CTMM Workshop

* Task: How do we account for
  + Temporal autocorr: Stochastic process model
  + Account for sampling irregularity & mismatch: continuous time models
  + Account for location error, if necessary: calibrated error model
  + Don’t assume models: model selection and testing assumptions
  + Don’t be satisfied with point estimates: estimate uncertainties
  + Propagate uncertainties into population estimates: hierarchical models
* Example : Black Bear movement sampling
  + When ignoring autocorrelation, we end up underestimating things like home range.
    - Autocorrelation is primarily caused by the time between sampling points, we are ignoring some of the landscape autocorrelation that would cause an individual to say in a location
  + KDE is statistically optimal non-parametric method of estimating distributions of independently sampled data
  + Conventional estimates (KDE) can be 2-20 times too small (Noonan et al., 2019)
  + Bias is worse when fewer range crossing are observed
* What do we do to relieve autocorrelation?
  + Thin the data based on time, useful for home range estimation, but less useful for anything else
* What if we don’t? Autocorrelated data can be useful information! It can be used to calculate speeds
* Continuous time bs discrete time
  + Conventional movement analysis may have step link distribution + angle distribution. This is implicitly discreet because things only happen at the measured points
  + Continuous time tries to also estimate what happens during the time between the measured/sampled points. This is analyzed and ends up in a ribbon strand of possible paths between points.
  + Benefits
    - Sampling may be irregular in time
    - Sampling schedules may differ across individuals. Model parameters are biological, not sampling dependent
    - Discree time models can be intrinsically scale dependent. Step selection functions tell you information about selection across the time scales at which it is analyzed.
    - Can accommodate speed, distance, acceleration, power and energy (first derivatives, calculus 1)
    - Location error is easy to model
* Building block continuous-time stochastics process models (ordered in historical commonality
  + Independent locations: KDE, MCP, RSF
  + Brownian Bridge + motion: locations are correlated from one space to another. Assume “infinite speed.” And does not have a home range and can diffuse forever. Cannot estimate home ranges
  + Ornstein-Uhlenbeck motion: Same as Brownian, but has a home range.
  + Integrated Ornstein-Uhlenbeck motion: Introduced in the marine context. Diffuses forever and does not have a home range. However, has a persistence of motion rather than jittering. Can estimate speeds, distances, and velocities. (crawl package)
  + OUF motion: Fleming model. Persistence of motion parameters and can estimate speed and distance, has a home range.
  + HOWEVER! Don’t assume you have one of the models, test your assumptions and select. Fit all the models and different variations, select, then estimate speed and home range.
* Other notes
  + When doing validation for movement data, split the data temporally (first half/second half)
  + As data get coarser, (time wise) whicle neglecting autocorrelation we end up estimating shorter movement paths between time periods than actual, and therefore underestimate individual speed

Noonan, M. J., Tucker, M. A., Fleming, C. H., Akre, T. S., Alberts, S. C., Ali, A. H., Altmann, J., Antunes, P. C., Belant, J. L., Beyer, D., Blaum, N., Böhning-Gaese, K., Cullen Jr., L., de Paula, R. C., Dekker, J., Drescher-Lehman, J., Farwig, N., Fichtel, C., Fischer, C., … Calabrese, J. M. (2019). A comprehensive analysis of autocorrelation and bias in home range estimation. *Ecological Monographs*, *89*(2), e01344. https://doi.org/10.1002/ecm.1344