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METHODOLOGY

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Very small collars: an evaluation of telemetry location estimators for small mammals

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Abstract

Background: Fine-scale tracking of animals such as *Peromyscus* spp. is still done with micro-very high frequency collars due to the animal's small size and habitat usage. In most cases, tracking micro-very high frequency collars requires manual telemetry, yet throughout the literature, there is little reporting of individual telemetry methods or error reporting for small mammal spatial analyses. Unfortunately, there is even less documentation and consensus on the best programs used to calculate fine-scale animal locations from compass azimuths. In this study, we present a strategy for collecting fine-scale spatial data on *Peromyscus* spp. as a model species for micro-very high frequency collars and assess multiple programmatic options and issues when calculating telemetry locations.

Results: Mice were trapped from April to October 2018–2019 with Sherman traps in Howard County, Maryland, USA. Collars were placed on 61 mice, of which 31 were included in the analyses. We compared the two most cited location estimator programs in the literature, location of a signal software and Locate III, as well as the Sigloc package in program R. To assess the programmatic estimates of coordinates at a fine scale and examine programmatic impacts on different analyses, we created and compared minimum convex polygon and kernel density estimator home ranges from locations produced by each program. We found that 95% minimum convex polygon home range size significantly differed across all programs. However, we found more similarities in estimates across calculations of core home ranges. Kernel density estimator home ranges had similar patterns as the minimum convex polygon home ranges with significant differences in home range size for 95% and 50% contours. These differences likely resulted from different inclusion requirements of bearings for each program.

Conclusions: This study highlights how different location estimator programs could change the results of a small mammal study and emphasizes the need to calculate telemetry error and meticulously document the specific inputs and settings of the location estimator.

Keywords: Home range, LOAS, Locate III, Location estimators, *Peromyscus leucopus*, Radio collar, Sigloc, Small mammal, Telemetry, Triangulation

Background

Analyses of wildlife home range patterns, movement patterns, and habitat use can address many different research questions and include analyses addressing basic animal ecology questions, conservation driven questions, or furthering the understanding of zoonotic disease ecology. These types of spatial analyses have become a large component of wildlife research because of the analytical ability to robustly address specific biological questions. Yet, the technology to track very small mammals has lagged, especially in urban and suburban areas. Small mammal studies are showing that past rudimentary methods of assessing habitat use were not accurate and better habitat analyses are needed for reintroductions and habitat management of critically threatened

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species [1, 2]. Additionally, small mammals play a major role in zoonotic disease ecology. For example, Lyme disease (caused by the etiological agent *Borrelia burgdorferi*) is the most common vector-borne disease and the sixth most common infectious disease in the United States [3]. White-footed mice (*Peromyscus leucopus*) are the main reservoir host for *B. burgdorferi* in the eastern United States [4]. To reduce the risk of tick-borne diseases, integrated pest management (IPM) studies are now focusing on host species ecology, and a recent study found that host species in suburban and urban environments have a great impact on tick density, infection prevalence, and connectivity of tick populations [5]. So, to manage the risk of tick-borne diseases in more urban areas, there is a need to explore the fine-scale movements of white-footed mice as they relate to areas of high human use or baited tick treatment devices [6].

Generally, the two common tracking technologies to gather needed terrestrial locational data are very high frequency (VHF) and Global Positioning System (GPS) trackers [7–14]. The newer, more advanced GPS trackers are efficient and accurate for medium and large mammals, and there have been some recent studies using smaller GPS trackers for smaller medium-sized mammals, like feral cats or hares [15–17]. As technology increases, we expect to see future increasing effectiveness, but GPS technology for very small mammals is still significantly limited because of collar weight or the inability to produce a recordable signal [7, 8, 12, 15, 16, 18–24]. Additionally, urban and highly suburban landscapes present specific challenges for GPS related to significant sky view interference, excessive signal reflection or rebounding, and signal disruption [12, 25, 26].

Over the last decade, researchers have continued to develop radio telemetry equipment for small mammals, and VHF collars remain a cost effective, preferred method of collecting locational information on small mammals that were under heavy forest canopies, burrow underground, or spend any time underwater [12, 27]. Recent advances in micro-VHF trackers (< 1.0 g) are enabling more accurate estimates of small mammal movements, resource selection, seasonal effects, territorial behaviors, and microhabitat use [27–32]. While these advancements in micro-VHF trackers are enabling us to address ecology and management needs of small mammals, there remain considerable limitations in tracking methodology for micro-VHF devices. Given the lag in GPS miniaturization, currently there are two primary methods of data collection from the micro-VHF trackers for small mammals: fixed, automated stations and manual triangulation via a simple, directional Yagi-Uda antenna and compass [14, 19, 27, 28, 30, 33, 34]. Unfortunately, while fixed, automated radio telemetry stations allow for increased data collection and reduce human interference with animal movements in the field, they are typically not viable in urban or highly suburban settings because of VHF signal interference in strength, directionality, and signal reflection or rebounding [35–38]. The remaining option is manual VHF telemetry. Manual telemetry is labor intensive, has higher error rates, experiences signal reflection, is impacted by vegetation cover and electromagnetic interference, among other issues [13, 14, 39]. Additionally, manual VHF limits the number of locations a researcher can obtain, which limits analysis options, as opposed to GPS that typically collects > 1000 + locations per animal [9]. Most importantly, the current biotelemetry literature lacks documentation, standardization, or guidance on telemetry for micro-VHF devices, and there is no consensus on the method of estimation of the actual geographic locations. This is especially glaring for telemetry done in urban or suburban environments.

When researchers collect home range and movement information on small mammals, they typically conduct manual triangulation during peak activity by a sole researcher or a small field research team [19, 29, 30, 33, 40]. The collection of bearings requires the calculation of geographic coordinates. The literature cites multiple ways to analyze azimuth data, but there is variation in method and inconsistency in reporting of methods of estimation, treatment of outliers, and the use of error polygons [16, 39]. In our search for current estimation programs, Location of a Signal (LOAS; Ecological Software Solutions LLC, Sacramento, California, USA), Locate III (Version 3.34, Pacer Computing, Tatamagouche, Nova Scotia, Canada), and the Sigloc package in program R [41, 42] were commonly cited and allowed for location estimates that could calculate a single or average location from different estimation procedures including Maximum Likelihood Estimation, and other common methods such as Andrews, Huber's, and Tukey Arithmetic Mean [43–45]. While these commercial and publicly available programs make estimating locations more simple for researchers, the programs and specific settings selected within those programs, along with telemetry error rates, have been recognized as underreported yet highly impactful [13, 26, 46]. Given the relative ease of use of these programs and the increasing ability to track small mammals using micro-VHF collars, the lack of documented setting selections and error reporting is significant because error polygon creation and exact XY locations could not be equivalent across programs [13, 17, 25], and small amounts of variation could lead to erroneous conclusions. More specifically, there is a significant lack of information on (1) standardized methodologies for collaring and tracking small mammals when geographic coordinates are the goal; (2) bearing error collection, calculation, and use in location estimation, and (3) specific location estimators and selected program input settings.

We studied white-footed mice, which are easy to capture, have large, sustainable populations, cover numerous types of habitat, and have major implications in vector-borne disease ecology. So, in this case study, we outlined a standardized, highly coordinated tracking technique for very small mammals. Then, we analyzed the performance of three radio telemetry location estimator programs by comparing the resulting sets of XY locations and the home ranges those points created based on program default settings. Finally, we investigated how different estimator programs could influence simple, example downstream analyses. These analyses tested the hypothesis that the specific estimator program selected could significantly impact a studies' findings. Our analyses also met our general objectives of providing a reference for collaring and telemetry methodology for urbanized study areas and establishing guidance on location estimator program documentation and selection for future researchers.

Methods

Study area

This study was conducted in Howard County, Maryland, USA. Howard County is in the Piedmont region of Maryland and received average annual precipitation of 116.6 cm [47, 48]. Howard County is currently a mixed hardwood forest dominated by oak/hickory [47, 49]. The total 2019 population for Howard County was estimated to be 325,690 persons [50]. More specifically, this study was conducted within a fragmented suburban/urban county park in Howard County, Maryland: Blandair Regional Park (60.7 ha). Blandair Regional Park (Blandair) had a substantial number of single-family homes bordering the park boundary and fell within the defined highly suburban landscape of the Howard County metropolitan zone [51, 52]. Blandair consisted of very small grasslands with a developing forest and some historical buildings. Dominant plant species within the park consisted of autumn olive [*Elaeagnus umbellate*], black cherry [*Prunus serotina*], black walnut [*Juglans nigra*], grapevines [*Vitis* spp.], Japanese stiltgrass [*Microstegium vimineum*], mile-a-minute [*Persicaria perfoliate*], oaks [*Quercus* spp] and wine berry [*Rubis* spp.].

Trapping

Small mammal trapping occurred from April to October in both 2018 and 2019. We randomly located two trapping grids in Blandair park along homeowner's lawn/forest edge specifically for conducting mouse telemetry. Our focal species was *Peromyscus leucopus* (white-footed mice). Within Maryland, white-footed mice are one of the most abundant species, and we used morphologic characteristics to distinguish between other species [53, 54]. Within each individual trapping grid, the transects ($n = 6$) were spaced 15 m apart (Fig. 1). Individual trap placement on each transect (6 traps per transect) started from the homeowner's lawn/forest edge and moved into the forest interior. Therefore, each trapping grid consisted of 36 traps for a total of 72 traps in Blandair. Trap locations were recorded with a Garmin GPSMAP 64ST Handheld GPS unit (Olathe, Kansas, USA) and marked with tree flagging and a numbered ground flag. Sherman live traps (3 × 3.5x9″, H. B. Sherman Traps, Inc. Tallahassee, FL, USA) were baited with apples and a mixture of peanut butter, nuts, and rolled oats. To minimize stress and exposure of captured small mammals, traps were set after 3 pm and checked a half-hour before sunrise [55]. Mice were transferred to a clean clear bell jar that contained Isoflurane-soaked cotton balls in a separated chamber, approximating a dosage of 0.08–2.5%mg/kg [56]. Breathing rate was monitored for reduction by 50% from pre-anesthesia levels (80–100 breaths/min) [56, 57].

Collaring methods

Only mice weighing > 17 g were considered for collaring to ensure collars weighed ≤ 5% of body mass [14]. Mice were collared with Holohil Systems Ltd model BD-2XC VHF collars. The micro-VHF Collars were distributed with the goal of tracking two mice at each trap distance interval, regardless of sex. Additional

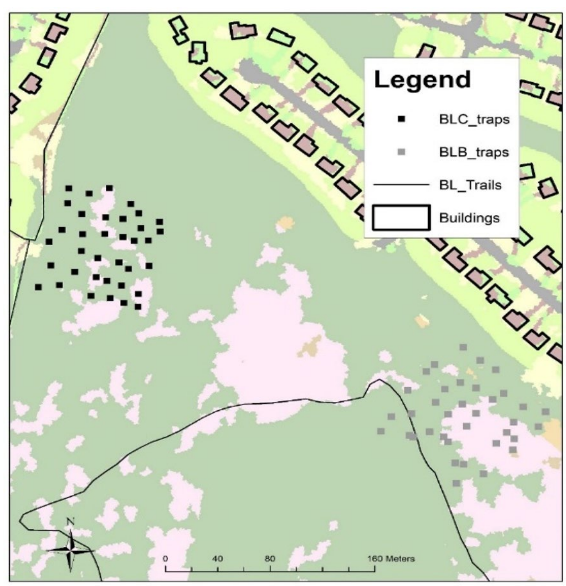

Fig. 1 Mouse trapping grids at Blandair Regional Park, Howard county, Maryland, USA, 2018–2019

collars were placed as appropriately sized mice were captured (Fig. 2). Given the small, often overlapping home range size of mice, collars were at least 0.40 MHz apart. The strap of each mouse collar was modified to a braided fiber fishing line that fit through flexible plastic tubing (Attachment Instructions, Holohil systems Ltd, Ontario, Canada). In total, the micro-VHF collars weighed 0.75 g and the estimated battery life was approximately 10 weeks.

When fitting collars, first, cotton yarn was used to measure the specific circumference of the mouse's neck. Then, the collar's length was trimmed to fit the specific mouse, and the antenna was wrapped through the plastic tubing to ensure a strong signal. The collar was put on the mouse and tightened to allow for limited rotation around the neck, but loose enough to have movement. The collar was able to rotate but not loose enough to allow the mouse to chew the antenna or slide a leg through the collar. Technicians made careful note of the mouse's general eye appearance before and after being collared, specifically noting any bulging of the eyes, which typically indicated an overly tight collar (Fig. 2). Once the collar had a proper fit, a crimp bead was used to secure the collar strap at the determined size (Holohil systems Ltd, Ontario, Canada). Finally, the magnet was removed, and the VHF signal was checked. Mice were placed in a mesh enclosure with extra cotton, bait, and a hand warmer to recover for up to 20 min to ensure no negative reaction to the collar. Mice that were lively and not focused on the collar were released back in the original trapping location. Mice that were hyper-focused on the collar had their collar removed and were released at the original trapping location.

Telemetry

Before collaring mice, technicians listened to collars from varying distances until the signal was consistently not detected to determine general signal strength. This allowed for the creation of a dimensional area around where mice were collared that ensured hearing the VHF signal while limiting disturbance of mice. After collaring, mice were tracked for approximately 6 weeks from May to July and again from August to October in both 2018 and 2019. Each week, nightly telemetry was done at each trapping grid, allowing each individual mouse to be tracked for ≥ 3 nights over each 6-week period. To ensure capture of large foraging movements of mice each night, telemetry started one hour before civil sunset. Each telemetry session lasted approximately 5 h from dusk until midnight. Telemetry entailed three or more technicians working in conjunction standing at fixed corners of the grid (100×100 m square). When in their consistent, initial position outside of the trapping grids, which was GPS recorded, they used synchronized stopwatches and recorded bearing angles for all mice in sequential order by mouse radio frequency. This process was initiated in 40-min intervals. During each interval, ≥ 3 bearings were obtained for each mouse within the plot. Although rare, if a mouse within the plot was not able to be detected, a technician would shift halfway down (50 m) the length of the telemetry transect and again attempt to collect locations on the missing collar. Telemetry was concluded

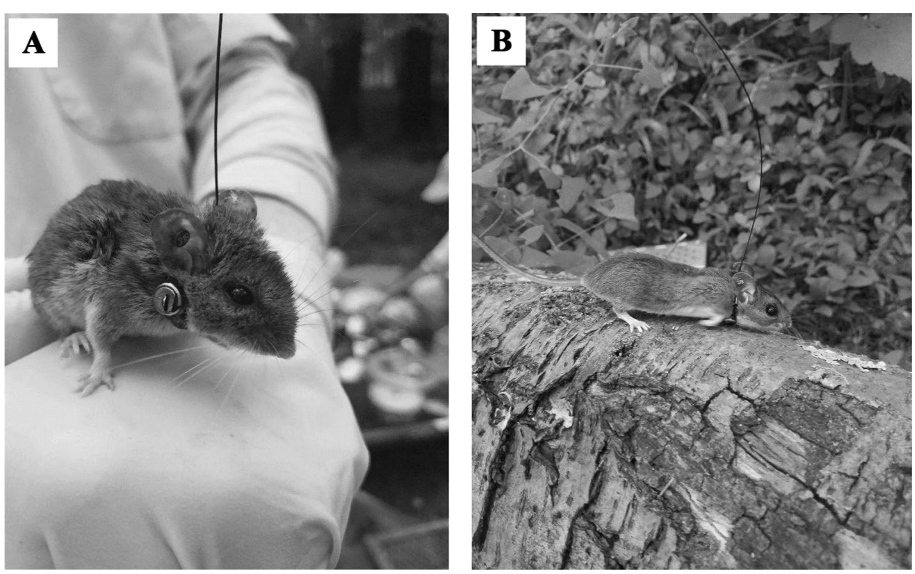

Fig. 2 Proper mouse collar fit with normal appearances of eyes as seen in **A** and typical mouse movements (**B**)

each night when we noted the obvious decrease or end of major movements via consistent bearing angles over one 40-min interval. After the 6 weeks of tracking concluded, recovery of all collars was attempted.

To assess technician telemetry accuracy, 5 mouse collars were hidden in randomly selected general areas and specifically placed in areas that mice might regularly inhabit such as downed woody debris, buried in leaf litter, or in tree cavities. The location of the error collars was recorded to within ≤ 2 m accuracy via GPS. Technicians were directed to within approximately 100 m of the hidden collar and asked to perform triangulation. The 10 technicians triangulated ≤ 5 collar locations, depending on their work schedule. To calculate the technician error, error polygons were created by creating waypoints (points) and bearings (polylines) using ArcGIS® Distance and Direction Editor Tool, and the centroid of the resulting polygon was calculated using ArcGIS® Calculate Geometry tool [58]. The error was recorded as the distance from the centroid of the error polygon to the true collar location. The weighted average of all telemetry error measurements was considered the measurement of telemetry bias or accuracy; weights were based on the frequency of telemetry performance by each technician. Then, differences in the bearing angles recorded by the technician versus the bearings that would have produced the exact true collar location were back-calculated using ArcGIS® Distance and Direction Editor Tool. Those angles represented the precision of the telemetry error of this study.

Location comparisons

We calculated locations from bearings in LOAS, Locate III, and the Sigloc package. LOAS and Locate III are stand-alone commercial programs and the Sigloc package, along with all other statistical analyses, were run in program R [42]. Given the almost complete lack of reported project-specific error and programmatic settings in the literature, we assumed that most researchers let the program estimate the error rate. Furthermore, many researchers created error polygons around estimated points after calculation, and incorporating errors across programs was not equivalent. For example, LOAS allowed error to be input and created different outputs, Sigloc-R required creation of unique code to incorporate error, and LOCATE was unclear how it was incorporating the only error it allowed for, bearing error. So, for initial comparisons, we did not adjust the default setting, no adjustment, for bias error and accuracy error within the programs. All three programs created confidence ellipses for each location. However, they are not ever accounted for in the literature, nor are they comparable to a manual error polygon, which has no firm statistical error estimate.

The only other setting that was an option to adjust was the output file type and the actual estimator. For all programs, we chose the Maximum Likelihood Estimator (MLE) as the location estimator given its popularity in the literature [14, 59, 60]. MLE is a statistical inference method, in this case an optimization method of estimating the location, that maximizes a likelihood function so that the observed data are most probable [59, 60]. MLE is widely used because the estimation method is repeatable and produces nearly optimal inference [23, 39, 61–63]. However, MLE can be sensitive to outlier bearing error, caused by issues like signal rebounding [13, 14, 59]. So, the three programs were comparable in all metrics that the user could control. For a mouse or its locations to be included in further analyses, we selected only mice that had ≥ 3 complete nights of telemetry data. Locations produced from all programs were visually evaluated in ArcGIS®. Any obvious outlier locations, such as a single point that fell significantly beyond the trapping grid (> 200 m), were assumed a recording error and assessed for input error and considered for removal. Individual mice were considered for exclusion if their predicted home ranges were nonsensical in size ($> 10{,}000 m^2$) [29, 57, 64–67] or more than one program failed to converge.

Several comparisons were made to assess the default program performance in a known situation. Using the known "true" locations, the original bearings for all test collars were input in LOAS, Locate III, and Sigloc, creating three sets of locations of the test collars. Then, the distance between the program outputs and the known collar locations was calculated. Next, we calculated the difference between the manual calculations of the centroids of the technicians' error polygons to the actual program estimates. Then, to better assess the magnitude of impacts of bias and precision issues, we input back-corrected, now "perfect", bearings for the known collar locations from one random set of waypoints for each technician into each program. Three sets of corrected locations were produced. The distance between those back-corrected outputs and the known collars was calculated. Finally, beyond the descriptive statistics calculated, we compared all outputs with Friedman tests.

Home range comparisons

Using the actual mouse data, a home range was created for each mouse using the three sets of geographic locations produced by each program. We did this using two different functions in the adehabitatHR package in Program R [68]. First, 95% and 50% Minimum Convex Polygon (MCP) home ranges were created because they are still a commonly reported home range approximation in the small mammal literature [28, 33, 65]. However, due to the advancement in home range analytics, we also create 95% and 50% kernel density estimates (KDE) for comparison of basic, downstream analyses [69, 70]. The KDE reference bandwidth (href) was selected as the most basic bandwidth based on the total lack of reporting of bandwidths used for very small mammals and to maximize the convergence of more limited data [70]. We tested home ranges individually as well as on average.

Based on the complex ecology of tick-borne diseases, differences in mouse home range size or shape and different preferences for yards, trails, or interior forest may influence the usage of rodent-targeted IPM devices and their placement. Given that knowledge, we first tested for simple differences in average home range size (for both MCP and KDE) using Friedman tests. Then, we analyzed differences in average home range size between pairs of programs using Wilcoxon sign-rank tests (for both MCP and KDE). Next, we calculated perimeter-to-area ratios, overlap, and land cover makeup for the KDE home ranges. Then we used a Levene's test to understand the variability in the perimeter-to-area ratios between pairs of programs. Finally, we compared the land cover categories that each program identified for the composite KDE home ranges using Friedman tests. Shapiro–Wilk tests and all other statistical tests were conducted in program R. Spatial GIS data came from the high-resolution 2013–2014 Chesapeake Bay watershed land cover dataset (1 m resolution) [71]. All spatial calculations were done in ArcGIS® [58]. Generally, values were found to be non-normal, so non-parametric tests were used along with a significance threshold of alpha = 0.05.

Results

Trapping

Overall, there were 4,896 traps set between 2018–2019. There were 239 captures of 165 unique individuals. Of the 165 individuals captured, 77 were appropriately sized to receive a collar (49 males and 28 females). Sixteen mice were predated almost immediately, leaving 61 mice (40 males and 21 females) with > 1 season worth of telemetry data.

Telemetry

From fall of 2018 through spring of 2019, 10 technicians located ≤ 5 different known collar locations, depending on time of employment, for a total of 43 full sets of bearings. The mean error distance from a known location collar was 6.59 ± 2.7 m. The mean bearing error was 13 ± 3.18 degrees from the true bearing. Of the 61 mice tracked at Blandair Park between 2018 and 2019, only 31 [(2018: $n = 18$, 11 m:7f) and (2019: $n = 13$, 8 m:5f)] met the inclusion criteria for the programmatic comparisons (≥ 3 complete nights of telemetry data). For those 31 mice, 5,835 unique bearings were recorded that could have resulted in 1,945 locations. However, each estimator produced a different number of gross locations, with the Sigloc package producing almost double the other programs (Sigloc = 1,745, Locate III = 968, LOAS = 984).

Interestingly, the distance from known collars to the ArcGIS® calculated centroid of the technicians' error polygon was the shortest (6.59 ± 2.70 m, Table 1), and Sigloc produced locations the furthest mean distance away (9.1 ± 7.50 m, Table 1). No one program produced locations significantly further than another from the true locations for the three programs ($X^2_3 = 1.33$, $P = 0.69$). When technician bearings were corrected, the programs performed very well and were extremely similar (Table 1), and there was no significant difference between corrected predictions across programs ($X^2_2 = 0.48$, $P = 0.79$). Finally, as expected, the Wilcoxon sign-rank tests indicated there were differences between the paired uncorrected and corrected programs' distances from the test collars (LOAS: $W_1 = 45$, $P = 0.004$; Locate III: $W_1 = 45$, $P = 0.004$; and Sigloc: $W_1 = 36$, $P = 0.008$).

Home ranges comparisons

One mouse was removed from all analyses because its MCP and KDE home ranges produced extraordinarily

Table 1 Distances between the known location of a collar and its predicted, manual, and back-corrected error polygon centroids

Comparison	*N*	Min	Median	Max	Mean	SD
Known versus ArcGIS® Centroid	39	1.70	6.30	12.10	6.59	2.70
Known versus LOAS	43	1.30	5.40	28.90	7.80	6.06
Known versus Locate III	42	1.30	5.85	29.50	7.90	6.13
Known versus Sigloc	41	1.10	7.20	34.80	9.10	7.50
Known versus corrected LOAS	10	0.02	0.07	0.42	0.15	0.15
Known versus corrected Locate III	10	0.02	0.08	0.42	0.15	0.15
Known versus corrected Sigloc	10	0.02	0.09	0.42	0.16	0.15

large area estimates for both Sigloc in program R (83,733,335m^2) and Locate III (4,736,553m^2). One additional mouse was removed from any calculations for program Locate III because of failed convergence. Calculations of mouse home range size varied widely between the three programs, ranging from an average 95% MCP of 1747m^2 to 19,667 m^2 (Fig. 3, Additional File 1). For 95% KDE the range was 7121m^2 to 37,640m^2 (Fig. 3, Additional File 2). However, the amount of variation or spread in home range sizes for a specific program, regardless of method or 95% versus 50%, did not differ (all p-values > 0.38). When average home range sizes were compared, all 3 programs differed at the 95% and 50% MCP and KDE home range levels (Table 2). When grouped by sex, home range areas were significantly different across the programs at both scales (Table 2), and paired Wilcoxon sign-rank tests supported differences between all groups (Table 3). Descriptive statistics on area of overlap indicated some shared space differed across programs (Additional File 3).

Overlap of the average 95% MCPs was significantly different ($X^2{}_2 = 38.35$, $P < 0.001$), but the overlap of the 50% MCPs was not significantly different ($X^2{}_2 = 3.09$, $P = 0.21$). Average KDE home ranges at both contour levels were found to be significantly different in terms of overlap (95%: $X^2{}_2 = 20.63$, $P < 0.0001$; 50%: $X^2{}_2 = 29.24$,

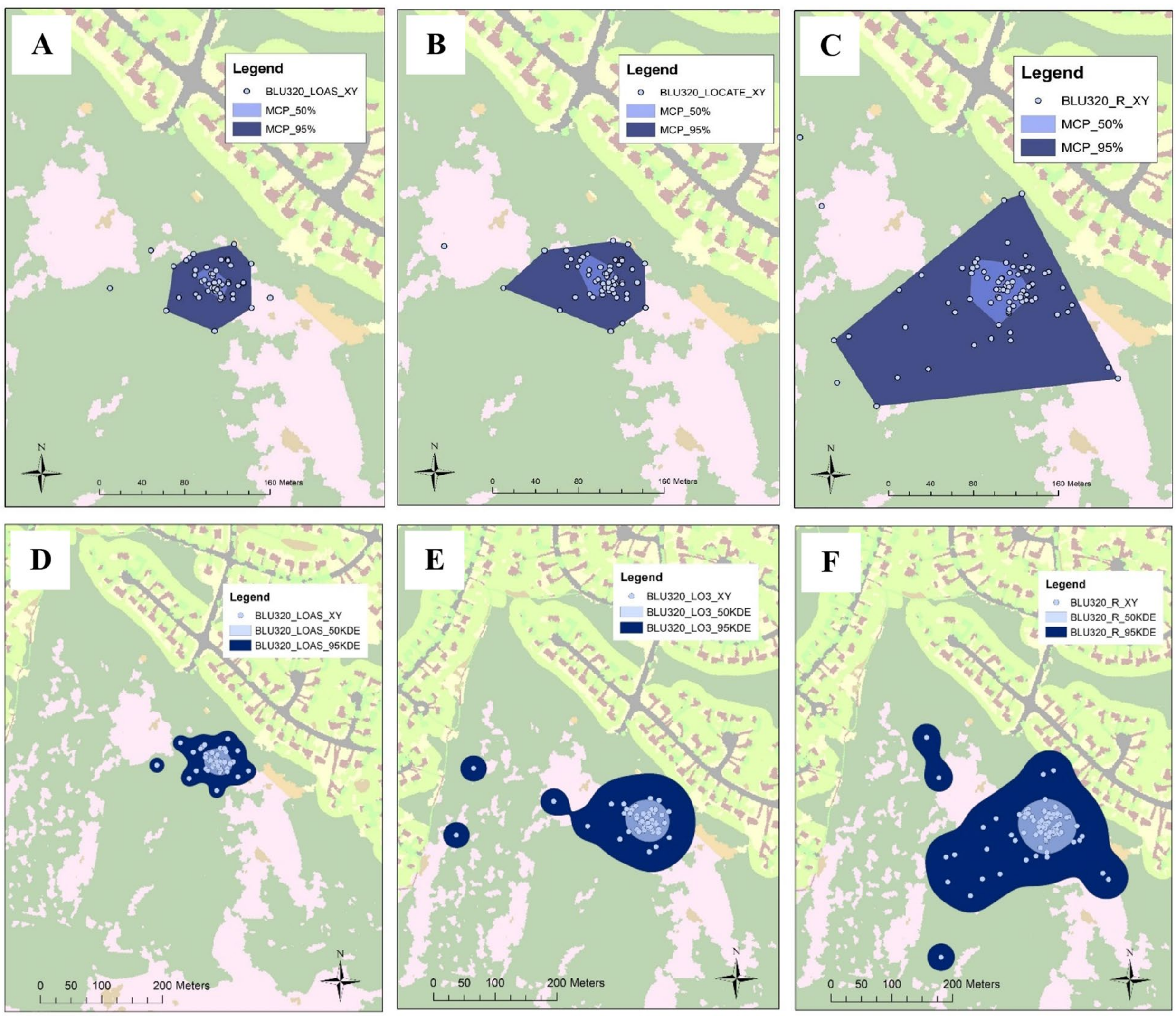

Fig. 3 Minimum convex polygon (MCP) and kernel density estimator (KDE) home ranges for an example mouse BLU320 calculated by three different estimator programs (MCP-LOAS [**A**], MCP-LOCATE III [**B**], MCP-program R Sigloc [**C**], KDE-LOAS [**D**], KDE-LOCATE III [**E**], and KDE-program R Sigloc [**F**])

Table 2 Minimum convex polygon (MCP) and kernel density estimator (KDE) home range size (m^2) compared across three location estimator programs (LOAS, Locate III, and Sigloc) for the same mice ($n = 31$) using the Friedman test

Home range	X^2	d.f	P
MCP—all			
95% MCP	46.40	2	< 0.001
50% MCP	30.89	2	< 0.001
MCP—males			
95% MCP	29.20	2	< 0.001
50% MCP	18.70	2	< 0.009
MCP—females			
95% MCP	18.20	2	0.008
50% MCP	13.20	2	0.001
KDE—all			
95% KDE	34.7	2	< 0.001
50% KDE	38.5	2	< 0.001
KDE—males			
95% KDE	19.5	2	< 0.001
50% KDE	23.4	2	< 0.001
KDE—females			
95% KDE	15.2	2	0.005
50% KDE	15.2	2	0.005

The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

Table 3 Minimum convex polygon (MCP) and kernel density estimators (KDE) home range size (m^2) were compared across programs using the pairwise Wilcoxon signed-rank tests for three estimator programs (LOAS, Locate III, and Sigloc)

Program pair	W	d.f	P
95% MCP			
LOAS versus Locate III	75	1	0.001
Locate III versus Sigloc	0	1	< 0.001
LOAS versus Sigloc	0	1	< 0.001
50% MCP			
LOAS versus Locate III	109	1	0.010
Locate III versus Sigloc	17	1	< 0.001
LOAS versus Sigloc	11	1	< 0.001
95% KDE			
LOAS versus Locate III	100	1	0.032
Locate III versus Sigloc	0	1	< 0.001
LOAS versus Sigloc	32	1	< 0.001
50% KDE			
LOAS versus Locate III	92	1	0.005
Locate III versus Sigloc	0	1	< 0.001
LOAS versus Sigloc	40	1	< 0.001

The mice ($n = 31$) were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

$P < 0.001$). Perimeter–area ratios for the average KDE home ranges differed across programs (95%: $X^2_2 = 32.07$, $P < 0.0001$; 50%: $X^2_2 = 38.34$, $P < 0.0001$; Additional File 4). Pairwise program comparisons indicated significant perimeter–area ratio differences between all programs at all levels, except 95% KDE home ranges created with LOAS and Locate III (Table 4). Land cover summary statistics consistently indicated a dominance of forested and herbaceous areas across all programs, although exact means varied. However, the amounts of land cover types in average KDE home ranges differed across all programs except in the categories of impervious surface and mixed open land cover, which were two of the smallest categories in terms of area (Table 5).

Discussion

Manually calculating telemetry locations and subsequent home range, movement, and resource selection calculations are heavily used within wildlife research. Yet over a decade later, some of the criticisms from Laver and Kelly still hold true within our own search to find appropriate ways to handle our small mammal telemetry data [72]. In their study, they reviewed 161 home range papers and concluded that although there is no one best technique, there should be a unified way of reporting methods for creating home ranges [72]. We agree with that statement and extend it to the need for a uniform way of justifying and reporting methods of collection, error assessment, and calculation of XY locations from manual telemetry.

In this study, mouse trapping, collaring, and tracking were heavily influenced by the suburban–urban environment of the study area. Field sites were relatively close to trails, human activity, and human influenced areas. Working in such a heavily suburban area can make telemetry very difficult given the ongoing signal

Table 4 A comparison of pairwise perimeter–area ratios produced for kernel density estimator (KDE) home ranges ($n = 31$) across three estimator programs (LOAS, Locate III, and Sigloc)

Perimeter/area ratio	W	d.f	P
95% KDE			
LOAS versus Locate III	130	1	0.162
Locate III versus Sigloc	425	1	< 0.001
LOAS versus Sigloc	379	1	< 0.001
50% KDE			
LOAS versus Locate III	324	1	0.020
Locate III versus Sigloc	465	1	< 0.001
LOAS versus Sigloc	386	1	< 0.001

The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

Table 5 Friedman tests were calculated for the quantity of land cover types across 95% and 50% kernel density estimate (KDE) home ranges ($n=31$) calculated by three different estimator programs (LOAS, Locate III, and Sigloc)

Land cover type by home range size	X^2	d.f	P
95% KDE			
Impervious surface road	29.3	2	< 0.001
Impervious surface non-road	33.42	2	< 0.001
Tree canopy over impervious surface	19.9	2	< 0.001
Forest	40.26	2	< 0.001
Tree canopy over turf	39.05	2	< 0.001
Mixed open	35.12	2	< 0.001
Turf/shrub/scrub	36.867	2	< 0.001
Turf grass/yard	40.75	2	< 0.001
Crop/pasture	27.02	2	< 0.001
50% KDE			
Impervious surface road	3.7	2	0.156
Impervious surface non-road	10.6	2	0.005
Tree canopy over impervious surface	9.4	2	0.008
Forest	40.35	2	< 0.001
Tree canopy over turf	7.3	2	0.025
Mixed open	3.9	2	0.139
Turf/shrub/scrub	31.7	2	< 0.001
Turf grass/yard	13.9	2	< 0.001
Crop/pasture	18.926	2	< 0.001

The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

interference and signal reflection. Given such constraints, a technician's accuracy and precision could highly alter locations produced by estimator programs. Unfortunately, few radio telemetry studies measure basic error within their study and inconsistently report accuracy and precision in their data [14]. The limited error reported in the literature ranged from 0.9 to 50 m depending on the animal [73–75]. Our approximate 6–7 m of location error was at the lower end of that range and closely approached the suggested distance of 5 m to maintain accuracy given our study area size (60.7 ha) and relative patch sizes (~5–10 ha) [46]. Current in-depth resource selection studies of small mammals using micro-VHF devices are limited and even fewer have detailed telemetry error assessments [1, 15, 17, 23, 31, 32, 76]. Therefore, it was difficult to gauge what distance would create an impactful bias in a small mammal study. Yet, these studies are becoming more common given advancements in technology and the increasing need to manage issues such as endangered species conservation and tick-borne zoonotic disease transmission.

To compare methods for VHF location estimation, we chose three commonly used programs and input data without changing the default settings because we found no basis for adjustments from the literature. Meaning, we did not include our field error measurements in the program settings and set each program to run an MLE. It is important to note that the choice of using MLE or M-estimators in different estimator software is not without issue [13, 62, 63]. Some of the primary concerns when using MLE are censoring of data, limitations on processing azimuths, and MLE being overly restrictive in its confidence intervals [13, 62, 63]. While it remains an exceedingly common method, the criticisms push us to more aggressively recommend unified reporting methodology to enable critical evaluation of location estimates.

While we took measures to ensure comparability, each estimator program had slight programmatic differences, although those exact mechanisms were not always clear in the program documentation. For example, at default, some programs forced the identification of a centroid, even when bearings did not overlap (Sigloc), while others had unclear mechanisms that culled locations before producing the output (Locate and LOAS). Yet, when considering our comparison of three predicted sets of back-corrected "perfect" bearings of the known location collars, the three programs were highly accurate with similar output of locations, although not exactly the same. This confirmed that, with highly accurate inputs, each program performed consistently and did well. However, when test data with normal rates of error were input into the programs, the output locations significantly differed. It is logical and expected that the more error in the bearings, the more variable the results. Further, the estimators did not differ in the amount they now varied from the known collar locations across the three programs. So, even though they did a worse job in terms of accuracy, the three programs generally erred the same. This indicated stability in the production of the sets of coordinates across programs even when there was known error in the data. Unfortunately, when extending the analysis to real mouse data that varied in quality and quantity, relevant differences occurred.

As the analysis moved downstream and actual sets of mouse locations were used to calculate three MCP and KDE home ranges, small variations in the produced locations, likely from the inclusion or elimination of locations, had rippling impacts for all programs. Our calculations of average home range size and overlap and home range size analyzed by sex all differed across the three estimator programs, regardless of home range calculation method. As expected, core home ranges were generally more consistent in size, and core MCP home ranges had no detectable differences. When analyzed by sex, both MCP and KDE had differences in even core home range areas. Because of differences in size, overlap, and perimeter-to-area calculations, different programs identified different dominant cover types or significant changes in percentage of land cover type across the KDE home ranges. While that difference is logical, it is worthy of consideration given the scale of and impact to small mammal resource selection analyses [31, 32, 76]. For animals that utilize such small spaces, in variable habitats, this could be highly impactful to a study's findings and conclusions.

The three estimators produced different sets of locations that in turn produced statistically different home ranges. We postulated that while typical variability and imprecision play a role in all VHF and GPS data acquisition, it seemed to occur in this study because of culled bearings before location estimation. This was supported given the contrasting results between total locations attained across programs. Originally, we expected some of this effect given that each program had its own, unspecified ruleset for whether a given set of bearings would be included to produce an actual location. Specifically, Sigloc included all possible bearings, but it was unclear how the two packaged programs functioned, yet Locate III and LOAS total locations were similar. Additionally, locations found on the 95–100% home range edge are known to be impacted by error from distance to transmitter [14, 77]. Yet, we specifically tested the detecting distances of our collars, which is something often left unreported in the literature. The small error effects on peripheral locations, while not significant in our programmatic comparison of the testing locations, still seemed to result in disparate findings in even simple downstream analyses based on mouse home range. This occurred despite us conducted our telemetry within the easily detectable 100-m range of our collars.

To further test this hypothesis, we added two simple post hoc analyses of the locations for a random selection of a male and female mice from each trapping session ($n = 8$). We compared distances between the produced points across programs and did a simple summary of where within the KDE points were not identified by each programs (Tables 6 and 7). The findings of those simple post hoc tests showed relatively small spread in location distances across programs,

Table 6 For a random selection of mice ($n = 8$), we calculated the number of sets of bearings that one program produced that had matching locations (< 10 m) produced by both other two programs, creating a triplicate of locations from that one set of bearings that fell within the same area of the home range (total possible locations = 234)

Mouse ID	**51–95% KDE**		
	Locate III	**LOAS**	**Sigloc**
140	3	3	1
161	7	7	4
411	9	9	1
209	6	6	2
244	1	9	0
337	3	9	0
387	6	13	8
412	9	13	3
Average (SD)[COV]	5.5 (2.7) [48]	8.6 (3.2) [37]	2.4 (2.5) [104]
Mouse ID	**0–50% KDE**		
	Locate	**LOAS**	***R***
140	16	17	18
161	18	18	22
411	16	15	24
209	26	26	30
244	14	6	15
337	16	15	23
387	30	24	28
412	44	39	51
Average (SD)[COV]	22.5 (9.7) [43]	20 (9.2) [26]	26.4 (10.4) [39]

These counts were summarized and averaged, including standard deviation (SD) and coefficient of variation (COV) across the core (0–50%) kernel density estimate (KDE) home range and the exterior edge KDE home range (51–95%) across three different estimator programs (Locate III, LOAS, and Sigloc). The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

Table 7 For a random selection of mice (n = 8), we calculated the distance between all sets of bearings that resulted in a location (n = 234) across three different estimator programs (Locate III, LOAS, and Sigloc).

Program comparison	Min	Max	Mean	SD
LOAS/R	< 0.01	78.06	9.01	13.60
LOCATE III/LOAS	0.00	49.91	1.92	6.85
LOCATE III/R	0.00	77.59	8.92	12.75

The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

with Sigloc R accounting for more variation (Table 7). For those 8 mice, when each program was able to produce a location ($n = 234$) from the same set of bearings, the average difference in locations was approximately 7 m. When comparing how the programs performed in the 0–50% and the 51–95% KDE contours, we saw similar variation between all three programs within the core home range (Table 6). Lastly, along with the inherent programmatic differences, some differences were likely due to wider ranging male mice, which created more variable location estimates, as well as possible unaccounted sources of error such as signal reflection, vegetation cover, and animal movement [14].

Our findings suggest that, when micro-VHF studies utilizing manual telemetry are limited to MCPs, regardless of location estimator used, core home ranges should be utilized for analyses. Given the variability in location estimation, 50% MCPs inherently provide more appropriate comparisons across and among small mammals. Using the more advanced kernel density estimators for small mammals is relatively new and has unique estimation considerations including choice of bandwidth or smoothing parameter [70]. We found that the KDE were more impacted by the Sigloc's estimated XY locations, likely because many were included that were culled from the other programs (Table 6). This emphasizes the importance of addressing issues of bias in location data collect, XY location estimator choice—especially how it culls bearings, and reporting more methods details in the literature [72]. For the research we were conducting, the results of these differing programs, even a 10-m difference in movements through microhabitat, could change where we placed specific insecticide-containing IPM devices, and the size and overlap of home ranges would dictate how many devices must be placed [25, 78, 79]. We suggest researchers carefully consider downstream analyses when investigating movements or habitat use of small mammals, test collar detection distances, and calculate their error in terms of accuracy and precision specific to their study sites before launching full telemetry studies.

Interestingly, manual calculations directly with ArcGIS®, while likely too time consuming for large studies, did quite well in our study and can easily be used to assess telemetry error. Information on detection distances and technicians' ability to triangulate will help guide the confidence in proper analyses of home range and habitat use. We most appreciated both LOAS and the Sigloc package, as they had more options in terms of user control. LOAS allowed the user to choose different types of estimators if desired and was a user-friendly packaged program, although its bearing culling mechanism was unclear. The Sigloc package allowed someone proficient in the coding of R to specify exactly how the locations would be assessed, created, and potentially culled if additional code was added. So, while the Sigloc package was liberal in its default settings, it provided the most flexibility, power, and would be the easiest to replicate given the access to the exact code. However, we highly suggest additional programming added to the Sigloc package to cull bearings or error polygons based on one's specific study telemetry error.

Conclusion

The goals of this paper were to document complications in collaring and tracking small mammals with micro-VHF collars and to investigate specific location estimator impacts on small mammal studies. We have illustrated the need for collar and error assessment, telemetry documentation, and shown the variation in three common location estimators. We have illustrated several ways in which these programs may influence other analyses, including general home range characteristics and changes in identified associated land cover. The results presented here illustrate that the program a researcher uses can significantly sway the biological outputs and significantly impact downstream analyses. As such, error measures and programmatic choices should be considered an integral component of study design, reporting of findings, as well as more thoroughly discussed in the literature, especially for microhabitat analyses of animals with very small ranges.

Abbreviations

KDE: Kernel density estimator; LOAS: Location of a signal (trademarked software); MCP: Minimum convex polygon; MLE: Maximum likelihood estimator; VHF: Very high frequency.

Supplementary Information

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Additional file 1. Descriptive statistics for 31 (19 males and 12 females) Minimum Convex Polygon home ranges for Peromyscus spp. The total home range areas in meters squared were 22 produced by three different estimator programs. The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019

Additional file 2. Descriptive area statistics for 31 (19 males and 12 females) Kernel Density Estimator home ranges for Peromyscus spp. The total home range areas in meters squared were produced by three different estimator programs. The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019.

Additional file 3. The amount of home range overlap (m2) produced by of the minimum convex polygon (MCP) and kernel density estimator (KDE) home ranges (n = 31) across three estimator programs (LOAS, LOCATE III, and Sigloc). The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019.

Additional file 4. Perimeter area ratio for kernel density estimator (KDE) home ranges (n = 31) across three estimator programs (LOAS, LOCATE III, and Sigloc). The mice were tracked via micro-VHF collars in a suburban park in Howard county, Maryland, USA, 2018–2019.

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Author contributions
JM and AL conceptualized the study. GH and JM designed the statistical analysis. GH and JM wrote the initial manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
All research followed ASM guidelines and the mouse trapping protocol was approved by the Animal Care and Use Committee (IACUC approval #16-023) of the United States Department of Agriculture Beltsville Agricultural Research Center.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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References
1. Schweiger BR, Frey JK, Cain JW. A case for multiscale habitat selection studies of small mammals. J Mammal. 2021;102:1249–65.
2. Winnard AL, Di Stefano J, Coulson G. Habitat use of a critically-endangered species in a predator-free but degraded reserve in Australia. Wildl Biol. 2013;19(4):429–38.
3. Rosenberg R, Lindsey NP, Fischer M, et al. Vital Signs: trends in reported vectorborne disease cases—United States and Territories, 2004–2016. MMWR Morb Mortal Wkly Rep. 2018;67:496–501.
4. Voordouw MJ, Lachish S, Dolan MC. The Lyme disease pathogen has no effect on the survival of its rodent reservoir host. PLoS ONE. 2015;10:2.
5. VanAcker MC, Little EAH, Molaei G, Bajwa MI, Diuk-Wasser MA. Enhancement of risk for Lyme disease by landscape connectivity, New York, New York, USA. Emerg Infect Dis. 2019;25:1136–43.
6. Schulze TL, Jordan RA, Williams M, Dolan MC. Evaluation of the SELECT Tick Control System (TCS), a host-targeted bait box, to reduce exposure to Ixodes scapularis (Acari: Ixodidea) in a Lyme disease endemic area of New Jersey. J Med Entomol. 2017. https://doi.org/10.1093/jme/tjx044.
7. Nations CS, Anderson-Sprecher RC. Estimation of animal location from radio telemetry data with temporal dependencies. J Agric Biol Env Stat. 2006;11:87–105.
8. Kie JG, Matthiopoulos J, Fieberg J, Powell RA, Cagnacci F, Mitchell MS, Gaillard JM, Moorcroft PR. The home-range concept: are traditional estimators still relevant with modern telemetry technology? Philos Trans R Soc Lond B Biol Sci. 2010;27(365):2221–31.
9. Walter DW, Onorato DP, Fischer JW. Is there a single best estimator? Selection of home range estimators using area-under-the-curve. Mov Ecol. 2015;3:10.
10. Cagnacci F, Boitani L, Powell RA, Boyce MA. Animal ecology meets GPS-based radiotelemetry: a perfect storm of opportunities and challenges. Phil Trans R Soc B: Biological Sciences. 2010;365(1550):2157–62.
11. Horne JS, Garton EO, Sager-Fradkin KA. Correcting home-range models for observation bias. J Wildlife Mangement Techniques Technol Note. 2005;71:996–1001.
12. Thomas B, Holland JD, Minot EO. Wildlife tracking technology options and cost considerations. Wildl Res. 2011;38:653.
13. Gerber BD, Hooten MV, Peck CP, Rice MB, Gammonley JH, Apa AD, et al. Accounting for location uncertainty in azimuthal telemetry data improves ecological inference. Mov Ecol. 2018;6:14.
14. Millspaugh JJ, Marzluff JM, editors. Radio Tracking and Animal Populations. San Diego, California: Academic Press; 2001.
15. Nottingham CM, Buckley HL, Case BS, Glen AS, Stanley MC. Factors affecting home range size of feral cats: a meta-analysis. NZ J Ecol. 2022;46:3476.
16. Grilo C, Molina-Vacas G, Fernández-Aguilar X, Rodriguez-Ruiz J, Ramiro V, Porto-Peter F, et al. Species-specific movement traits and specialization determine the spatial responses of small mammals towards roads. Landsc Urban Plan. 2018;169:199–207.
17. Rettie JW, Mcloughlin PD. Overcoming radiotelemetry bias in habitat-selection studies. Can J Zool. 1999;77:1175.
18. Slade NA, Russell LA. Distances as indices to movements and home-range size from trapping records of small mammals. J Mammal. 1998;79:346–51.
19. Kalcounis-Rüppell MC, Millar JS. Partitioning of space, food, and time by syntopic *Peromyscus boylii* and P. *Californicus*. J Mammal. 2002;83:614–25.
20. Parmenter RR, Yates TL, Anderson DR, Burnham KP, Dunnum JL, Franklin AB, et al. Small-mammal density estimation: a field comparison of grid-based vs web-based density estimators. Ecol Monogr. 2003;73:1–26.
21. Püttker T, de Barros C, Martins TK, Sommer S, Pardini R. Suitability of distance metrics as indexes of home-range size in tropical rodent species. J Mammal. 2012;93:115–23.
22. Gerber BD, Parmenter RP. Spatial capture–recapture model performance with known small-mammal densities. Ecol Appl. 2015;25:695–705.
23. Mayer M, Ullmann W, Heinrich R, et al. Seasonal effects of habitat structure and weather on the habitat selection and home range size of a mammal in agricultural landscapes. Landscape Ecol. 2019;34:2279–94.

24. Campion D, Pardo I, Elósegui M, Villanua D. GPS telemetry and home range of White-backed Woodpecker Dendrocopos leucotos: results of the first experience. Acta Ornithologica. 2020;55:77–87.
25. Frair JL, Fieberg J, Hebblewhite M, Cagnacci F, DeCesare NJ, Pedrotti L. Resolving issues of imprecise and habitat-biased locations in ecological analyses using GPS telemetry data. Philos Trans R Soc Lond B: Biological Sciences. 2010;365:2187–200.
26. Bartolommei P, Francucci S, Pezzo F. Accuracy of conventional radio telemetry estimates: a practical procedure of measurement. Hystrix Italian J Mammal. 2013;23:12.
27. Collins CR, Kays RW. Patterns of mortality in a wild population of White-footed mice. Northeast Nat. 2014;21:323–36.
28. Stradiotto A, Cagnacci F, Delahay R, Tioli S, Nieder L, Rizzoli A. Spatial organization of the Yellow-Necked mouse: effects of density and resource availability. J Mammal. 2009;90:704–14.
29. Gaitan J, Millien V. Stress level, parasite load, and movement pattern in a small-mammal reservoir host for Lyme disease. Can J Zool. 2016;94:565–73.
30. Larsen AL, Homyack JA, Wigley TB, Miller DA, Kalcounis-Rueppell MC. Altered understory characteristics affect rodent spatial and foraging behaviors and reproduction patterns. Forest Ecol Management. 2018;409:119–28.
31. Dutt NR, Veals AM, Koprowski JL. Resource selection of a montane endemic Sex-specific differences in white-bellied voles (Microtus longicaudus leucophaeus). PLoS ONE. 2020;15:e0242104.
32. Lees DM, et al. Microhabitat selection by small mammals in response to fire. Aust J Zool. 2022;2022(69):67–79.
33. Ribble DO, Wurtz AE, McConnell EK, Buegge JJ, Welch KC Jr. A comparison of home ranges of two species of Peromyscus using trapping and radiotelemetry data. J Mammal. 2002;83:260–6.
34. Paxton KL, Baker KM, Crytser ZB, Guinto RMP, Brink KW, Rogers HS, Paxton EH. Optimizing trilateration estimates for tracking fine-scale movement of wildlife using automated radio telemetry networks. Ecol Evol. 2022. https://doi.org/10.1002/ece3.8561.
35. Ward MP, Sperry JH, Weatherhead PJ. Evaluation of automated radio telemetry for quantifying movements and home ranges of snakes. J Herpetol. 2013;47:337–45.
36. Tucker CR, Radzio TA, Strickland JT, Britton E, Delaney DK, Ligon DB. Use of automated radio telemetry to detect nesting activity in Ornate box turtles *Terrapene ornata*. Am Midl Nat. 2014;171:78–89.
37. Skupien GM, Andrews KM, Norton TM. Benefits and biases of VHF and GPS telemetry: a case study of American alligator spatial ecology. Wildl Soc Bull. 2016;40:772–80.
38. Lenske AK, Nocera JJ. Field test of an automated radio-telemetry system: tracking local space use of aerial insectivores. J Field Ornithol. 2018;89:173–87.
39. White GC, Garrott RA. Analysis of Wildlife Radio-Tracking Data. San Diego, California: Academic Press; 1990.
40. Ribble DO, Stanley S. Home ranges and social organization of syntopic *Peromyscus boylii* and *P. truei*. J Mammal. 1998;79:932–41.
41. Berg SS. The package "Sigloc" for the R software: a tool for triangulating transmitter locations in ground-based telemetry studies of wildlife. Bull Ecol Soc Am. 2015;96:500–7.
42. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2021. URL https://www.R-project.org/. Accessed 01 Feb 2022.
43. Tukey JW. A survey of sampling from contaminated distributions. In: Olkin I, Ghurye SG, Hoeffding W, Madow WG, Man HB, editors. Contributions to Probability and Statistics. Redwood City: Stanford University Press; 1960. p. 448–85.
44. Huber PJ. Robust estimation of a location parameter. Ann Math Stat. 1964;35(1):73–101.
45. Andrews DF, Bickel PJ, Hampel FR, Huber PJ, Rogers WU, Tukey JW. Robust estimates of location: survey and advances. Princeton: Princeton University Press; 1972.
46. Montgomery R, Roloff G, Ver HJ. Implications of ignoring telemetry error on inference in wildlife resource use models. J Wildl Manag. 2011;75:702–8.
47. Kraft J. Soil survey of Howard County, Maryland. United States Department of Agriculture, Natural Resources Conservation Service. 2008. https://www.nrcs.usda.gov/Internet/FSE_MANUSCRIPTS/maryland/MD027/0/MDHoward5_08.pdf. Accessed 01 Dec 2021.
48. National Climate Data Center (NCDC). Climate at a glance: Maryland. National oceanic and atmospheric administration, Asheville, North Carolina. 2015.
49. United States Department of Agriculture (USDA). Forests of Maryland. Forest Service, Northern Research Station, Newtown Square, Pennsylvania. 2013.
50. United States Census Bureau (U.S. Census). 2010 Census of Population and Housing. https://www2.census.gov/library/publications/decennial/2010/cph-2/cph-2-1.pdf. Accessed 01 Aug 2021.
51. Demographic Profile Summary File: Technical Documentation. August 2011. https://www2.census.gov/programs-surveys/decennial/2010/technical-documentation/complete-tech-docs/summary-file/dpsf.pdf. Accessed 01 Feb 2021.
52. Brown DG, Johnson KM, Loveland TR, Theobald DM. Rural land-use trends in the conterminous United States, 1950–2000. Ecol Appl. 2005;15:1851–63.
53. Hansen AJ, Knight RL, Marzluff JM, Powell S, Brown K, Gude PH, et al. Effects of exurban development on biodiversity: patterns, mechanisms, and research needs. Ecol Appl. 2015;15:1893–905.
54. Reed AW, Kennedy PK, Beck ML, Kennedy ML. Using morphologic characters to identify Peromyscus in Sympatry. Am Midl Nat. 2004;152:190–5.
55. Shipp-Pennock MA, Webster WD, Freshwater DW. Systematics of the White-footed mouse (*Peromyscus leucopus*) in the Mid-Atlantic Region. J Mammal. 2005;86:803–13.
56. Lackey JA, Huckaby DG, Ormiston BG. Peromyscus leucopus. Mamm Species. 1985;247:1–10.
57. Kirkland GL. Guidelines for the capture, handling, and care of mammals as approved by the American Society of Mammalogists. J Mammal. 1998;79:1416–31.
58. Naughton D. The Canadian Museum of Nature White-footed Mouse (Peromyscus leucopus). In: Naughton D, editor. The Natural History of Canadian Mammals. Toronto: University of Toronto Press; 2012. p. 191–3.
59. ArcGIS Pro. Esri Inc. 2020. Version 2.5. https://www.esri.com/en-us/arcgis/products/arcgis-pro/overview. Accessed 01 Feb 2021.
60. Lenth RV. On finding the source signal. Technometrics. 1981;23(2):149–54.
61. Lenth RV. Robust measures of location for directional data. Technometrics. 1981;23:77–81.
62. Efron B. Why isn't everyone Bayesian. Am Stat. 1986;40:1–11.
63. Cole SR, Chu H, Greenland S. Maximum likelihood, profile likelihood, and penalized likelihood: a primer. Am J Epidemiol. 2014;179:252–60.
64. Chambers RL, Steel DG, Wang S, Welsh A. Maximum likelihood estimation for sample surveys. Boca Raton: CRC Press; 2012.
65. Marrotte RR, Gonzalex A, Millien V. Functional connectivity of white-footed mouse in Southern Quebec, Canada. Landscape Ecol. 2017;32:1987–98.
66. Wolff JO. The effects of density, food, and interspecific interference on home range size in *Peromyscus leucopus* and *Peromyscus maniculatus*. Can J Zool. 1985;63:2657–62.
67. Wilder SM, Meikle DB. Variation in effects of fragmentation on the white-footed mouse (*Peromyscus leucopus*) during the breeding season. J Mammal. 2006;87:117–23.
68. Morris DW, Davidson DL. Optimally foraging mice match patch use with habitat differences in fitness. Ecology. 2000;81:2061–6.
69. Calenge C. The package adehabitat for the R software: a tool for the analysis of space and habitat use by animals. Ecol Model. 2006;197:516–9.
70. Fleming CH, Fagan WF, Mueller T, Olson KA, Leimgruber P, Calabrese JM. Rigorous home range estimation with movement data: a new autocorrelated kernel density estimator. Ecology. 2015;96:1182–8.
71. Bauder JM, Breininger DR, Bolt MR, Legare ML, Jenkins CL, McGarigal K. The role of the bandwidth matrix in influencing kernel home range estimates for snakes using VHF telemetry data. Wildl Res. 2015;42:437.
72. The Conservation Innovation Center. High-Resolution Land Use Data. 2018. Chesapeake Conservancy, Annapolis, MD. https://www.chesapeakeconservancy.org/conservation-innovation-center/high-resolution-data/land-use-data-project/. Accessed 01 Feb 2021.
73. Laver PN, Kelly MJ. A critical review of home range studies. J Wildlife Management. 2008;72(1):290–8.

74. Morzillo AT, Feldhamer GA, Nicholson MC. Home range and nest use of the Golden mouse (*Ochrotomys nuttalli*) in Southern Illinois. J Mammal. 2003;84:553–60.
75. Edelman AJ, Koprowski JL. Seasonal changes in home ranges of Abert's squirrels: impact of mating season. Can J Zool. 2006;84:404–11.
76. Harrington LA, Macdonald DW. Spatial and temporal relationships between invasive American mink and native European polecats in the Southern United Kingdom. J Mammal. 2008;89:991–1000.
77. Goheen JR, Swihart RK. Resource selection and predation of North American red squirrels in deciduous forest fragments. J Mammal. 2005;86:22–8.
78. Dolan CM, Schulze TL, Jordan RA, Dietrich G, Chulze CJ, Hojgaard A, Ullmann AJ, Sackal C, Zeidner NS, Piesman J. Elimination of *Borrelia burgdorferi* and *Anaplasma phagocytophilum* in rodent reservoirs and Ixodes scapularis ticks using a doxycycline hyclate-laden bait. Am J Trop Med Hyg. 2011;85:1114–20.
79. Milholland MT, Eisen L, Nadolny RM, et al. Surveillance of ticks and tick-borne pathogens in suburban natural habitats of Central Maryland. J Med Entomol. 2021;58:1352–62.
80. Berl JL, Kellner KF, Flaherty EA, Swihart RK. Spatial variation in density of white-footed mice along edges in fragmented habitat. Am Midl Nat. 2018;179:38–50.

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