How does human activity affect the movement patterns of wild animals?

An analysis of selected data sets from the Movebank animal tracking database

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1 Abstract

We investigate how human activity influences the movement patterns of wild animals. Using tracking data from red foxes, bobcats, and coyotes across rural and remote areas in England, Canada, and the US, we analyze home range sizes, temporal activity shifts, and habitat selection in relation to human footprint and land use data.

2 Introduction

Research questions:

1. Home Range Implications: Do animals exhibit smaller home ranges in high human-impact areas? Similar to Doherty, Hays, and Driscoll (2021) (TBD download via ZHAW)
2. Temporal Shifts in Activity Patterns: Do animals become more nocturnal in high human-impact areas to avoid direct human encounters?
3. Habitat Selection in Human-Dominated Landscapes: How do animals select habitats (e.g., forests, agriculture) under varying levels of human influence?

Different data sets will be used for each research question. Relying on Movebank data, as described in Section 3.2.1, presents additional challenges stemming from the facts that (1) the data will be used for purposes it was not originally collected for and (2) data from different studies that was collected in different manners will be compared, and (3) subsets for existing data set will be employed, i.e. only some of the animals from the existing studies are considered.

3 Material and Methods

This section describes the data sets, the steps taken to prepare and process the different data sets in use, and the methodological approach that was employed.

3.1 Data sets

The Movebank database by Kays et al. (2022) provides means for researchers to publish animal tracking data for public use, e.g. under Creative Commons licenses. The following data was selected:

- Red fox data from Porteus et al. (2024) for the outskirt areas of villages in Wiltshire, UK and from Lai et al. (2022) for the highly remote uninhabitated islands Bylot and Herschel, Canada, and
- Bobcat and coyote data from Prugh et al. (2023) for remote areas with some rural structures in northern Washington, US.

For the human footprint data, the global 100 meter resolution terrestrial human footprint data (HFP-100) by Gassert et al. (2023) was chosen. For land use, the ESA WorldCover data Zanaga et al. (2022) is employed.

3.2 Data preparation and processing

3.2.1 Movebank

All Movebank data sets have the same schema. This simplifies data handling, enables code re-use, and requires the data contributors do perform preprocessing and data cleaning on their side to provide the data in an appropriate format. A library for data processing and trajectory handling in R is provided by Kranstauber, Safi, and Scharf (2024).

The R code for data download, preprocessing, and serialization of relevant data and charts can be found the the following linked documents: Red fox: UK wader nesting season home range, Red fox: montly home ranges.

3.2.2 HRP-100

This raster data set uses the Mollweide projection as described by Lapaine (2011). The 2020 version of the data was used. Since the data set is very large, only the relevant areas were downloaded using a 200 km buffer around the tracking points.

3.2.3 ESA WorldCover

The ESA WorldCover 2021 data at 10m resolution was downloaded via the Microsoft Planetary Computer STAC API [link] for simple programmatic access in R.

3.3 Data exploration and analysis

3.3.1 Red fox data

The Wiltshire data was collected between 2016 to 2019 during the UK wader nesting season, which was defined to be March 15th to June 15th, for 35 foxes in total. It was sampled at 10 or 60 minute rates. The research team could set the sampling rate remotely to save battery at times the data was considered less interesting.

The Bylot/Herschel Canadian data was collected all year round, at a much lower sampling rate of once per day, at random afternoon times of the day. The collection period was June 2009 to Feb 2010 for Herschel and from 2011 to 2015 for Bylot, for two foxes per island. Figure 1 provides an overview of the amount of data points available per year. There is much more data from Wiltshire because of the higher number of foxes and the higher sampling rate.

Looking at the breakdowns by month as shown in Figure 2 reveals seasonal differences in the amount of data available.

3.4 Methodology

3.4.1 Trajectory Analysis

Movement paths will be analyzed to identify patterns in speed, direction, and habitat use. Step lengths and turning angles will help infer behavioral states. Step-selection functions (SSFs) as described by Fortin et al. (2005) will be employed as a statistical model for habitat preferences relative to movement patterns, allowing us to quantify how animals respond to environmental covariates such as human footprint and land use.

3.4.2 Home Range Assessment

The red fox data will be used for home range assessment present for a rural and a remote location. Home range sizes will be calculated using minimum convex polygons (MCPs). This will provide estimates of the area used by each individual.

As discussed in Section 3.3.1, the data for the two locations have different temporal scale. Laube and Purves (2011) have found that the choice of temporal scale has considerable effects on movement parameter calculations, in turn affecting home range results.

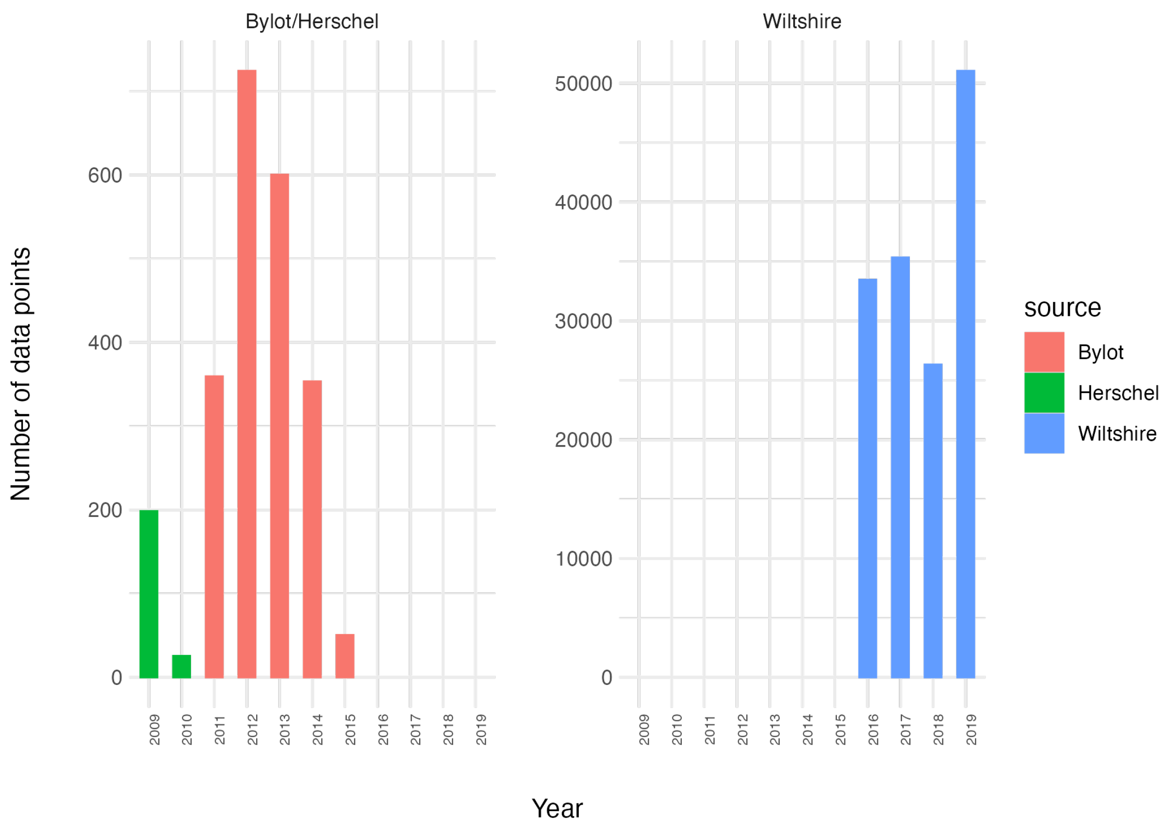

Figure 1: Data points per year

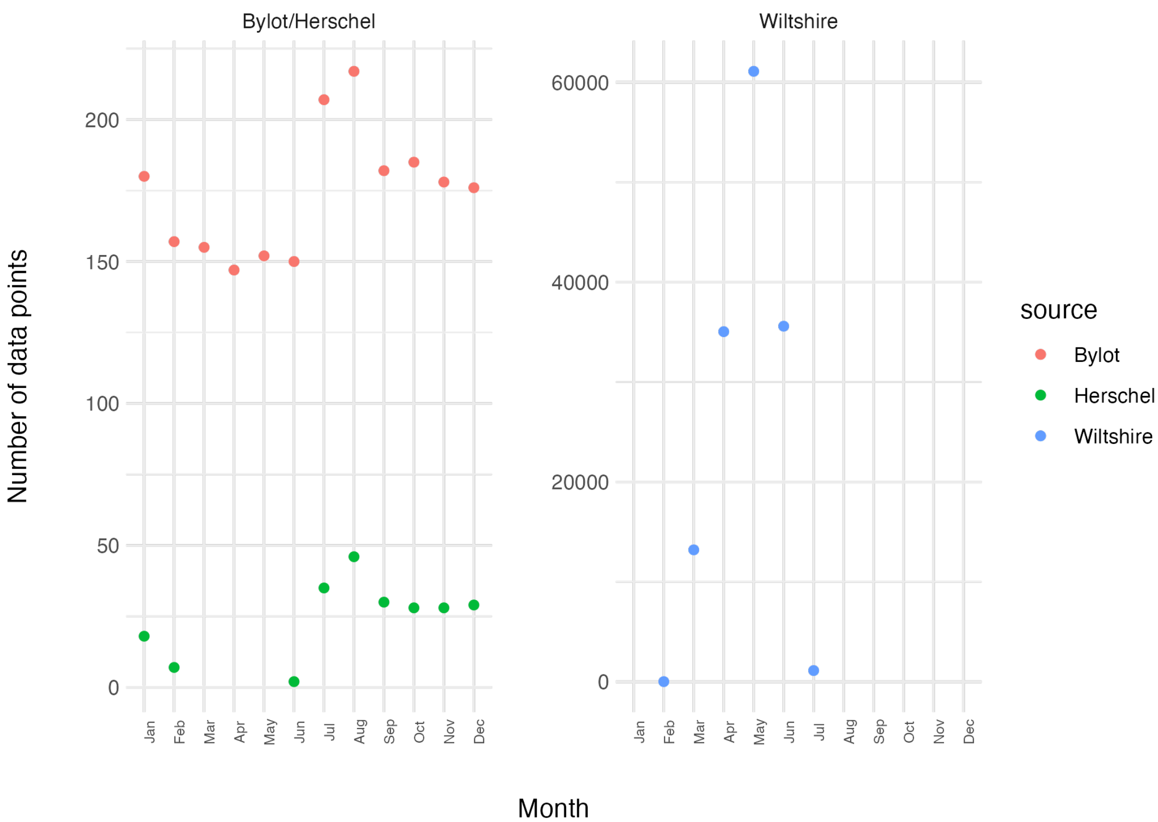

Figure 2: Data points per month

How to make this data comparable? Problem #1 is that the sampling intervals are different. Problem #2 is that the data coverage varies by time of the year. Problem #3 is that there are highly different amounts of data. Selecting the means and parameters for the comparison involves complex choices that will influence the results.

For #1, a possible approach to achieve similar sampling intervals would be to sample a random afternoon data point for each 24 hour window. However, this would include the implicit assumption that foxes will follow similar daily patterns in the different environments. For #2, a possible approach would be to compare the data for the same time of the year. However, the geographical locations are different. The seasonal weather conditions will differ for the same day of the year, likely leading to different animal behavior. For #3, aggregated comparisons can solve the issue, assuming there is enough data for the smaller data source.

For data exploration the simplest possible imperfect approach was employed, which is to ignore the different sampling intervals for problem #1, to compare the data for the same time of the year for problem #2 even if animal behavior might be different, and to use exploratory data analysis to find out if a representative answer can be found given the amount of data present for problem #3. Note that this approach has obvious limits. Among them is that the Herschel data is not applicable, since it has minimal overlaps with the Wiltshire data (cf. Figure 2).

To explore the impact of sampling intervals for problem #1, the home ranges for the Wiltshire data were additionally calculated on downsampled data, where a random data point from every 24 hour period was selected. Finally, an analysis of monthly home ranges was conducted on all three data sets as an alternative solution to address problem #2.

3.4.3 Temporal Activity Patterns

Movement rates will be used to quantify diel activity shifts. We will test whether animals in high human-impact areas exhibit increased nocturnality, potentially as a strategy to avoid direct human encounters. This analysis will reveal how temporal behavior adapts to human presence.

3.4.4 Habitat Selection

SSFs will quantify selection for human-modified habitats (e.g., agricultural areas, urban edges) relative to natural habitats. By comparing selection patterns across species and regions, we will assess how habitat preferences vary with human influence.

4 Results

The resulting home ranges for the UK wader nesting season time frame are shown in Figure 3 and Figure 4. The median home rage size for the foxes in Herschel (75.3 km2) is more than 65 times bigger compared to the foxes in Wiltshire (1.1 km2). The home range for the sampled Wiltshire data is shown in Figure 5. It is 0.56 km2 for the sampled data, which is roughly half as for the full data. This demonstrates that the influence of sampling intervals is definitely present, but is dwarfed in comparison to the difference in fox behavior.

The same effect with differences in order of magnitude between remote and rural fox home range can be seen Figure 6 which shows the results for monthly home ranges.

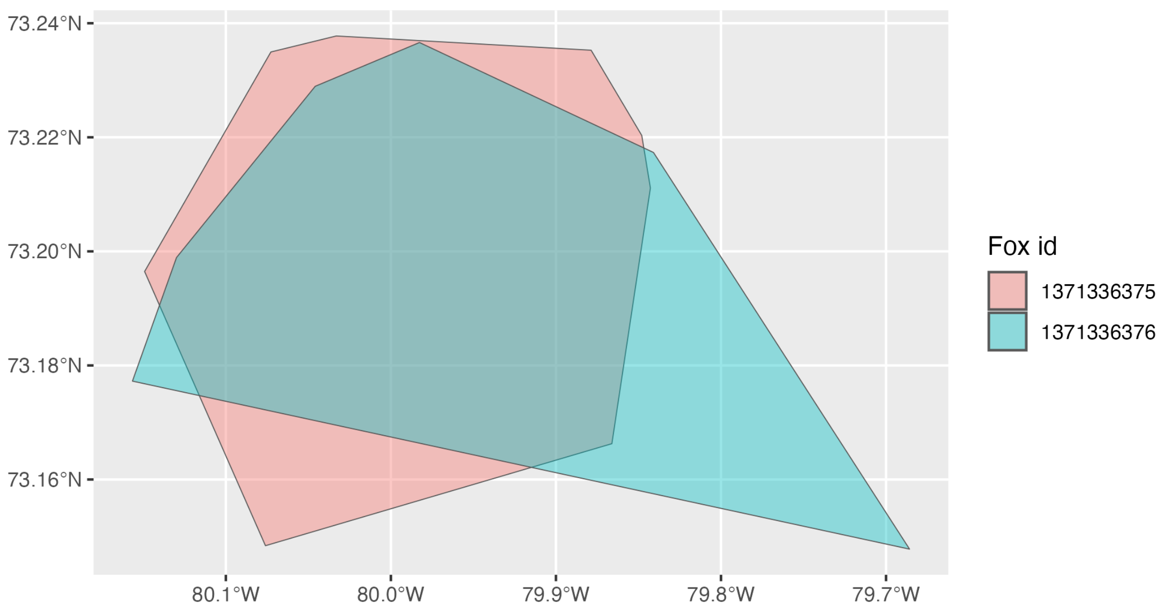

Figure 3: Home ranges for Bylot foxes (March 15th to June 15th, 2012)

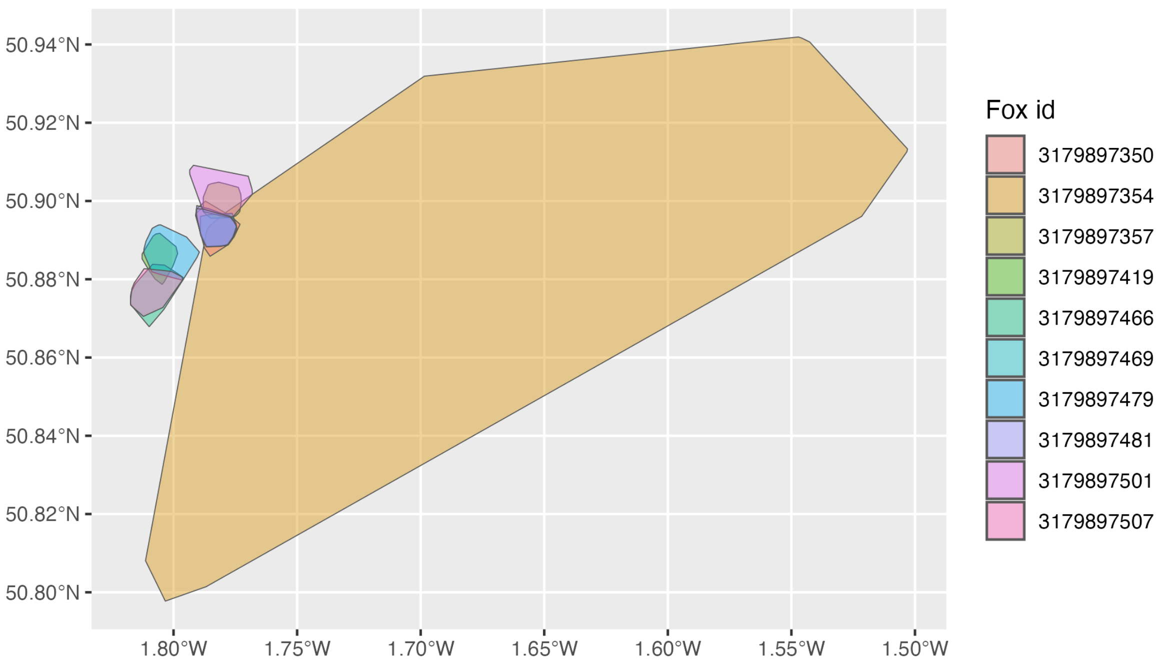

Figure 4: Home ranges for Wiltshire foxes (March 15th to June 15th, 2019)

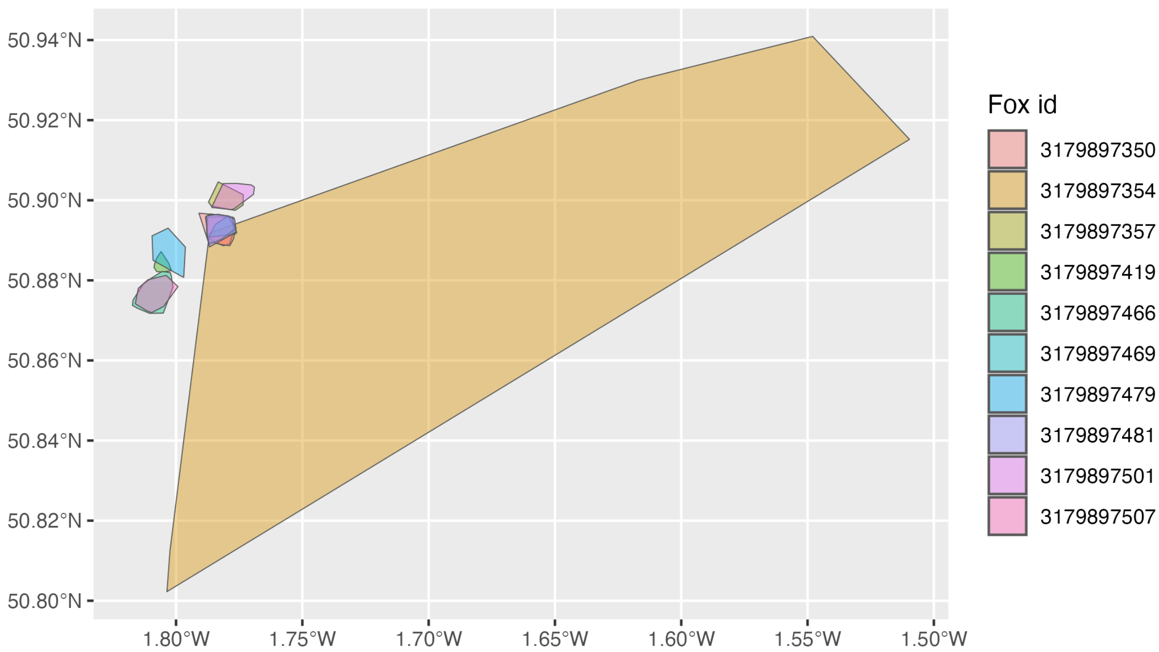

Figure 5: Home ranges for Wiltshire foxes (March 15th to June 15th, 2019, 24 hour sampling interval)

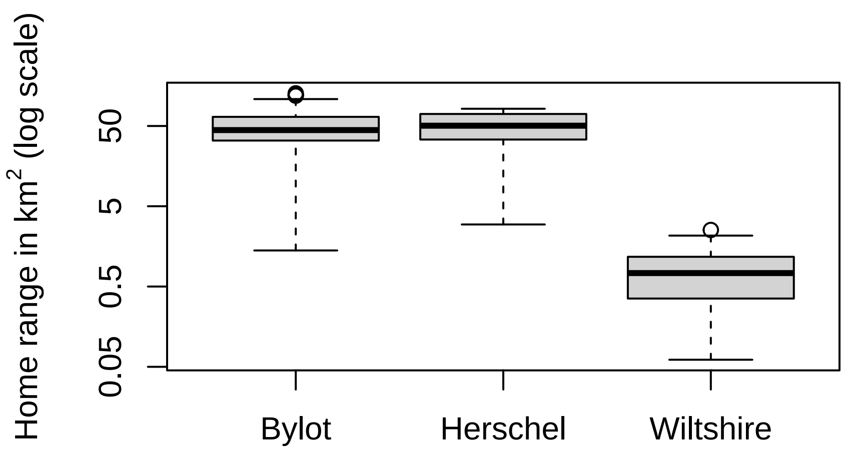

Figure 6: Box plot comparing monthly home ranges (outliers removed)

4.1 Result validation

5 Discussion

The fox home range results differ enormously between rural and remote areas. We can conclude that human presence impacts fox movement behavior significantly, with availability of anthropogenic food sources likely being relevant. The influence of technical aspects like sampling intervals on home range calculation results is significant. However, it plays a secondary role in comparison to the difference in fox behavior, which enables the chosen approach of comparing data from heterogeneous sources.

6 Appendix

6.1 Don't do

- There are several ways to calculate home range, we could compare (and could focus on only that)
- Do home range for foxes first, for bobcat and coyote data later, potentially even cross-species analysis
- Use kernel density estimation (KDE)

6.2 Wordcount

Method	koRpus	stringi
Word count	1457	1450
Character count	9373	9396
Sentence count	85	Not available
Reading time	7.3 minutes	7.2 minutes

6.3 Use of Large Language Models and Generative AI

Elke used NotebookLM (2025) for querying the papers cited in the references.

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