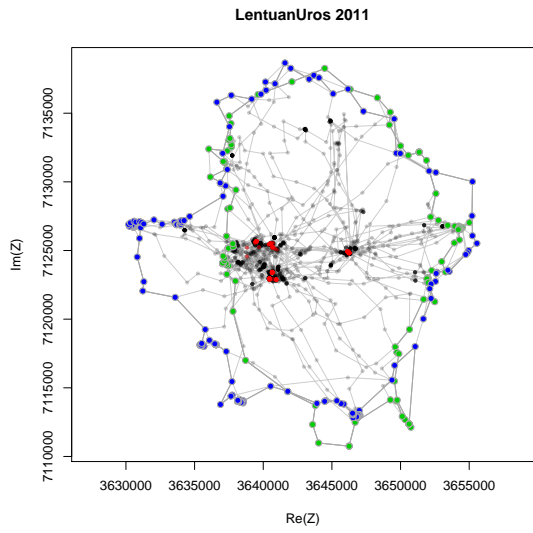
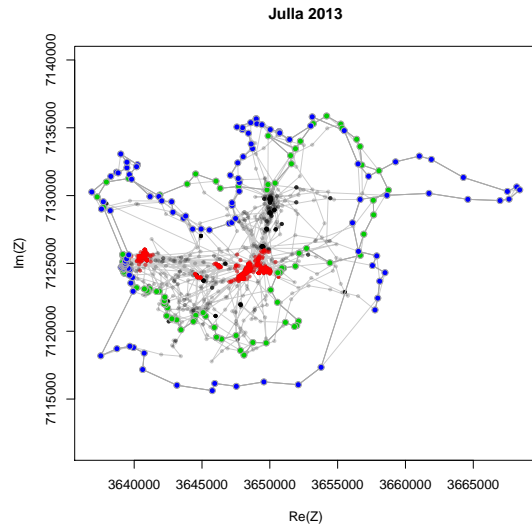
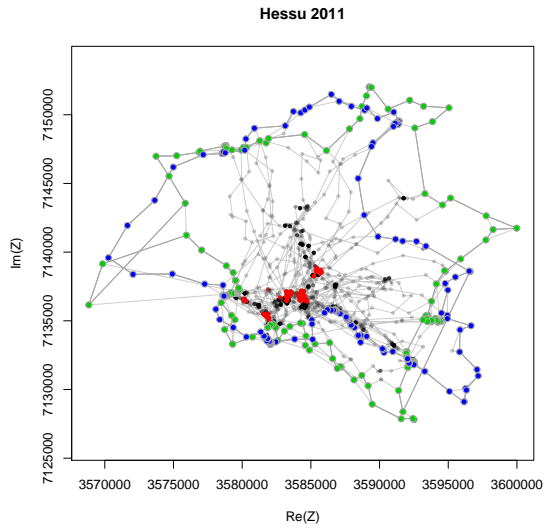


Figure A.1. Visualization of the boundary memory algorithm for Niki 2008. The first panel shows the set of points Z_{mcp} after one iteration of the algorithm (red points). The second panel shows the set of points Z_{mcp} after ten iterations of the algorithm. The third panel shows the final set Z_{mcp} after all of the iterations of the algorithm have completed using a threshold angle of $\theta^* = \frac{\pi}{2}$. For this data set, it took 32 iterations to obtain the final boundary locations.



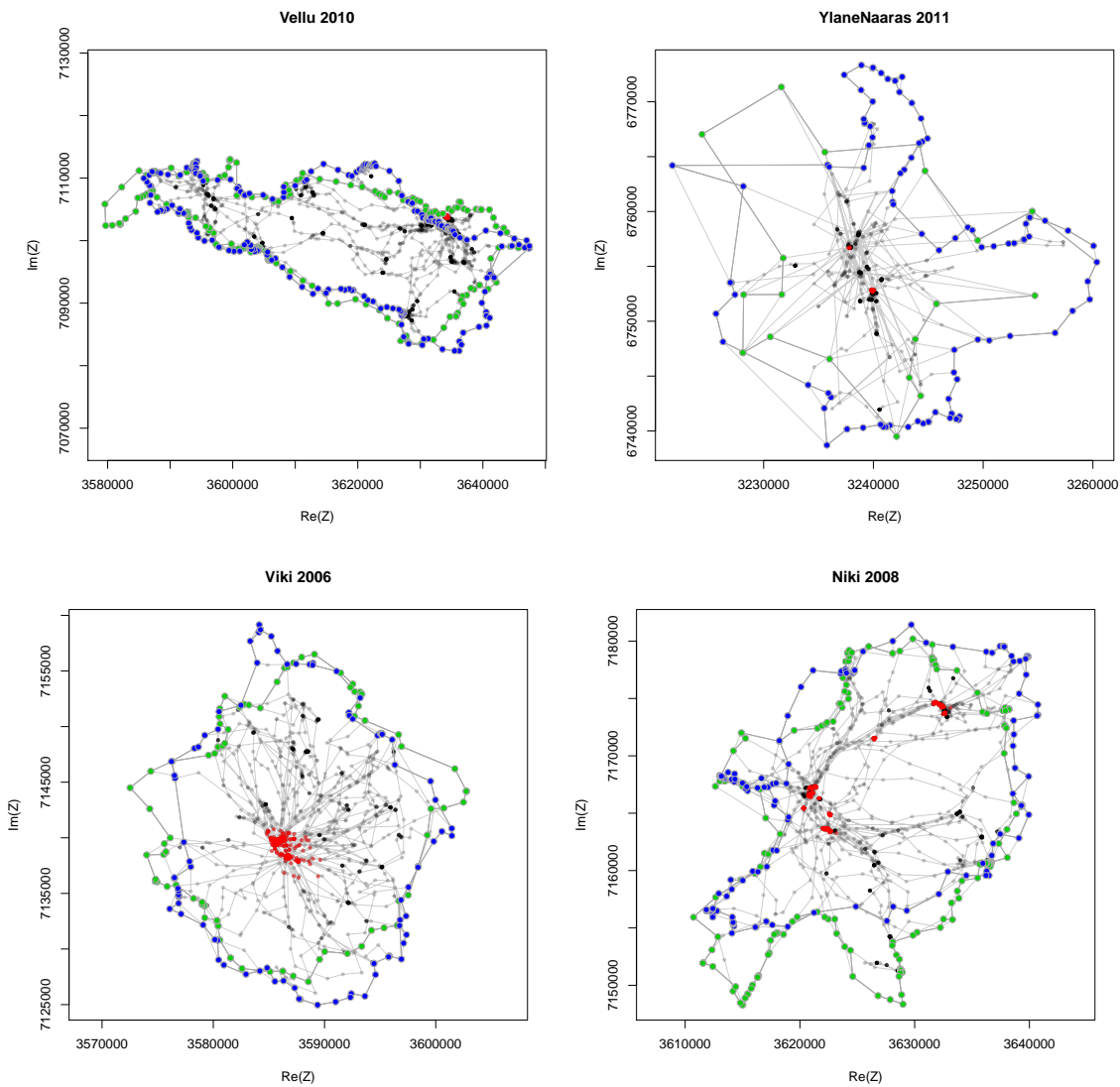


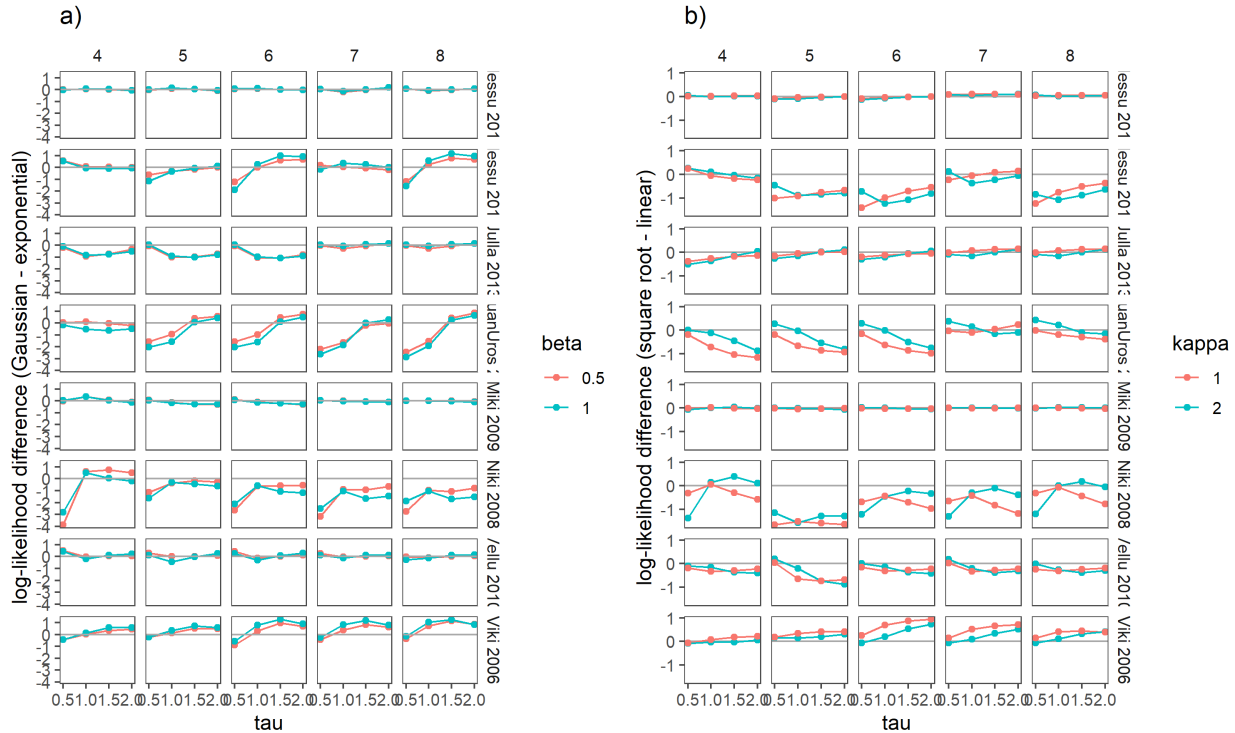
Figure A.2. Final boundary estimation (here and previous page) for all wolf studies. Blue and green colors indicate boundary determinations for the first month (June 1 to June 30) and second month (July 1 to July 30), respectively.

B Prey mass scaling and memory shape

Two parameters that are central to the predation memory component but of relatively less interest from a cognitive ecology point of view are the prey mass scaling parameter (α in equation 3) and the shape parameter of memory decay (κ). We compared two values of each: $\kappa = 1$ and 2, corresponding to an exponential and Gaussian shaped memory decay in time; and $\alpha = 0.5$ and 1, corresponding to a square root and linear scaling of valuing prey mass.

To assess these, we fitted the discrete choice model with predation only across a limited set of parameter values: number of zones ranging from 4 to 8; time-scale of predation memory τ_p set to 0.5, 1, 1.5 and 2; κ 1 and 2; and α 0.5 and 1. We then compared the log-likelihoods of the fitted models across those two central comparisons. The results are presented below.

Figure B.1. Difference in likelihood between (a) Gaussian and exponential models, and (b) linear and square root weighting of prey across various predation memory time scales (x -axis), number of zones (panels, left to right) for each of the 8 wolf studies.



C Assessing the role of the effort term

The per kill predation score in equation 3 was assumed to be indirectly proportional to the time spent between leaving the den and the kill (E_i), a reasonable but somewhat strong structural assumption. To assess whether the term was necessary, we fitted models in which the effort term was removed, i.e. E_i was set equal to 1. We then fitted the predation only discrete choice model across a range of parameter values: number of zones from 4 to 8; time-scale of predation memory τ_p set to 0.5, 1, 1.5 and 2. The predation scaling coefficient was fixed to $\beta = 0.5$, and the memory decay was Gaussian ($\kappa = 2$). We then compared the results of models with and without effort included in the predation covariate. Model comparisons, as Δ AIC values, are presented in Figure C.1. Across all parameter values, Viki

2006 and Niki 2008 and LU 2011 had ΔAIC values below -2, with minima between -3.33 and -5.17, indicating much better fits for the effort model. The range of ΔAIC for the remaining wolves all straddled 0. We also performed this analysis with the complete model (predation + boundary + repetition), which revealed the same results and patterns.

Figure C.1. Difference in AIC between models fit with and without the effort term in the predation score. Negative values, especially below -2, indicate that models that include effort improve the fit.

