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Space-time home range estimates and resource selection for the Critically Endangered Philippine Eagle on Mindanao

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Abstract

Quantifying home range size and habitat resource selection are important elements in wildlife ecology and are useful for informing conservation action. Many home range estimators and resource selection functions are currently in use. However, both methods are fraught with analytical issues inherent within autocorrelated movement data from irregular sampling and interpretation of resource selection model parameters to inform conservation management. Here, we apply satellite remote sensing technologies to provide updated estimates of home range size and first estimates of fine-scale resource selection for six adult Philippine Eagles (*Pithecophaga jefferyi*), using a space-time autocorrelated kernel density estimate (AKDE) home range estimator and non-parametric resource selection functions. All six adult eagles showed distinct site fidelity, with continuous range residency between two to 18 km one month after tagging. The space-time AKDE home range estimators had a median 95% home range size = 68 km^2 (CI = 62-74 km^2, range: 39-161 km^2), with the median 50% core range size = 13 km^2 (CI = 11-14 km^2, range: 9-33 km^2). From the resource selection functions, all adult Philippine Eagles used habitat high in photosynthetic leaf and canopy structure but avoided areas of old growth biomass and denser areas of vegetation. This is possibly due to foraging forays into secondary forest and fragmented agricultural areas away from nesting sites. For the first time, we determine two important fine-scale spatial processes for this critically endangered raptor that can help in directing conservation management. Rather than employing traditional home range estimators and resource selection functions, we recommend that analysts consider space-time approaches and non-parametric resource selection functions to animal movement data to fully explore space-time and resource selection.

Keywords: habitat selection, home range, Philippine Eagle, *Pithecophaga jefferyi*, remote sensing, satellite telemetry

Introduction

Estimating animal home range size and habitat resource selection is a fundamental aspect in wildlife ecology and conservation (Hooten *et al.* 2017). Quantifying home range behaviour and resource selection using satellite telemetry devices is used to inform conservation management and policy (Fieberg *et al.* 2021; Silva *et al.* 2021). Therefore, it is crucial that reliable and robust metrics are used for both. Since the inception of the home range concept (Burt 1943), many home range estimators have been used (Signer & Fieberg 2021). However, finding a reliable home range estimator has proven difficult due to the analytical challenges inherent with animal movement data that are often autocorrelated, have irregular sampling, or small sample sizes (Silva *et al.* 2021). Similarly, estimating resource selection functions by comparing environmental covariates at an individual's used locations to those environmental locations assumed to be available with logistic regression is popular (Johnson *et al.* 2006). However, interpreting resource selection model parameters to inform management is non-trivial and often difficult (Fieberg *et al.* 2021).

An animal's home range is formally defined as those movements regularly used for foraging and breeding but excluding occasional sallies outside of this area (Burt 1943; Fieberg & Borger 2012). Thus, an animal's home range reflects its ecological needs and the decisions that result from these environmental requirements (Tétreault & Franke 2017). Home ranges are therefore expected to differ amongst individuals within a species over space and time dependent on shifting ecological needs and varying resources (Signer & Fieberg 2021). Further, selection of a specific home range estimator can in itself explain as much of the variation in home range size as the ecological processes influencing it (Signer *et al.* 2015; Tétreault & Franke 2017). In current practice, the utilization distribution is an extension of the original home range concept (Burt 1943), where an animal's use of space is defined by a probability density function that quantifies the chance the animal will be found at any given location within its home range (Van Winkle 1975; Worton 1987).

Kernel density estimators (KDEs, Worton 1989) are a non-parametric probabilistic home range estimator, traditionally fitted with both fixed and adaptive kernel bandwidths to account for over smoothing (Wand & Jones 1994). However, traditional KDEs can overestimate home range sizes, even when accounting for bandwidth over smoothing with an adaptive kernel (Silva *et al.* 2021). Recently, autocorrelated kernel density estimates (AKDE, Fleming & Calabrese 2017) have been proposed as an improvement on fixed and adaptive KDEs. AKDEs first fit an Ornstein-Uhlenbeck (Uhlenbeck & Ornstein 1930) continuous-time stochastic process movement model to the animal locations, and then incorporate the movement model into an area-corrected home range estimator with weighting that accounts for autocorrelation and irregular sampling (Calabrese *et al.* 2016; Silva *et al.* 2021). Space-time home range estimates are therefore expected to provide more robust estimates of the utilization distribution because they account for the important third dimension of time in animal movement patterns (Keating & Cherry 2009).

Within an animal’s home range, resource selection functions (RSFs) are used to infer the probability of resource selection for a given individual within that defined area (Manly *et al.* 2002). Standard parametric logistic regression is the most popular method to quantify resource selection (Johnson *et al.* 2006) but has been criticized because used locations (species presence) are continuous points but are compared to available locations (raster pixels) in discrete space (Keating & Cherry 2004; Fieberg *et al.* 2021). Poisson point processes have been proposed as an alternative to standard parametric resource selection functions to make habitat selection analyses easier to understand and more accessible to a wide range of end users (Baddeley *et al.* 2012). For ease of interpretation, non-parametric RSFs can be fitted directly to the species locations without accounting for available locations using a point process intensity probability density function based on a kernel density estimate (Baddeley *et al.* 2012).

The Philippine Eagle (*Pithecophaga jefferyi*) is a globally threatened tropical forest raptor (Sutton *et al.* 2023), currently classified as ‘Critically Endangered’ on the IUCN Red List (BirdLife International 2018). This large eagle is endemic to four islands in the Philippine archipelago (Mindanao, Leyte, Samar, and Luzon; Kennedy 1977), with a restricted distribution across lowland and montane tropical forests (Salvador & Ibañez 2006; Sutton *et al.* 2023). The latest global population estimate from inferred habitat area calculated a potential breeding population of 392 pairs, with 59% expected to be resident on Mindanao (Sutton *et al.* 2023). The Philippine Eagle is an opportunistic predator that takes a wide range of prey including mammals, birds and reptiles but primarily civet cats (Family Viverridae) and flying lemur (*Cynocephalus volans*) (Ibañez *et al.* 2003). The two key threats to its future survival are habitat loss, driven by intensive agriculture and logging, further compounded by human persecution (Salvador & Ibañez 2006; Ibañez *et al.* 2016). Despite its elevated extinction risk, fundamental aspects of Philippine Eagle ecology such as home range size and fine-scale habitat selection are relatively unknown. Indeed, the IUCN Red List suggests that further research into ecological requirements is urgently required to inform conservation actions (BirdLife International 2018).

Previously, home range estimates for the Philippine Eagle used three standard approaches (Gaussian KDE, local convex hulls, minimum convex polygons; Sutton *et al.* 2023), which are viewed as robust estimators, but do not account for movement patterns, autocorrelation, and irregular sampling. Therefore, these current home range estimates need re-evaluating with a more robust estimator that can account for these disparities such as AKDE. This is important because AKDE is known to estimate larger home range sizes than traditional approaches (Silva *et al.* 2021), as used a previous study for the Philippine Eagle (Sutton *et al.* 2023). Additionally, little is known about fine-scale habitat selection of Philippine Eagles away from nest sites, which may be important for directing conservation action compared to recommendations from a previous range-wide assessment of habitat use (Sutton *et al.* 2023). Solely focusing conservation efforts on breeding areas may then miss implementing important policy and conservation mitigation measures across the wider landscape used for foraging by Philippine Eagles.

Here, we use satellite telemetry locations from six GPS tagged adult Philippine Eagles to (**1**), calculate home range size using a space-time estimator, and (**2**), quantify fine-scale habitat selection with non-parametric resource selection functions. Finally, we outline how quantifying these key ecological processes can inform conservation action for this raptor of conservation concern. We expect that home range estimates for Philippine Eagles using AKDE will be larger than previous estimates and that adult eagles should display clear site fidelity in range residency, similar to other tropical forest raptors. In addition, we expect Philippine Eagles to select dense forested areas in their respective core ranges from their daily movement patterns related to nesting but utilize more of their home range outside of core areas in fragmented landscapes when foraging.

Methods

Study area

Mindanao is a mountainous island in the Philippine archipelago and is the second largest island by area with a human population of approximately 26 million people, making it the seventh most populous island globally. Mindanao is a key agricultural area for the Philippines, resulting in a fragmented landscape, with most lowland tropical forest cleared by logging and for intensive agriculture. The remaining tropical forest is largely restricted to the mountainous areas of the island, many of which have some form of protected status as national parks or biodiversity areas. Mindanao is the current stronghold for the Philippine Eagle, with a potential breeding population of 233 pairs inferred from modelled area of habitat (Sutton *et al.* 2023)

GPS telemetry data

We sourced Philippine Eagle satellite telemetry locations from the Philippine Eagle Foundation that are archived in the Global Raptor Impact Network (GRIN, McClure *et al.* 2021), a data information system for global population monitoring for all raptors. For the Philippine Eagle, GRIN includes GPS fixes from six breeding adult Philippine Eagles (four females, two males) on the island of Mindanao. All Philippine Eagles were trapped using either a modified Bal-Chatri (Miranda & Ibanez 2006) or a large bownet baited with domestic rabbit (*Oryctolagus cuniculus*). Two eagles were instrumented with solar-powered Global Positioning System-Global System for Mobile Communications (GPS-GSM) transmitters (weight = 70 g; Microwave Telemetry, Inc) while four eagles had battery-powered LC4™ Argos-GPS platform transmitter terminal (PTT) fitted (weight = 105g; Microwave Telemetry, Inc), harnessed with Teflon-coated nylon ribbon backpacks. All tags weighed < 3% of the body weight for all adults tagged. Tags were programmed to transmit on a 2-hr fix interval for adults 001F, 002F, 004M, 006F, with adult 003F at 24 hrs and adult 005M at 2 mins. All GPS transmitter harnessing was conducted with a Gratuitous Permit to trap and tag the birds in the presence of a veterinarian as required by the national government of the Philippines.

We removed all duplicated records and used all raw GPS fixes for each bird except 005M which we sub-sampled using a 2-hr interval to reduce the number of fixes to 7872 to efficiently fit the AKDE for adult 005M (Table 1). We assessed how effective the number of GPS relocations was at capturing the utilization distribution using an incremental analysis with bootstrapped minimum convex polygons (*n* = 100), quantifying when the number of relocations within the MCP area reached an asymptote (Walls & Kenward 2012), using the 'hrBootstrap' function in the R package move (Kranstauber *et al.* 2020). To test for range residency, we calculated semi-variance functions visualised with empirical variograms to identify unbiased estimates of stationary movement periods of site fidelity with data containing time-averaged autocorrelation structure in the R package ctmm (Calabrese *et al.* 2016). Variograms represent the average square distance travelled within a specified time lag. We used a median sampling interval for the time lag bin widths and Markovian Confidence Intervals for calculating the maximum number of non-overlapping lags (Calabrese *et al.* 2016).

Home range estimation

Utilization distributions were constructed to estimate the probability of relocating an individual within a given home range going beyond the standard definition in two-dimensional space (Van Winkle 1975; Worton 1987, 1989), to three-dimensional space-time (Keating & Cherry 2009). We fitted 95% probability of use contour isopleths to represent the home range utilization distribution (Laver & Kelly 2008), and 50% probability of use contour isopleths to represent a core range utilization distribution, characteristic of a territorial area (White & Garrott 1990). We selected a core range of 50% probability of use because this is the standard definition, thus comparable to other tropical forest raptors. However, we recognise that defining a 50% core range is not always appropriate because core range percentages are likely to vary amongst individual animals (Vander Wal & Rodgers 2012).

We calculated utilization distributions using autocorrelated kernel density estimates (AKDEs; Fleming & Calabrese 2017) in the R package ctmm (Calabrese *et al.* 2016) with a movement model that best explains the autocorrelated structure of our data. We used a perturbative Hybrid Residual Maximum Likelihood parameter estimator (pHREML), which is a form of maximum likelihood estimation that reduces bias in variance/covariance estimation (Silva *et al.* 2021). AKDEs were fitted with a continuous-time stochastic process movement model to overcome the autocorrelated nature of our GPS tracking fixes and mitigate small absolute and effective sample sizes (Calabrese *et al.* 2016). All home range area estimates were calculated in a Universal Transverse Mercator (UTM, zone 51) projection in R (v3.5.1; R Core Team 2018) and following recommendations from Laver & Kelly (2008) to first assess site fidelity, serial autocorrelation and home range asymptotes for each eagle before calculating home range sizes.

We evaluated a pool of candidate movement models for each individual eagle from Ornstein-Uhlenbeck movement patterns including both isotropic (symmetrical diffusion) and anisotropic (asymmetrical diffusion) variants, along with the standard

KDE assumption of independent and identical distributed (IID) data, based on Akaike's Information Criterion (Akaike 1974) adjusted for small sample sizes (AICc; Hurvich & Tsai 1989). We considered all models with a $\Delta AIC_C < 2$ as having strong support (Burnham & Anderson 2004). From our candidate models, the best supported movement process for all eagles was an Ornstein-Uhlenbeck anisotropic process, except for 005M which had an Ornstein-Uhlenbeck foraging anisotropic process as the best supported model ($\Delta AIC_C = 0.0$; Supporting Online Information, Table S1). We then fitted each respective movement process into an area-corrected AKDE home range estimator with additional weighting that upweights fixes in under-sampled times and down-weights fixes in over-sampled times (Silva *et al.* 2021). We did this because Philippine Eagles are forest-dependent raptors inhabiting dense forest canopies where we expected under sampling but also are observed moving over more open ground where we expected potential over sampling.

Resource Selection

Habitat covariates

We quantified resource selection using the GPS fixes and three habitat covariates derived from satellite remote sensing data using 16-day 250-m composite surface reflectance band imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS, https://modis.gsfc.nasa.gov/) product MCD13Q1. We used two surface reflectance bands that represent unclassified raw measures of vegetation structure and composition, used previously to represent vegetation patterns (Morán-Ordóñez *et al.* 2012; Shirley *et al.* 2013; Van doninck *et al.* 2020). Band 2 Near Infrared (NIR; 841-876 nm) represents leaf and canopy biomass, with Band 7 Short Wave Infrared (SWIR; 2105-2155 nm) related to senescent or old growth biomass (Shirley *et al.*

2013). All surface reflectance bands contain spectral reflectance values estimated by target at surface, calibrated with cloud detection and atmospheric corrections. Reflectance values are expressed as the ratio of reflected over incoming radiation, meaning reflectance can be measured between the values of zero and one. Absolute reflectance values of 3-4 indicate healthy vegetation (Huete *et al.* 2004).

Additionally, we used Enhanced Vegetation Index (EVI) processed using all four MODIS surface reflectance bands using the ‘spectralIndices’ function in the R package RStoolbox (Leutner *et al.* 2019). EVI ranges on a scale from -1 to 1, with positive values closer to 1 indicating dense, healthy vegetation, and negative values indicating low vegetation cover. EVI is an optimized vegetation index responsive to canopy structure variations and with improved sensitivity in areas of high biomass through reduction in background noise and atmospheric influences (Huete *et al.* 2002). We selected EVI due to its superior performance at capturing dense vegetation characteristics and canopy structure in tropical regions compared to other spectral indices such as Normalised Difference Vegetation Index (NDVI; Qiu *et al.* 2018), which tends to saturate in densely vegetated areas (Huete *et al.* 2002). We downloaded imagery corresponding to the start and end dates over the time period of each tracked eagle using the R package MODIStsp (Busetto & Ranghetti 2016) and calculated mean surface reflectance values over each respective time period to use in processing the covariates. All covariates used for each respective eagle had low collinearity with Variance Inflation Factors <2.

Resource Selection Functions

We thinned GPS fixes using a 250-m spatial filter (Table 1) to match the resolution of the covariate rasters and fitted presence points and the three covariates to individual RSFs following third-order home range resource selection (Johnson 1980). We defined a resource selection home range for each individual eagle by merging the 95% maximum likelihood AKDE with a 100% minimum convex polygon to fully capture the total potential home range and thus all the spatially filtered GPS fixes therein (Northrup *et al.* 2013). We fitted non-parametric RSFs where we only considered resource selection at presences using a point process intensity probability density function using the 'rhohat' function in the R package spatstat (Baddeley & Turner 2005). RSFs were fitted by computing a non-parametric kernel smoothing estimate of locations as a point process intensity function $\lambda(u)$ of the three spatial covariates over each respective eagles' home range window following the formulation of Baddeley *et al.* (2012),

$$\lambda(u) = \rho(Z(u))$$

where Z is the spatial covariate and $\rho(z)$ is the resource selection function to be estimated, with u representing location. We fitted Gaussian kernel densities with variable-bandwidth kernel smoothing using cross-validated bandwidth selection which assumes a Cox process for clustered data (Diggle 1985) and an isotropic edge correction for polygon windows derived from Ripley's K-function (Ripley 1988). Additionally, we corrected for sampling bias with Horvitz-Thompson weighting (Horvitz & Thompson 1952), where each GPS fix in the sample is weighted by the reciprocal of its sampling probability. We fitted all RSFs with 95% Confidence Intervals.

Results

Home Range Estimation

A total of 80,481 fixes were obtained from four adult females and two adult males from April 2013 to September 2021, 92% of which were from a single adult, male 005M (Table 1). From our bootstrapped MCP estimates, the number of relocations for all six adults was sufficient at capturing the MCP utilization distribution, ranging from asymptotes of 100 relocations for adult 003F to 1000 relocations for adult 005M (Supporting Online Information, Fig. S1). All six adults showed site fidelity with clear asymptotes ranging between two to 18 km continuous range residency behaviour after three to nine day short time lags and all less than one calendar month from tagging (except adult 006F which was less than two calendar months), supporting the application of home range analysis (Figs. 1 & 2).

The median 95% home range estimate from the weighted AKDEs was 68 km^2 (CI = 62-74 km^2), with the median 50% core home range estimate 13 km^2 (CI = 11-14 km^2), comprising 21% of the 95% home range area (Table 2, Fig. 3). Adult female 003F and adult male 005M had the smallest home range sizes (39 and 41 km^2 respectively), with adult female 006F having the largest home range size (161 km^2). The ratio of percent space use for the 50% core range within the 95% home range was generally consistent for all eagles between 19-24%, with a median of 21% (Table 2). Thus, adult Philippine Eagles on average are spending 79% of space-time use outside of core territorial areas.

Resource selection

From the non-parametric RSF response functions, all six adult eagles were associated with Band 2 Near Infrared values peaking between 0.34-0.39 (Fig. 4), indicating selection for dense, healthy leaf and forest canopy structure. Band 7 Shortwave Infrared values peaked between 0.07-0.14, indicating an association with areas of lower percent old growth biomass for all adults (Fig. 4). All six adults were more likely to be associated with EVI values between 0.35-0.55 (Fig. 4), indicating resource selection of moderately dense vegetation averaged over the annual vegetation growth cycle.

Discussion

Quantifying animal space use and habitat selection is fundamentally important in understanding the ecological processes influencing an individual animal's behaviour and movement (Hooten *et al.* 2017). Using a space-time home range estimator, our results demonstrate that adult Philippine Eagles on Mindanao have relatively small home ranges averaging 68 km^2, with 79% of space-time use outside of their core territorial range. Interestingly, our median AKDE home range estimate was smaller than a previous median estimate of 73 km^2 using a traditional KDE (Sutton *et al.* 2023). Additionally, most adults selected habitats high in photosynthetic leaf and canopy biomass but tended to avoid areas of old growth biomass and denser areas of vegetation, possibly due to extended foraging movements outside of densely forested nesting areas. Our results quantify two key fine-scale ecological processes that are useful for informing conservation management for this critically endangered raptor.

Home Range Estimation

Despite the relatively small home range estimates, there was wide variance in home range sizes for each individual eagle between 39-161 km^2 for the 95% home range and 6-33 km^2 for the 50% core range. Though we did not test this directly, we assume that high variance in home range estimates amongst individual eagles is driven by varying resource needs for each eagle across fragmented forest on Mindanao. Additionally, these differences could be sex-related, or due to breeding failure, with non-breeding adults possibly moving less when there is reduced pressure to find food to feed young. Tagging more eagles would confirm if these assumptions are consistent for the Philippine Eagle. Interestingly, all six eagles only spent on average a fifth of space-time within their respective core ranges. The most intensive space use was outside of these core areas within a wider home range, most likely spent searching for food or defending a territory. We suspect this is possibly driven due to the highly fragmented landscape across Mindanao, forcing eagles to spend long periods away from core nesting areas but this assumption would need further testing.

Previous home range estimates for the Philippine Eagle calculated median 95% home range sizes between 64-90 km^2 (Sutton *et al.* 2023), with a standard KDE estimating a slightly higher home range area (73 km^2) than our median estimate here of 68 km^2. These consistent estimates are not surprising because Sutton *et al.* (2023) used the same satellite telemetry dataset to calculate home range sizes but using a fixed Gaussian KDE, a radius LoCoH and a minimum convex polygon as estimators. Prior to these quantitative home range estimates, Rabor (1968) suggested a home range of 40-50 km^2 for the Philippine Eagle, lower than our median 95% estimate, with Gonzales (1968, 1971) suggesting up to 100 km^2, which are both within our range of individual 95% estimates. However, Kennedy (1977) calculated much lower home range sizes of between 13-25 km^2 based on polygon and circular estimates from observer sightings of a pair of breeding eagles within an approximately 5x5 km^2 area. Assuming these sightings were of a nesting territorial pair then they are remarkably similar to our median 50% core territorial range estimates.

Resource selection

Resource selection by animals will often give contrasting results related to issues of scale (Boyce 2006). Our results showed all eagles were associated with medium levels of Band 2 Near Infrared reflectance values, representing healthy photosynthetic leaf and canopy biomass but low Band 7 Shortwave Infrared values representing old growth forest, in contrast to a previous range-wide habitat use assessment (Sutton *et al.* 2023). Thus, solely using GPS fixes from the six adults captured the finer scale home range resource selection, which is generally outside of old growth forest areas. This is possibly related to adults foraging over secondary forest and cleared agricultural land (Kennedy 1977; Salvador & Ibañez 2006). These foraging areas are distant from nest sites which are generally within denser forested areas (Salvador & Ibañez 2006; Ibañez *et al.* 2003). This assumption is further supported by the general association with medium values of EVI, indicating most adults are using areas of canopy vegetation density between EVI values of 0.35-0.55 over the annual vegetation growth period (see Fig. 4).

Human-eagle conflicts are one of the key threats to the future survival of the Philippine Eagle (Ibañez *et al.* 2016). Due to the habitat preferences identified here for secondary forest and agricultural land, the likelihood of human-eagle encounters is high, which often results in death or severe injury for eagles. This is mainly through retaliatory trapping due to eagle predation on domestic animals, or accidental trapping in snares set by hunters. This is further exacerbated in secondary forest because these areas are often designated as buffers or multiple use zones in protected areas which may not offer the protection needed for Philippine Eagles. Previously, conservation priorities for the Philippine Eagle have been focused on protecting nest sites in densely forested areas (Sutton *et al.* 2023). However, whilst this is still important, we show that adult eagles spend 79% of space-time outside of core nesting areas in human fragmented landscapes. We recommend that promoting eagle-friendly lifestyles within forest communities as part of area-based conservation is also necessary at nest sites located in secondary forest, along with community incentives to reduce human-eagle conflict (Ibañez *et al.* 2016).

We recognise there are limitations to our inferences due to the low sample size of individual eagles tagged. However, the financing of expensive GPS telemetry devices, along with capturing adult eagles in rugged and remote tropical forest terrain is non-trivial. Tagging more adult eagles, including beyond Mindanao, would allow further interpretation of fine-scale movement patterns and habitat selection across the Philippine Eagle range. We also recognise the large differences in the number of GPS fixes between adults and the subsequent potential bias in our results. However, all our sample sizes were within the range deemed suitable for estimating home range size (Bekoff & Mech 1984; Seaman *et al.* 1999) and resource selection (Northrup *et al.* 2013). The disparity between GPS location sample size is largely due to tagged adults being deliberately killed (Ibañez *et al.* 2016), or tags failing. There is little we can do about this in the context of the current study. However, accounting for these disparities in sample size, rates, and intervals using methods such as AKDE, whilst improving GPS device setting protocols, can remedy these issues for home range estimation.

The use of modern satellite tracking devices, combined with environmental data derived from satellite remote sensing has revolutionized our collective understanding of animal movement ecology and resource selection (Seidel *et al.* 2018). Building on the analyses here by incorporating movement models using either Hidden Markov models (HMMs; Langrock *et al.* 2012) or integrated Step-Selection Functions (iSSFs; Avgar *et al.* 2016), would further identify the drivers of Philippine Eagle space and resource selection from latent behavioural states and movement patterns. Rather than using traditional home range estimators, we implemented a robust space-time estimator, along with easily interpretable resource selection functions to assess fine-scale spatial processes. This allowed us to accommodate variation in space and resource selection across individual eagles to help inform conservation management. We recommend that analysts consider various statistical approaches to animal movement data to fully explore space-time and resource selection, ensuring that model outputs are interpretable to conservation managers and practitioners.

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Data Accessibility Statement

The data that support the findings of this study are openly available on the data repository *figshare* https://figshare.com/account/articles/21029380

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Tables

Table 1. Global Positioning System (GPS) telemetry metadata for six satellite tagged adult Philippine Eagles from the island of Mindanao, used for home range estimation. Totals for 250m fixes are the number of spatially thinned fixes using a 250m spatial filter.

ID	Sex	From	To	Raw fixes	250m fixes
001F	Female	16/02/2014	10/05/2015	1487	290
002F	Female	22/12/2014	20/01/2016	1370	311
003F	Female	11/04/2013	19/02/2014	263	138
004M	Male	19/04/2014	05/08/2014	240	144
005M	Male	17/11/2019	12/09/2021	74098	822

006F	Female	15/10/2019	05/06/2021	3023	444
Total				80481	

Table 2. Autocorrelated kernel density estimates (AKDE) for six adult Philippine Eagles on the island of Mindanao. Estimates calculate 95% probability of use contour isopleths to represent the home range utilization distribution and 50% probability of use contour isopleths to represent a core range utilization distribution with 95% Confidence Intervals (CI). All area values in the 95% and 50% columns are km^2.

	Autocorrelated KDE		
ID	95% (CI)	50% (CI)	% core
001F	64 (59-70)	12 (11-13)	19
002F	71 (64-78)	13 (12-14)	18
003F	39 (33-45)	9 (8-11)	24
004M	108 (85-133)	24 (18-29)	22
005M	41 (37-46)	9 (8-10)	22
006F	161 (133-192)	33 (28-40)	21
Median	68 (62-74)	13 (11-14)	21

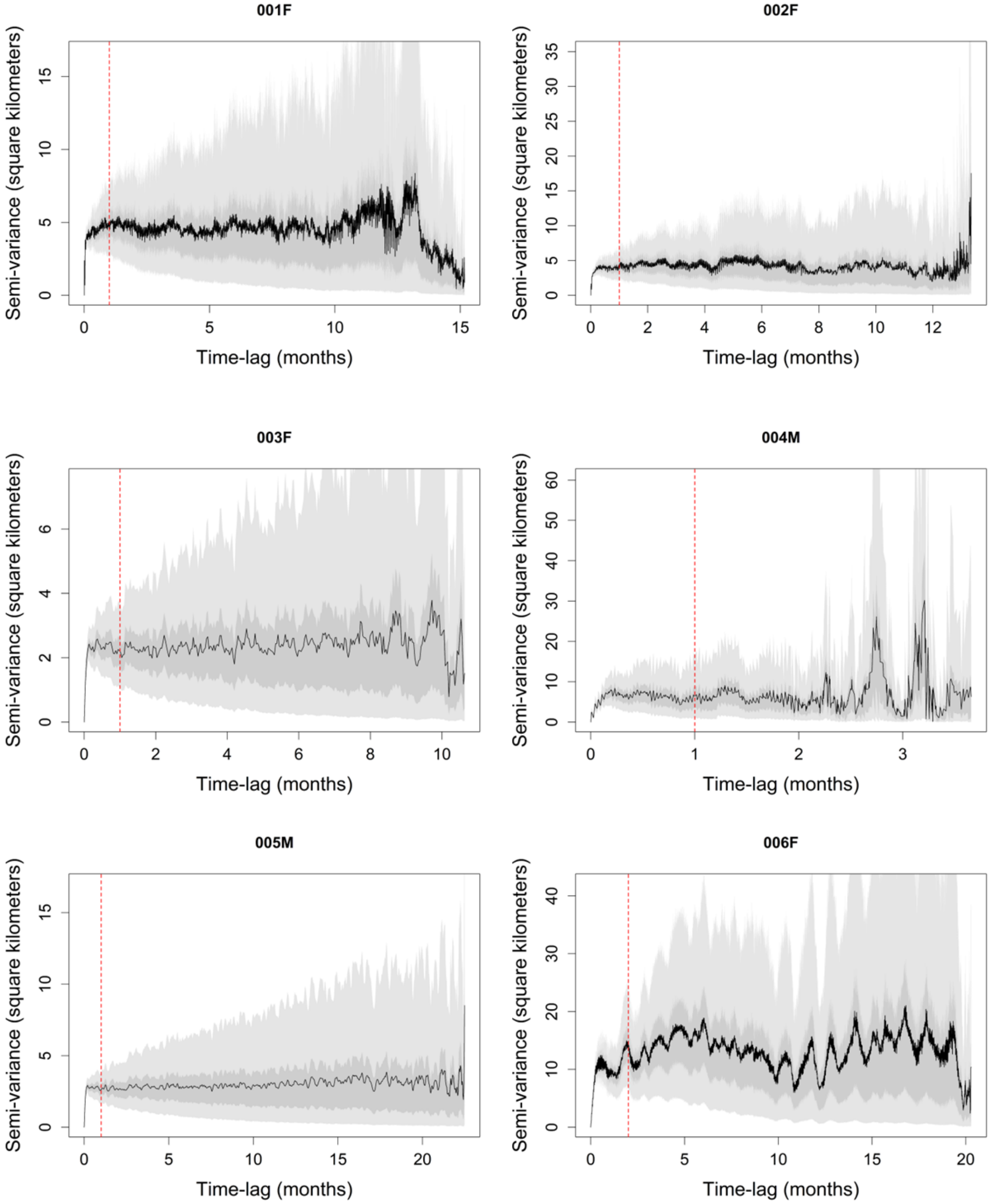

Figure 1. Range residency tests calculated over the entire sampling period for six adult Philippine Eagles on the island of Mindanao using semi-variance functions visualised with empirical variograms to identify unbiased estimates of stationary movement periods of site fidelity. Red vertical line

indicates range residency asymptote with Markovian Confidence Intervals for calculating the maximum number of non-overlapping lags.

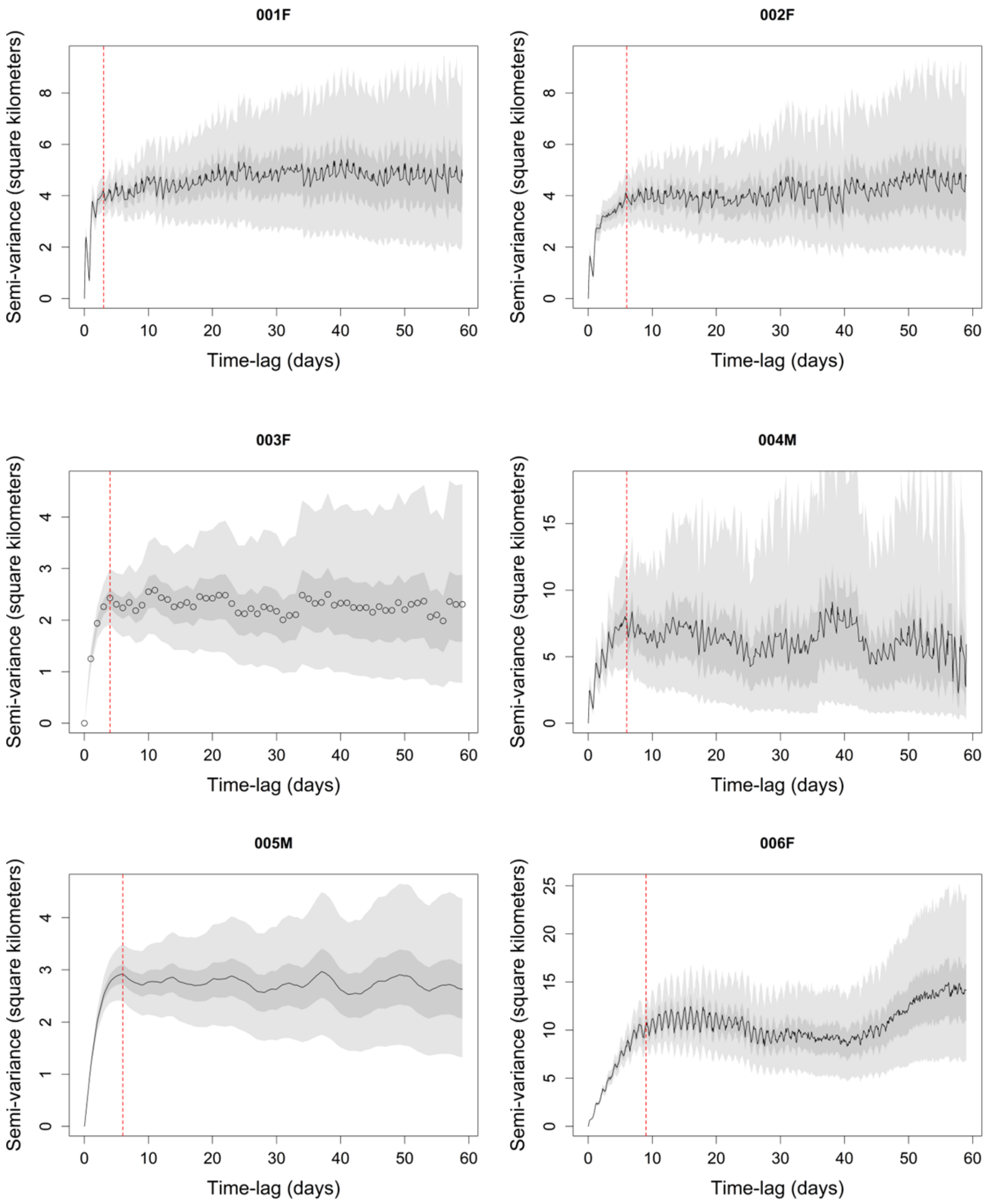

Figure 2. Range residency tests calculated over a 60-day sampling period for six adult Philippine Eagles on the island of Mindanao using semi-variance functions visualised with empirical variograms to identify unbiased estimates of stationary movement periods of site fidelity. Red vertical line

indicates range residency asymptote with Markovian Confidence Intervals for calculating the maximum number of non-overlapping lags.

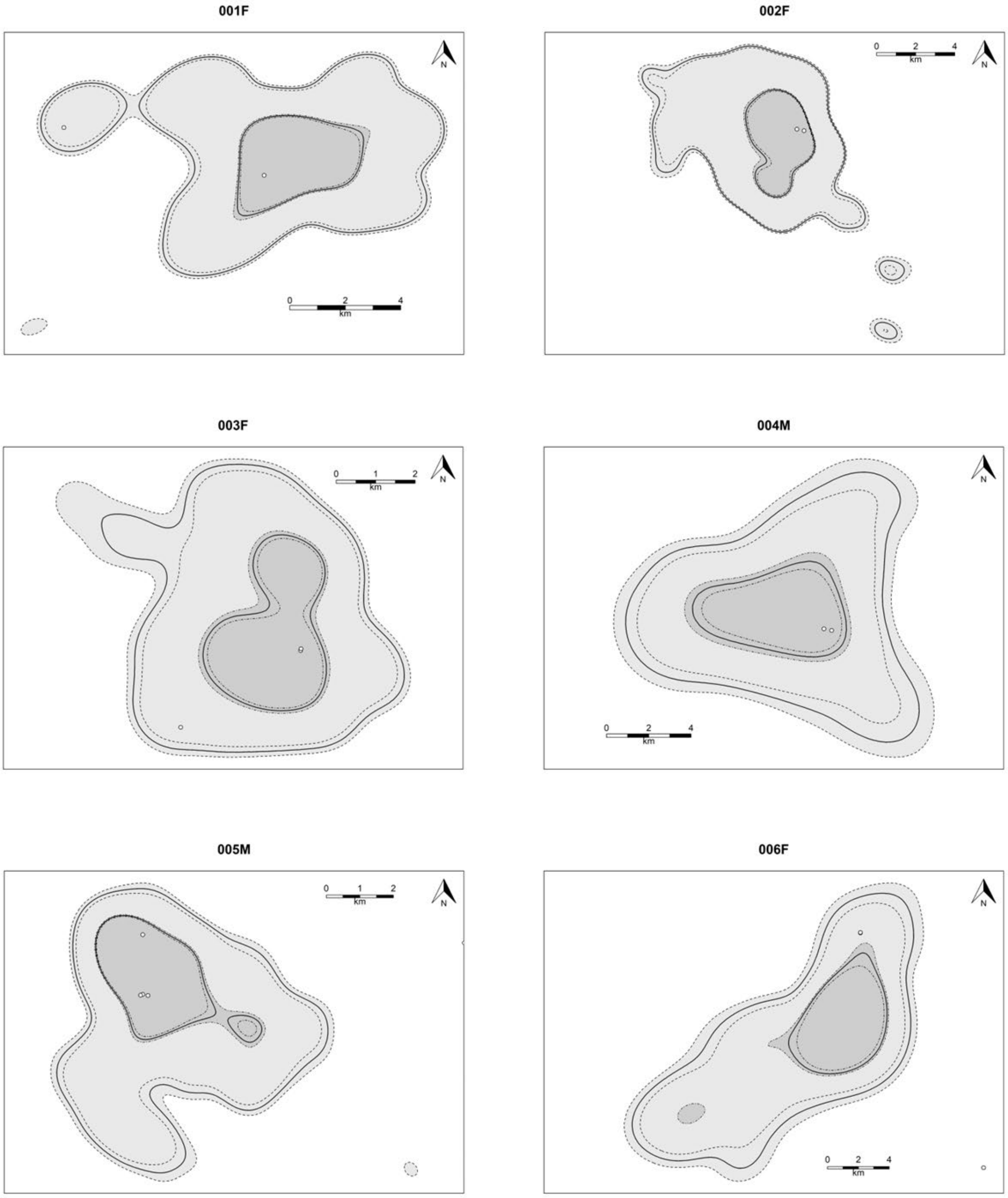

Figure 3. Autocorrelated kernel density estimates (AKDE) for six adult Philippine Eagles on the island of Mindanao. Maximum likelihood estimates (bold black lines) calculate 95% probability of use (light grey) to represent the home range utilization distribution and 50% probability of use (dark grey) to represent a core range utilization distribution. Hashed lines show 95% Confidence Intervals for both

home and core range maximum likelihood estimates. White points indicate nest sites. GPS fixes omitted for clarity but see Figure S2 in Supporting Online Information for replicate figure with raw fixes included.

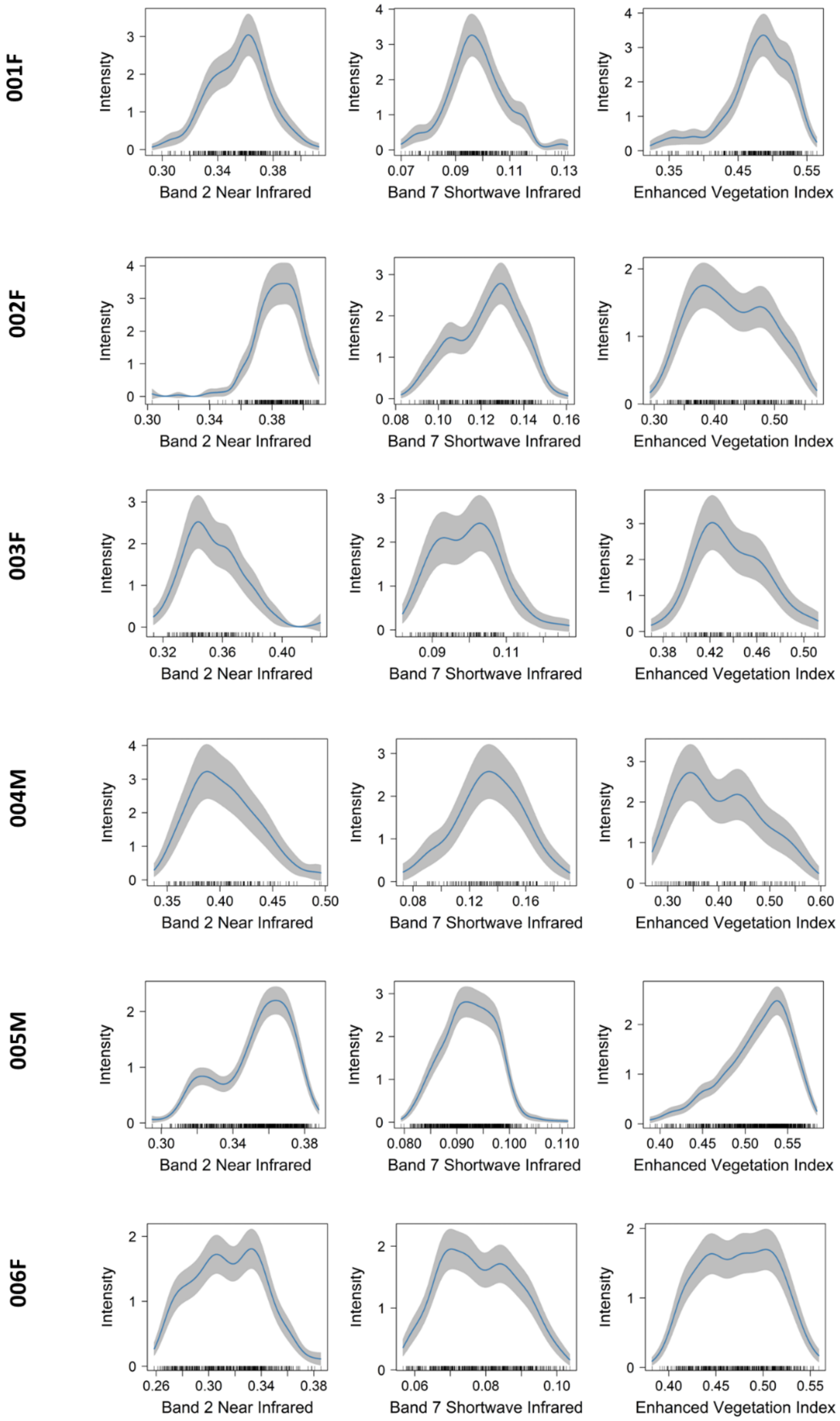

Figure 4. Non-parametric resource selection response curves (blue lines) using point process intensity probability density functions for six adult Philippine Eagles on the island of Mindanao. Grey shading represents 95% Confidence Intervals.