Movement ecology of vulnerable lowland tapirs across a gradient of human disturbance

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**Running head:** Lowland tapir space use

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**Statement on human or animal subjects:** NEED PATI HERE

# 1 Abstract

**Keywords:**

# 2 Introduction

While agriculture, urbanisation, and transportation infrastructure are critical to human socio-economic improvement (Esfahani and Ramı́rez 2003), the associated habitat transformations represent a major threat to species survival (Fahrig 1997; Venter et al. 2006; Powers and Jetz 2019). Of particular concern is the impact of human activities on animal movement and space use (Allen and Singh 2016; Tucker et al. 2018; Doherty, Hays, and Driscoll 2021). Animal movement governs how individuals, populations, and species interact with each other and the environment (Schick et al. 2008; Martinez-Garcia et al. 2020; He et al. 2021) and mediates key ecological processes (Bauer and Hoye 2014). The capacity for individuals to move unhindered across complex landscapes is therefore critical for species survival and ecosystem function. Problematically, human development has been reducing the amount of habitat available to wildlife (Brooks et al. 2002; Cardinale et al. 2012; Hooper et al. 2012). This has spurred substantial changes in animal movement behaviour across the globe (Fahrig 2007; Tucker et al. 2018; Doherty, Hays, and Driscoll 2021), with potential consequences including reduced fitness and survival, altered predator-prey dynamics, reduced seed dispersal, genetic isolation and local extinction (Fahrig 2007; Dickie et al. 2017; Cosgrove, McWhorter, and Maron 2018; Tucker et al. 2021).

Notably, human disturbance has been shown to have differential effects across species (Toews, Juanes, and Burton 2018; Doherty, Hays, and Driscoll 2021), even for closely related taxa occupying the same habitat (Thatte et al. 2020). Responses to human activities are thus largely taxa and context specific (Doherty, Hays, and Driscoll 2021) and there are no clear *a priori* expectations as to how any given species might be expected to respond to human disturbance. For instance, although Wall et al. (2021) found a tendency for African elephants (*Loxodonta spp.*) to have reduced movement in human modified landscapes, Morato et al. (2016) noted that jaguars (*Panthera onca*) living in regions with high human population densities occupied home ranges that were orders of magnitude larger than those of jaguars living in more pristine habitats.

As human disturbance is only expected to worsen over the next decade it is critical to better understand how species respond to human disturbance in order to develop effective conservation strategies. To this end, here we focus on understanding how the movement behaviour of lowland tapirs (*Tapirus terrestris*, henceforth ‘tapirs’) varies across three biomes in southern Brazil, the Pantanal, Cerrado, and Atlantic Forest. Tapirs are herbivores of the order Perissodactyla that can reach over 2.5 meters and weigh up to 250kg (Myers et al. 2006) and are distributed throughout South America (Gardner 2008). Tapir populations have suffered severe reductions, with local and regional extirpations, and are currently classified as vulnerable to extinction (Varela et al. 2019). PATI THIS SECTION IS MOSTLY UP TO YOU AS NOT MUCH HAS BEEN PUBLISH ON LOWLAND TAPIR BIOLOGY/ECOLOGY. We use an extensive telemetry dataset collected over XX years to describe the movement ecology of tapirs and study how changes in human disturbance influence their movement and space use. Currently, almost nothing is known about the movement ecology of tapirs (but see C. H. Fleming et al. 2019). Because large herbivores tend to increase (Doherty, Hays, and Driscoll 2021) our underlying hypothesis was that tapirs should exhibit greater movement distances and larger home range areas when living in human-modified landscapes. Findings are directly applicable to developing management plans, not only for tapirs but possibly also to other medium-large herbivores throughout South America.

# 3 Methods

## 3.1 Study area and data collection

The data was collected in three different ecosystems in southern Brazil (Fig. 3.1): south-western Cerrado (savannah, control environment), Pantanal (wetland, agricultural environment), and western Mata Atlântica (forest, degraded environment).

*Add details on climate and land use?*

Animals were tracked using VHF tracking (all three regions) and GPS tracking (Pantanal and Cerrado). *Add details on capturing and tracking devices*

A total of 74 tapirs were tracked starting in July of 1997 until October of 2019, with the majority of the data being in the Pantanal (46), while 17 and 11 were from the Cerrado and Mata Atlântica regions, respectively.

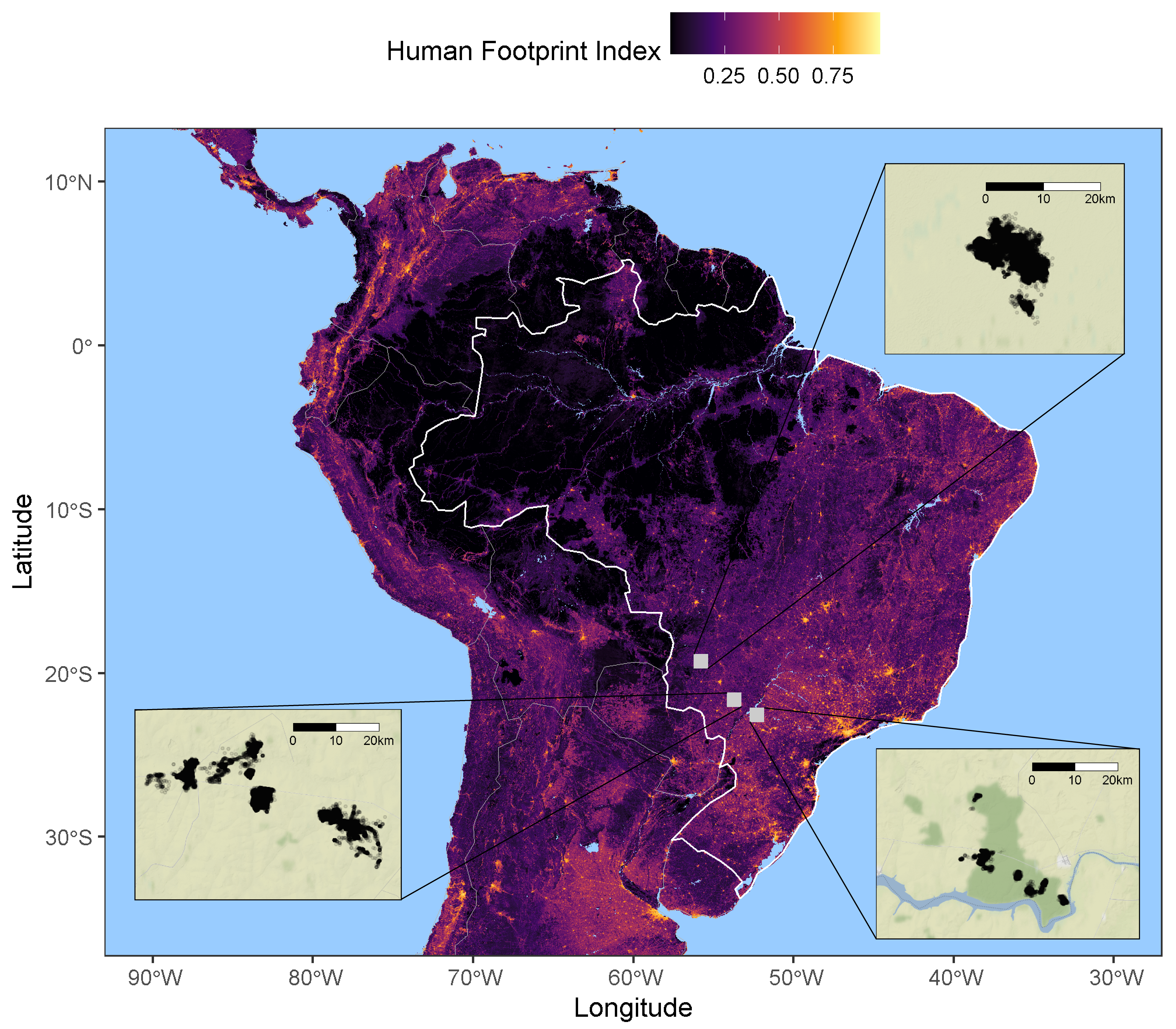


Figure 3.1: Location of the tree study sites (Pantanal, Cerrado, Mata Atlântica) over a raster of machine-learning-based human footprint index (ml-HFI), an index of human pressure on the landscape that is derived from remotely sensed surface imagery and ranges on a scale between 0 (no human impact), and 1 (high human impact).

## 3.2 Data analysis

All statistical analysis and plotting were performed using R (version 4.0.5, R Core Team 2021) using packages ctmm (version 0.6.1, “Ctmm: Continuous-Time Movement Modeling,” n.d.), mgcv (version 1.8-36, Wood 2017), ggplot2 (version , Wickham 2016) ggmap (version , Kahle and Wickham 2013). The furrr package (version 0.2.2, Vaughan and Dancho 2021) was used for parallel computation on Windows machines. All R code can be found in the GitHub repository at <https://github.com/StefanoMezzini/tapirs>.

### 3.2.1 Data calibration and cleaning

Before analysis, we performed an error calibration and data cleaning process in order to minimise the impacts of GPS measurement error and outliers on our subsequent analyses (C. H. Fleming et al. 2020). Data cleaning and calibration were carried out using the methods methods implemented in the ctmm R package (“Ctmm: Continuous-Time Movement Modeling,” n.d.). For this process, location estimates collected via VHF telemetry were assumed to be free from any meaningful measurement error and raw, uncalibrated locations were carried forward in the analyses. Location estimates collected via GPS tracking were calibrated using a unitless Horizontal Dilution of Precision (HDOP), which estimated the accuracy of each positional fix. We then estimated an equivalent range error with the HDOP values from 883 and 174 measurements from tags in fixed locations in the Pantanal and Cerrado, respectively. This allowed for the unite-less HDOP values to be converted into estimates of measurement error in meters. After calibration, data points were considered as outliers (and removed) if they had a large (error-informed) distance from the median location and the minimum speed required to explain the displacement was unusually high (m/s). The Mata Atlântica dataset contained a total of 4 082 observations, 8 of which were removed as outliers; the Pantanal dataset contained 139 138 observations, 914 of which were removed; while the Cerrado dataset contained 90 402 observations, 193 of which were removed. *(no speed outliers found when I (Stefano) was cleaning the datasets, but 1105 outliers had already been removed)*

### 3.2.2 Movement modelling and home range estimation

For each of the monitored tapirs we quantified a number of key movement metrics and home range related characteristics that allowed us to test for an effect of human disturbance on tapir movement behaviour. For this we first identified the best Continuous-Time Movement Model (CTMM) for each animal using the ctmm.select function from the ctmm package. This fits a series of CTMMs to location data using perturbative Hybrid Residual Maximum Likelihood (pHREML, Christen H. Fleming et al. (2019)) and chooses the best model using small-sample-sized corrected Akaike’s Information Criterion (AICc). The models used here are insensitive to sampling frequency (Michael J. Noonan et al. (2019)) and they account for spatio-temporal autocorrelation in the data (when necessary), so they are robust to irregular or frequent sampling frequency (C. H. Fleming et al. 2018), HR underestimation (M. J. Noonan et al. 2019), and significance inflation [META PAPER IN PREP WHICH WE CAN CITE WHEN IT’S ON THE ARCHIVE]. The parameter estimates from each individual’s movement model provided information on the tapir’s home range crossing time (in days), and directional persistence timescale (in hours).

We then conditioned off of the selected CTMMs to estimated each animal’s 95% home range (HR) area (in km) using small-sample-size bias corrected Autocorrelated Kernel Density Estimation (AKDE) (Christen H. Fleming and Calabrese 2017), and average daily speed (in km/day) using continuous-time speed and distance (CTSD) estimation (Michael J. Noonan et al. 2019).

### 3.2.3 Movement pattern analyses

We were first interested in understanding how home-range areas and movement metrics differed across the three biomes, as well as between animals of different age and sex. For these comparisons, home range estimates were compared using the meta-analysis methods implemented in the ctmm package [CITE META PAPER], whereas other movement metrics were analysed using the meta-regression model implemented in the R package metafor (Viechtbauer 2010), which allowed uncertainty in each individual estimate to be propagated into the population level estimate when making comparisons.

To test whether environmental modification significantly altered the animals’ behavior, the HR sizes and average daily speeds were regressed against their HR’s average machine machine-learning-based human footprint index (ml-HFI) (Keys, Barnes, and Carter 2021). The ml-HFI is an index of human pressure on the landscape that is derived from remotely sensed surface imagery and ranges on a scale between 0 (no human impact), and 1 (high human impact). For these models we applied Generalized Linear Models (GLMs) with a Gamma distribution and a log link for the response. The Gamma distribution allows for more accurate significance testing, while the log link scale allows HFI to have a multiplicative effect on the response. The GLMs were fit using the mgcv package (Wood 2017), and Restricted Maximum Likelihood (REML).

# 4 Results

## 4.1 Individual variation in movement and space use

*change values to more appropriate estimates; currently using mean +/- 1.96 sd/sqrt(n)*

The mean home range size across all monitored tapirs was 5.82 km (95% CI: 4.71 - 7.12), ranging between 1 km and 29.7 km (Fig. 4.1a). Tapirs had HR crossing times of 0.72 days on average (95% CI: 0.35 - 1.10), ranging from 0.05 to 12.8 days (Fig. 4.1b), and a mean velocity autocorrelation timescale of 0.44 hours (95% CI: 0.39 - 0.49), ranging from 0.17 to 1.88 hours (Fig. 4.1c). We estimated that tapirs had mean movement speeds of 11.2 km/day (95% CI: 10.2 - 12.1), ranging from 1.51 to 25.96 km/day (Fig. 4.1d). There was no evidence that average daily speed differed between sexes (females: 10.5 km/day, 95% CI: 9.19 - 12.0; males: 11.9 km/day; 95% CI: 10.3 - 13.7, , 4.2a), and there was little to no evidence of it differing between age groups (adults: 11.8 km/day, 95% CI: 10.6 - 13.2; sub-adults: 9.52 km/day, 95% CI: 7.94 - 11.4; , Fig. 4.2b).

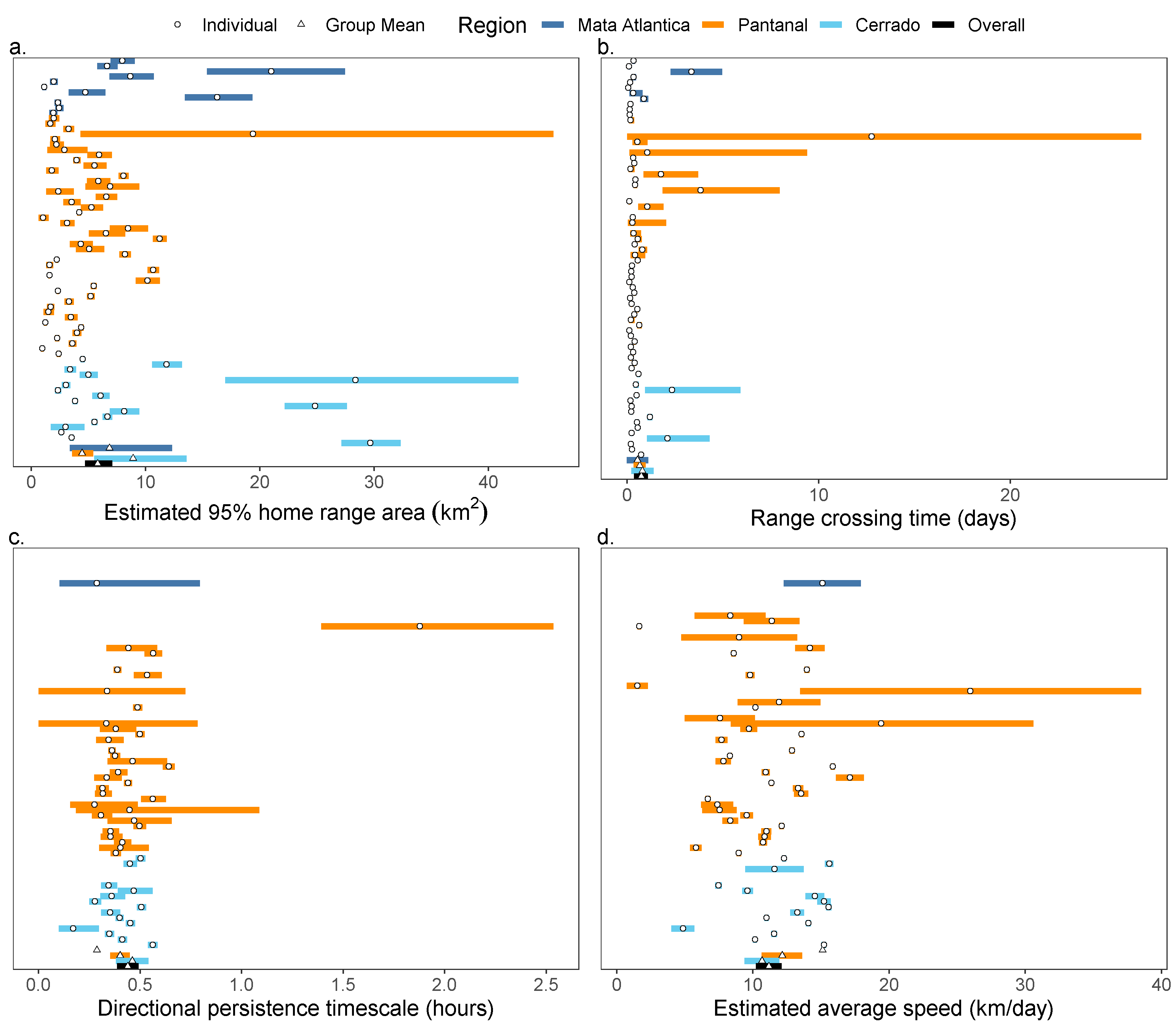


Figure 4.1: Parameter estimates from each tapir’s movement model (circles) and group means (triangles), with 95% confidence intervals. Individuals with a movement model that does not allow for inferences in movement speed are left blank.

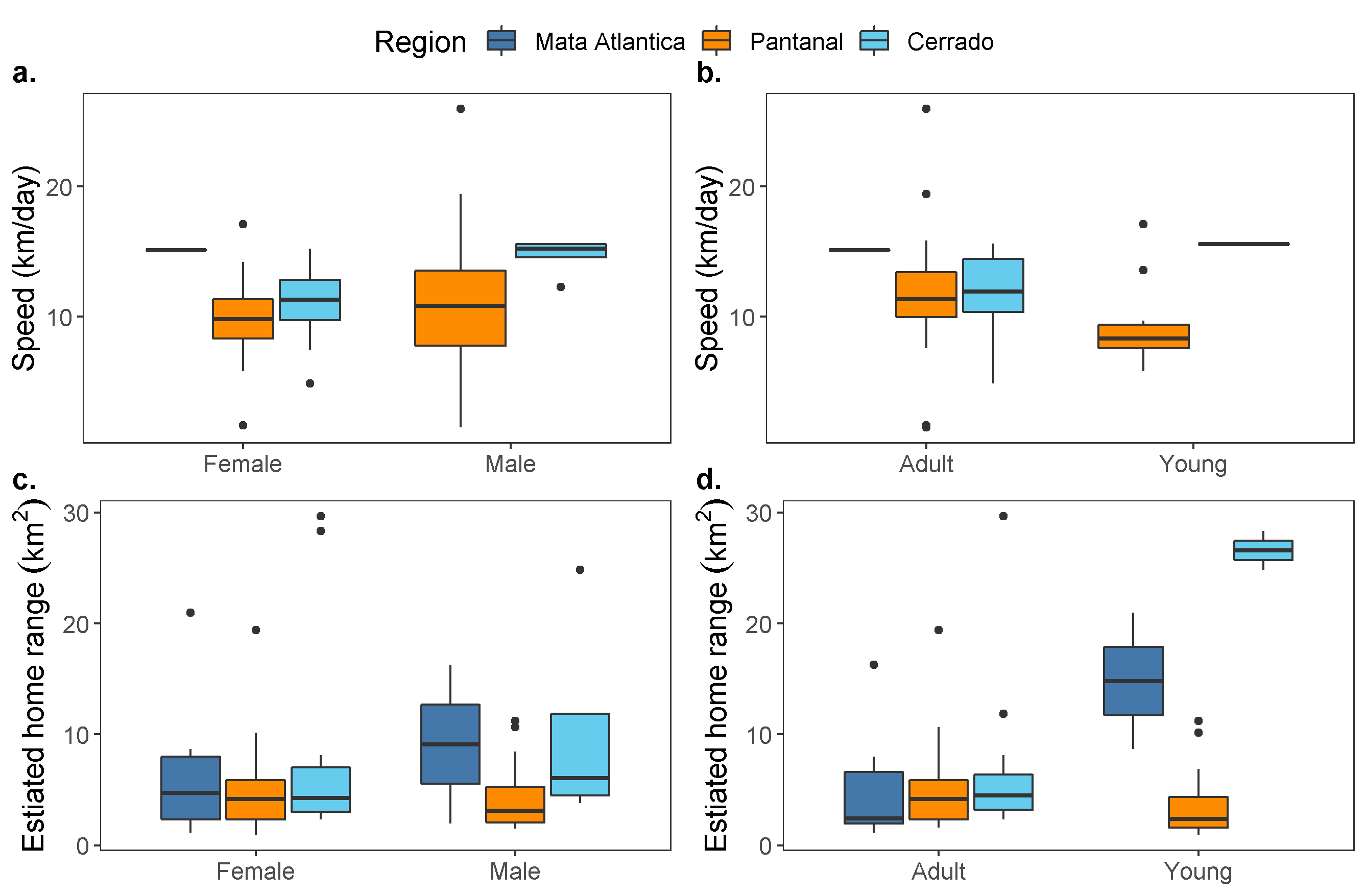


Figure 4.2: Boxplots of daily average speed (a, b) and estimated home range size (c, d) by sex and age group.

There was no evidence that home ranges sizes differed between sexes (males: 5.43 km, 95% CI: 3.84 - 7.68; females: 6.27 km, 95% CI: 4.64 - 8.48; , Fig. 4.2c) nor between age groups (adults: 5.47 km, 95% CI: 4.21 - 7.1; sub-adults: 7.01 km, 95% CI: 4.63 - 10.6; , Fig. 4.2d).

## 4.2 Variation in movement across biomes and gradients of human disturbance

The Atlantic Forest, Cerrado, and Pantanal varied substantially in habitat composition, levels of human disturbance, and tapir population densities (*PATI, IS THERE A SOURCE TO SUPPORT THIS STATEMENT?*). Despite this, we found that lowland tapir movement behaviour and space use were consistent across all three biomes (Fig. 4.1.

We also found [no] relationship between home range area and HABITAT LAYER RESULTS (Fig. XXX). Similar trends were observed across all other movement parameters (Fig. XXX).  
HFI had no significant effect on either lowland tapir home range size (p-value = 0.90; Fig. XXXa), nor average daily movement speed (p-value = 0.53; Fig. XXXb). A tapir living in a near pristine environment (HFI = 0.004) was estimated to have a home range of 7.77 km (95% CI: 2.12 - 28.6) and an average speed of 13.19 km/day (95% CI: 7.82 - 22.1), while a tapir from the most altered habitat we monitored (HFI = 0.31) had an estimated home range area of 6.93 km (95% CI: 3.36 - 14.3) and an average speed of 10.43 km/day (95% CI: 8.27 - 13.2).

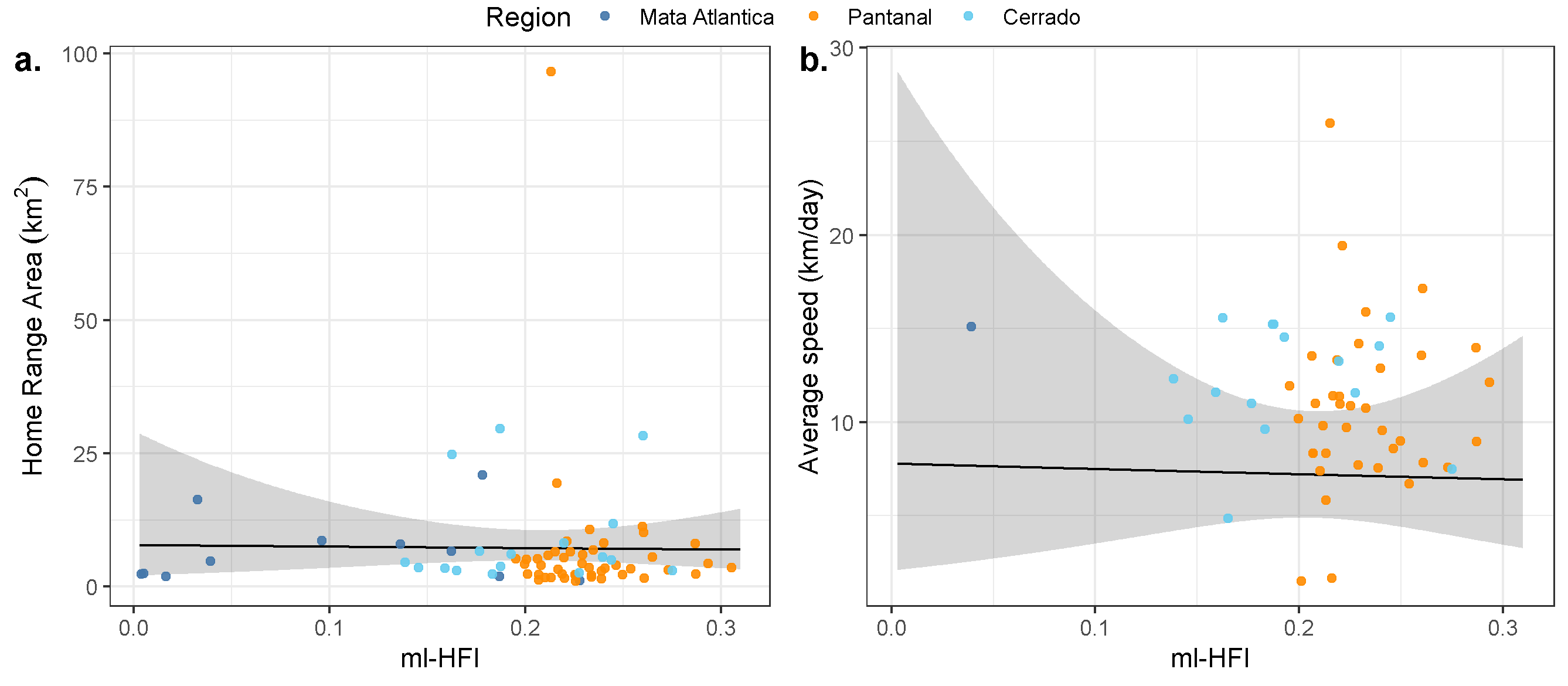


Figure 4.3: Estimated mean effect of machine-learning-based human footprint index (ml-HFI) on the tapirs’ estimated home range area and estimated average daily speed.

***ADD AKDE RESULTS*** (Fig. 4.4)

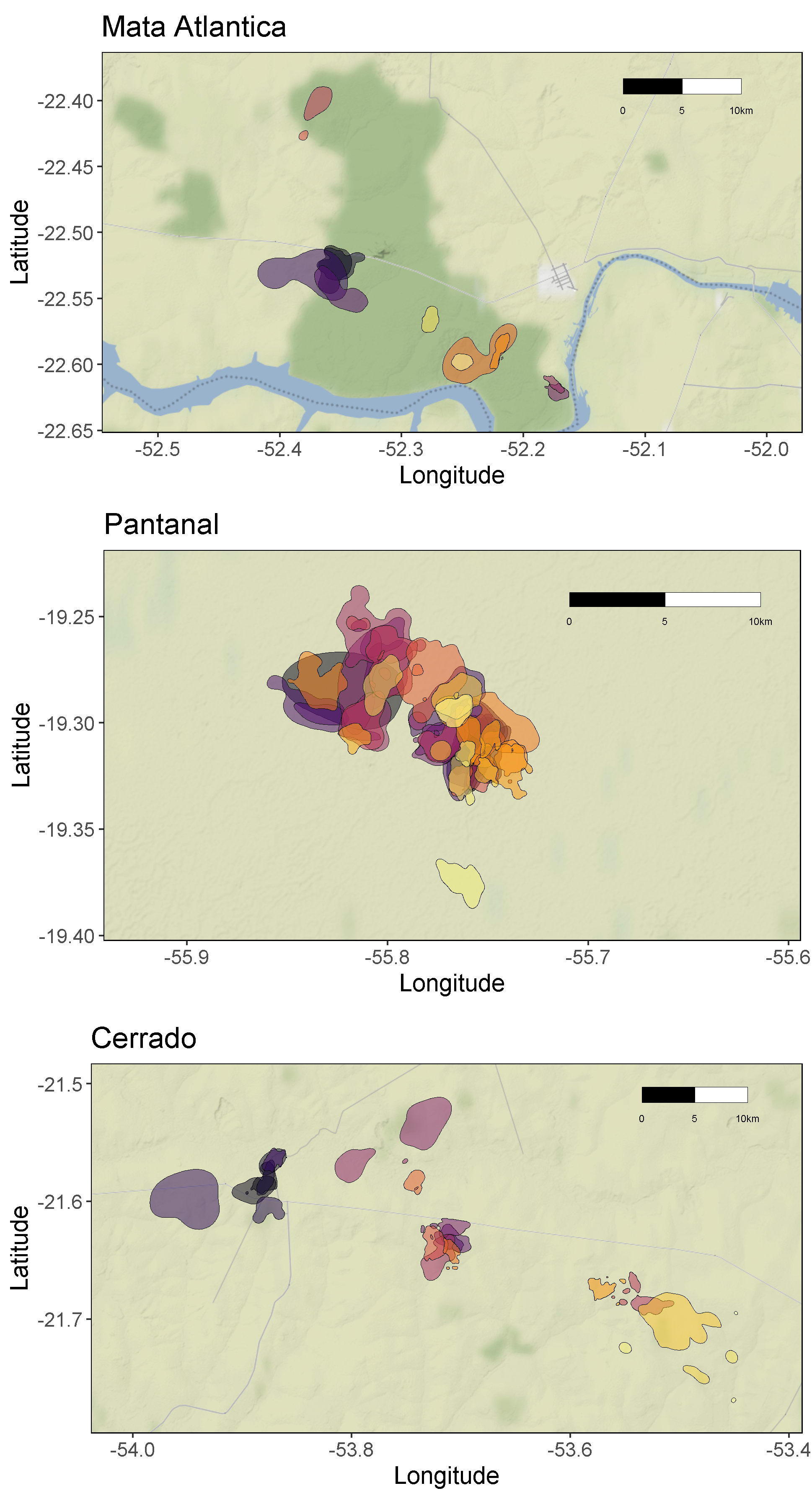


Figure 4.4: Autocorrelated kernel density estimations of each tapir’s 95% home range. THESE LOOK GOOD, BUT I THINK WE’RE GOING TO WANT BETTER UNDERLYING MAPS. WE SHOULD BE ABLE TO USE THE HABITAT LAYER RASTERS AFTER WE GET THOSE.

# 5 Discussion

# 6 Acknowledgments

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