Techniques and Technology Article

Effects of Telemetry Location Error on Space-Use Estimates Using a Fixed-Kernel Density Estimator

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ABSTRACT Fixed-kernel density estimates using radiotelemetry locations are frequently used to quantify home ranges of animals, interactions, and resource selection. However, all telemetry data have location error and no studies have reported the effects of error on utilization distribution and area estimates using fixed-kernel density estimators. We simulated different home range sizes and shapes by mixing bivariate-normal distributions and then drawing random samples of various sizes from these distributions. We compared fixed-kernel density estimates with and without error to the true underlying distributions. The effects of telemetry error on fixed-kernel density estimates were related to sample size, distribution complexity, and ratio of median Circular Error Probable to home range size. We suggest a metric to assess the adequacy of the telemetry system being used to estimate an animal's space use before a study is undertaken. Telemetry location error is unlikely to significantly affect fixed-kernel density estimates for most wildlife telemetry studies with adequate sample sizes. (JOURNAL OF WILDLIFE MANAGEMENT 71(7):2421–2426; 2007)

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KEY WORDS cross validation, error ratio, fixed kernel, home range, location error, radiotelemetry, space use, utilization distribution.

An animal's space use is often studied using radiotelemetry to obtain locations during a specified time period. These locations can then be used to quantify aspects of space use using a variety of estimators. One of the most common space-use estimators in wildlife studies today is the fixed-kernel density estimator (hereafter fixed kernel). Fixed kernels have been used to estimate animal home ranges (Worton 1989), interactions (Millspaugh et al. 2004), and resource selection (Marzluff et al. 2004, Millspaugh et al. 2006).

The properties of fixed kernels have been well-studied (e.g., Worton 1989, Seaman and Powell 1996, Seaman et al. 1999). The fixed kernel has superior properties compared to other home range estimators because it 1) is nonparametric, 2) is unbiased, 3) calculates an animal's utilization distribution (UD), 4) is robust to autocorrelation, and 5) is not sensitive to outliers (Kernohan et al. 2001). Some authors have also suggested that fixed kernels are relatively robust to telemetry error compared to other space-use estimators (e.g., Marzluff et al. 2001). Although this seems logical given the smoothing function of the kernel, no published studies have assessed the effects of telemetry error on fixed-kernel estimates. Telemetry error has the potential to affect the size (i.e., extent) and shape of the UD. Although a few, small location errors would likely have little impact on the UD, large, systemic location error could alter the size and shape of the UD, thus affecting estimates of home range, animal interactions, and resource selection.

Telemetry error is frequently unreported in animal space-use studies. Hupp and Ratti (1983) were one of the first to note that 75% of radiotelemetry papers did not report location error. Although this rate has improved over the last 20 years, a recent review by Withey et al. (2001) found that nearly half of all radiotelemetry studies recently published in the *Journal of Wildlife Management* inadequately reported telemetry error or did not report it at all, suggesting these studies either did not consider telemetry error to be an important factor in their space-use estimates or did not know how to deal with error. Our objective was to provide a tool to assess the effects of telemetry error when using fixed kernels to estimate animal space use.

METHODS

Telemetry Error

We developed an error ratio (ER) that relates telemetry error to the size of the home range. The ER is defined as:

$$ER = CEP_{0.50}/A$$

where $CEP_{0.50}$ is the median Circular Error Probable (Moen et al. 1997), which is the circle with a radius around a known location that contains 50% of the test locations, and A is the approximate home range area of the animal under study. We use the median location error rather than the mean because the mean is a poor estimator of central tendency for telemetry location error when errors are not normally distributed. The ER must be expressed in similar units (e.g., m/m^2). This ratio can usually be estimated before a study is initiated because most researchers know or can estimate the average error of the telemetry system they are using and can also estimate the home range size and complexity of the animal they are studying from published literature or pilot studies.

Simulations

We simulated utilization distributions that represented various levels of space-use complexity, similar to previous studies (Seaman and Powell 1996, Seaman et al. 1999, Horne and Garton 2006). We used mixtures of bivariate-

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normal distributions to create 1-, 4-, and 8-mode UDs. We found in pilot simulations that greater complexity did not contribute substantial information; thus, we limited our study to the 3 mixtures above. We randomly selected parameter values from normal distributions with mean (x, y) from 0 to 20, standard deviation from 1.5 to 6, covariance from −1 to 1, and we selected mixing proportions from 0 to 1 with the constraint that the proportions summed to one (Horne and Garton 2006).

We simulated 40 realizations for each of the 3 types of bivariate-normal mixes by randomly selecting different parameter values for each realization. We drew random samples of 25, 50, 100, 250, and 500 points from each realization to simulate telemetry locations. We replicated each sample size 100 times for each of the 40 realizations and 3 bivariate mixes, for a total of 60,000 simulated location samples. We simulated location error by adding random numbers to (x, y) sample coordinates drawn from the true distributions. Errors were randomly selected from normal distributions with (x, y) mean zero and standard deviations ranging from 1 to 250. We used ArcView 3.2 Geographic Information System (GIS) to estimate the median location error resulting from adding random error values to the (x, y) sample coordinates, and then we calculated error ratios based on the median error and the 95% true distribution extents. Error ratios of simulated distributions ranged from 0 to 0.20 and we sorted and binned them according to the following intervals: 0, 0.001–0.009, 0.010–0.049, and 0.050–0.200. We used the no error category as a reference. We set the lowest error ratio at the interval 0.001–0.009 by reviewing a broad suite of telemetry studies and determining ERs for the telemetry systems and animals under study. Most wildlife telemetry studies fell within this interval. We set the interval 0.010–0.049 because it represented some telemetry studies with high ERs such as might be found using relatively inaccurate telemetry systems, and the interval 0.050–0.200 because it represented extreme cases with telemetry error that would probably be considered unacceptable to most researchers interested in accurately estimating home range sizes.

Kernel Calculations

We calculated fixed-kernel density estimates for each sample using a standard bivariate-normal kernel (Silverman 1986). Fixed kernels are sensitive to the type of smoothing factor or bandwidth values (Silverman 1986). Several bandwidth-selection procedures have been evaluated for use in fixed-kernel estimates, and least-squares cross-validation ($LSCV_h$) is the most widely accepted (Seaman and Powell 1996). However, several new bandwidth-selection procedures have recently been evaluated and shown to perform well (Gitzen et al. 2006, Horne and Garton 2006). No single smoothing parameter is likely to perform well in all conditions. Therefore, we used 2 automatic methods for choosing the smoothing parameter. For smoothing, we chose $LSCV_h$ because it is the most widely used method and generally performs well with sample sizes ≥50 (Seaman et al. 1999, Horne and Garton 2006), and likelihood cross-validation (CV_h) because it has been shown to be a better procedure for small sample sizes and for obtaining more accurate estimates in high-use areas (Horne and Garton 2006). For each bandwidth method we simulated 60,000 home ranges for a total of 120,000 fixed-kernel UDs.

Comparisons

We compared the fixed-kernel estimates from each sample using both bandwidth-selection procedures to the true distribution using 2 measures. We used the volume of intersection (VI) index to assess the fit of the sample UD to the true UD (Seidel 1992, Millspaugh et al. 2004). The VI is a value between zero (no overlap) and 100 (complete overlap) and is an easily interpreted metric of how well the estimated UD fits the true UD. The VI is calculated by summing the UD volume shared by 2 distributions. The amount of shared volume within each pixel of the evaluation grid is summed to obtain the VI. The VI is defined as:

$$\left[VI = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \min\left[f_1(x,y), \hat{f}_2(x,y)\right] dxdy \times 100\right]$$

where f_1 is the true mixture distribution and $\hat{f}_2$ is the estimated distribution. The VI can be used to assess how well a kernel estimates the intensity or probability of space use because it is most sensitive to discrepancies where the UD density is highest, such as the inner contours of fixed-kernel estimates. We assessed the VI over a grid of points bounded by the 99.9% contour of the UDs.

We also compared areas associated with the 50% and 95% contours of the sample UDs ($\hat{A}$) versus the true distributions (A) using Percent Relative Bias (PRB) defined as:

$$\mathrm{PRB} = (\hat{A} - A)/A \times 100$$

We chose these areas because the 50% contour is often used as an estimate of an animal's core use area (Samuel et al. 1985), whereas the 95% contour is commonly used as an estimate of an animal's home range (Kernohan et al. 2001). Bias in the 50% contour may result in a poor estimate of space use within the core area, whereas bias in the 95% contour may lead to an inaccurate depiction of an animal's home range size. Positive bias would indicate an overestimate of area, whereas negative bias would indicate an underestimate of the area.

We graphically compared mean VI and PRB of all estimated UDs with and without error to the true distributions. Of particular interest was how well kernel UDs estimated with location error performed compared to kernel UDs estimated without location error. Of secondary interest was how well kernel UDs estimated without location error performed compared to true UDs. We did not include standard errors in figures because they were too small to display due to the large sample sizes. We computed all simulations and calculations using Visual Basic 6.0 (Microsoft Corporation, Redmond, WA).

Case Study

We wanted to assess the effectiveness of using satellite platform transmitter terminals (PTTs) and the Argos system

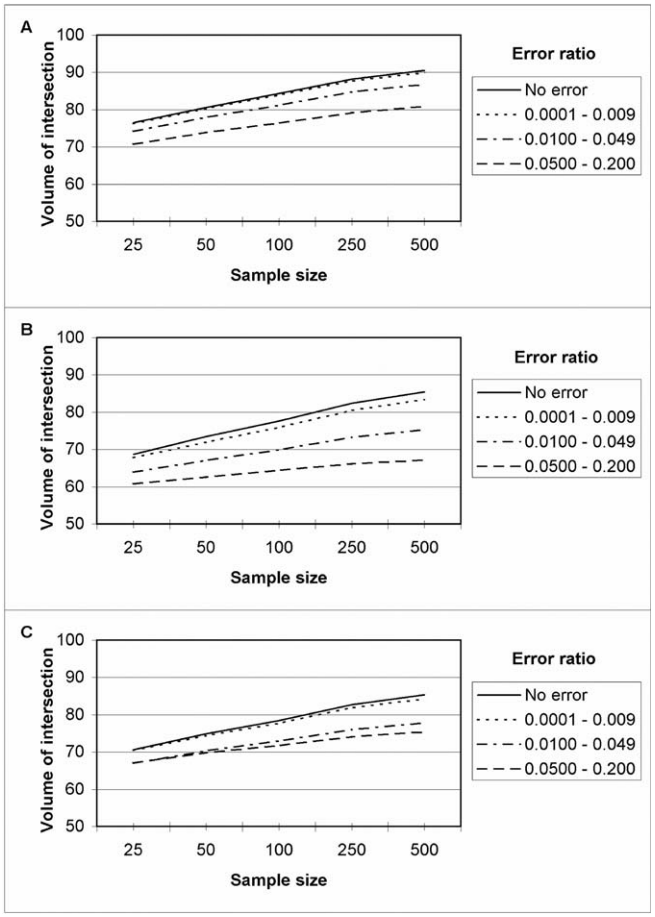

Figure 1. The effects of telemetry location error on volume of intersection scores for A) 1-mode mixtures, B) 4-mode mixtures, and C) 8-mode mixtures.

to estimate space use of the northern goshawk (*Accipiter gentilis*), a central-place forager that likely has a unimodal UD during the breeding season. We placed 20-g and 30-g bird-borne PTTs (North Star Science and Technology, King George, VA) at 65 locations systematically spaced in a forested landscape in northern Idaho to test PTT accuracy across a variety of cover types and topography. We generated beacon locations in a GIS and identified them on the ground using aerial photographs and Global Positioning System (GPS). We placed a PTT in the field at a beacon for one 12-hour duty cycle. We conducted all tests in 2005 after Argos implemented a new algorithm incorporating digital elevation models in the location calculations. Because previous studies have demonstrated Argos location class (LC) 1s to be highly inaccurate (e.g., >1,000 m; Keating et al. 1991), we considered only the more accurate LC 2 and 3s for the error analysis.

RESULTS

Simulations

The effects of telemetry error on fixed-kernel UD and area estimates were similar between the 2 bandwidth selection methods. Mean volume of intersection scores differed by <1% for the 2 methods, and mean percent relative bias differed by <5%. Therefore, to conserve space and simplify the results we present graphs for only the CV_b bandwidth-selection method.

For all comparisons, VI scores increased with sample size and decreased with increasing ER (Fig. 1). Location error had a relatively small effect on VI for 1-mode distributions except at the highest ER (Fig. 1A). However, even at the highest error level VI scores were only reduced by approximately 5%. At the lowest error level, volume of intersection scores passed the 80% mark at sample sizes of ≥50 and increased to approximately 90% for $n = 500$.

Location error had a more marked effect on VI scores for the more complex distributions (Fig. 1B, C). Fixed-kernel estimates, however, performed better with telemetry error for the 8-mode relative to the 4-mode distributions. Volume of intersection scores reached 80% for no error and low ER values at $n > 175$ for the 8-mode distributions. Scores failed to reach 80% even at $n = 500$ for the 2 highest ERs for the 4-mode distributions.

For all 95% contour comparisons, percent relative bias decreased with sample size and increased with increasing ER (Fig. 2). The lowest level of telemetry error had a <4% positive relative bias effect on 95% contour estimates for 1-mode distributions compared to no error estimates (Fig. 2A). The highest error level resulted in a <10% positive relative bias for all sample sizes compared to the no error estimates.

More complex distributions resulted in higher levels of relative bias (Fig. 2). The percent relative bias caused by the low ER in 4-mode distributions was <20% for sample sizes compared to the no error estimates. The higher ERs resulted in relative bias >40% across all sample sizes compared to the no error estimates (Fig. 2B). Low error in 8-mode distributions resulted in percent relative bias of <5% when $n > 50$ compared to no error estimates. The higher ERs resulted in positive relative bias >35% for all sample sizes when compared to no error estimates (Fig. 2C).

Patterns of relative bias were similar for the 50% contour estimates, although relative bias generally increased compared to 95% area estimates (Fig. 3). Again, percent relative bias decreased with sample size and increased with increasing ER (Fig. 3). Low ER did not affect estimates for 1-, 4-, or 8-mode distributions by >10% when compared to no error estimates (Fig 3). However, the higher ERs in the more complex distributions resulted in positive relative bias >75% for all sample sizes when compared to the no error estimates (Fig. 3B, C).

Case Study

Our satellite PTT LC 3s and 2s had a median error of 225 m and 305 m, respectively. The combined median error for LC 2s and 3s was 254 m. Using the median error as a radius to calculate a $CEP_{0.50}$, and a published goshawk home range of approximately 25,000,000 m^2 (Squires and Reynolds 1997), the calculated ERs for LC 3s, 2s, and combined were 0.006, 0.012, and 0.008, respectively. Based upon our simulations we determined that location error for both LC 2s and 3s was unlikely to affect our fixed-kernel space use

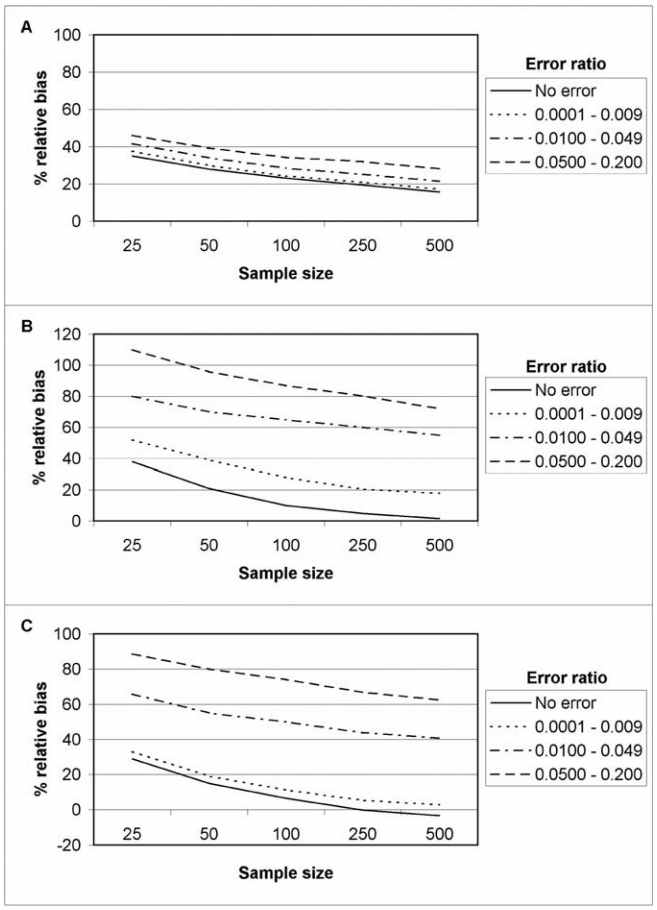

Figure 2. The effects of telemetry location error on percent relative bias for 95% fixed-kernel contour estimates for A) 1-mode mixtures, B) 4-mode mixtures, and C) 8-mode mixtures.

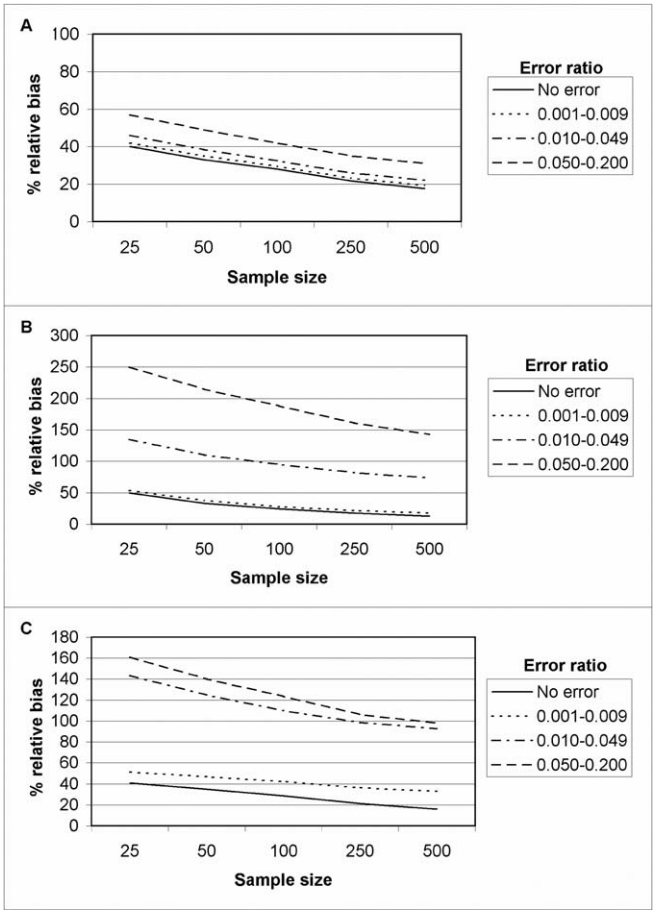

Figure 3. The effects of telemetry location error on percent relative bias for 50% fixed-kernel contour estimates for A) 1-mode mixtures, B) 4-mode mixtures, and C) 8-mode mixtures.

estimates by >10% regardless of the metric used to judge the estimates.

DISCUSSION

Error ratios for most telemetry studies are below the 0.01 limit that we demonstrated had a relatively small effect on fixed-kernel density estimates. Studies using telemetry systems with a relatively high median location error may be appropriate as long as the home range is large, relative to the size of the $CEP_{0.50}$. Our case study using PTTs designed for use on northern goshawks is a good example because the Argos system is one of the least accurate telemetry systems available (Rodgers 2001). However, the northern goshawk is a relatively wide-ranging central-place forager (Squires and Reynolds 1997), which mitigates the effects of location error. On the other hand, a species with a small home range relative to $CEP_{0.50}$ would require a much more accurate telemetry system. A recent study by Kauhala and Tiilikainen (2002) demonstrated that the median error using very high frequency (VHF) telemetry to assess mountain hare (*Lepus timidus*) home ranges was 218 m. Using published home ranges of 113 ha for males and 89 ha for females (Hewson and Hinge 1990), the ERs would be 0.13 and 0.17, respectively. Error ratios this high would likely lead to kernel estimates that are highly inaccurate or biased.

Wildlife telemetry studies using GPS will probably have low ERs based on a published median location error of 5.9 m (D'Eon et al. 2002). Because most GPS transmitters are too heavy (i.e., >45 g) to go on smaller animals with relatively small home ranges, they are limited to larger animals (particularly mammals) that have larger home ranges. Because large home ranges relative to location error will result in low ERs, fixed-kernel estimates based on GPS telemetry will likely be satisfactory for most studies.

Telemetry location sample sizes >50, such as those obtained using satellite telemetry, generally lead to improved kernel estimates (Seaman et al. 1999) but can potentially lead to autocorrelation issues depending on the sampling interval (Swihart and Slade 1997). Estimates using clustered, autocorrelated points tend to have high failure rates using $LSCV_h$ (Hemson et al. 2005). In addition, $n >$ 100 have been shown to adversely affect kernel estimates when using $LSCV_h$ (Hemson et al. 2005). Fixed-kernel density estimates using CV_h tend to fail less often when points are clustered (Horne and Garton 2006). Large numbers of highly correlated locations may be better suited to space use estimators that explicitly incorporate time

between successive locations, such as Brownian bridge analyses (Horne and Garton 2007).

We did not control for home range shape per se in our study, nor did we attempt to assess the accuracy of the home-range shape estimates. The shape and location of fixed-kernel contours may be important for use in assessing animal interactions, habitat use, and habitat availability. Location error is likely to affect the shape and location of fixed-kernel contours and, thus, may affect studies that use these contours. Furthermore, although we reported effects of error relative to home range size, estimates of resource selection may be affected by absolute error, regardless of home range size. Further simulation studies could elucidate these effects on contours using Monte Carlo integration (e.g., Kong et al. 2003).

Location error is likely to affect home range estimates differently for animals that use narrow, linear landscape features compared to animals that more uniformly use a landscape (e.g., Blundell et al. 2001). Researchers should be aware that linear home ranges or those with multiple linear features will be more sensitive to location error, and our results may not be as applicable.

Accurate fixed-kernel estimates were a trade-off between telemetry error and sample size. Sample sizes of $\geq$50 appear to be appropriate for most telemetry studies, although our estimates generally continued to improve to $n = 500$. Although large sample sizes may be difficult to obtain in studies using VHF telemetry, they are more easily obtained using satellite telemetry and are recommended as long as serial correlation does not adversely affect estimates (Hemson et al. 2005).

Simulation studies such as ours are useful for understanding real-world phenomena. However, rarely are the methods able to simulate all estimators, field conditions and telemetry systems. We simplified our simulations to make analyses and interpretations easier. Many types of kernel estimators are available, and their use may lead to different conclusions than ours. In addition, real telemetry error may not be distributed the same as our simulated locations. We recommend researchers seek to understand the estimator they are using, the properties of their data, and how both of these might affect their space-use estimates, including estimates of the UD, home range area, and contour shape and placement.

MANAGEMENT IMPLICATIONS

We have provided wildlife researchers with a tool to evaluate the effects of telemetry error on fixed-kernel density estimates before a telemetry study is undertaken. We demonstrated that the level of location error found in most telemetry studies will not greatly affect fixed-kernel UD and contour area estimates. However, researchers must determine the acceptable level of telemetry error based on the objectives of their study. In addition, all telemetry studies should estimate and report location error, and median error is a more appropriate measure of central tendency than the mean when the distribution of location errors is skewed. Using the median location error to compute the $CEP_{0.50}$ and an a priori estimate of an animal's home range, researchers can determine whether the expected fixed-kernel estimates are suitable for their study objectives.

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