Interpreting and Predicting (exponential) HSFs & (integrated) SSFs

Tal Avgar

Interpreting eHSF: what's in a β?

The natural logarithm of the selection strength for location x_1 relative to location x_2:

$$ln\left(\frac{exp[\beta_0 + \sum_{i=1}^{n} \beta_i \cdot h_i(x_1)]}{exp[\beta_0 + \sum_{i=1}^{n} \beta_i \cdot h_i(x_2)]}\right) = \sum_{i=1}^{n} \beta_i \cdot [h_i(x_1) - h_i(x_2)]$$

- The selection coefficient for habitat covariate i, β_i, is thus the lnRSS for x_1 vs x_2, conditional on $[h_i(x_1) - h_i(x_2)] = 1$ and all other covariates being equal
- The selection coefficient for habitat covariate i, β_i, is thus the conditional effect size of h_i

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Avgar, T., Lele, S.R., Keim, J.L. & Boyce, M.S. (2017). Relative Selection Strength: Quantifying effect size in habitat- and step-selection inference. *Ecol. Evol.*, 7, 5322–5330.

Interpreting iSSF: what's in a β?

For m step attributes (e.g., habitat quality or step length), $z_j(x)$:

$$p[x_t = x_i] = \frac{exp\left[\sum_{j=1}^{m} \beta_j \cdot z_j(x_i)\right]}{\int exp\left[\sum_{j=1}^{m} \beta_j \cdot z_j(x)\right] dx}$$

If x_1 and x_2 are endpoints of two alternative steps originating from $x_{t-\tau}$:

$$\frac{p[x_t = x_1]}{p[x_t = x_2]} = \frac{exp\left[\sum_{j=1}^{m} \beta_j \cdot z_j(x_1)\right]}{exp\left[\sum_{j=1}^{m} \beta_j \cdot z_j(x_2)\right]} = exp\left[\sum_{j=1}^{m} \beta_j \cdot \left[z_j(x_1) - z_j(x_2)\right]\right]$$

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β_j is thus the ***lnRSS*** for a step ending at x_1 relative to a step ending at x_2 given the two steps are identical in all attributes but z_j, which is one unit larger for the step ending at x_1 than for the step ending at x_2

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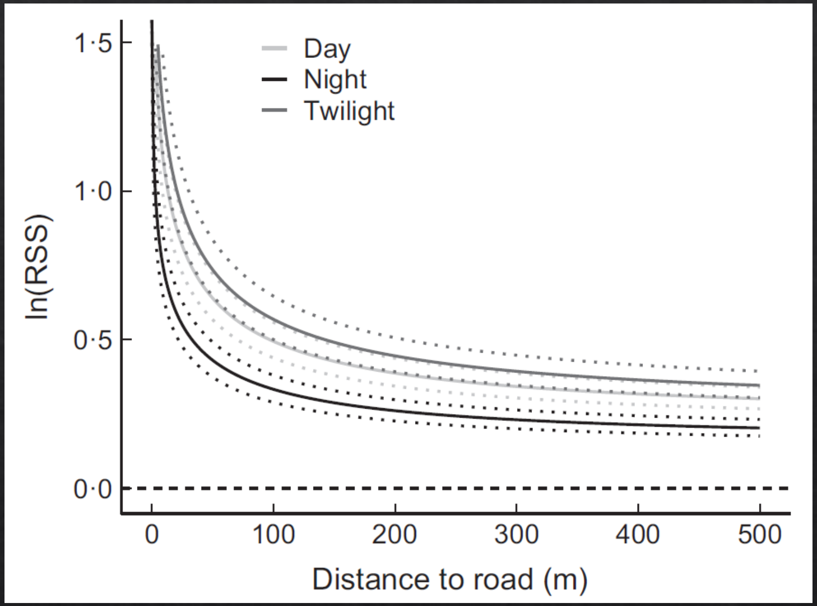
Characterizing wildlife behavioral responses to roads using iSSA

lnRSS for one location in relation to another, which is 250 m closer to a road, as a function of the distance of the second location from the road



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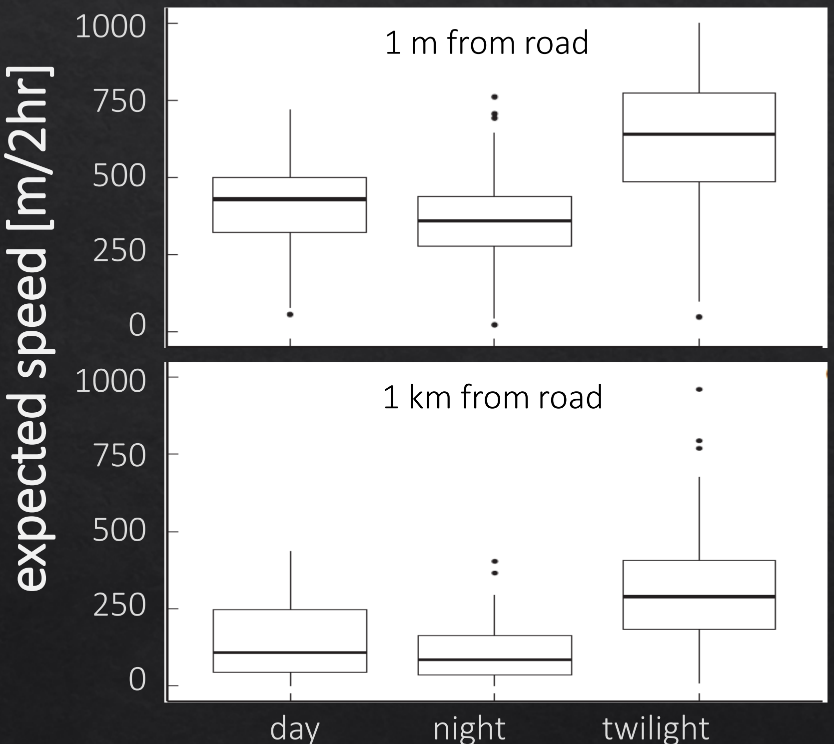

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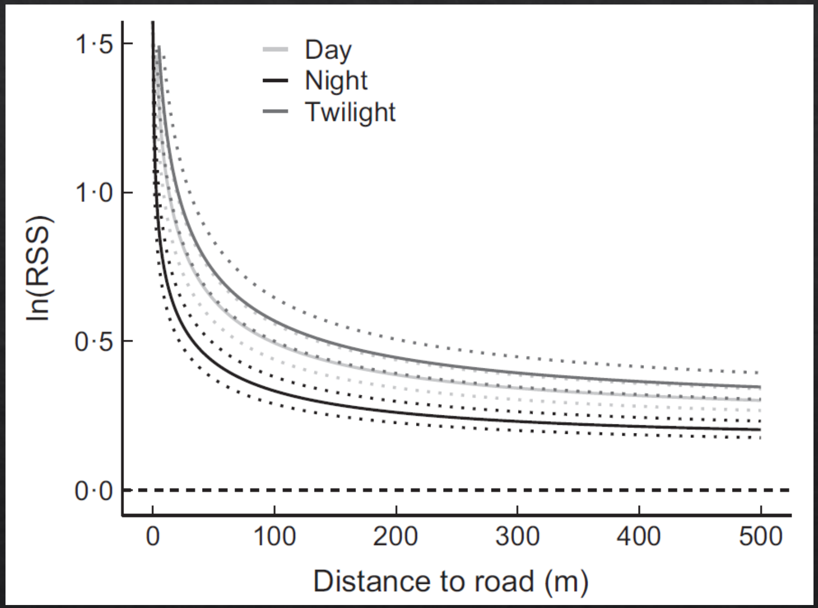

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The **Utilization Distribution (UD)**: the probability density of animal occurrence over space – a map of space-use intensity

- Steady-state UD: the expected UD after an infinitely long time, independent of the starting point
- Transient UD: the expected UD after a finite time, conditional on the starting point

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The **Utilization Distribution (UD)**: the probability density of animal occurrence over space – a map of space-use intensity

- **Steady-state** (stationary) **UD**: the expected UD after an infinitely long time, independent of the starting point
- **Transient** (non-stationary) **UD**: the expected UD after a finite time, conditional on the starting point

Predicting the UD based on eHSF

The probability that location x will be used (occupied; have population density > 0) is given by:

$$w(x) = c \cdot exp[\sum_{i=1}^{n} \beta_i \cdot h_i(x)]$$

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The UD is a probability density, and should thus sum to 1:

$$UD(x_j) = \frac{w(x_j)}{\sum_{j=1}^{\Omega} w(x_j)} = \frac{exp[\sum_{i=1}^{n} \beta_i \cdot h_i(x)]}{\sum_{j=1}^{\Omega} exp[\sum_{i=1}^{n} \beta_i \cdot h_i(x)]}$$

Predicting the UD based on eHSF

Exponential habitat-selection functions are parametrized under the assumption that used points were observed with a probability that is exactly proportional to the *steady-state UD*. Consequently, mapping of the parametrized HSF onto a habitat raster can be interpreted as the steady-state UD, but provides no information on transient dynamics

Predicting the UD based on iSSF

- Cannot be done by applying $exp\left[\sum_{j=1}^{m} \beta_j \cdot z_j(x_i)\right]$ to the habitat raster; the relative residence time in x depends on the conditional probability of all the steps leading to and from x
- An iSSF-based UD must be simulated: an iSSF is a fully parametrised individual-based simulation of a locally biased random walk
- Simulations are stochastic and must be repeated many (many) times
  - The steady-state UD is approximated by running the simulation for many (many) steps and/or starting it from various starting positions across the spatial domain
  - The transient UD is approximated by running the simulation for fewer steps, always starting from the same initial position within the spatial domain

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Concluding remarks

- Exponential habitat-selection models make strong assumptions about independence and stationarity, making UD estimation relatively simple (if you are willing to accept these assumptions)
- Integrated step-selection models relax these assumptions, making them more ecologically plausible, and inferentially flexible, but also more complex to use as a UD estimator
- Grain (resolution; scale) matters: UD's should always be estimated using the same spatial, and, in the case of iSSF, temporal, grain (pixel size, step durations) as the data's

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