Geospatial Share

https://github.com/swforrest/geospatial_share_animal_movement

Animal Movement Workshop

May 2024

Scott Forrest^{1, 2, 3, 4}

¹School of Mathematical Sciences, QUT

²Centre for Data Science, QUT

³Applied Mathematical Ecology Group, QUT

⁴CSIRO Environment













Acknowledgement of Traditional Owners

- QUT Turrbal and Yugara
- Ngāi Tahu as lwi of Otago where the kākā data was collected
- Central Arnhem Land, NT Dalabon, Rembarrnga and Mayili
- Normanby and Archer River Cape York, QLD Balngarrawarra, Wik

Understanding and predicting animal movement

- Understanding where animals are and predicting where they will go is a cornerstone of ecology and management
 - threatened species
 - invasive species





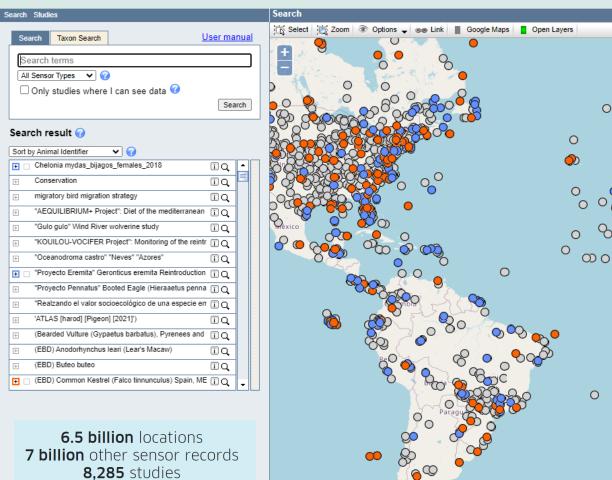


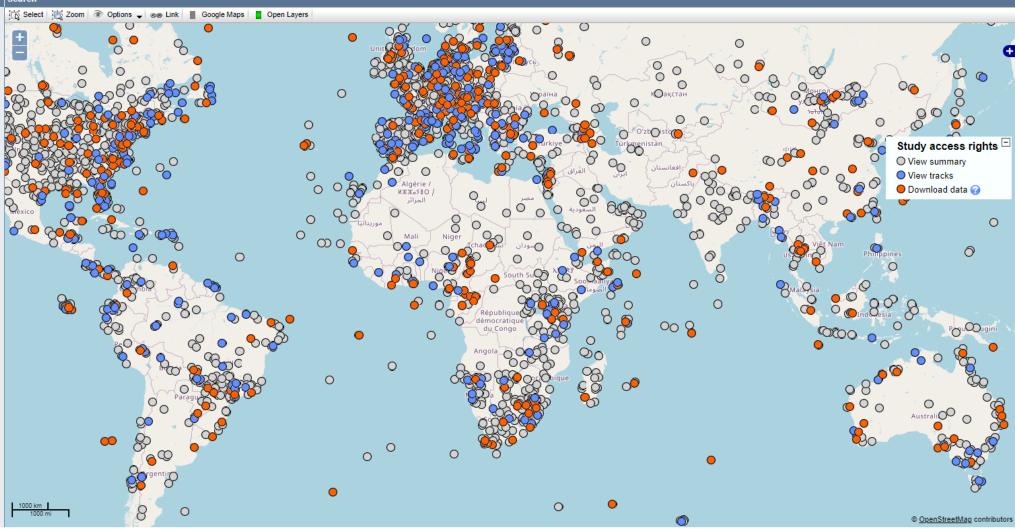


How to

Archiving

Sign Up Q





Downloads Privacy **Imprint** Contact

1,402 taxa 4,180 data owners







Movebank is coordinated by the Max Planck Institute of Animal Behavior, the North Carolina Museum of Natural Sciences, and the University of Konstanz.



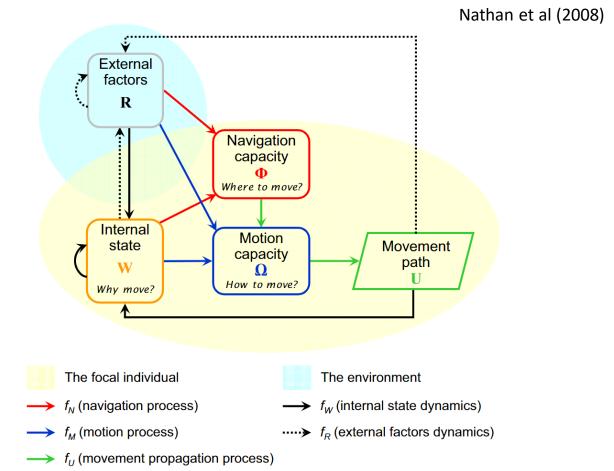
Animal movement — what drives it?

external factors

- resources
- abiotic factors
- other animals

internal state

- sex
- age
- memory
- energetic status
- breeding status









Current kākā Distribution (approximate)

Kākā (Nestor meridionalis)

- South Island subspecies (N. m. meridionalis)
- 450 690g forest-dwelling parrot
- Nationally Vulnerable¹ (NZTCS)

- Require a high-level of pest control²
- Require large areas of forest³







¹: Kākā, Department of Conservation, accessed 30th November 2020

²: Wilson, PR et. al (1998)

^{3:} Leech, TJ, Gormley, AM, & Sedfort, PJ (2008)







Fence erected – 2007 Kākā translocated – 2008

Kākā banded since 2008:

~ 100

Kākā detectable from monitoring:

~ 40-50

Tītipounamu D

Dave Curtis

Toutouwai

Dave Curtis



Orokonui Ecosanctuary

GPS Tags

- -10x PinPoint VHF 350
- SWIFT fixes
- 3-hour fix interval
- 1-minute activity data

GPS tags funded by:





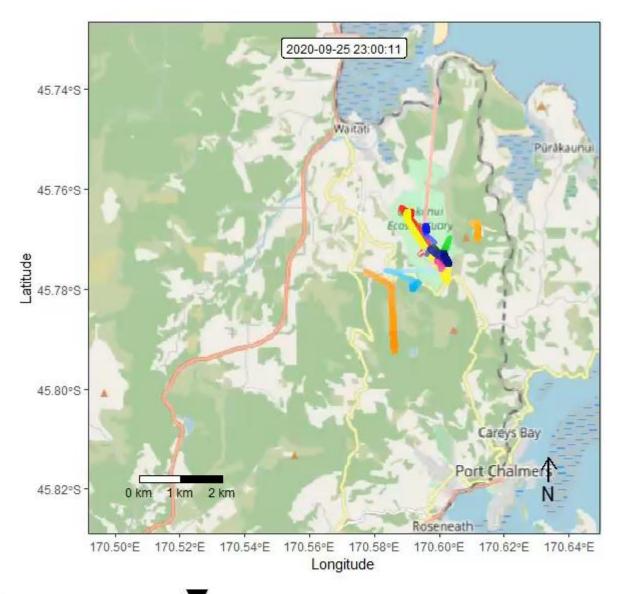
Lotek

https://www.lotek.com/products/pinpoint-gps-vhf/









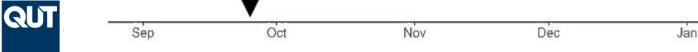
Average days:

144 (range 111 - 163)

Successful fixes:

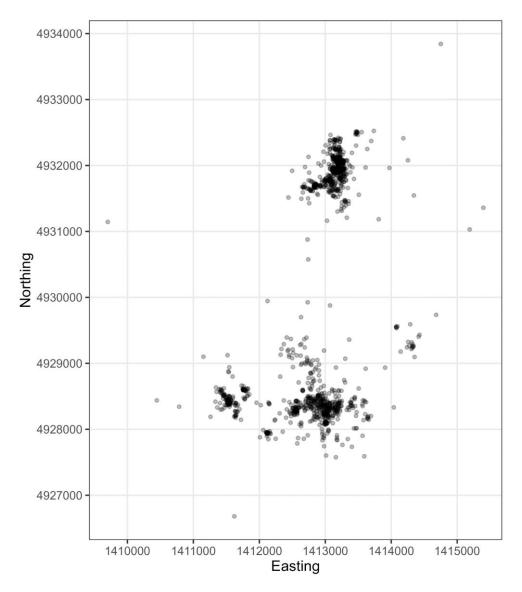
10,755

(13,590 attempted)











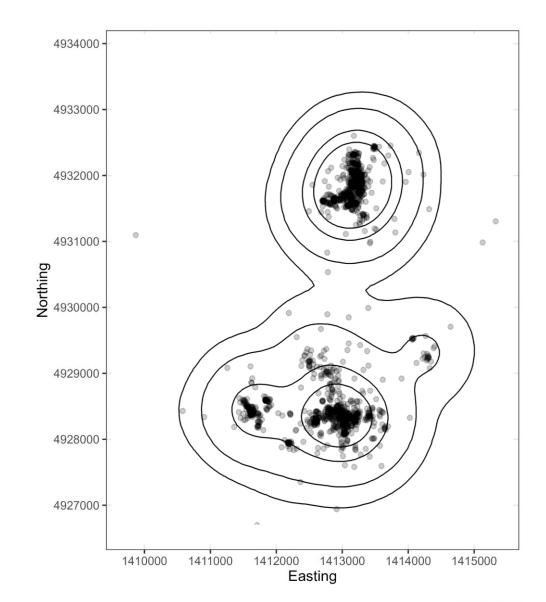
Tag ID: 45505







 Where did the animal go?



Scott Forrest | School of Mathematical Sciences



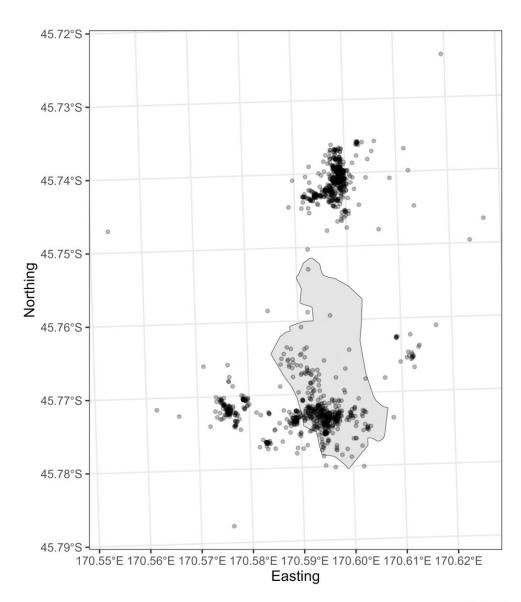
Tag ID: 45505







- Where did the animal go?
 - what did it overlap with?



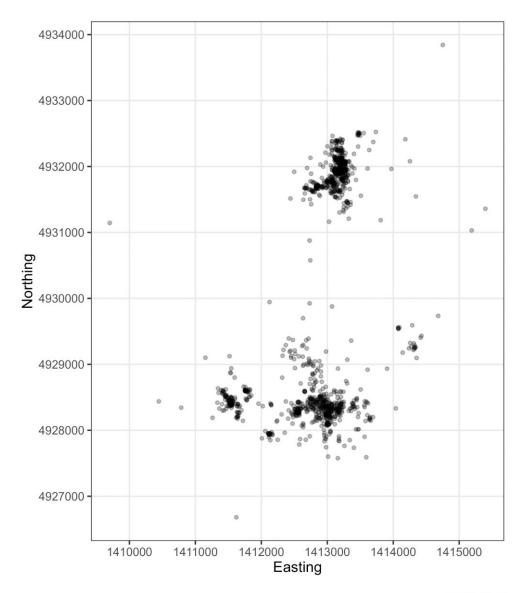


Tag ID: 45505











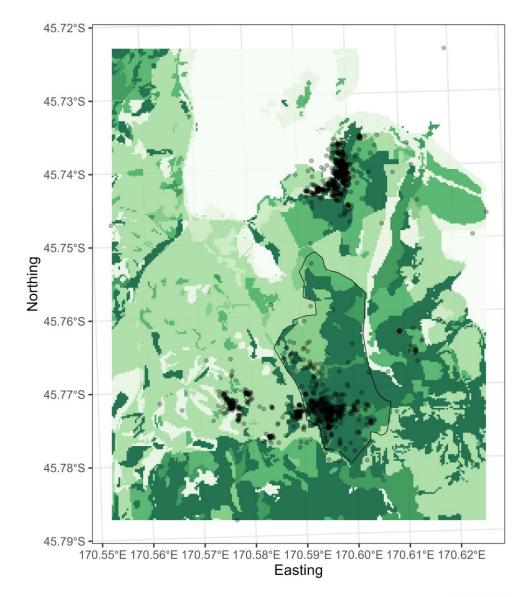
Tag ID: 45505







Why was the animal there?



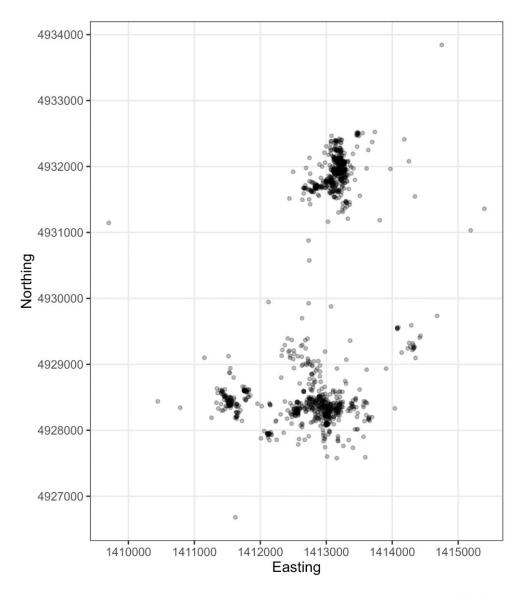


Tag ID: 45505











Tag ID: 45505

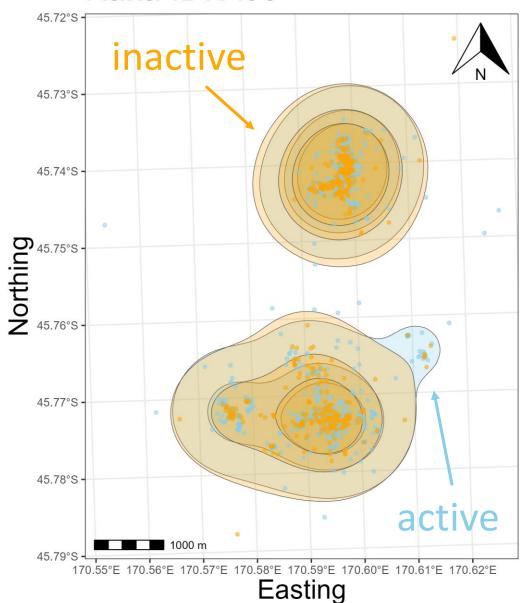






What was the animal doing?

Kākā ID: A05





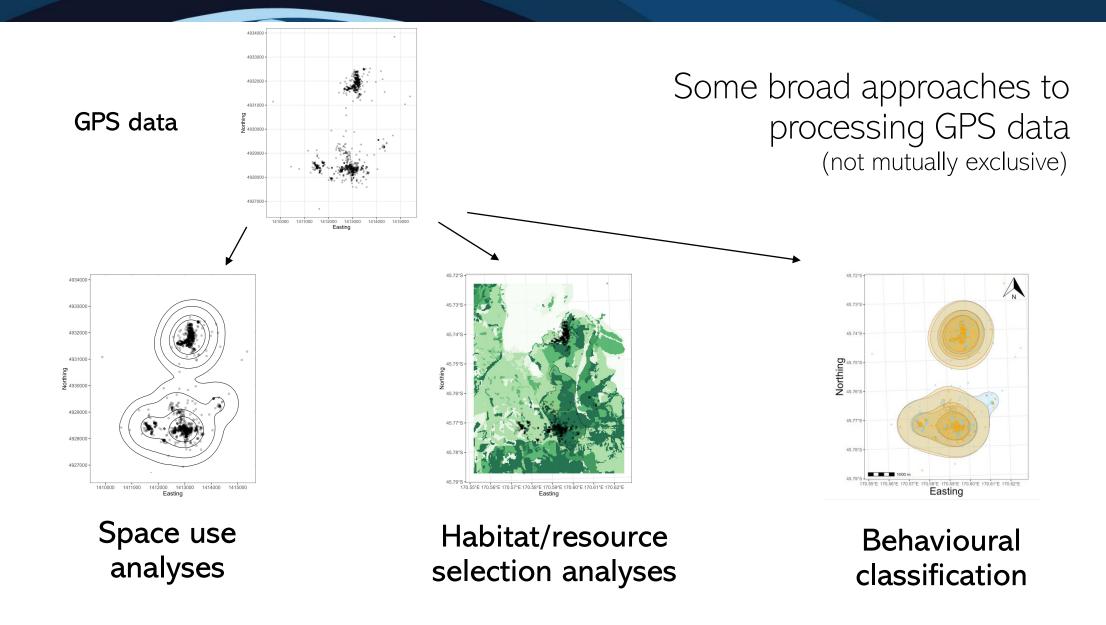
Tag ID: 45505

















Space use analyses

To quantify where an animal spent its time

- home range analyses (range distribution)
- where the animal was during the tracking period (occurrence distribution)
 - overlap with locations of interest (safety/risk, other individuals)

Some considerations

- GPS locations are typically correlated in space and time
- locations are not independent
- the animal travelled between the successive locations









Some common approaches and resources

4834000 - 4832000 - 4832000 - 482800

Earlier approaches (assume 'independent' data)

- Kernel Density Estimation (KDE)
 - Worton, B. J. (1989). Kernel methods for estimating the utilization distribution in home-range studies. *Ecology*, 70(1), 164–168. https://doi.org/10.2307/1938423
- Minimum Convex Polygons (MCP)

More recent approaches

- Brownian bridge approaches (BBMM and dBBMM)
 - Kranstauber, B., Kays, R., Lapoint, S. D., Wikelski, M., & Safi, K. (2012). A dynamic Brownian bridge movement model to estimate utilization distributions for heterogeneous animal movement. *The Journal of Animal Ecology*, *81*(4), 738–746. https://doi.org/10.1111/j.1365-2656.2012.01955.x
- Autocorrelated Kernel Density Estimation (AKDE)
 - Silva, I., Fleming, C. H., Noonan, M. J., Alston, J., Folta, C., Fagan, W. F., & Calabrese, J. M. (2022). Autocorrelation-informed home range estimation: A review and practical guide. *Methods in Ecology and Evolution / British Ecological Society*, 13(3), 534–544. https://doi.org/10.1111/2041-210x.13786

Conceptual considerations (range vs occurrence distributions)

Alston, J. M., Fleming, C. H., Noonan, M. J., Tucker, M. A., Silva, I., Folta, C., Akre, T. S. B., Ali, A. H., Belant, J. L., Beyer, D., Blaum, N., Böhning-Gaese, K., de Paula, R. C., Dekker, J., Drescher-Lehman, J., Farwig, N., Fichtel, C., Fischer, C., Ford, A. T., ... Calabrese, J. M. (2022). Clarifying space use concepts in ecology: range vs. occurrence distributions. In *bioRxiv* (p. 2022.09.29.509951). https://doi.org/10.1101/2022.09.29.509951







Tutorials

- KDE, BBMM, dBBMM, LoCoH (older style R code)
 - https://ecosystems.psu.edu/research/labs/walter-lab/manual/home-rangeestimation/link-to-pdf
- AKDE
 - https://ecoisilva.github.io/AKDE_minireview/code/AKDE_R-tutorial.html
 - Signer, J., & Fieberg, J. R. (2021). A fresh look at an old concept: homerange estimation in a tidy world. *PeerJ*, *9*, e11031. https://doi.org/10.7717/peerj.11031







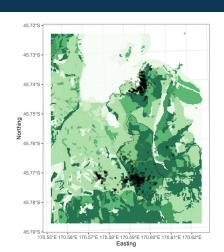
Habitat/resource selection analyses

To quantify how the animal was associating with the surrounding environment

- determine 'preferences' (description or inference)
- generate predictions (prediction)

Some considerations

- locations are not independent
- we never get true absences







Some common approaches and resources

45.72°S - 45.73°S - 45.75°S - 45.76°S - 45.76°

Earlier approaches (assume independent data)

- Resource Selection Functions (RSF)
 - Boyce, M., & McDonald, L. (1999). Relating populations to habitats using resource selection functions. *Trends in Ecology & Evolution*, 14(7), 268–272. https://doi.org/10.1016/s0169-5347(99)01593-1
 - Fieberg, J., Signer, J., Smith, B., & Avgar, T. (2021). A "How to" guide for interpreting parameters in habitat-selection analyses. *The Journal of Animal Ecology*, 90(5), 1027–1043. https://doi.org/10.1111/1365-2656.13441
 - this paper has good code for RSFs and for SSFs (on the next slide)

More recent approaches (typically assume independent data)

- Species Distribution Models (SDM)
 - Franklin, J. (2009). Mapping Species Distributions: Spatial Inference and Prediction (p. 340). Cambridge University Press. https://play.google.com/store/books/details?id=sQ7bngEACAAJ
 - Guisan, A., Thuiller, W., & Zimmermann, N. E. (2017). *Habitat suitability and distribution models: With applications in R* (pp. 1–478). Cambridge University Press. https://doi.org/10.1017/9781139028271







Some common approaches and resources

More recent approaches (assume dependent data)

- Step Selection Functions (SSF)
 - Thurfjell, H., Ciuti, S., & Boyce, M. (2014). Applications of step-selection functions in ecology and conservation. *Movement Ecology*, 2(1), 4. https://doi.org/10.1186/2051-3933-2-4
 - Avgar, T., Potts, J. R., Lewis, M. A., & Boyce, M. (2016). Integrated step selection analysis: bridging the gap between resource selection and animal movement. *Methods in Ecology and Evolution*, 7(5), 619–630. https://doi.org/10.1111/2041-210x.12528
 - Northrup, J. M., Vander Wal, E., Bonar, M., Fieberg, J., Laforge, M. P., Leclerc, M., Prokopenko, C. M., & Gerber, B. D. (2022). Conceptual and methodological advances in habitat-selection modeling: guidelines for ecology and evolution. *Ecological Applications*, 32(1), e02470. https://doi.org/10.1002/eap.2470

• Mixed (hierarchical) modelling for RSFs and SSFs

• Muff, S., Signer, J., & Fieberg, J. (2020). Accounting for individual-specific variation in habitat-selection studies: Efficient estimation of mixed-effects models using Bayesian or frequentist computation. *The Journal of Animal Ecology*, 89(1), 80–92. https://doi.org/10.1111/1365-2656.13087

Generating predictions from SSFs (including simulation)

- Potts, J. R., & Börger, L. (2023). How to scale up from animal movement decisions to spatiotemporal patterns: An approach via step selection. *The Journal of Animal Ecology*, *92*(1), 16–29. https://doi.org/10.1111/1365-2656.13832
- Signer, J., Fieberg, J., Reineking, B., Schlägel, U., Smith, B., Balkenhol, N., & Avgar, T. (2023). Simulating animal space use from fitted integrated Step-Selection Functions (iSSF). Methods in Ecology and Evolution. https://doi.org/10.1111/2041-210x.14263









170.55°E 170.56°E 170.57°E 170.58°E 170.59°E 170.60°E 170.61°E 170.62°E

Tutorials and coding examples

These papers have very useful code for SSFs

- Signer, J., Fieberg, J., & Avgar, T. (2019). Animal movement tools (amt): R package for managing tracking data and conducting habitat selection analyses. *Ecology and Evolution*, *9*(2), 880–890. https://doi.org/10.1002/ece3.4823
- Fieberg, J., Signer, J., Smith, B., & Avgar, T. (2021). A "How to" guide for interpreting parameters in habitat-selection analyses. *The Journal of Animal Ecology*, *90*(5), 1027–1043. https://doi.org/10.1111/1365-2656.13441

For hierarchical models

Muff, S., Signer, J., & Fieberg, J. (2020). Accounting for individual-specific variation in habitat-selection studies: Efficient estimation of mixed-effects models using Bayesian or frequentist computation. *The Journal of Animal Ecology*, 89(1), 80–92. https://doi.org/10.1111/1365-2656.13087



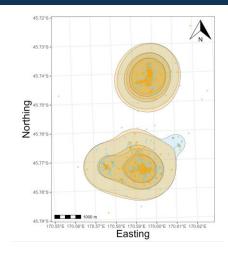




Behavioural classification

To quantify how the animal was spending its time

activity budgets (resting/foraging/...)



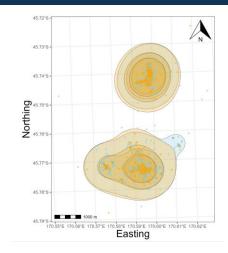
Can be related to certain areas in space (as in the plot) but is typically non-spatial. There are recent approaches that combine step selection functions and behavioural classification (Pohle et al 2024 on next slide).







Some common approaches and resources



Most common approaches

- Hidden Markov Models (HMM)
 - Langrock, R., King, R., Matthiopoulos, J., Thomas, L., Fortin, D., & Morales, J. M. (2012). Flexible and practical modeling of animal telemetry data: hidden Markov models and extensions. *Ecology*, *93*(11), 2336–2342. https://doi.org/10.1890/11-2241.1
 - McClintock, B. T., & Michelot, T. (2018). momentuHMM: R package for generalized hidden Markov models of animal movement. *Methods in Ecology and Evolution / British Ecological Society*, *9*(6), 1518–1530. https://doi.org/10.1111/2041-210X.12995
- Combining HMMs and step selection functions
 - Pohle, J., Signer, J., Eccard, J. A., Dammhahn, M., & Schlägel, U. E. (2024). How to account for behavioral states in step-selection analysis: a model comparison. *PeerJ*, 12, e16509. https://doi.org/10.7717/peerj.16509

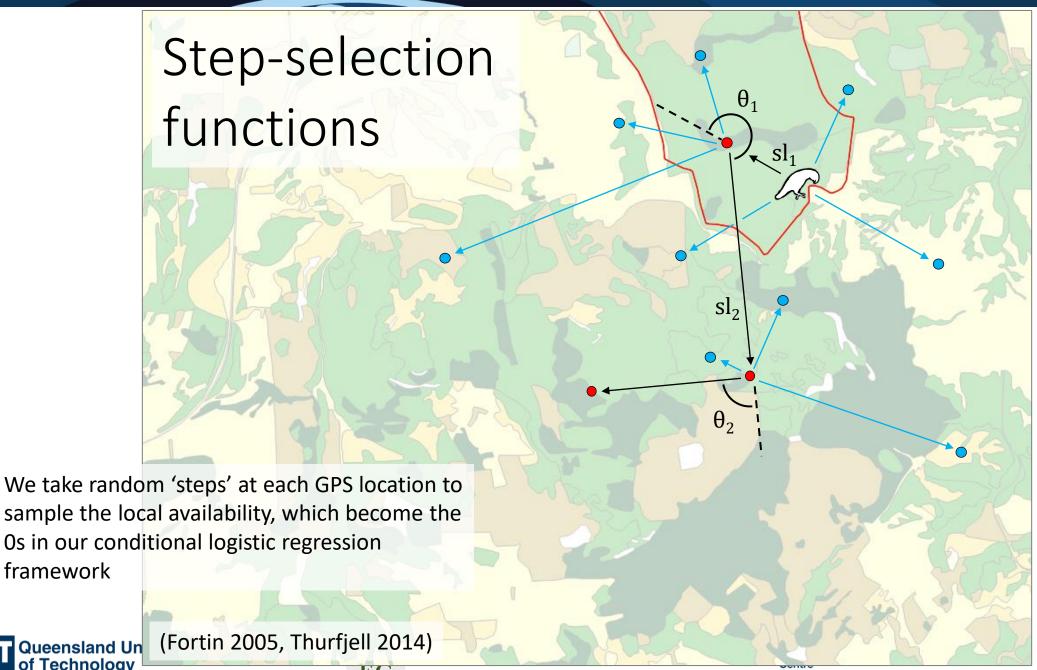
More recent approaches

machine/deep learning techniques







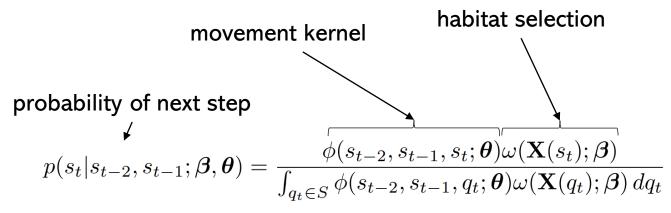




framework

Step selection function

we are trying to estimate the movement parameters, θ , and the habitat selection parameters, β from our observed and randomly sampled steps

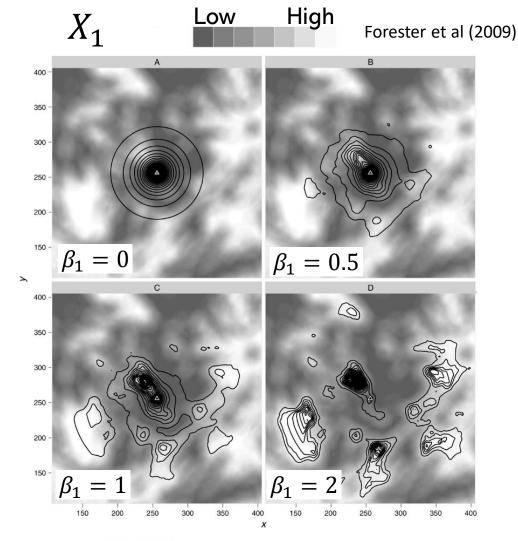


 s_t is a location in space at time t

 β are habitat selection parameters

 θ are movement parameters

X are habitat covariates



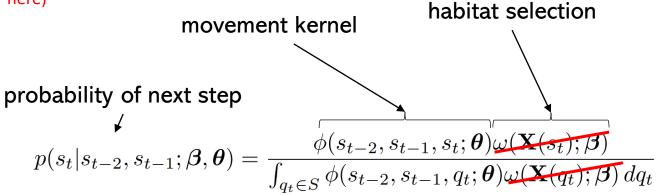




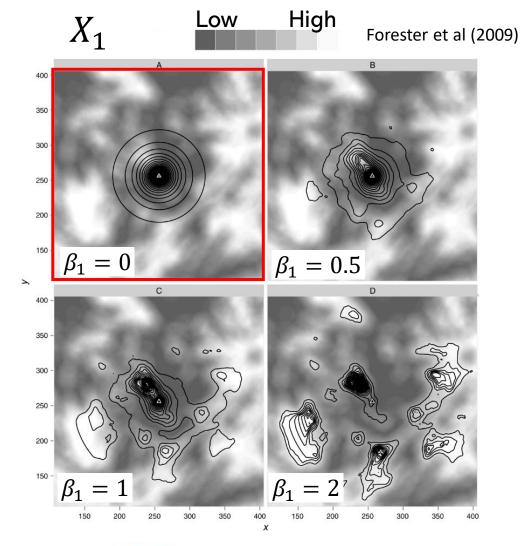


Step selection function

if we set our habitat selection component to 0, we are left with the 'intrinsic' movement dynamics of the animal, which is typically some function that decays with distance from the current location, such as an exponential or gamma distribution. There is often also correlated turning angles (but shown as uniform here)



 s_t is a location in space at time t β are habitat selection parameters θ are movement parameters X are habitat covariates



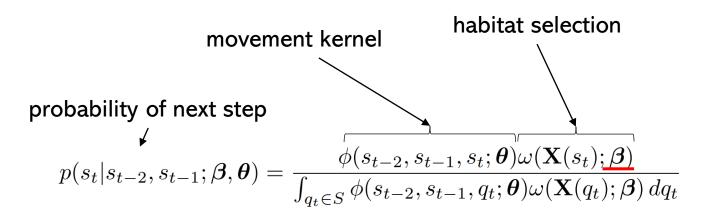






Step selection function

when the habitat selection parameters are large, then the habitat is very influential on where the next step is likely to land

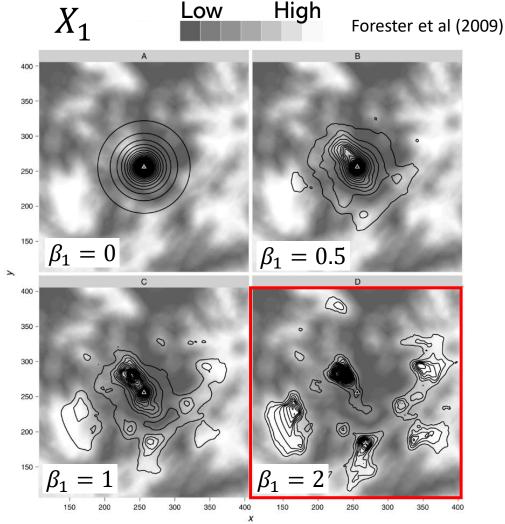


 s_t is a location in space at time t

 β are habitat selection parameters

 θ are movement parameters

X are habitat covariates









Step selection coding example

Code and data available from the GitHub repo below, as well as rendered html files which include all of the outputs:

https://github.com/swforrest/geospatial share animal movement





