EFFECTS OF SAMPLE SIZE ON KERNEL HOME RANGE ESTIMATES

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Abstract: Kernel methods for estimating home range are being used increasingly in wildlife research, but the effect of sample size on their accuracy is not known. We used computer simulations of 10–200 points/home range and compared accuracy of home range estimates produced by fixed and adaptive kernels with the reference (REF) and least-squares cross-validation (LSCV) methods for determining the amount of smoothing. Simulated home ranges varied from simple to complex shapes created by mixing bivariate normal distributions. We used the size of the 95% home range area and the relative mean squared error of the surface fit to assess the accuracy of the kernel home range estimates. For both measures, the bias and variance approached an asymptote at about 50 observations/home range. The fixed kernel with smoothing selected by LSCV provided the least-biased estimates of the 95% home range area. All kernel methods produced similar surface fit for most simulations, but the fixed kernel with LSCV had the lowest frequency and magnitude of very poor estimates. We reviewed 101 papers published in *The Journal of Wildlife Management* (*JWM*) between 1980 and 1997 that estimated animal home ranges. A minority of these papers used nonparametric utilization distribution (UD) estimators, and most did not adequately report sample sizes. We recommend that home range studies using kernel estimates use LSCV to determine the amount of smoothing, obtain a minimum of 30 observations per animal (but preferably ≥50), and report sample sizes in published results.

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Kernel methods have recently become popular for home range estimation, and a number of programs are available to implement them (Seaman et al. 1998). Previous work has demonstrated that kernel methods can provide more accurate home range estimates than the harmonic mean or minimum convex polygon (MCP) models (Naef-Daenzer 1993, Worton 1995, Seaman and Powell 1996, Swihart and Slade 1997). Boulanger and White (1990) demonstrated that other popular home range estimators perform more poorly than the harmonic mean.

Kernel methods produce a density estimate that can be interpreted as a UD (van Winkle 1975). A strength of UD estimators is that they provide 3-dimensional estimates of home ranges. The third dimension corresponds to the amount of time the animal spent in any given area of its home range and is useful for assessing issues such as habitat selection (Mitchell 1997).

All estimators are subject to sampling error, which diminishes as sample size increases. Additionally, the accuracy of any estimator depends on the distribution of the data. For example, normal-theory statistical estimators are unbiased only for normally distributed data. Because animal home ranges rarely conform to simple statistical distributions, estimators that rely on distributional assumptions are likely to perform poorly as home range estimators. Kernel estimators are nonparametric, meaning they are not based on an assumption that the data conform to specified distributional parameters. Nevertheless, the accuracy of the estimates they produce will vary depending on the distribution of the data.

No analytical method is available to determine the necessary sample size for nonparametric home range estimators because they do not have an associated variance estimator (White and Garrott 1990). Several studies with the MCP home range estimator have used area-

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observation curves on radiotelemetry data or on simulated locations to determine adequate sample size. These studies have concluded that 100–300 locations are necessary to reach asymptotic levels for the MCP (Bekoff and Mech 1984, Laundre and Keller 1984, Harris et al. 1990).

Silverman (1986) calculated the sample size requirements for multivariate kernel estimators. He used only a very restricted case where he specified the desired level of precision for the density estimate at a single point at the center of a normal distribution. For bivariate normal distributions with desired precision (relative mean squared error) of 0.1, he calculated a necessary sample size of 19. Swihart and Slade (1997) explored the effects of several sampling parameters (autocorrelation, study duration, sampling rate, sampling style, sample size) on the bias of MCP and fixed kernel home range size estimates. Their emphasis was on the parameters other than sample size, but they noted that bias decreased with larger sample sizes.

We expected that accuracy of kernel home range estimates would depend on sample size and shape of the home range. Therefore, we used Monte Carlo methods with various numbers of locations and shapes to evaluate the accuracy of kernel methods for estimating the area and the UD surface fit of simulated home ranges. We reviewed papers published in *JWM* between 1980 and 1997 that reported original estimates of animals' home ranges. We tabulated the home range estimation techniques they used, and what information they reported about sample sizes.

METHODS

Simulations

We assumed an animal's home range could be represented by a UD and created home range distributions that were simple or complex in shape (Fig. 1). Simple distributions consisted of a single bivariate normal distribution. Complex distributions had characteristics frequently seen in animal home ranges: they were multimodal (i.e., had multiple centers of activity), had occasional disjunct areas, were nonconvex, and were nonuniform (i.e., the distribution was not the same height across the entire area of the home range).

We simulated 3 types of home ranges by randomly sampling locations from a single bivariate normal distribution or from mixtures of 4 or 16 bivariate normal distributions (Fig. 1). The values of the means, standard deviations, and covariances of the bivariate normal distributions were randomly selected from uniform distributions. Mean values for the X-Y coordinates of the components were randomly selected within the range 0 to 20; standard deviations ranged from 1 to 6; X-Y covariances (ρ) ranged from -1 to 1; and mixing proportions were >0 and

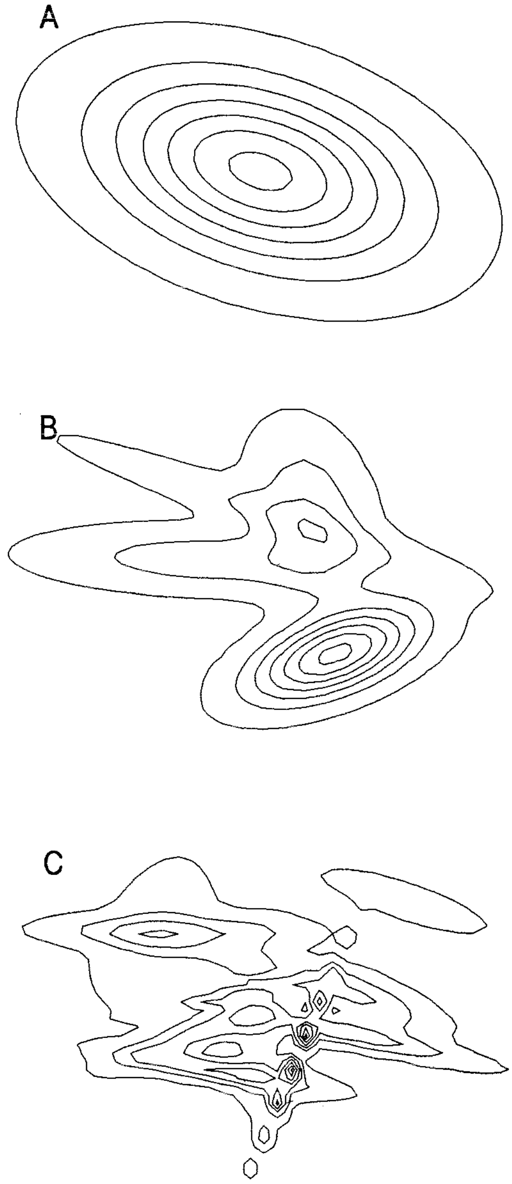

Fig. 1. Example of shapes of simulated home ranges composed of (A) 1, (B) 4, and (C) 16 bivariate normal distributions.

constrained to sum to 1 (Seaman and Powell 1996). The shape of the simulated UD was determined by calculating the density at grid points via the normal density function (Hogg and Craig 1995:147)

$$D_n = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \times \exp\left\{-\frac{1}{2(1-\rho^2)} \times \left[\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\left(\frac{x-\mu_x}{\sigma_x}\right)\left(\frac{y-\mu_y}{\sigma_y}\right)\right]\right\}.$$

The 3 types of home ranges (1, 4, or 16 components) were each represented by 10 realizations (i.e., 10 different sets of parameters defining the components of the mixture). Each of these 30 home ranges was sampled with 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, and 200 points. We ran 100 replicates at each sample size for each home range, for a total of 36,000 simulations. We used the variance of the 100 replicates as an empirical estimate of precision because variance estimators do not exist for nonparametric home range estimators. Simulated true home range shapes that could not be estimated within the available computer memory were discarded and new home ranges were simulated in their place.

Area Bias

Home range analyses usually estimate the area of home ranges, so it is useful to know the accuracy of kernel area estimates. We calculated the minimum area that contained 95% of the estimated UD ($\hat{A}$) and calculated the percent relative bias (PRB) with respect to the 95% area of the true distribution (A) via the following:

$$\mathrm{PRB} = [\hat{A} - A]/A \times 100.$$

Although home range studies often focus on the 95% use area, the bias at the 95% contour may not be representative of bias at other contours. Therefore, we analyzed the bias at 10 contours of the UD, 10–90% contours at 10% intervals, and the 95% contour.

Surface Fit

We measured the accuracy of the 3-dimensional surface estimate assessed over a regular grid of evaluation points as the relative mean squared error (RMSE):

$$\mathrm{RMSE} = \frac{1}{n}\sum_{i=1}^{n}\frac{[\hat{f}(x) - f(x)]^2}{f(x)},$$

where n is the number of grid points, x is a vector of the grid point coordinates, $\hat{f}$ is the estimated density at the grid point, and f is the true density at the grid point. This measure is only calculated for grid points within the 95% UD of the true home range, within the 95% UD of the estimated home range, or both. Calculating RMSE for grid points within the 95% UD minimized the effects of small errors in the tails of the UD (cf. Seaman and Powell 1996). Also, measuring the surface fit at grid points is a more complete measure than is obtained from the observation coordinates (cf. Worton 1989).

The measure of error for surface fit (RMSE) uses the squared errors and therefore contrasts with bias because RMSE is nondirectional. We chose this measure for surface fit because it is more interesting in this context. An estimated surface that is low over a portion of the UD and high over another could have a mean error of zero but a large RMSE. However, an estimated surface that is only slightly too high over the entire distribution would have a positive error and a small RMSE. The latter estimate would be more desirable despite its positive bias.

Estimation Programs and Methods

The home range estimates in this study were produced by the algorithm used in program KERNELHR (Seaman et al. 1998). This algorithm was incorporated into a different program (MISE) that also calculated RMSE. Initial home range estimates were made via the fixed and adaptive kernels, with the amount of smoothing determined by the REF method and by LSCV (Worton 1995, Seaman and Powell 1996).

Upon inspection of the initial simulations, we evaluated whether the large RMSE at small sample sizes was due to sampling error or the behavior of LSCV with small sample sizes. Sampling error is the result of random selection of points not representative of the true distribution and is more influential with small sample sizes. However, poor estimates could also result from incorrect smoothing, which may occur if LSCV is unable to operate effectively with small sample sizes (regardless of whether they are representative of the true distribution). To investigate this question, we assumed LSCV had selected the correct smoothing for sample sizes of 150–200 (Bowman 1985, Seaman and Powell 1996), then we applied this smoothing value to all home ranges and sample sizes. The mean amount of smoothing selected by LSCV for large sample sizes was about 50% of the reference value, so we applied 50% of the reference value smoothing to all sample sizes.

Literature Review

We performed a computer search of research papers published in *JWM* between 1980 and 1997, using the keywords "home range" and "movements." We began the search with 1980 because that was when UD estimation became generally available to wildlife researchers (Dixon and Chapman 1980). We examined each paper that reported original home range estimates to determine which home range estimators were used and how sample sizes were reported. Sample size reporting was categorized as (1) no information; (2) total number of observations (for all study animals combined); (3) minimum number of observations per animal; and (4) sample size for each animal, or the mean or range for all animals.

RESULTS

Area Bias

When we used LSCV to select the amount of smoothing, small sample sizes (<50 observations) greatly overestimated home range area. For these estimates, larger sample sizes reduced bias and increased precision (indicated by smaller standard errors) for both the fixed and adaptive kernels. For the fixed kernel estimates (Fig. 2A), these improvements approached an asymptote at a sample size of about 50 for the 1 and 4 component ranges, but the 16 component ranges continued to improve slightly as sample sizes increased to 200. Adaptive kernel estimates (Fig. 2B) did not reach a clear asymptote, but improvements were smaller at sample sizes >50.

Estimates from the fixed kernel with smoothing selected by LSCV (Fig. 2A) generally had the smallest bias for all 3 home range types. The only exception was for 1-component ranges, which had less bias when we used the fixed kernel with smoothing selected by the reference method.

When we used REF to select the amount of

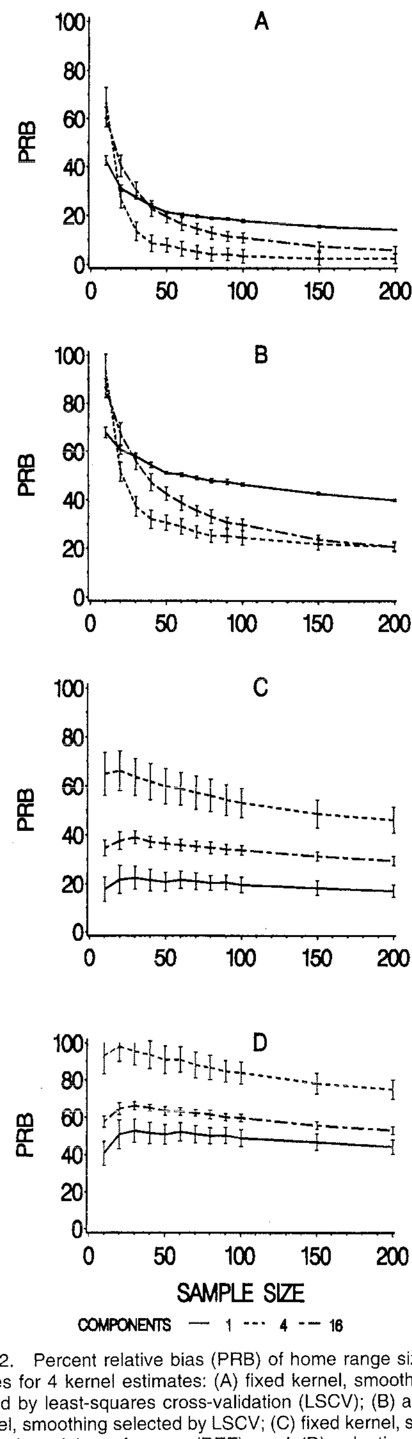

Fig. 2. Percent relative bias (PRB) of home range size estimates for 4 kernel estimates: (A) fixed kernel, smoothing selected by least-squares cross-validation (LSCV); (B) adaptive kernel, smoothing selected by LSCV; (C) fixed kernel, smoothing selected by reference (REF); and (D) adaptive kernel, smoothing selected by REF (D). Point estimates are means of 1,000 replicates (100 replicates for 10 home range shapes), and vertical bars represent ± 1 standard error.

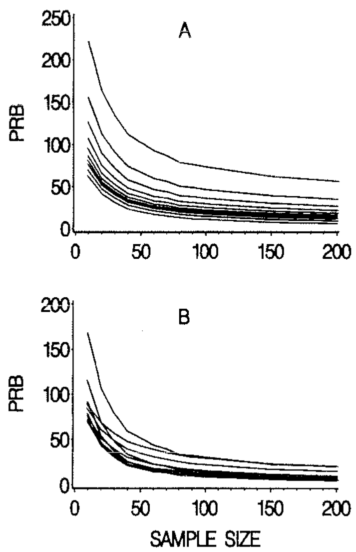

Fig. 3. Percent relative bias (PRB) of the estimate of home range area within 10 contours. Estimates used smoothing selected by least-squares cross-validation on home ranges composed of 16 bivariate normals. (A) Fixed kernel estimates, lines represent the 10, 20, 30, 40, 50, 60, 70, 80, 90, and 95% utilization distribution contours from top to bottom at sample size of 200; (B) adaptive kernel estimates, lines represent the 95, 90, 10, 80, 70, 60, 50, 40, 30, and 20% use contours from top to bottom at sample size of 200. All values are means of 1,000 replicates for each sample size. Note different scales for *Y*-axis in (A) and (B).

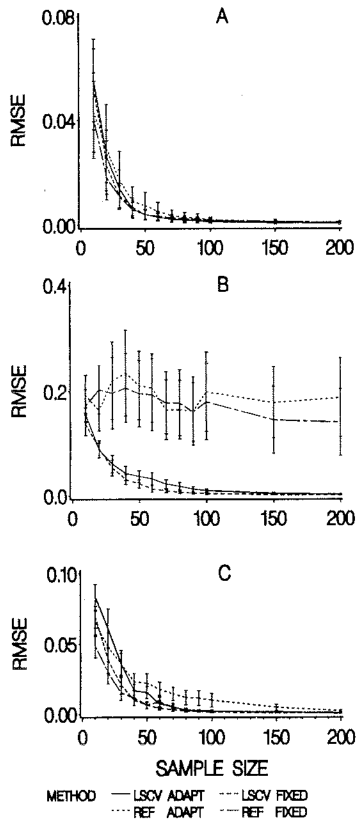

Fig. 4. Relative mean squared error (RMSE) for kernel estimates for 3 home range types composed of (A) 1, (B) 4, and (C) 16 bivariate normal distributions. Point estimates are means of 1,000 replicates (100 replicates for 10 home range shapes), and vertical bars represent ± 1 standard error. Methods are least-square cross-validation (LSCV) and reference (REF).

smoothing, sample size had little effect on estimates (Figs. 2C,D), and REF estimates had greater bias overall than those with smoothing selected by LSCV (Figs. 2A,B). Of the 3 types of home ranges, the 4-component home ranges showed the greatest reduction in bias with smoothing selected by LSCV as opposed to REF (Figs. 2A,B vs. 2C,D).

Bias of the inner contours was greater than bias of the 95% contour for fixed kernel estimates (Fig. 3A). The general trend for adaptive kernel estimates was opposite of the fixed kernel estimates: outer contours were most biased and inner ones least biased (Fig. 3B). However, the results for the adaptive kernel estimates are less clear because adaptive kernels use many local adjustments to the amount of smoothing, which causes local variation in the bias at all contours.

Surface Fit

Surface fit improved as sample size increased to about 50 observations (Fig. 4) and was largely unaffected by kernel methodology (fixed vs. adaptive, or smoothing selected by LSCV vs. REF). The exception was for 4-component home ranges that never achieved good fit with smoothing selected by REF (Fig. 5B).

Most home ranges had RMSE values ≤1.0, but 8% of home range estimates had much larger RMSE (range = 1.0–4.6 × 10^{36}; Table 1). When the home ranges with RMSE >1.0 were included with all other home ranges, they obscured the general trends; therefore, they were analyzed separately. The fixed kernel with smoothing selected by LSCV produced the fewest estimates with extreme error values. Large RMSE values were most common when smoothing was selected by REF, particularly with the adaptive kernel. Large RMSE occurred most frequently with very small sample sizes (10–20), and was quite rare (<0.3% of replicates) for the fixed kernel with LSCV when sample sizes were >30. Large RMSE occurred

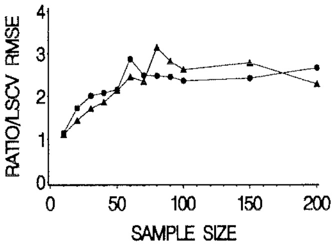

Fig. 5. Mean change in relative mean squared error (RMSE) with smoothing amounts selected by 0.5 × REF (RATIO) versus least-squares cross-validation (LSCV), excluding RMSE >1.0. Values are ($RMSE_{RATIO}$ / $RMSE_{LSCV}$) for the fixed (triangles) and adaptive (circles) kernel estimates. Values >1.0 indicate poorer accuracy with smoothing selected by RATIO than by LSCV.

in only about 5% of LSCV and 14% of REF home range estimates.

The RMSE of the surface fit was larger with smoothing set at 50% of REF (RATIO) than with smoothing selected by LSCV for all 3 home range types (Fig. 5). The number of occurrences of large RMSE was essentially equivalent with smoothing selected by RATIO and LSCV. However, the magnitude of these large RMSE estimates was much smaller with smoothing selected by RATIO for home ranges with 10–30 observations (Table 1). On average, LSCV performs best, but with <30 observations it occasionally performs very badly.

Literature Review

We identified 101 papers published in *JWM* between 1980 and 1997 that reported original home range estimates. Some papers used >1 estimator, 88 (87%) reported an MCP or minimum area estimate, 22 (22%) reported a harmonic mean, 7 (7%) reported a kernel, and 7 (7%) reported a bivariate normal ellipse. Many papers included scanty information about sample size: 21 (21%) did not report sample size at all, 17 (17%) reported only the total number of observations for the entire study, and 14 (14%) reported the minimum sample size used. Almost half of the papers (49 [49%]) reported reasonably complete sample size information, including either the number used for each home range, or the mean or range of sample sizes used for all home range estimates.

DISCUSSION

Kernel estimates of home range size and surface fit were highly influenced by sample size in these simulations when the amount of smoothing was chosen by the preferred method

Table 1. Mean surface fit for home ranges with relative mean squared error >1. Adaptive and fixed kernel results are given for each of 3 methods of determining the amount of smoothing: least-squares cross-validation (LSCV), reference (REF), and 0.5 × the reference value.

Sample	LSCV				REF				0.5 × REF			
size[a]	n[b]	Fixed	n	Adaptive	n	Fixed	n	Adaptive	n	Fixed	n	Adaptive
10	682	3.6×10^{25}	848	3.4×10^{29}	635	4.2×10^{14}	782	5.8×10^{19}	692	1.7×10^{3}	863	2.1×10^{7}
20	237	1.1×10^{11}	388	7.2×10^{18}	447	4.9×10^{11}	562	3.2×10^{30}	246	9.1×10^{1}	406	3.1×10^{6}
30	76	2.7×10^{8}	181	2.4×10^{11}	383	2.6×10^{6}	471	1.7×10^{14}	83	1.6×10^{1}	197	8.7×10^{2}
40	27	8.0×10^{5}	101	6.2×10^{2}	352	7.7×10^{6}	440	9.4×10^{17}	39	3.2×10^{6}	114	5.8×10^{5}
50	9	3.7	46	1.3×10^{1}	323	1.6×10^{6}	379	1.9×10^{11}	10	1.7	62	2.0×10^{1}
60	10	2.5×10^{1}	39	4.8×10^{2}	301	6.9×10^{4}	391	1.9×10^{18}	15	1.0×10^{2}	61	1.7×10^{1}
70	2	6.2	30	3.7×10^{4}	284	1.6×10^{4}	373	6.4×10^{9}	4	4.2	52	8.7
80	4	2.3	19	1.3×10^{1}	268	3.7×10^{2}	371	3.1×10^{9}	5	1.8	35	3.5×10^{1}
90	1	2.5×10^{1}	9	2.5	252	4.7×10^{1}	345	2.6×10^{11}	1	2.2×10^{1}	22	5.9
100	0	0	10	3.0	221	7.0×10^{1}	334	4.3×10^{9}	1	9.4	22	5.2
150	0	0	1	1.2	166	6.5	306	5.7×10^{3}	1	1.1	3	7.6
200	1	1.9	0	0	99	3.7	276	2.6×10^{5}	1	0.0	2	2.6

[a] Number of locations used to estimate home range.
[b] Number of home range replicates (out of 3,000) with relative mean squared error >1.

(LSCV). A sample of ≥50 observations was necessary to reduce average size bias or RMSE near asymptotic levels.

The pattern of overestimation of home range size with small sample sizes is opposite the findings for MCP estimators (Bekoff and Mech 1984, Laundre and Keller 1984, Harris et al. 1990). Our results also contrast with those of Hansteen et al. (1997) who found that small sample sizes produced generally smaller kernel home range estimates. They used kernel estimates with REF smoothing (from program RANGES IV) and a range of sample sizes from the locations of 3 root voles (*Microtus oeconomus*). We believe the differing patterns result from the behavior of LSCV versus REF, idiosyncrasies of home ranges, and differences in definitions of home range area. Small sample sizes provide little information about the true shape of the distribution, and the LSCV process increases the amount of smoothing, which results in larger home range size estimates. The MCP and some kernel programs use a percentage of the sample points to describe the home range (Seaman et al. 1998), which means that small sample sizes will have poor representation in the tails of the distribution, and the area estimate will be too small. In contrast, the definition of the home range in KERNELHR is based on the volume of the estimated UD (Seaman et al. 1998). The estimated area is larger because the tails of the UD are estimated from the information contained in the entire sample and do not depend entirely upon the few points that actually fall in the tails of the distribution. Since the accuracy of an estimator depends on the underlying distribution that the sample is drawn from, it is hard to generalize about the behavior of an estimator from results with a small number of home ranges (e.g., the 3 voles used by Hansteen et al. [1997]). Even the greater replication of our simulations needs to be confirmed with locations of many real animals.

We found limited support for our expectation that larger sample sizes would be required to obtain accurate estimates for more complex home range shapes. With smoothing selected by LSCV, simple (1-component) ranges had the smallest PRB at sample size 10, and complex ranges required sample sizes of 30–40 to achieve smaller PRB than simple ranges. In contrast, with smoothing selected by REF, 1-component ranges had the smallest PRB regardless of sample size. Low PRB is expected with smoothing selected by REF for 1-component ranges because they meet the REF method assumption of bivariate normality (Silverman 1986). Although the RMSE was clearly better for 1- than for 4-component ranges, 16-component ranges were nearly as good as the simple ranges.

Caution must be used in extrapolating from simulations to real data. We believe that mixtures of parametric distributions mimic real data more closely than samples from uniform distributions with simple geometric shapes (e.g. square, circular). However, our simulations do not give precise quantitative predictions about the performance of the estimators with real data. Also, all simulated observations were independent; we did not investigate the effects of serial autocorrelation (Swihart and Slade 1997). In field studies, there generally will be some sequential autocorrelation between observations, which will often increase as locations are recorded more frequently.

Estimates of 95% home range size were sensitive to the amount of smoothing. This sensitivity was demonstrated by the large difference in the bias between estimates with smoothing selected by LSCV and REF. In contrast, the surface fit was relatively insensitive to the amount of smoothing; all kernel estimators provided good estimates of the surface fit. Overall, the fixed kernel with smoothing selected by LSCV produced estimates with the lowest bias and lowest surface fit error and is recommended of the methods tested here. However, most of the difference between the fixed and adaptive kernel estimates occurred in the outer contours (>80% of the UD, data not shown); adaptive kernel estimates with smoothing selected by LSCV are satisfactory up to the 80% UD contour.

The unreliability of estimates in the outer contours has significant implications for home range analyses. Most studies report results for 95% home range estimates, but the peripheral area has the least data to support an estimate, probably has the least biological significance for the animal, and has the most opportunity to influence numerical results. It is important to acknowledge that our ability to make accurate estimates is limited in this region, while recognizing that the peripheral area is a necessary part of the home range for fulfilling the animals' biological requirements. We recommend that future studies emphasize the central parts of animals' home ranges for comparative numerical analyses (e.g., comparisons of home range size between populations, measures of overlap between neighbors) and habitat selection.

Choosing the correct amount of smoothing is important for obtaining accurate kernel estimates. The REF method is often referred to as the "optimal" smoothing width because it is optimal for bivariate normal distributions. However, the reference method should be avoided for home range estimation because it produces estimates with high bias and poor surface fit for distributions such as the complex ones simulated here. The LSCV method is preferable to the REF method for choosing the amount of smoothing, but other methods also deserve investigation (e.g., "solve-the-equation plug-in" [Sheather and Jones 1991, Jones et al. 1996]; biased cross-validation [Sain et al. 1994]).

Surface fit was better (RMSE was lower) with smoothing selected by LSCV than with smoothing set at 50% of REF in almost all simulations. The only exceptions were for large RMSE (Table 1) at small sample sizes (10–30 locations). In these cases, LSCV had consistently selected a large bandwidth (data not shown). These inconsistant results at small sample sizes demonstrate that the only reliable means of obtaining accurate home range size estimates and low RMSE is to collect >30 locations.

Collecting more frequent locations may result in increased autocorrelation between points. However, several authors (Andersen and Rongstad 1989, Reynolds and Laundre 1990, Minta 1992, McNay et al. 1994, Swihart and Slade 1997, Otis and White 1999) have argued that adequate sample size is more important than independence between points. In view of their conclusions and our results, we recommend that home range studies to be analyzed with kernel estimators obtain a representative sample of ≥30 locations, and preferably ≥50 locations.

Home range estimates are significantly affected by sample size (Bowen 1982, Bekoff and Mech 1984, Laundre and Keller 1984, Ackerman et al. 1990, Harris et al. 1990, this study) and by the estimator used (Boulanger and White 1990, Worton 1995, Seaman and Powell 1996). Even within kernel-based methods, variations (fixed vs. adaptive, LSCV vs. REF smoothing) can have large effects on the resulting estimates (Worton 1995, Seaman and Powell 1996, this study). Valid comparisons between studies cannot be made when sample sizes and estimation methods differ. Therefore, we strongly recommend that authors report sample sizes and the exact home range estimation method used.

The MCP remains the most commonly used home range estimator, despite widespread recognition of its weaknesses (Jennrich and Turner 1969, Worton 1987, Harris et al. 1990, White and Garrott 1990). Reasons cited for using the MCP include its value for comparison to previous work and its ease of calculation. These reasons are inadequate, because comparisons to previous work are unreliable given the extreme sensitivity of MCP to sample size (which is often unreported), and computer programs are now available that perform more sophisticated home range estimates with ease (Seaman et al. 1998).

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