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Abstract

Introduction

Methods

Data

In this study, we used [GPS collar data] collected on 500 pigs in the United States of America and Canada (Fig. 1). The date of collection for these data ranged from May, 2004 to November, 2017, with the per pig duration ranging from X to X (see supplementary material). The average time between fixes varied by study, ranging from between X - X across X unique studies.

While the movement models that we describe below account for variable fix times both between pigs within a study and across studies, too large of a gap between fix times results in a large amount of uncertainty regarding where a pig was in between two fixes. To account for this, we excluded all fixes that were less or equal to *c.* 120 minutes hours apart. Moreover, we only analyzed movement trajectories that had greater than or equal to 200 fixes that met this timing criteria. We chose 200 because at our minimum fix time of 15 minutes this trajectory spans just over two days of fix times, which is the minimum time span needed for inference on diel patterns of movement (i.e. two daily cycles). Using this criteria, our analysis contained X pigs and a total of X fix times.

Finally, we cleaned trajectories for errant fixes using the non-movement criteria described in Bjorneraas *et al.* (2010). [DESCRIBE THIS MORE]

Covariates

The goal of our analysis was to understand how the availability of crops on a landscape affected the movement and resource selection of feral swine. Moreover, we sought to understand how the availability of [natural] forage affected the selection of crop resources on a landscape. Finally, we explored how these interactions between natural forage and crop forage varied seasonally and geographically.

To address these goals, we first compiled covariates related to natural forage resources and agricultural forage resources. For natural forage resources, we considered two proxies for availability of natural forage: plant productivity as measured by NDVI and density of masting trees (Mikey citation, Table 1). For agricultural forage resources, we downloaded crop data layers from CropScape (X) which provides yearly raster layers at a 30m by 30m scale across the contiguous US for X different crop types (TABLE X). [WHAT ABOUT CANADA?]. Rather than considering all X crop types, we grouped the CropScape data at two different levels. First, we grouped the crops into 11 types based on [RYAN'S CRITERIA]: cereals, oilseed, tobacco, beverage and spice, leguminous, grasses, sugar, root and tuber, fruit and nuts, vegetables and melons, and other crops. Second we considered a generic "crop" covariates, in which these eleven crop groups were considered equivalent. While previous studies have shown that feral swine can preferentially select crop types (e.g. Herrero *et al.* 2006), the generic grouping of crop allowed us to more easily explore how the effect of agricultural forage on pig movement varied across space and time.

While our primary goal of this analysis was to understand the effect of forage availability on pig movement, pig movement and resource selection are also driven by a collection of other variables, including cover, water availability, temperature, pressure, human development, mammal diversity, MORE, (McClure *et al.* 2015; Garza *et al.* 2017; Kay *et al.* 2017) [MORE]. Cover and proximity to water are generally found to important predictors of pig presence as these variables are critical for pig thermoregulation and protection from predators (Mayer & Brisbin 2009; Kay *et al.* 2017). For a cover covariate, we used percent forest cover data from the National Landcover Database (Table 1). For a water covariate, we used the National Wetland Inventory (NWI) Database and calculated the distance to the nearest permanent and semi-permanent water source on a landscape. We also included mean monthly temperature, total monthly precipitation, and distance to developed land as additional covariates. Note that while the inclusion of these covariates is inevitably import for capturing pig movement, our questions were focused the forages resources, such that we considered these covariates and "blocking" covariates and did not exhaustively explore their potential relationships and interactions beyond what had already been shown in the literature [VAGUE!].

To explore how interactions between selection for natural forage and crop forage varied geographically, we also included population-level covariates such as drought severity, ecoregion, local pig density, and MORE. These population-level variables were included at the secondary stage of the analysis as described below.

Using movement models to predict resource-use

To understand the interaction between natural forage resources and agricultural forage resources on pig resource selection, we used the modeling framework of Hanks *et al.* (2015) and Wilson *et al.*

(2018). Generally, this framework leverages auto-correlated animal movement data and gridded raster covariates to make inference about the (potentially time-varying) resource utilization of an animal (Hanks *et al.* 2015; Buderman *et al.* 2018; Wilson *et al.* 2018). To answer the questions posed in this study, this approach is advantageous because it uses a continuous-time movement model to account for unequal fix times within and across pig trajectories, allowing for inference on resource selection at the same temporal scale.

Specifically, this approach can be broken into two distinct steps. The goal of the first step is to estimate animal movement as a function of continuous time at some particular temporal grain (e.g. 15 minutes). To do this, we used a phenomenological functional movement model (FMM) (Buderman *et al.* 2016; Hooten *et al.* 2017), which is a non-mechanistic, continuous-time movement model that can capture an animal's movement patterns at some desired-level of detail (Buderman *et al.* 2016). The phenomenological FMM can be represented as a series of basis functions, which allow for large flexibility in animal movement patterns. In particular, we use a B-spline basis expansion [check lingo] to model the longitude and latitude of an animal as a function of time (see Supplementary Material for additional detail).

After fitting the phenomenological FMM to each pig trajectory, we used this model to predict a pig's location at 15 minute intervals as this was the minimum [WHY 15 minutes? Computational time? Choosing an interval such that pigs won't]. We repeated this 1X times to account for the uncertainty in the movement path (Hanks *et al.* 2015; Buderman *et al.* 2018). All the analyses described next were repeated on each of the 1X imputed data sets to account for uncertainty in the movement trajectory.

Using the 15 minute trajectories, we then explored how agricultural and natural forage resources on a landscape affected pig movement. The modeling approach of Hanks *et al.* (2015) considers two types of drivers on movement: location-based drivers and directional drivers of movement. Location-based drivers are a result of the cell that an animal is currently in and affect how long an animal remains in the current cell. For example, masting tree density may be a location-based driver of pig movement such that if a pig is in a cell with high masting tree density it tends to remain in that cell longer than a cell with lower masting tree density. Directional drivers of movement determine the direction that a pig might move once it leaves the cell it is currently occupying. For example, masting tree density might also be a directional driver of pig movement if, upon leaving the currently occupied cell, a pig tends to move in the direction of increasing masting tree density, relative to its current positive [TODO: THIS IS A LOCAL GRADIENT EFFECT...SHOULD I ALSO EXPLORE GLOBAL EFFECTS AT SOME

POINT?]. Table 1 shows which covariates we considered as location-based drivers, directional drivers, or both.

Given these location-base and directional covariates, built a model describing how these covariates affected the rate at which a pig moved from some cell i to cell j, λ_{ij}. The full model that we specified can be conceptually broken into two components: the blocking effects and the forage resource effects. The blocking effects component contains variables that we know influence pig movement, but are not the focus of this current study. This component of the model is given by [TODO: WHY NO Intercept?]

$$
\begin{aligned}
\log(\lambda_{ij}) = & \beta_1 \text{CRW} + \beta_2 \text{Male} && (1) \\
& \quad \text{(Individual-level effects)} && (2) \\
& + \beta_3(h)\text{canopy cover} && (3) \\
& \quad \text{(Time-varying effect of cover over a day)} && (4) \\
& + \beta_5(m)\text{distance to water} && (5) \\
& \quad \text{(Time-varying effect of water over a year)} && (6)
\end{aligned}
$$

CRW defines a correlated random walk. If β_1 is positive, that means an animal tends to move in the direction that it was moving. If β_1 is negative, this means that the animal tends to the move in the opposite direction that is was moving.

The second component of the model defines the effects of forage resources on pig movement. This portion of the model is given by

$$+ \text{crop location} \times (\beta_6 + \beta_7 \text{NDVI gradient} + \beta_8(m)\text{Masting gradient}) \tag{7}$$

$$\text{(When in crop, how do natural forage resources affect a pigs time in the crop)} \tag{8}$$

$$+ \text{crop gradient} \times (\beta_9 + \beta_{10}\text{NDVI location} + \beta_{11}\text{NDVI gradient} \tag{9}$$

$$+ \beta_{12}(m)\text{Masting location} + \beta_{13}(m)\text{Masting gradient}) \tag{10}$$

$$\text{(When not in crop, how do natural forage resources influence the tendency of pigs to move toward crops)} \tag{11}$$

$$+ \beta_{14}\text{NDVI location} + \beta_{15}\text{NDVI gradient} \tag{12}$$

$$+ \beta_{16}(m)\text{Masting location} + \beta_{17}(m)\text{Masting gradient} \tag{13}$$

$$\text{(Main-effects of natural forage resources)} \tag{14}$$

After obtaining the discretized and imputed predictions from our continuous-time FMM [LOL, way to jargony], the second step of the analysis sought to understand how resources affected the movement trajectories of animals on the landscape.

Results

Discussion

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