A Euclidean distance metric to index dispersion from radiotelemetry data

L. Mike Conner and Bruce D. Leopold

Abstract Home range area is used frequently to quantify space-use patterns of wildlife. In many instances, however, home range area is used when other techniques may provide more precise and less biased estimates. Herein, we evaluate the average distance (AD) between all locations as a measure of dispersion among animal locations. We used radiotelemetry data collected on fox squirrels (*Sciurus niger*) to compare precision (i.e., coefficients of variation, CVs) and relative bias (RB) between adaptive kernel home range area (KHR) estimates and AD. When adequate data existed to estimate KHR (i.e., >50 locations/animal), precision of AD ($\bar{x}$ CV=7.08) was similar (P=0.288) but approximately 10 times less biased ($\bar{x}$ RB=0.012, P<0.001) than KHR ($\bar{x}$ CV=7.22, $\bar{x}$ RB=–0.144). When data were sparse (i.e., <25 locations/animal), AD was more precise ($\bar{x}$ CV=15.21, P<0.001) and approximately 5 times less biased ($\bar{x}$ RB=0.062, P<0.001) than KHR ($\bar{x}$ CV =21.47, $\bar{x}$ RB=-0.338). We compared dispersion of telemetry locations between male and female fox squirrels to provide an example application of AD. Male AD (304±21.44 m, $\bar{x}$±SE) was larger (P<0.001) than female AD (158.28±9.76 m). We also used regression analysis to describe the relationship between AD and KHR for fox squirrels. Although we do not advocate using AD to predict KHR, we found a strong linear relationship (r^2=0.85, P<0.001) between AD and KHR, indicating the metrics are very related. The AD should be used to analyze telemetry data when spatial dispersion, as opposed to home range area, will suffice to address research objectives. Novel approaches to investigate space-use patterns may emerge by integrating AD with home range estimates.

Key words dispersion, fox squirrel, home range, radiotelemetry, *Sciurus niger,* space-use index

Home ranges are commonly derived from radiotelemetry data and are often used to explore space-use patterns of wildlife. However, home range estimates often are not required to meet study objectives, and in such cases, the data itself rather than a model of the data should be used to make inferences (White and Garrott 1990). Although evaluating certain aspects of animal behavior directly from telemetry data is common (e.g., movement rates derived from sequential locations), spatial dispersion of locations is seldom measured directly from data.

Home ranges are often used when study objectives could be addressed directly from animal locations. For example, home range area is often related to sex (McCullough et al. 2000), season (Judas and Henry 1999), habitat quality (Relyea et al. 2000), or other ecological variables. Although use of home range area to address these issues may be relevant in some cases, an assessment of dispersion may be equally, if not more, relevant.

Koeppl et al. (1977) suggested that the average Euclidean distance (i.e., the average linear distance, hereafter abbreviated AD) between all possible pairs of animal locations provided a good index of spatial dispersion. This statistic is interpreted easily; larger values are indicative of greater dispersion. However, the AD approach has not been used widely to

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analyze radiotelemetry data, perhaps because the procedure has received limited exposure in the literature relative to various home range models.

Although AD was reported and evaluated as a metric to index dispersion of locations (Koeppl et al. 1977), there has been no comparison of the merits of the technique relative to home range estimators, and the technique has not been evaluated using real data. We acknowledge that home range and AD do not provide estimates of the same parameter, but we suggest that the most precise and least biased estimator that meets study objectives should be used. This is particularly important given the recent emphasis on estimation as opposed to hypothesis testing (Johnson 1999). Therefore, we used actual telemetry data to compare precision and bias of AD and KHR estimators when data are too sparse (<25 locations) and when data are adequate (>50 locations) to estimate KHR (Seaman et al. 1999). We also provided an example of how AD can be used to test hypotheses that are normally addressed using home range models by determining whether AD differed between males and females. Lastly, we assessed the relationship between AD and KHR when number of locations is adequate to calculate KHR.

Methods

We chose to compare precision and relative bias of AD to KHR because kernel estimates have superior qualities relative to other home range methods (Worton 1995) and the KHR method is popular in wildlife studies (Hodges et al. 2000, McCullough et al. 2000). Furthermore, KHR can provide reasonable estimates of home range area when number of locations is $\geq$30 (Seaman et al. 1999). In contrast, other home range estimators often require >150 locations to provide reliable home range estimates (Bekoff and Mech 1984).

We used radiotelemetry data collected during a fox squirrel study to make our comparisons and to assess the relationship between KHR and AD. Fox squirrels were tracked during March 1998-December 1999 at the Joseph W. Jones Ecological Research Center in southwest Georgia. We partitioned data into calendar seasons and omitted fox squirrels with <10 locations within a given season from further analysis.

We created 2 sets of data for our analysis. The first data set used composite data (i.e., all locations on each animal), with >50 locations/animal, to represent a situation in which data are considered adequate to estimate home range area (Seaman et al. 1999). The second data set used seasonal data, with 10-23 locations/animal, to represent a sparse-data scenario (i.e., a scenario in which data are insufficient to reliably estimate home range area).

Bootstrapping (i.e., sampling with replacement) allows estimation of variability and bias associated with a metric (Manly 1997). We used HOME RANGER (Hovey 1998) to estimate KHR, average KHR, and KHR variability. Similarly, we used a FORTRAN program (available from the senior author) to calculate AD (Equation 1), average AD, and AD variability. Estimates of average KHR, KHR variability, average AD, and AD variability were derived from 100 bootstrapped samples of locations taken on each animal in each data set (Manly 1997).

$$AD = \frac{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}}{\frac{N(N-1)}{2}}, \qquad (1)$$

where: number of locations ranges from $i=1$ to N, $\times$ is the x-coordinate, and Y is the y-coordinate.

We calculated coefficients of variation (CV) using the average bootstrapped estimates of KHR and AD and their associated estimates of variability to compare precision between KHR and AD. Because the CV reports variability relative to the mean, CVs are comparable regardless of the unit of measurement (Zar 1996).

We estimated bias for KHR and AD as the observed value of the metric minus the bootstrapped average of the metric. We then calculated RB as bias divided by the bootstrapped average of the metric. Relative bias, then, is similar to the CV in that RB is scaled relative to the mean and RBs are comparable regardless of the unit of measurement. We compared CVs and RBs between KHR and AD using Wilcoxon signed rank tests (Zar 1996). Because KHR tended to be biased negatively and AD tended to be biased positively, we performed hypotheses tests of RB between the 2 methods using absolute values of RB. However, we report only actual RB because actual values provide more information concerning direction of bias (i.e., positive or negative).

It is often useful to determine whether space use is similar between males and females (McCullough et al. 2000). Therefore, we illustrated the utility of AD to address this problem by using a t-test to evaluate the hypotheses that AD did not differ between male and female fox squirrels.

We used composite data sets and simple linear regression (Kleinbaum et al. 1988) to assess the relationship between KHR area and AD. For this analysis, we predicted KHR as a function of AD. We used SAS (SAS Institute 1995) for all statistical analyses.

Results

When we used composite data (N=39 data sets) to represent an adequate-data scenario, mean (±SE) KHR was 23.3±2.8 ha and mean AD was 199.6± 14.0 m. Number of locations/animal within the composite data set ranged from 50 to 171. When we used seasonal data (N=201 data sets) to represent a sparse-data scenario, mean KHR was 23.8± 2.1 ha and mean AD was 173.86±6.9 m. Number of locations/animal within the seasonal data set ranged from 10 to 23.

When we calculated bootstrapped estimates of KHR, AD, and their associated variability for composite data sets, mean AD CV was similar (N=39, T=77, P=0.288) to mean KHR CV (7.1±0.6, range= 3.0–24.2 and 7.2±0.3, range=4.0–11.4, respectively). However, the mean |RB| of AD was less (N=39, T= 385, P <0.001) than the mean |RB| of KHR (RB= 0.012±0.012, range=-0.026–0.036 and RB=-0.144± 0.013, range=-0.294–0.065, respectively). Approximately 92% (i.e., 36 of 39) of KHR estimates were biased negatively and approximately 90% (i.e., 35 of 39) of AD estimates were biased positively.

When we calculated bootstrapped estimates of KHR, AD, and their associated variability for seasonal data sets, mean AD CV was less (N=201, T= 6,821.5, P<0.001) than mean KHR CV (15.2±0.4, range=7.3–50.7 and 21.5±1.2, range=5.0–217.7, respectively). The mean |RB| of AD was less (N= 201, T=9,927.5, P <0.001) than the mean |RB| of KHR (RB=0.062±0.003, range=-0.025–0.398 and RB= -0.338±0.013, range= -0.970–0.667, respectively). Approximately 94% (i.e., 188 of 201) of KHR estimates were biased negatively and approximately 90% (i.e., 180 of 201) of AD estimates were biased positively.

Using composite data, male AD (304±21.44 m) was larger (t_{37}=7.15, P<0.001) than female AD (158.28±9.76 m). There was a strong linear relationship ($F_{1,38}$=230.4, r^2=0.85, P<0.001) between AD and KHR (Figure 1).

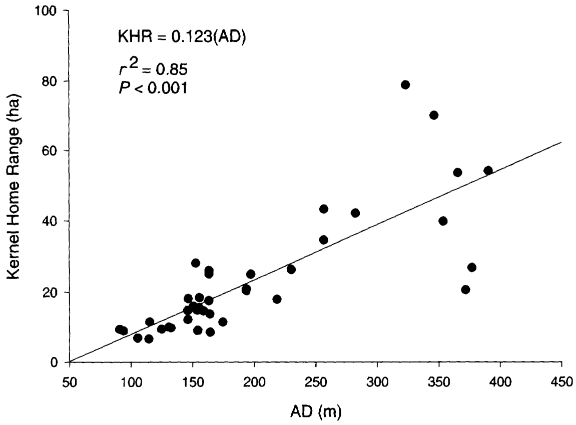

Figure 1. Fox squirrel kernel home range (KHR) size as a function of the mean Euclidean distance (AD) between all pairs of points. Data were collected in southwest Georgia, 1998–1999.

Discussion

The 2 methods we chose to compare do not estimate the same parameter. However, we agree with White and Garrott (1990) that when possible, inferences from locations should be based on the actual locations rather than a model of the locations. We standardized estimates of precision and bias (i.e., CV and RB) associated with AD and KHR and compared these standardized estimates. Our results demonstrated that AD provides a summary statistic of location dispersion that is more precise and less biased than a commonly used home range approach (i.e., KHR).

Hypotheses concerning dispersion are addressed easily using AD. We compared dispersion of locations between sexes as an example application of AD. This analysis indicated that among our fox squirrels, male AD was larger than female AD. The AD also could be used to address questions that are generally addressed using home range models. For example, AD could be used to determine whether dispersion differed as a function of season (Judas and Henry 1999) or habitat quality (Relyea et al. 2000).

Using AD to index spatial dispersion is not a new technique (Koeppl et al. 1977), but the technique is not used widely among wildlife researchers. Many studies, however, could benefit from using AD instead of traditional home range area, especially when data are sparse. Whenever researchers are interested in evaluating space-use patterns (e.g., effect of food abundance on space use), home range area is generally the metric chosen for the evaluation. This is likely due to the ease in understanding the concept of home range area (i.e., it is straightforward to discuss dispersion using area concepts as opposed to distances). We suggest, however, that AD is more appropriate to analyze location dispersion than are home range models.

Although we provided a model of the relationship between AD and KHR to show that the 2 metrics are related strongly, we do not advocate estimating home range area from AD when data are inadequate for direct home range estimation. We caution readers that the relationship between AD and home range area will likely vary among species and habitats, but we suggest that this variability may present opportunities for further research.

There are drawbacks to the AD approach. Assessing spatial overlap is often a study objective and there is no intuitive approach to apply AD to address this objective. Furthermore, if an estimate of the area required by an animal is a research objective, then home range area should be derived directly from animal locations rather than modeled from AD.

There are several computer packages that can be used to calculate AD. BLOSSOM (Cade and Richards 2000) is an interactive program that performs a variety of statistical comparisons based on permutation tests. The AD statistic can be calculated as an intermediate statistic within the MRPP routine in this package. A similar MRPP routine can be found in PC-ORD (McCune and Mefford 1999). A program that specifically calculates AD and permits batch processing is available from the senior author.

Future research

Our comparison of AD to home range was performed using real data collected on radio-monitored fox squirrels. Although our approach permitted discussion of the use of AD with telemetry data and allowed some comparison of AD to a common home range model, simulations are needed to thoroughly evaluate AD relative to standard home range approaches. Specifically, our data provided some indication that AD may perform better that KHR with sparse data, but simulations are required to determine sample sizes required for adequate estimation of AD.

Future research should address integrating AD and home range models to provide a more thorough investigation of animal space-use patterns. For example, a residual analysis of a regression of home range size as a function of AD can identify animals that have more, or less, dispersed locations relative to home range size. Once identified, causal mechanisms that influence space-use patterns can be suggested and explored experimentally.

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