

HOME RANGE AND CORE AREA ESTIMATION USING GIS

Summary

1. Home-range estimation has traditionally been achieved through use of specific software packages. Such systems are inherently limited in their flexibility of analysis. GIS offers the potential of performing such estimation, of integrating habitat data and of performing two and three-dimensional analysis. Additionally, their increased flexibility should allow more complex hypotheses regarding animal movement to be tested.
2. To develop a GIS-based home-range estimation package it is first necessary to determine the limitations of in-built functions of GISs. Methods of home-range estimation were developed in a proprietary GIS, ArcInfo[®] (Environmental Systems Research Institute, Inc., Redlands, California). Methods developed include minimum-convex-polygon, gridcell, harmonic-mean, fixed kernel and digitised polygon estimators.
3. Red fox and American Bittern data-sets were used to test the estimators. Comparison with the output from a commercial GIS software package, RangesV (ITE, Furzebrook, 1992) showed that methods developed in ArcInfo give significantly different home-range area estimations that RangesV. However, a comparison with a related GIS-based package, ArcView[®] (Environmental Systems Research Institute, Inc., Redlands, California) indicated that there were no significant differences between mcp estimates, as would be expected, suggesting that output from the RangesV package should be treated with caution. However a comparison of harmonic-mean and fixed kernels estimators between ArcInfo and RangesV shows that both methods pick-out similar internal range-use configurations.
4. The use of in-built functions in a proprietary GIS to develop home-range estimators is, thus, possible. Developing an integrated GIS-based home-range package is more difficult because of the statistical limitations of currently in-built functions, thus at present there is a need for soft linkages to other software packages.
5. Preliminary work shows that GIS has the potential for novel methods of core-area estimation to be developed, however time limitations prevented these being developed sufficiently.

Key Words: Core area estimation, GIS, home range analysis,utilization distribution

Introduction

Geographic Information Systems (GIS) are integrated systems of hardware and software for the analysis and display of spatially distributed data and have traditionally been the domain of geographers in which GISs were developed for specific applications, for example hydrologic modelling. An emphasis in current years has been to extend GIS into other subject areas becoming increasingly general and more flexible in their ability to link with other data formats and software (Batty and Xie 1994). The traditional emphasis on data organisation and mapping (Batty and Xie 1994) has meant that basic operations which are relevant to all spatial analyses are integrated within proprietary GISs. However, one drawback of this historical reliance on specific applications has been that in-built features are often limited and thus an increasing emphasis in GIS development has been an attempt to link existing software to GIS through the use of macro-language. Before this is done is useful to see what the limits of in-built functions are, thereby allowing areas which need further development to be identified.

The use of GIS in ecology dates back to the late 1980s, mainly within the emerging discipline of landscape ecology. The first ecological-GIS publication was presented in 1990 (Johnston 1990) and whilst the number of such publications has grown steadily they are still relatively uncommon. The use of GIS in wildlife management is no exception. Its use has been limited to habitat mapping, design of management units for specific species (see Waller and Mace 1997) and the development of habitat suitability models (see Kliskey *et al.* 1999). There have been limited application of GIS in the arena of animal movement analysis. Rather, animal movements have traditionally been analysed through the use of specialist software. GIS has much to offer in this arena: it is capable of both two and three dimensional analysis; it allows the integration of multiple layers of spatial data; has the ability to analyse spatial data, and allows an investigation of species-habitat relationships.

The aim of this research is to show how a well-developed proprietary GIS, ArcInfo[®] (Environmental Systems Research Institute, Inc., Redlands, California), can be used to extend the traditional use of GIS into the arena of wildlife management and animal movement analysis in particular. ArcInfo[®] was chosen as the GIS of choice since it is well established with access

by many researchers and professionals alike, thereby our methods will be easy to replicate by others. Additionally, ArcInfo is being made increasingly general with respect to its functionality and availability on a diverse range of hardware platforms. Emphasis here will be on the use of in-built functions and so analyses can also be implemented on other proprietary GISs and it is therefore the principles of the analysis which are important.

Specifically our aim here is to extend ArcInfo's abilities into the arena of home-range and core-area estimation. Home range estimators will be developed and used to provide home-range estimates using 11 data-sets of animal fixes of urban red foxes (*Vulpes vulpes*) and American Bittern (*Botaurus lentiginosus*). The resulting estimates will then be compared to the outputs of another commercial home-range package: RangesV[®] (ITE, Furzebrook, 1992). MCP estimates will also be compared to the output of ArcView's Animal Movement Analysis Extension (AMAE) in which home-range estimators have been incorporated through use of Avenue Scripts (Hooge, Eichenlaub and Solomon 1999).

HOME-RANGE ESTIMATION

The concept of the home-range was introduced in 1943 (Burt 1943, quoted in Seaman and Powell 1996) in which it was defined as "that area traversed by the individual in its normal activities of food gathering, mating, and caring for young." This definition has led to more explicit definitions such as the 'Utilization Distribution' (UD), first developed by Van Winkle (1975) as "the two-dimensional relative frequency distribution for the points of an animal over a period of time". Thus the UD is a probabilistic model which describes the relative amount of time that an animal spends in one place.

Home-range estimation has interested biologists for decades. An analysis of an animals movement patterns allows the testing of many types of hypotheses about animal behaviour (including static and dynamic interactions (cf. Doncaster 1990)), its use of resources (for example species habitat relationships), and animal distributions at various spatial scales. Such investigations require information on how an animal uses its range and many methods have been developed to estimate home-range usage. Such 'estimators' can be conveniently categorised into three types: those methods which estimate the home-range using information on the peripheral

points, such as the mcp, the second are parametric methods, which make statistical assumptions about home-range use, and finally the non-parametric methods, which do not involve such assumptions.

GIS offers the potential to develop a fully automated package with all components strongly coupled so that home-range functions are presented. Such a venture should be seen as a long-term goal and will necessitate the use of ArcInfo's macro-language interface (Arc Macro Language - AML). The work undertaken here is a necessary step towards this goal as it identifies current limits of the in-built functions and identifies areas of ArcInfo GIS which will need further development.

We have focussed on the development of polygon and non-parametric methods of home-range estimation. Parametric methods were avoided because of their reliance on often complex statistical functions which are not integral functions of GIS as proprietary GISs can often only perform rudimentary statistical operations (Johnston 1998).

HOME RANGE ESTIMATORS

The theory behind currently used home-range estimators, their utility in home-range estimation together with their advantages and disadvantages have received much attention in the literature and thus these will not be repeated here. Rather, the readers attention is drawn to several reviews of home-range estimators (Priede 1992, White and Garrott 1990, and Worton 1989). The basics of each estimator to be developed are mentioned below:

MINIMUM CONVEX POLYGON (MCP)

The mcp estimator is one of a number of 'polygon' methods which link the peripheral locations in a given data set such that all interior angles are less than 180° (see Worton 1987 for information on other polygon methods). Due to its simplicity and comparability the MCP has become one of the widest used home-range estimator, however because of this simplicity the MCP has many disadvantages. The method gives no information on the internal space usage, areas are included

which are likely never visited by the animal and the resulting size of the home range is highly correlated with the number of locations used in the analysis especially at low sample size.

GRIDCELL

The gridcell estimator uses a grid upon which the animal fixes are superimposed. Each cell is given a value based on the number of coincident points (Voight and Tinline 1980). The home-range is then calculated by summation of the areas of cells including fixes. The method gives information not only on the home-range boundary but on the internal space-use including areas of concentrated activity and areas of disuse. There are a number of variations of the simple grid-cell method which link successive observations by various joining rules (see Voight and Tinline 1980), however only the simple grid-cell method is developed here.

HARMONIC-MEAN ESTIMATOR

The harmonic-mean method calculates the mean of the inverse distances from each point in a lattice to all activity loci. Areas of equal value can then be joined by contouring to give isopleths, interpreted as the average distance from the isoline to the activity loci. The harmonic-mean value for each lattice point is calculated according to equation (1) (Dixon and Chapman 1980):

$$\sqrt[p]{M^{-1}} = \frac{1}{\frac{1}{P} \sum_{x=1}^P \frac{1}{r_{jx}}} \quad (1)$$

FIXED KERNEL

The most sophisticated non-parametric method for estimating the UD are the kernel methods described by Worton (1989). The kernel estimator can be thought of as follows: a probability density function, the kernel, is placed over each data point and the UD is estimated by summation of the individual kernels (for further discussion see Brunson 1995 or Silverman 1986 and Fig. 3). Thus where there is a concentration of points the kernel estimate has a higher density than when there are few points. Since each kernel is a density function the resulting estimate is a true probability density function. The smoothing parameter, h , controls the amount

of variation in each component of the estimate. If a small value of h is used, the fine details of the data can be observed, while a larger value of h obscures all the most prominent features. The simplest estimator is where the smoothing parameter is fixed over the entire plane, called the fixed kernel.

There are several methods of choosing the smoothing parameter, but the most commonly used are:

- Standard Distance, or *SD* (Fotheringham, Brunsdon, and Charlton, 2000)
- Reference Bandwidth, or *REFER* (Silverman 1986)
- Least Squares Cross Validation, or *LSCV* (Silverman 1986)
- A method quoted in Wray *et al.* (1992) which we will refer to as *WORTON* which is followed by visual inspection of UD's calculated with varying proportions of *WORTON*, selecting the value of h which gives a stable UD (see Appendix 2 for further details).

ADAPTIVE KERNEL ESTIMATORS

The adaptive kernel estimator is similar to the fixed kernel estimators except that rather than utilising a fixed smoothing parameter to estimate the UD, the adaptive kernel estimator varies the smoothing parameter based on the local density of points (Silverman 1986).

CORE-AREA ESTIMATION

Core-areas can be defined as areas of the home-range in which activity is concentrated. An investigation of such areas should be of great interest to ecologists since it is these areas in which feeding, resting and rearing young are likely to be focussed. The subject has received little attention in the literature however. Several methods have been developed to estimate core-areas:

- Wray *et al.* (1992) developed guidelines for the identification of core-areas in which the core-area is said to resolve at between those isopleths separated by the greatest increase in area.
- Wray, Cresswell and Rogers (1992) developed a non parametric using Dirichlet Tessellations.

- Samuel, Pierce and Garton (1985) developed a technique of identifying core-areas which received more activity than would be expected from a uniform distribution.
- White, Saunders and Harris (1996) identified core areas as those areas enclosed by the isopleth containing 50% of the maximum kernel density.

METHODS

The following home-range estimators were developed in ArcInfo:

- Minimum-Convex Polygon
- Grid-Cell
- Harmonic-Mean
- Fixed Kernel
- Digitized Polygons

Additional home-range functions developed are included in Appendix 2

The approach taken to develop the estimators was to reduce the computation time wherever possible, to reduce the number of steps in each aml (by reducing the number of coverages and grids needed), to reduce the amount of end-user input and to reduce the amount of filespace required to carry out an analysis. Below I describe the general approach taken for each estimator and the in-built functions used. More in-depth information and the AMLs developed can be found in Appendix 2.

Home-range areas obtained in ArcInfo were compared between methods using Wilcoxon's signed ranks test to see if there were significant differences between estimates for each data set. Results were tested between packages to see if they were significantly different from zero by using paired t-tests. However, such area comparisons are not sufficient to compare different estimators since not all home-range estimators should be used for home-range boundary delineation. Therefore, in addition, the utility of our methods for examining internal-range use was examined by visual inspection of contours between outputs from ArcInfo and RangesV. To see whether data-sets had sufficient fixes for mcp estimates the results of our `asymptote.aml` were compared to the results of an mcp bootstrap routine included in ArcView's AMAE.

DEVELOPMENT OF HOME-RANGE ESTIMATORS IN ARCINFO

MCP

To develop an mcp home-range estimator in ArcInfo we used the concept of the Triangulated Irregular Network (TIN). A TIN is a type of vector data structure which is built from known points into a series of triangles based on a Delauney Triangulation. Each animal fix is represented by a node and these are connected to each neighbouring node by pointers. The total mcp area is then calculated by summation of the areas of individual triangles. The outer boundary of the mcp is shown by drawing the hull, or the outermost nodes of the resulting TIN. Fig. 1 shows an example of a TIN and the resulting mcp outer boundary for the American Bittern data-set br96224.

GRID-CELL

Implementation of the gridcell estimator in ArcInfo is simple. The point coverage, containing the animal fixes, is converted to a grid using the POINTGRID command with the value of each grid cell reflecting the number of coincident datapoints. An example of the output from the gridcell estimator is given in Fig. 2 for the fox data-set m1800au. Choice of grid-cell size should be based on the error inherent in gaining the animal locations. Home-range area is calculated using a zonal function.

HARMONIC-MEAN ESTIMATOR

The concept of finding the proximity of a set of points to a centre is one which has a well established basis in GIS through the analysis of Networks.

The ArcInfo function ACCESSIBILITY provides an aggregate measure of how accessible a location is to other locations. The basic principle being that the effect of one location on another is directly proportional to its supply and inversely proportional to its distance. The effects of distance can be scaled to model a particular phenomenon using a distance-decay function (β) and

appropriate supply and demand functions for each centre and each individual point respectively (*ArcInfo help*). Accessibility values are calculated according to equation (2):

$$P_i = \sum_{j=1}^n W_j d_{ij}^{-\beta} \quad (2)$$

Equations (1) and (2) are essentially of equivalent form. However they are not numerically equivalent. To do this, equation (2) must be multiplied by the reciprocal of the number of points in the data set, and the distance-decay function, beta and the attractiveness of location j, W_j , should be set to 1. These additional steps are easily done in ArcInfo. First, the lattice must be converted to a grid, using the accessibility values for each lattice point as the resulting grid cell values. The grid can then be manipulated easily within GRID. The attractiveness, W_j , and the distance-decay function, β can be given a value of one in the accessibility command.

Visualisation of the surface is done by converting the lattice to a TIN and contouring the surface.

It is common to delineate the home-range boundary as the isopleth containing 95% of activity loci. This requires a method of determining the number of points within a given isopleth. This was done by selecting values above a given threshold value and then using a zonal function to determine the number of points within this new grid. This must be done a number of times until the 'correct' level is found by trial and error. This adds both user input-time, computation time and increased disk space requirements. In ArcInfo this method is difficult to automate without resorting to programming, which, whilst conceptually easy, is outside of the scope of this research project. We attempted to partially automate the method by displaying on screen the percentage of points enclosed by the harmonic-mean value used in the AML. However this method is not accurate and often gives values over 100% even when data points are clearly outside the level are enclosed. It is thought that this is a problem in using the POINTDENSITY command to generate the data for the zonal function rather than a problem with our reasoning and methodology.

A flow diagram of the steps necessary is given in Appendix 1.

FIXED KERNEL METHOD

The POINTDENSITY function calculates the density of points in a specified neighbourhood around each output grid cell. There are several options with the POINTDENSITY command. The KERNEL option utilises a probability density function, or kernel, to fit a smoothly tapered surface to each point. The resulting surface is then calculated by summing the individual probability density functions:

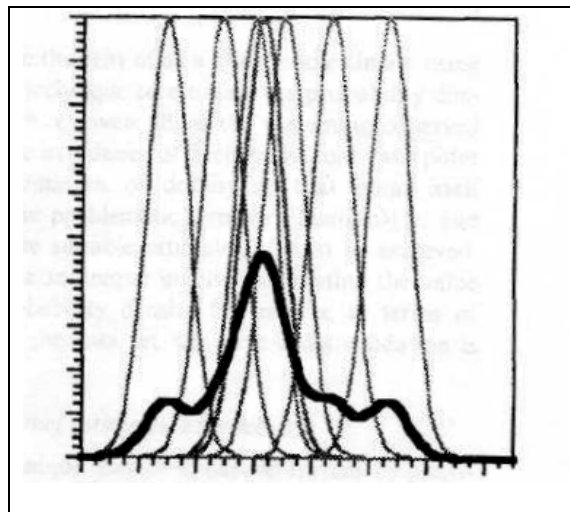


Figure 3. Kernel density estimation through summation of individual probability density functions. Individual kernels are represented as thin lines and the UD is shown as a thick line. Taken from Brunson (1995).

The radius of each individual kernel is equivalent to the smoothing parameter, h . There are a number of kernel functions, each with a different form, which can be used. However, Worton (1989) argues that the form of the kernel is unimportant and that the choice of smoothing parameter is important. Despite this, the kernel function used in the POINTDENSITY function has several advantages:

$$K_2(x) = \begin{cases} 3\pi^{-1}(1 - x^T x)^2 \\ 0 \end{cases} \quad \text{if } x^T x < 1$$

This function has high differentiability properties thereby making computation time minimal (Silverman, 1986). Additionally, Silverman (1986) suggests using as coarsest grid as possible to reduce computation time however, in our experience this is unnecessary when using the POINTDENSITY command because it takes very little time to compute in ArcInfo (a matter of several seconds) even for large data-sets.

ADAPTIVE KERNEL

In order to develop this method in ArcInfo a way of altering the value of h across the grid is needed. Using the KERNEL option it is possible to specify the radius of the individual kernels, however there is no option to vary the radius in any way. If it were possible to vary the kernel radius dependent on the density of points within a neighbourhood then it would be a simple operation to develop an adaptive kernel estimator. However, as Worton (1989) has noted, the adaptive kernel estimator has few advantages over the fixed kernel estimator and indeed the fact that adaptive kernel estimators do not have rigorously tested statistical properties makes their use in home-range studies disadvantageous (Seaman and Powell 1996). Thus, we made no further attempt to develop this estimator further.

DP

DP was originally developed within a GIS. The method used here was as stated in the original paper (Ostro et al. 1999). The basic approach is to link successive points, then buffer with a user-defined width and then to include areas which are too large to be lacunae (a subjective judgement) and then to use a zonal function to calculate the resulting area.

CORE-AREA ESTIMATION

We were unable to successfully develop the method of Samuel, Pierce and Garton (1985) in ArcInfo. In order to compare the UD with a uniform distribution it is necessary to sum the

volume of the UD and calculate an 'average usage' per unit area. This should be possible, however due to time restraints this was not attempted.

Equally, the method of Wray et al. (1992) should be possible to implement in ArcInfo. However, it is not clear whether using this method results would be comparable. It is not stated at what intervals contouring should be carried out in order to identify the point of core area resolution. It is likely that since the UD is continuous, there are many values at which the core-area would appear to resolve and which of these is chosen would clearly depend on the choice of contouring interval. The core-area boundary would then be somewhat subjective. Because of uncertainties in contouring, and a lack of time this method was not fully developed.

The method of White, Saunders and Harris (1996) also has notable problems. There is no reasonable argument which suggests that 50% of the maximum kernel density corresponds to 50% of the UD (and thus the area where the animal is active 50% of the time). This argument is developed further in the discussion section. An alternative methodology is adopted here where the volume of the UD is summed and then proportions selected out. This should more accurately reflect the range-usage. However, this way of selecting core-areas is still problematic since the delineation of the boundary may have little biological meaning; a true core-area boundary should reflect a disproportionately large rate-of-change in space-usage. We partially developed a method with this aim in mind (see Appendix 2, Fig. 13 and 'further work' section for further details).

Additionally we partially developed the method of Wray, Cresswell and Rogers (1992). However, we were unable to fully develop this method. See Appendix 2 for further details.

Thus, the development of methods for the identification of core-areas has not been successful, however this is due more to time restraints rather than the in-built limitations of ArcInfo.

RESULTS

Table 1 gives the estimated home-range areas obtained in ArcInfo using 5 home-range estimators for the 11 data-sets. Friedman's test showed that there are significant differences between area measurements for each data-set using ArcInfo (chi squared = 24.10, df = 4, $P < 0.001$). This is to be expected due to the differing ways of delimiting home-range boundaries by different estimators.

MINIMUM CONVEX POLYGON

Area estimates for the three home-range packages, ArcInfo, ArcView and RangesV, are given in Table 2. Wilcoxon's signed ranks test showed that area estimates were significantly different between RangesV and the other methods (RangesV–ArcInfo: $Z = -2.934$, $p = 0.003$ and RangesV–ArcView: $Z = -2.943$, $p = 0.003$) but that our method was not significantly different from the ArcView package (ArcInfo–ArcView, $Z = -0.460$, $p = 0.646$). Fig. 4 gives an example of the output from each package. This significant result is likely due to a consistent difference between the RangesV output and ArcInfo and ArcView outputs, however the Friedman test indicated that the differences in area estimates between RangesV and the other packages are significantly different from zero (RangesV–ArcInfo: chi squared = 24.10, df = 4, $P < 0.001$; RangesV–ArcView: chi squared = 11, df = 1, $P = 0.001$) but that the difference in area between the two GIS packages is not significantly different from zero (ArcInfo–ArcView: chi squared = 0.5, df = 1, $P = 0.48$).

MCP ASYMPTOTES

The number of data-points at which an mcp asymptote was reached using our method is shown in Table 1. All data sets, except m2332su and br96224, reached an indicating that data collection was sufficient in all but these cases. Fig. 5 shows that m2332su does not reach an asymptote but rather the mcp area continues increasing in a step-wise fashion despite the data-set consisting of 673 locations. The method used in the ArcView's AMAE, which is more rigorous, shows a different pattern. Fig. 6 shows that, using this method, the m2332su mcp does reach an

asymptote although the point at which this is reached is diffuse. Because of time restraints only several data-sets were tested in ArcView.

GRIDCELL

Table 1 shows the area estimates for all data-sets using the gridcell estimator. It can be seen that area estimates for the fox data-sets are comparable to the other home-range estimators and are very similar to the mcp estimates, however the gridcell estimator seriously underestimates the home-range area for the American Bittern data. Fig. 2 gives a visual comparison between gridcell and mcp estimators for the br96025 and m1800au data-sets.

DIGITIZED POLYGONS (DP)

DP estimates for all data-sets are shown in Table 1. The dp estimator serious underestimates the home-range area for the American Bittern data-sets but is comparable to the other methods for the fox data-sets. Fig. 7 gives a visual comparison between dp and mcp estimators for two data-sets, br96025 and m1800au.

HARMONIC-MEAN METHOD

Table 1 shows the harmonic-mean area estimates for all data-sets. Wilcoxon's signed ranks test showed that there are significant differences for area estimates between ArcInfo and RangesV ($Z = -2.934$, $P = 0.003$). Fig. 8 shows boxplots of the areas estimates for all data-sets. The ArcInfo method tends to underestimate the home-range area.

Fig. 9 visually compares the internal structure of the 3 data-sets calculated using ArcInfo and RangesV. The ArcInfo method represents the home-range differently than RangesV, especially for the American Bittern data-sets. However, superficially it identifies similar internal structures for all data-sets. We made no attempt to examine the stability of internal contours.

FIXED KERNEL ESTIMATOR

Table 1 shows the fixed kernel area estimates for all data-sets. Wilcoxon's signed ranks test showed that there are significant differences between our method and the RangesV fixed kernel area estimates ($Z=-2.934$, $P = 0.003$). Fig. 10 shows a boxplot of fixed kernel area estimates for all data-sets using ArcInfo and RangesV. Thus ArcInfo tends to overestimate the home-range area.

WORTON was used to estimate the smoothing parameter used to calculate the data in Table 1. Fig. 11 shows that the choice of smoothing parameter is a critical factor for visualisation of the internal structure of the home-range. Table 3 shows the smoothing parameters for all data-sets calculated using three different methods. Smoothing parameters calculated by LSCV are similar to those calculated using WORTON but these are largely different from those calculated using the STANDARD DISTANCE method. Fig. 11 shows that using LSCV gives an undersmoothed surface whereas using STANDARD DISTANCE gives a grossly oversmoothed surface. In contrast WORTON appears to give a slightly oversmoothed surface.

Fig. 12 compares the internal structure for three data-sets using ArcInfo and RangesV. ArcInfo tends to represent the outer home-range boundary differently than RangesV however the internal structure is surprising similar between packages. It could be argued that our method delineates core-areas more clearly than the RangesV package.

DISCUSSION

Each home-range estimator has its own advantages and disadvantages. The lack of commonality between estimators makes comparisons difficult and each method should be evaluated with this in mind. Because of this we chose to use a variety of techniques to compare our methods with other home-range estimation packages. In addition to area estimates and the internal structure variables such as the time of computation, ease of use, amount of user input required, and file-space requirements were used.

MCP

A comparison of areas is satisfactory for the mcp since it is only useful for delimiting home-range boundaries. That our method gives different mcp area estimates is understandable because of the different algorithms used in different software packages (Worton 1989). However, that these differences are significant is surprising. Given that the mcp area estimates using ArcInfo are not significantly different from those obtained using ArcView suggests that the problem is with RangesV rather than with our method. This also highlights that comparisons with RangesV should be treated with caution and therefore additional comparisons with other packages would be useful. Further comparisons with the Calhome software package (Kie, Baldwin and Evans 1996) were planned, however this package is only capable of using a maximum of 500 locations and there are uncertainties of how the package calculates the smoothing parameters for adaptive kernel estimators; thus further comparison was not done.

The method we used to determine whether an asymptote for mcp is reached, whilst useful, is clearly not sufficient. Our method is simple relying on the sequential deletion of data points with no replacement. The method used in ArcView's AMAE is more rigorous relying on bootstrapping using random deletion with replacement. A comparison of Figs 5 and 6 show that the conclusions drawn from our method are unreliable. The ArcInfo method should not be used and the asymptote results in Table 1 treated with caution.

GRIDCELL

The importance of using a data-set with sufficient data-points to be representative of the home-range, is shown in Fig. 2. The estimated distance error for the American Bittern data-sets is 56.6m (Azure, 1998), therefore our choice of a 50m grid cell-size is appropriate. However it is difficult to ensure that a data-set adequately represents internal range-usage. It is common practice, when collecting preliminary data, to check that the data-set gives an asymptote for an mcp, however this is not routinely done for other methods of home-range estimation. There is no reasonable argument to assume that because a data-set gives an asymptote for an mcp it is sufficient for other methods of home-range estimation. Additionally whilst it may be possible to determine the minimum number of points needed to produce an asymptote for a home-range area for a given estimator, it does not follow that there are sufficient points to adequately describe internal range-usage.

DIGITIZED POLYGONS

DP is not appropriate for every data-set. It was designed to be used for which a group spread, or the average spacing of a group of individuals within a group, can be estimated. Thus, dp is likely to be most useful when applied to flock of birds or a variety of mammal species, especially highly social animals and group herbivores. For red foxes, dp may well be appropriate as they live in social groups, although direct interaction between members of social groups is often minimal (Doncaster and Macdonald 1990). Therefore its suitability is a matter for discussion. Despite this, it gives similar area estimates for both gridcell and mcp for all fox data-sets (see Table 1). An advantage of using dp is in an investigation of avoidance of lacunae. When the dp estimator is integrated with habitat data it should be possible to determine if lacunae are due to topographical features or, more interestingly, unsuitable habitat or areas which are avoided for other reasons such as human disturbance. However, whether an area is classed as 'use' or as 'lacunae' in this method is highly dependent on two factors, 1) the choice of group spread and 2) the definition of lacunae being larger than 1% of the mcp area, a seemingly arbitrary value. Despite this, important aspects of a species ecology may be inferred from the integration of the dp estimator with habitat data.

To the best of my knowledge American Bitterns do not travel in social groups or flocks and thus the dp method is unlikely to be appropriate in this case.

HARMONIC-MEAN METHOD

There are several problems with our harmonic-mean method. Firstly it tends to underestimate the home-range area when compared to RangesV. In order to verify this, it would be useful to compare with other home-range estimation packages, however because of time limitations this was not possible. Despite this, our method does pick out similar internal structures to RangesV. The harmonic-mean method is mostly commonly used for this specific purpose and so this is not be a significant problem. The ArcInfo method also identifies similar internal structures to the ArcInfo Kernel estimator thereby confirming its utility. Additionally it appears that our method seems to be influenced more than other methods by individuals point locations; this is likely because our lattice was fairly coarse (we used a 50 by 50 lattice for all data-sets). Again, this is not likely to be a significant problem when examining internal range-use, merely that it is less visually appealing. The resolution of the lattice was not changed since this significantly increasing computation time. For the largest data-set (970 points) computing ACCESSIBILITY took circa. 5 minutes which is not unreasonable for a data-set of this size. Thus, our harmonic-mean method is useful for examining the internal-usage of the home-range but should not be used as an areal estimator nor a boundary delimiter. Because of its utility in examining internal range-use it is also likely to be a good method for delimiting core-areas.

FIXED KERNEL METHOD

The first thing that should be mentioned when assessing the use of the fixed kernel method is the problem of choosing the optimal smoothing parameter. Many studies have shown that the LSCV method is the most reliable and gives a good estimate (for example see Seaman and Powell 196, Silverman 1986, and Worton 1989). Our research here has indicated that the LSCV method gives a grossly undersmoothed surface (see Fig. 11) which is contradicted by all previous work. In contrast, the STANDARD DISTANCE method gives a grossly oversmoothed surface. We found that the WORTON method was most useful. However, it does have notable drawbacks, at least in the way it was developed in ArcInfo. Firstly, the method requires a great deal of user input and

repetition. We automated the method as much as possible without resorting to programming however the user must still add significant amounts of information into the amls at numerous stages of the process and this takes considerable time. It is puzzling that RangesV uses and yet using this value with our method gives a grossly undersmoothed surface. This suggests that there is a problem of our method, most likely with units, however I was unable to find an error in the units used. This is clearly an avenue for further work. Despite these problems, our method works well using the WORTON method followed by visual inspection. An added advantage of our method is the small amount of time it takes to calculate the appropriate surface once the correct smoothing parameter is known. Even with the largest data-set (970 points), the pointdensity command took just several seconds to compute. As noted earlier this is partially due to the choice of kernel function used in the pointdensity command.

Our method gives a significantly larger home-range area estimate than any other estimators we developed. This is because during the method a kernel density function is placed over the outermost points (which lie along the vertices of the mcp), therefore depending on the value of h (equivalent to the radius of the density function), the area of the kernel method will always be larger (shown in Fig. 13(e)). The larger the value of h , the larger the resulting home-range. The way we select out 95% of the UD goes somewhat towards correcting this since much of this outer area, which will have low usage, is removed by selecting out the areas of lowest usage. Indeed the method of selecting 95% is likely to be different from RangesV and other home-range packages. There are a number of options:

- 1) To select out 95% of the kernel area enclosed by the outer boundary,
- 2) Take 95% of the maximum kernel density,
- 3) Take 95% of the UD which was first standardized to an approximate bivariate normal distribution.

The first option is clearly insufficient as it does not take into account different rates of usage within the home-range. I suspect that RangesV and other home-range packages use the second option although this could not be substantiated from the literature which accompanied the software. However this is the method used in the software program Calhome (Kie, Baldwin, and Evans, 1996). The second method has been used to select out core areas (for example see Azure

1998 and White, Saunders and Harris 1996) at the 50% level. This method is flawed since 50% of the maximum kernel density will not correspond to 50% of the UD. Thus the third method deserves more attention. Here we realise that the only true way of selecting 95% of the UD is to sum the volume of the UD and then to select 95% of this volume. This is possible by finding the cut-off kernel density (by subtracting 1.645 standard deviations from the mean value (for a one-tailed distribution)), however this assumes a bivariate normal distribution. Instead we took the approach of first standardising the distribution to an approximate bivariate normal, then selecting 95% of the volume and then transforming back to the original distribution. We found that using a square-root transformation works reasonably well for most distributions but in some cases a cube root was necessary. The user must check the distribution before and after transformation and alter the transformation accordingly. This is easily done in ArcInfo.

Above I have shown that it is been possible to successfully develop the most commonly used home-range estimators in a proprietary GIS. These methods are generally comparable with other commercially available packages of home-range estimation. Whilst they often give differing area estimates for each method this is not only to be expected but of little importance since most home-range estimators are used for examining internal range-usage. The methods developed in ArcInfo do indeed show similar patterns of internal usage and despite problems with selecting the appropriate smoothing parameter for the fixed kernel estimator, it can be argued that it is possible to use in-built functions to extend the capabilities of ArcInfo into the arena of wildlife management. There is a clear argument for further extending its capabilities through the use of AML which would enable an integrated home-range package to be developed; this is even more apparent when one considers the statistical limitations of ArcInfo. Currently, however, soft linkages with other software are needed.

Further Work

Given the potentially significant problems with calculating an optimal smoothing parameter for the fixed kernel estimator I believe this should be a priority area in future work. However, it will first be necessary to determine why LSCV gives a grossly undersmoothed surface in ArcInfo as this contradicts previous work.

Due to time and file-space limitations, our foray into core-area estimation and use of species-habitat relationships was limited. This is unfortunate as GIS has great potential for furthering of their understanding. However, now that the basic home-range estimators have been developed it should be relatively straightforward to develop methods of core-area estimation as discussed above. The development of methods to examine species-habitat relationships is likely to take more effort, however GIS offers the ability to integrate the UD with habitat data and use the probabilistic nature of the UD to further an understanding of habitat selection, rather than relying on an examination of animal fixes and habitat data. This would be a significant step forward.

The subject of core-area identification has received little attention in the literature. We attempted to develop a novel method of identifying core-areas but were unable to develop the method sufficiently. Preliminary results are shown in Fig. 13. Here we use the SLOPE and CURVATURE functions used commonly in hydrologic modelling to identify areas of the UD for which the rate of usage drops off disproportionately greater than would be expected from the rest of the UD. It is clear from Fig. 13. that this method needs much development, however, this is an area in which we should be able to develop novel techniques using GIS. Much of the attention which has been given to core-area estimation identifies core-area boundaries with little biological significance (in the sense that although use is concentrated in these areas there appears to be no biological reason for delimiting a boundary). Our method offers the possibility of identifying biologically-relevant core-area boundaries which is essential if this information is to be used to look at species-habitat relationships amongst others. Above I have discussed the other methods used to delineate core-areas, despite their problems these should be developed, at least for comparative purposes. It is clear that this is possible in ArcInfo.

Word Count: 6014

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Table 1. Areas of home-range estimators for red fox and American Bittern data sets. All areas are in hectares.

File	Points	cell size	MCP area	MCP asymptote	Gridcell area	95% Fixed Kernel area	95% Harmonic mean area	Digitized Polygon area
m2332au	970	19	22.469	606	22.75	36.653	15.915	19.914
m2332sp	195	16	14.544	800	14.25	31.501	10.675	13.553
m2332su	673	25	21.156	180*	18	49.737	12.688	17.062
m1800au	679	28	51.75	400	44.25	103.877	35.986	40.768
m1800su	488	25	45.281	439	38.5	83.21	39.25	
br96025	27	79	216.74	22	6.5	795.285	63.034	36.158
br961510	44	68	207.732	33	10	610.102	59.187	
br96224	39	48	160.297	no asymptote	8.5	312.352	36.403	
mo96025	32	59	156.443	10	7.75	369.899	45.601	21.197
mo961510	14	151	773.047	9	3.5	1814.73	123.15	
mo96224	38	23	34.822	38	6.5	70.607	13.278	10.506

* m2332su seems not to reach an absolute asymptote but continues increasing in steps. This may indicate a temporally changing home-range.

Table 2. MCP area results for three home-range packages. ArcView uses a bootstrap routine and so area measurements are the mean over 50 bootstraps. All areas are in hectares.

File	ArcView mean mcp area	ArcInfo mcp area	Rangesv
br96025	201.8	216.74	217.21
br961510	207.7324	207.732	208.15
br96224	160.2969	160.297	160.61
m1800au	51.75	51.75	51.92
m1800su	45.28125	45.281	45.44
m2332au	22.46875	22.469	22.59
m2332sp	14.54375	14.544	14.64
m2332su	21.15625	21.156	21.26
mo96025	140.77205	156.443	156.81
mo961510	773.04715	773.047	773.97
mo96224	34.8219	34.822	34.97

Table 3. Smoothing parameters for red fox and American Bittern files calculated using three different methods. Note the similarity between WORTON and LSCV methods but the difference between these methods and STANDARD DISTANCE.

File	WORTON	SD	LSCV
m2332au	40.6	180.3	34.537
m2332sp	47.5	161.4	31.87
m2332su	37.9	364.8	32.069
m1800au	68	286.7	78.221
m1800su	76	257	72.53
br96025	336.5	808.8	284.61
br961510	255	670.2	248.7
br96224	166.5	428	155.36
mo96025	223.7	554.8	177.24
mo961510	709.6	217.9	690.72
mo96224	85	1501.2	83.622

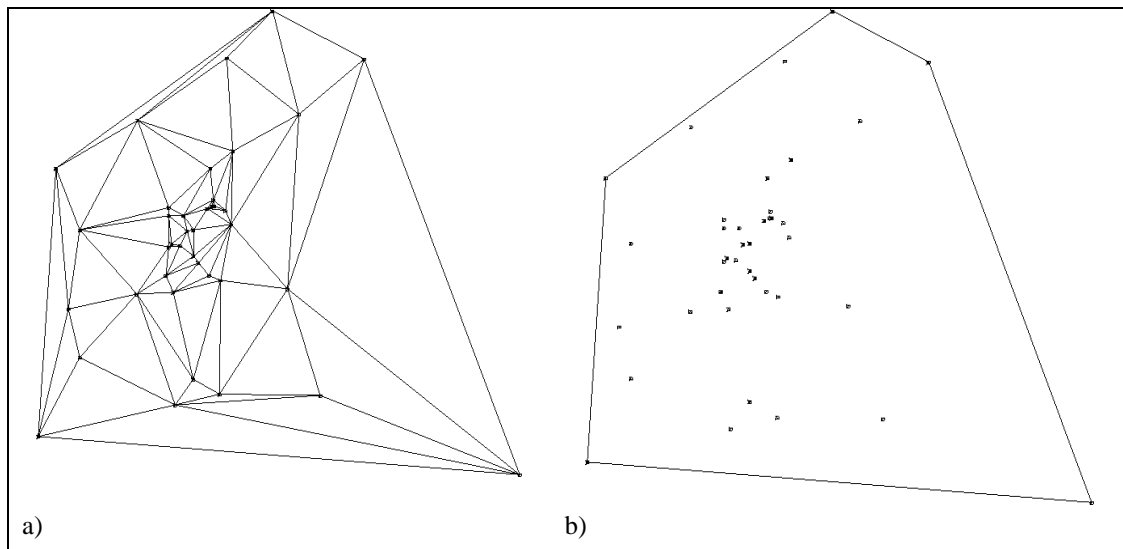


Figure 1. (a) Delauney triangulation for br96224. Locations occur at each node forming triangles. The mcp area is calculated by summing the areas of each triangle. The outer boundary of the mcp (b) is formed when the outermost nodes are drawn forming a hull.

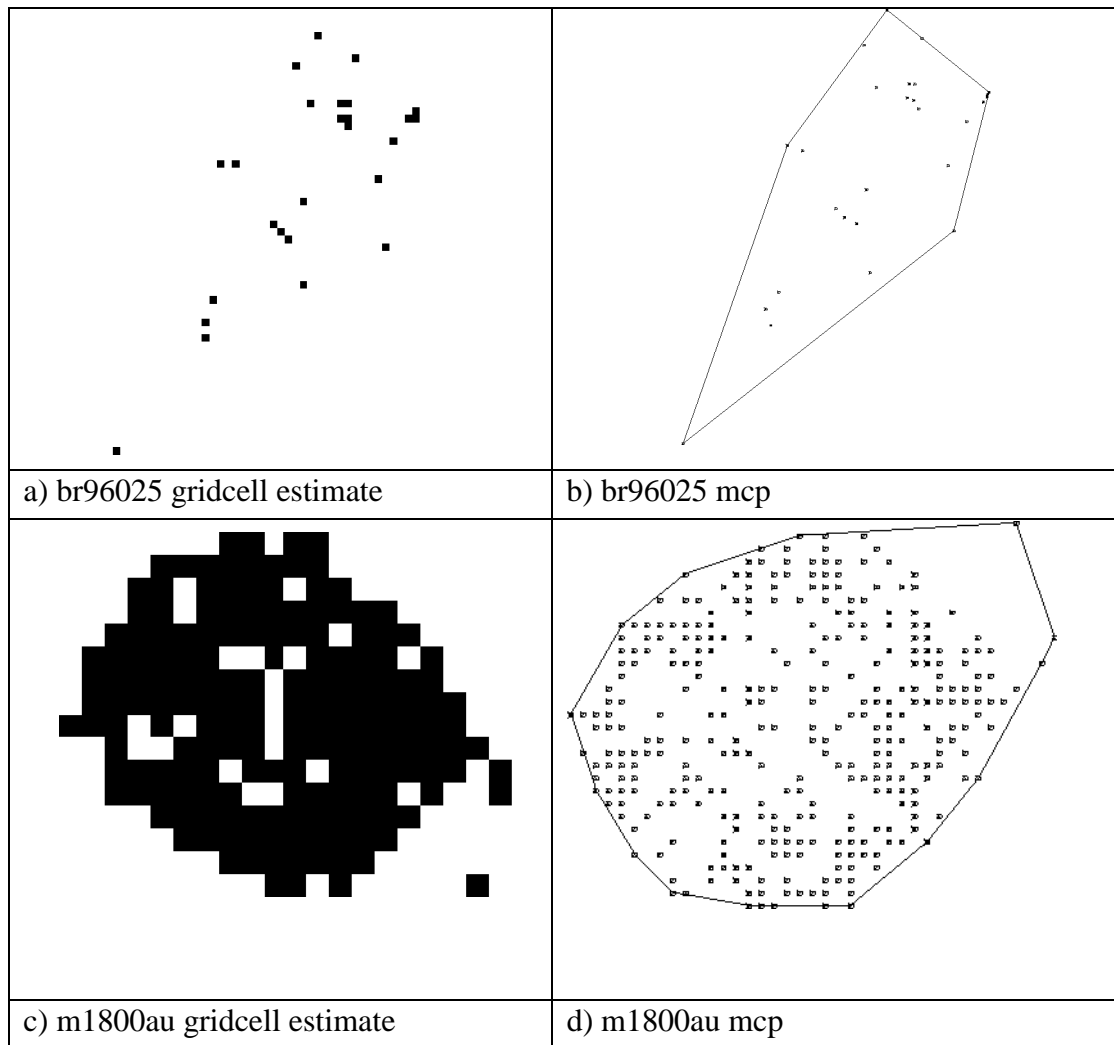


Figure 2. Comparison between gridcell and mcp home-range estimators using one bittern data-set, br96025, and one fox data-set, m1800au. A grid cell size of 50m was used for each since this is suitable for the fox data-set (White, Saunders and Harris, 1996). A poor estimation for the bittern data-set is likely because the data-set comprises too few locations to accurately describe internal usage of the home-range.

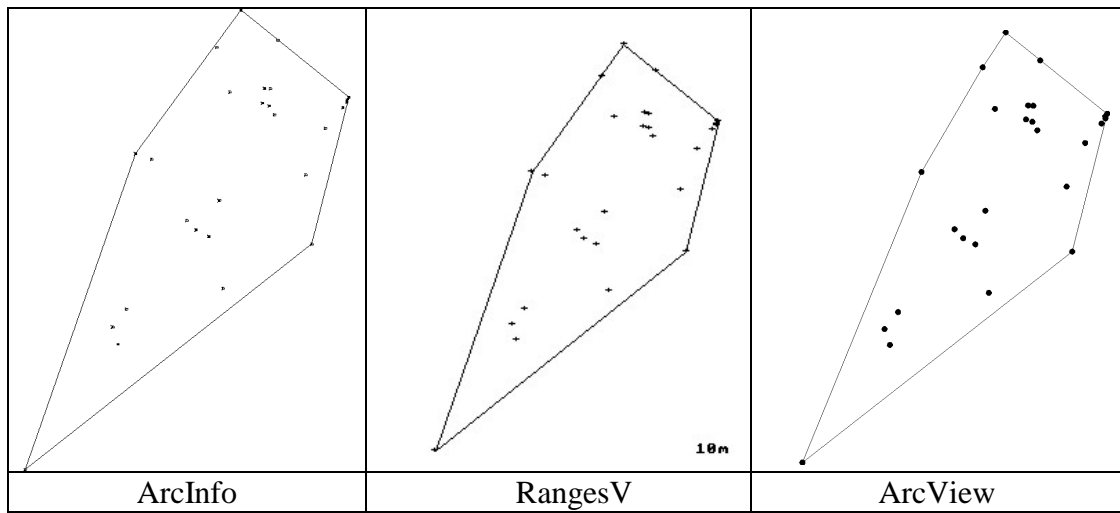


Figure 4. MCP home-ranges for br96025 using three home-range packages. Animal locations are superimposed.

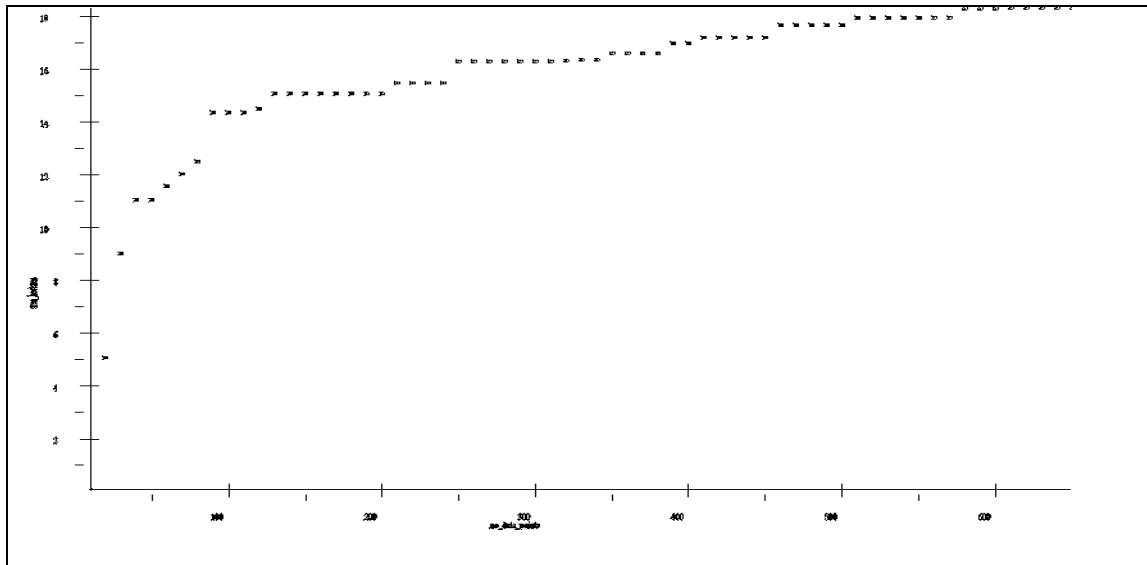


Figure 5. Effect of sample size on mcp home-range area in ArcInfo for m2332su dataset. Note how the mcp area increases dramatically at low sample sizes but begins to reach an asymptote. However the data set never actually reaches an asymptote despite having 673 points. This may indicate a 'drifting' home-range (cf. Doncaster and MacDonald 1990) or a non-linear relationship between sample size and home-range area (cf. Gautestad and Myrsterud 1995).

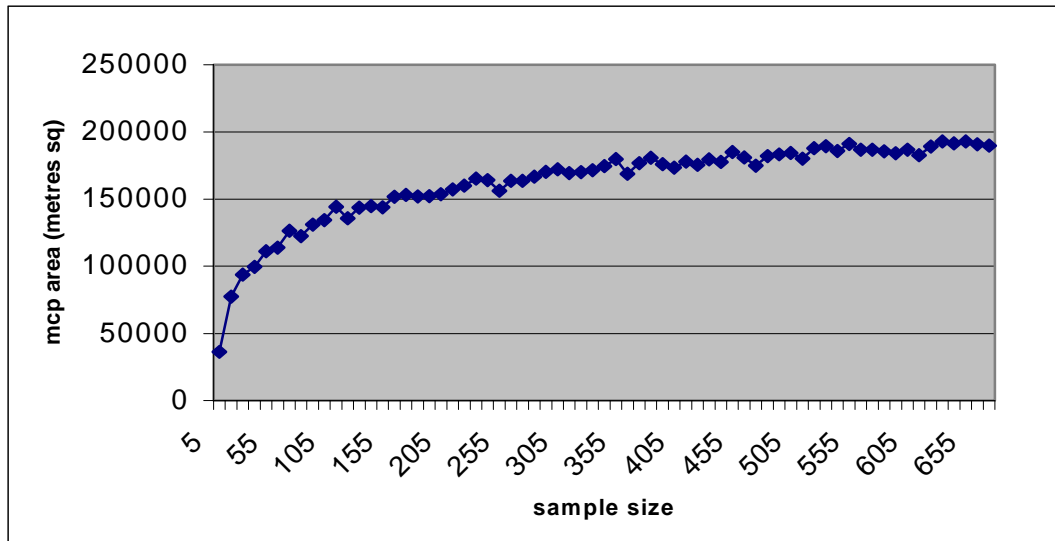


Figure 6. Effect of sample size on mcp area using ArcView's Animal Movement Analysis Extension for data-set m2332su. A bootstrap routine is utilised with replacement thereby increasing accuracy. A comparison with figure 3 shows the differences between the method developed in ArcInfo and this, more complicated, method.

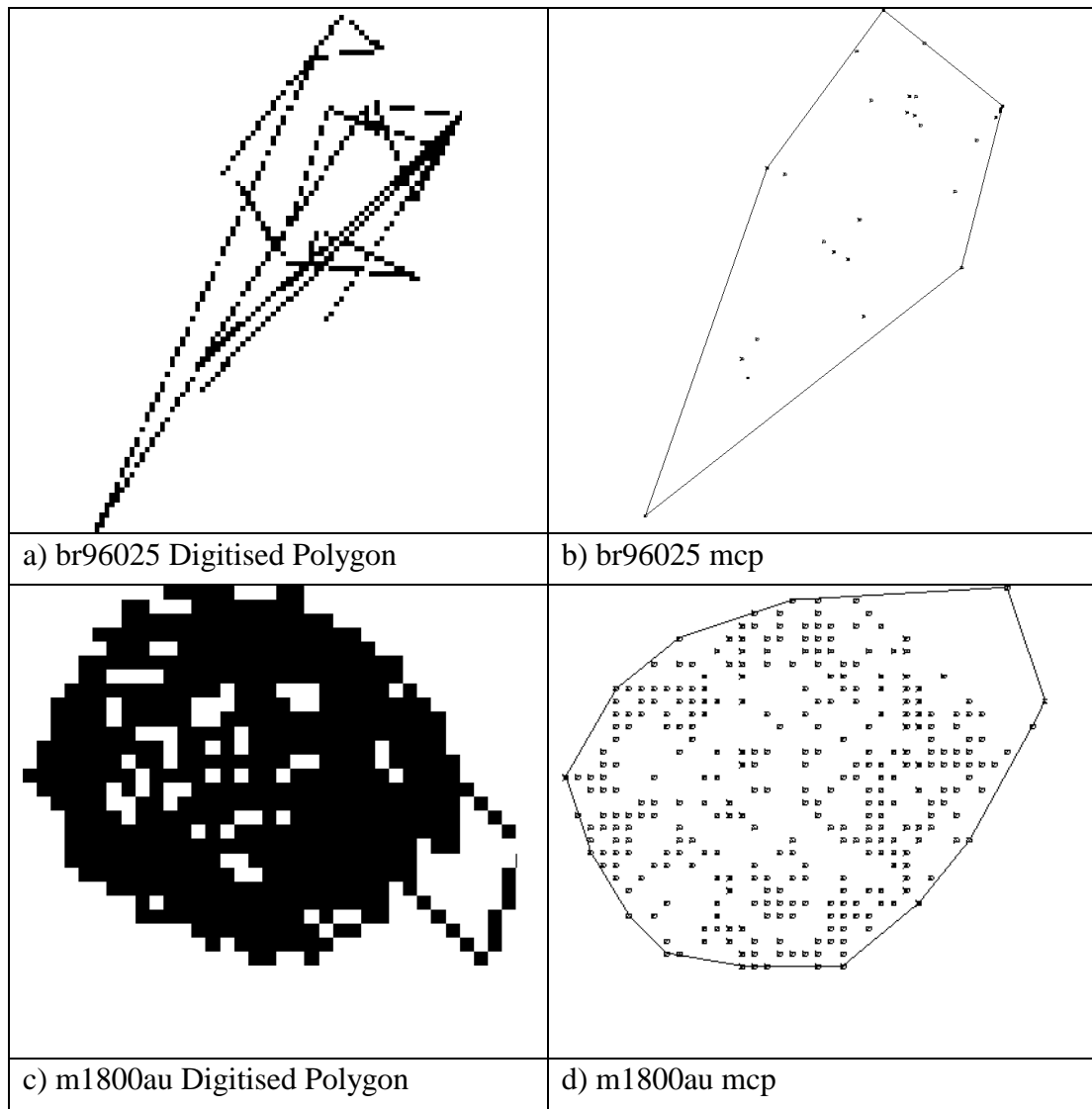


Figure 7. Comparison between Digitised Polygon and fixed kernel home-range estimators for br96025, and m1800au. Both dp estimates used a path width of 50m.

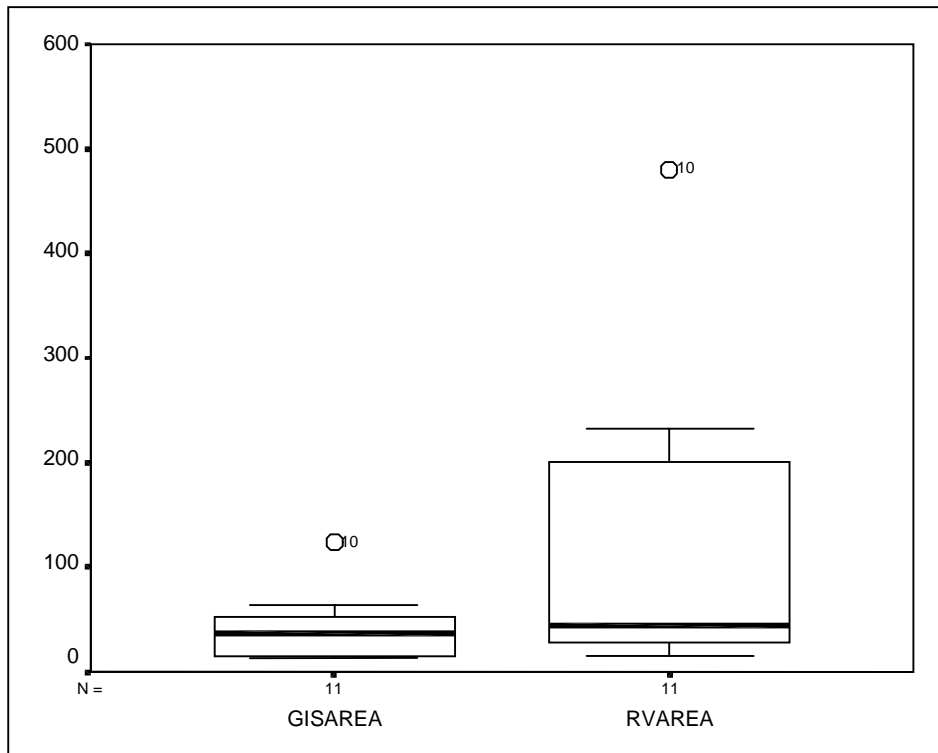


Figure 8. Boxplots showing the variation in area estimates using the harmonic-mean estimator for all data-sets using ArcInfo (GISAREA) and RangesV (RVAREA). ArcInfo tends to underestimate the home-range area which is defined as the area enclosed by the isopleth containing 95% of animal fixes.

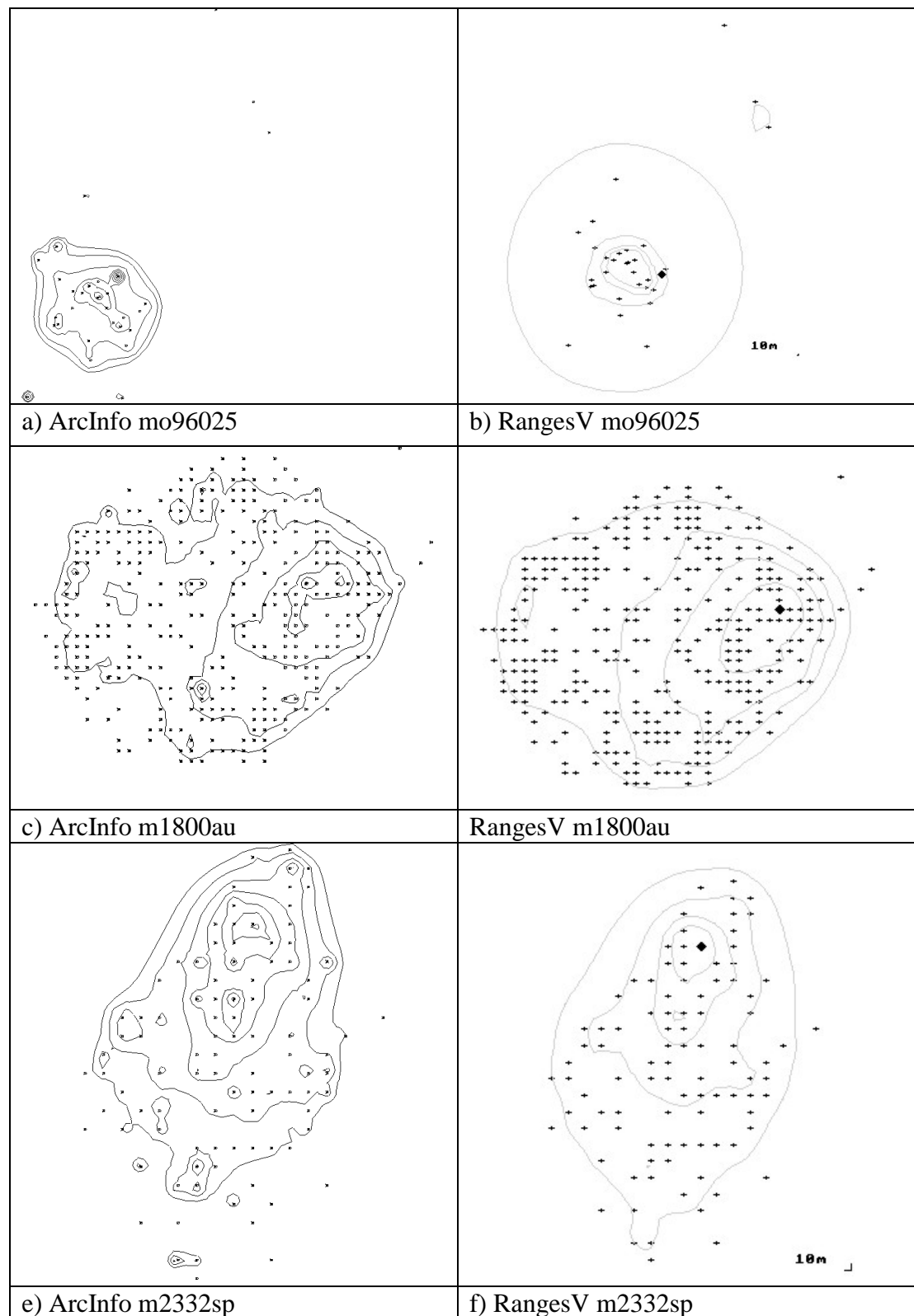


Figure 9. Comparison of harmonic-mean method of home-range estimation for three data-sets using the ArcInfo and RangesV packages. Note that RangesV gives a different outer boundary especially with the bittern data-sets (br96025), however both methods tend to pick out similar internal structures.

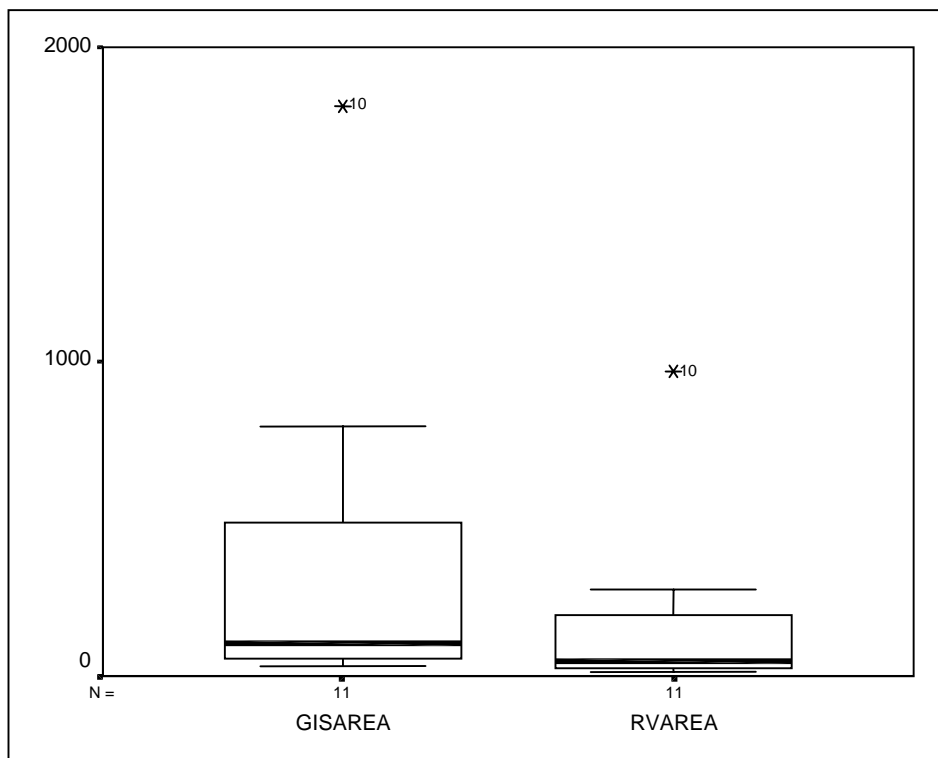


Figure 10. Boxplots for fixed kernel estimates calculated using ArcInfo (GISAREA) and RangesV (RVAREA). ArcInfo tends to overestimate the home-range area (defined as the area enclosed by the isopleth which includes 95% of the Utilisation Distribution). This may be due to the way we define our outer boundary. See discussion section for further details.

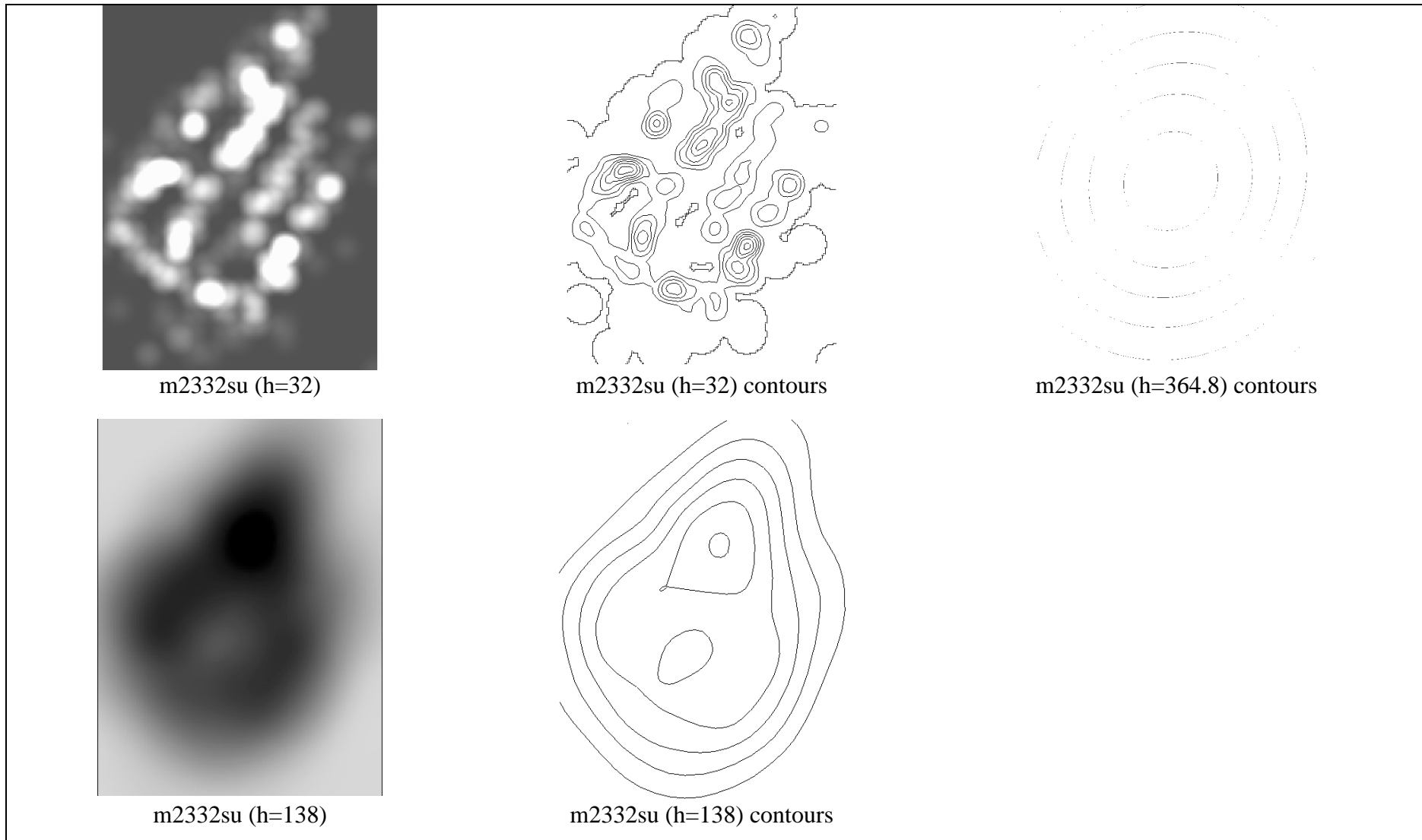


Figure 11. Effect of altering the smoothing parameter, h , on fixed kernel home-range estimates. Shown are the grids and their resulting contours for m2332su. Surfaces were calculated using the pointdensity command for three values of h calculated by the LSCV method ($h = 32$), STANDARD DISTANCE ($h=364.8$), and WORTON ($h = 138$). Note that the resulting contours differ significantly. Therefore conclusions about internal range-use are likely to be greatly affected by the choice of smoothing parameter.

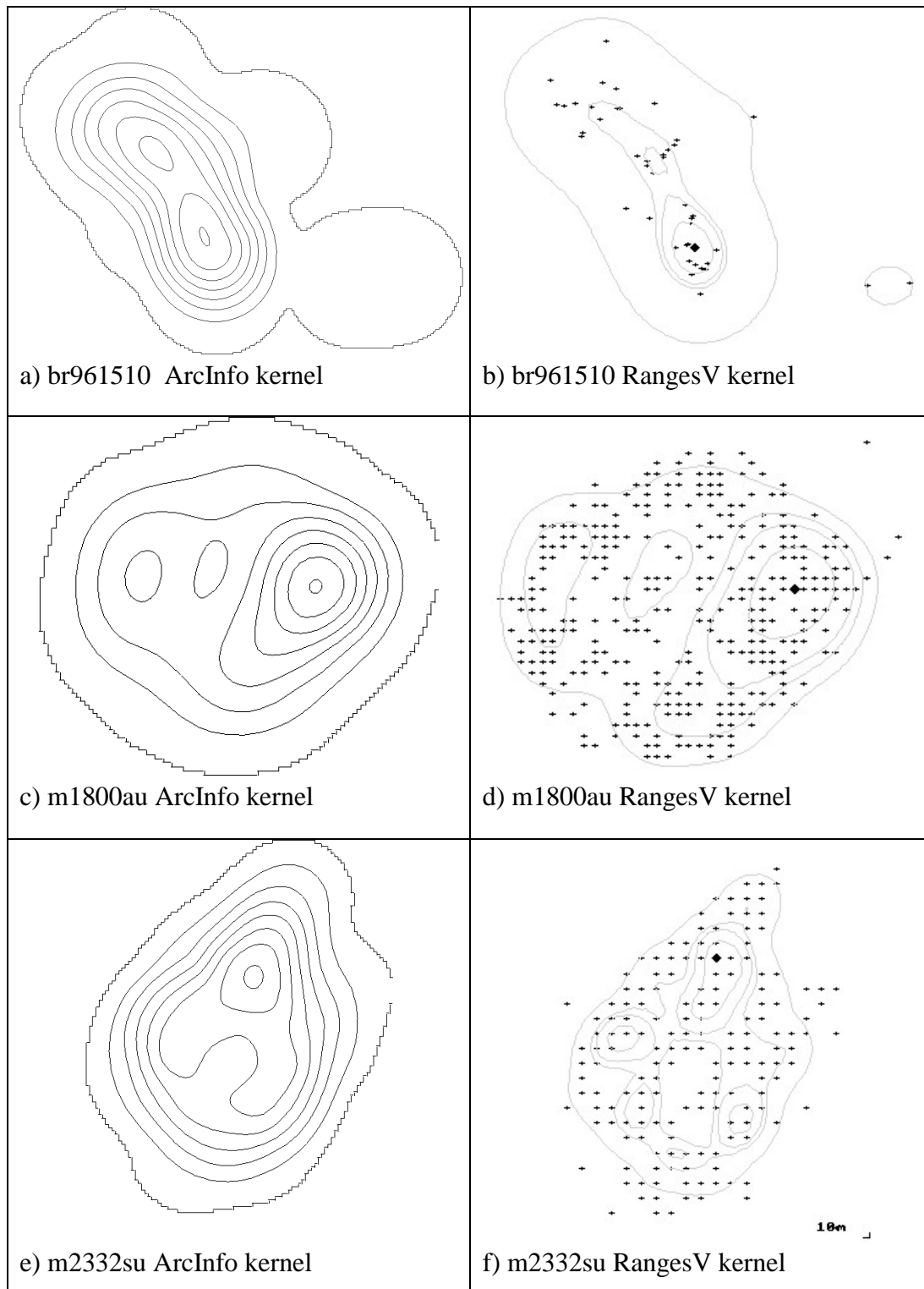


Figure 12. Fixed kernel home-range estimates for 3 datasets using ArcInfo and RangesV packages. Note the similarity in internal structure for all data-sets shown. However, the outer boundaries are not consistent between the two packages. For some data-sets, for example br961510, (a) and (b), our method, arcInfo seems better at delineating core-areas.

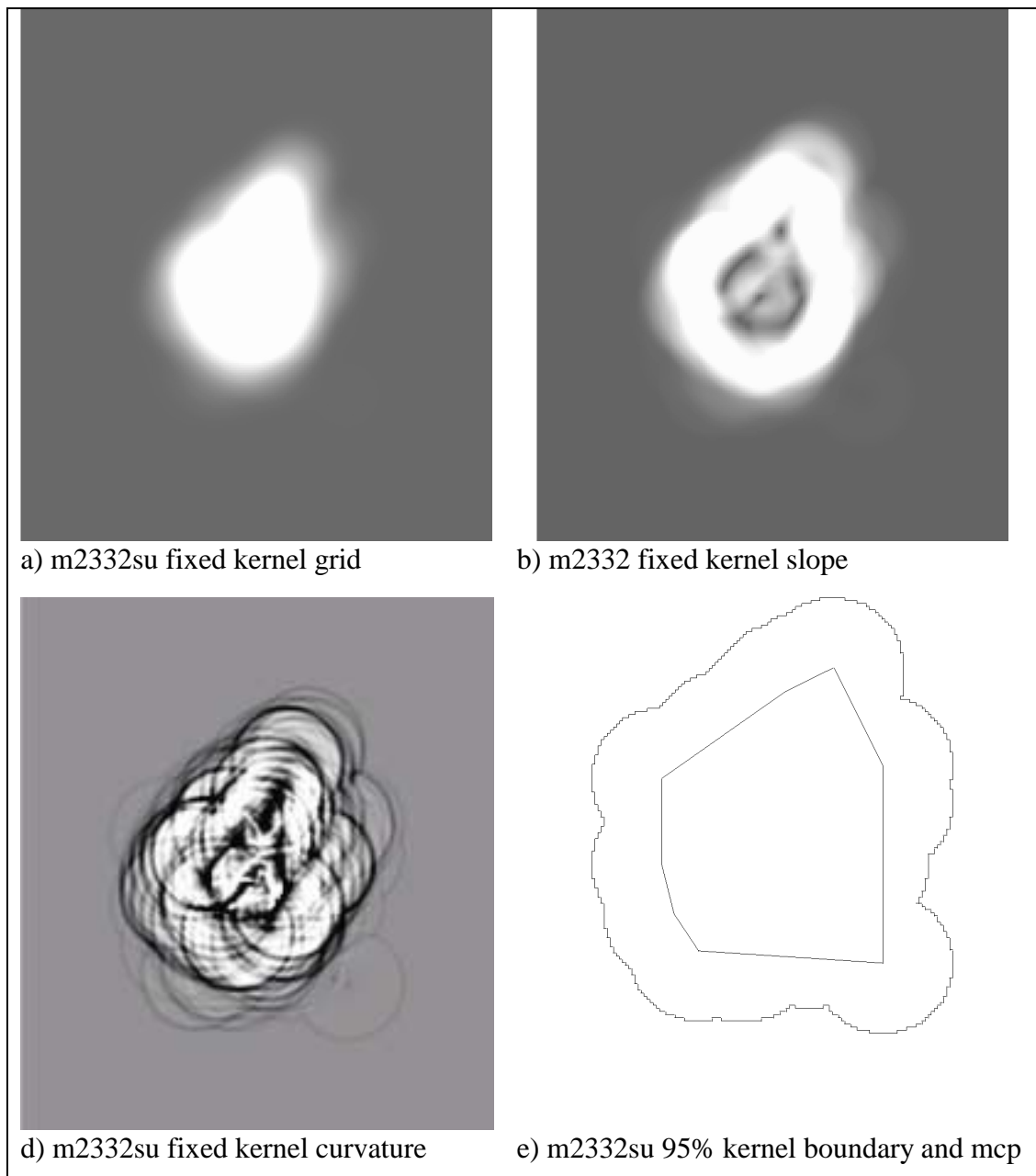
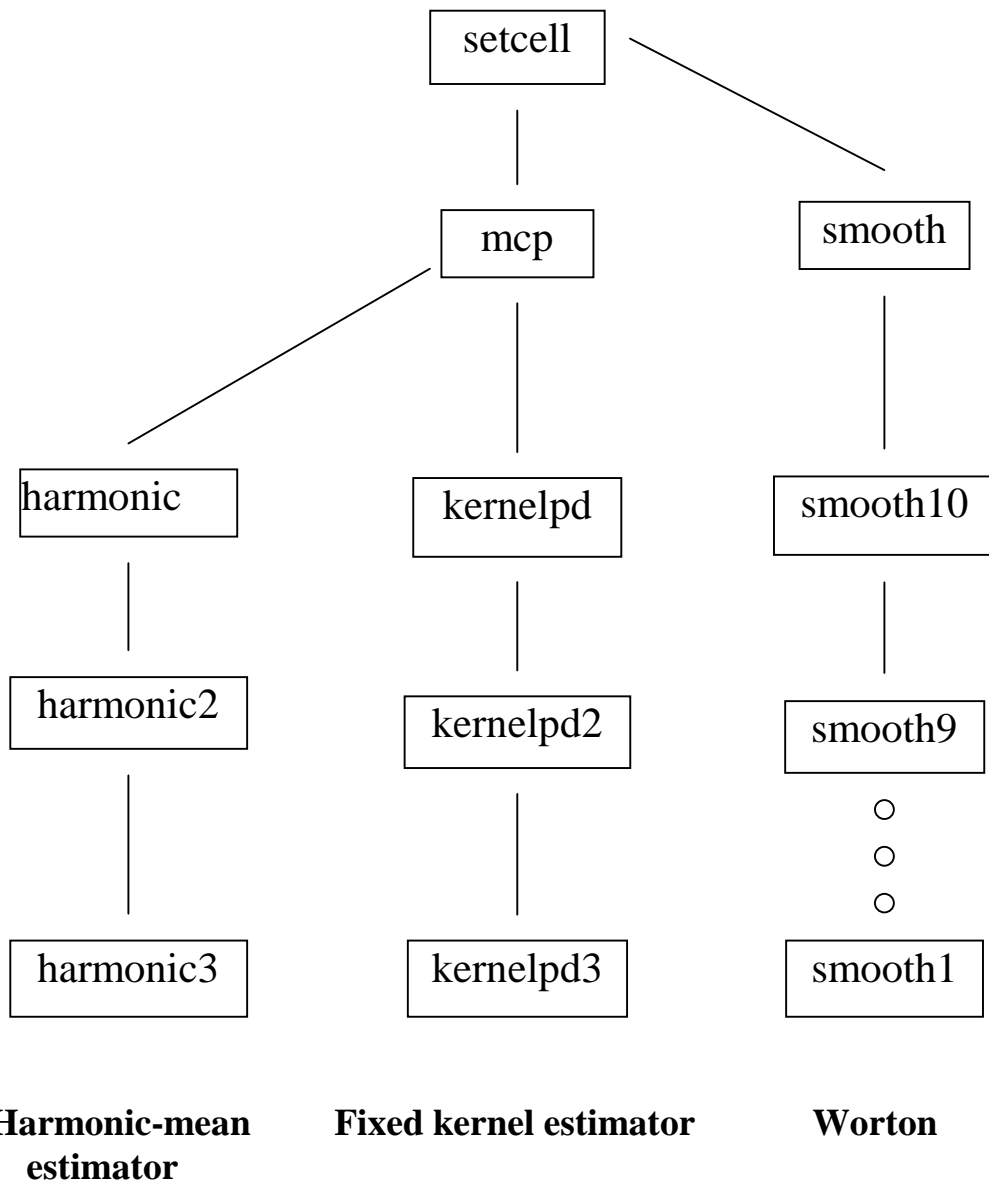


Figure 13. Developing novel methods of identifying core areas using slope and curvature functions within ArcView. (a) shows the Utilization Distribution surface calculated using ArcInfos pointdensity command, (b) shows the first derivative, or slope, of the UD grid, (c) shows the second derivative, or curvature, of the UD. (d) shows the 95% fixed kernel boundary and the mcp as a reference. The first derivative should pick out areas of rapidly changing use within the home-range whilst the second-derivative should pick out breaks in the slope. Neither has been developed sufficiently to be used as a method of identifying core areas.

Appendix 1. Flowcharts showing the order in which amls must be used for home-range estimators.



Note: For the fixed kernel estimator, WORTON should be run first to determine the appropriate smooth parameter.

Appendix 2. AML files for home-range estimation. Areas which need user-input are shown in {} and italics.

SETCELL

<pre> Generate sites input {data-file} points quit build sites point tables select sites.pat additem sites.pat spot 4 4 b calculate spot = 1 select sites.bnd calculate XMAX = XMAX + {x} calculate XMIN = XMIN - {x} calculate YMAX = YMAX + {x} calculate YMIN = YMIN - {x} additem sites.bnd cellsize 4 4 b calculate cellsize = ((XMAX - XMIN) + (YMAX - YMIN)) / 100 list select sites.pat quit </pre>	<div style="font-size: 3em; line-height: 1; padding: 0 10px;">}</div>	<p>Creates an ArcInfo point coverage from data-file</p>
<pre> calculate XMAX = XMAX + {x} calculate XMIN = XMIN - {x} calculate YMAX = YMAX + {x} calculate YMIN = YMIN - {x} </pre>	<div style="font-size: 3em; line-height: 1; padding: 0 10px;">}</div>	<p>Increases the boundary of the point coverage by 1 kernel radius (x)</p>
<pre> calculate cellsize = ((XMAX - XMIN) + (YMAX - YMIN)) / 100 </pre>	<div style="font-size: 3em; line-height: 1; padding: 0 10px;">}</div>	<p>Calculates and lists the cellsize needed to give a 50 x 50 grid</p>

MINCP

<pre> createtin tin cover sites point end arcplot display 9999 mapex mcp tinhull tin points sites volume tin </pre>	<div style="font-size: 3em; line-height: 1; padding: 0 10px;">}</div>	<p>Creates a TIN from the ArcInfo coverage</p>
<pre> display 9999 mapex mcp tinhull tin </pre>	<div style="font-size: 3em; line-height: 1; padding: 0 10px;">}</div>	<p>Displays mcp, overlays the point coverage and lists the mcp area.</p>

ASYMPTOTE

```

generate asy
input {data-file}
points
quit
build asy point
tables
select asy.pat
additem asy.pat spot 4 4 b
calculate spot = 1
quit
reselect asy asy1 point
reselect asy# < x
~
n
n
createtin tasy1
cover asy1 point
end
volume tasy1 # asym
kill asy1
kill tasy1
reselect asy asy2 point
reselect asy# < {# of data points}
~
n
n
createtin tasy2
cover asy2 point
end
volume tasy2 # asym
kill asy2
kill tasy2
reselect asy asy3 point
reselect asy# < {# of data points}
~
n
n
createtin tasy3
cover asy3 point
end
volume tasy3 # asym
kill asy3
kill tasy3...
tables
select asym
additem asym hectares 4 12 f 3
calculate hectares = area / 10000

```

Creates a new ArcInfo coverage from original the data-set

Reselects a number of points and calculates an mcp and its area.

This step must be repeated a user-defined number of times with a sequentially greater number of points.

```

additem asym no_data_points 4 4 b
calculate no_data_points = $recno * {# of divisions}
quit
arcplot
display 9999
graphextent asym info no_data_points hectares
graphlimits 3 3 16 12
units graph
axis horizontal
axisruler no_data_points
axis vertical
axisruler area_hectares
graphpoint asym info no_data_points hectares

```

Draws a graph of mcp area against number of points

GRIDCELL

```

pointgrid sites gridcell spot
{grid cell-size}
y
nodata
grid
gridcellarea = zonalarea(gridcell) / 10000
display 9999
mapex gridcellarea
gridshades gridcellarea
cell gridcellarea *

```

Converts point coverage to a grid

Calculates total gridcellarea and visually displays estimate

DP

```

generate dig
input {data-file}
lines
quit
build dig lines
buffer dig dp ## {buffer width} # line
polygrid dp bufgrid inside
{grid cell-size}
y
polygrid dp lacgrid area
{grid cell-size}
y
grid
if(lacgrid < {1% of mcp area}) lacgrid2 = 1 else
lacgrid2 = 0
if(lacgrid2 == 1 or bufgrid == 100) dpgrid = 1
endif
dparea = zonalarea(dpgrid) / 10000
display 9999
mapex dparea

```

Creates a line coverage from the original data-file in which sequential points are linked.

— Lines are buffered and converted to a grid.

— Selects out lacuane with areas <1% mcp

— Calculates total area of DP

```
gridshades dparea
cell dparea *
HARMONIC
```

```
tinarc tin hmpoly poly
grid
setcell {grid cell-size}
setwindow sites
latgrid = polygrid(hmpoly)
latgrid2 = isnull(latgrid)
if (latgrid2 >= 0) latgrid3 = 1
endif
quit
gridpoint latgrid3 lat
tables
select lat.pat
additem lat.pat spot 4 4 b
quit
append hm point
sites
lat
~
y
y
build hm point
arcplot
accessibility hm point access # spot
quit
pointgrid hm hmgrid access
{grid cell-size}
y
nodata
grid
setcell {grid cell-size}
setwindow sites
hmgrid3 = {# of data-points} / hmgrid
hmgrid4 = con(isnull(hmgrid3), 1, hmgrid3)
countgrid = pointdensity(sites, spot, #, simple, #, rectangle, {grid cell-size},
{grid cell-size})
countgrid2 = countgrid * ({grid cell-size} * {grid cell-size} )
quit
tables
select hmgrid3.sta
additem hmgrid3.sta range 4 12 f 3
calculate range = ( MAX - MIN ) / 20
additem hmgrid3.sta l1 4 12 f 3
calculate l1 = MIN + range
additem hmgrid3.sta l2 4 12 f 3
calculate l2 = l1 + range
additem hmgrid3.sta l3 4 12 f 3
```

— Converts mcp TIN to a polygon coverage

Creates a 50 x 50 lattice.

Joins lattice and point coverage to new coverage

Calculates accessibility values for each lattice point

Creates a grid where the cell values are equivalent to the accessibility values of the coincident points

— Converts accessibility values to the numerical equivalent of the Harmonic-mean (equation 1)

— Calculates the number of points in each gridcell

Calculates and lists 20 levels between the maximum and minimum values from which to choose the level which includes 95% of the points.

```

calculate l3 = l2 + range
additem hmgrid3.sta l4 4 12 f 3
calculate l4 = l3 + range
additem hmgrid3.sta l5 4 12 f 3
calculate l5 = l4 + range
additem hmgrid3.sta l6 4 12 f 3
calculate l6 = l5 + range
additem hmgrid3.sta l7 4 12 f 3
calculate l7 = l6 + range
additem hmgrid3.sta l8 4 12 f 3
calculate l8 = l7 + range
additem hmgrid3.sta l9 4 12 f 3
calculate l9 = l8 + range
additem hmgrid3.sta l10 4 12 f 3
calculate l10 = l9 + range
additem hmgrid3.sta l11 4 12 f 3
calculate l11 = l10 + range
additem hmgrid3.sta l12 4 12 f 3
calculate l12 = l11 + range
additem hmgrid3.sta l13 4 12 f 3
calculate l13 = l12 + range
additem hmgrid3.sta l14 4 12 f 3
calculate l14 = l13 + range
additem hmgrid3.sta l15 4 12 f 3
calculate l15 = l14 + range
additem hmgrid3.sta l16 4 12 f 3
calculate l16 = l15 + range
additem hmgrid3.sta l17 4 12 f 3
calculate l17 = l16 + range
additem hmgrid3.sta l18 4 12 f 3
calculate l18 = l17 + range
additem hmgrid3.sta l19 4 12 f 3
calculate l19 = l18 + range
additem hmgrid3.sta l20 4 12 f 3
calculate l20 = l19 + range
list
y
quit

```

HARMONIC2

```

if(hmgrid4 < {value from harmonic}) level = 1
endif
lcont = zonalsum( level, countgrid2 ) / {# of data points /100}
display 9999
mapex lcont
gridshades lcont value linear
points sites
cell lcont *

```

- Selects out the appropriate level
- Calculates the percentage of points in the new level
- Lists the percentage of points within the level

HARMONIC3

```
area = zonalarea( level ) / 10000
```

```
display 9999
```

```
mapex area
```

```
gridshades area
```

```
harcon = contour(hmgrid4, list, {desired contour value},.....)
```

```
arcs harcon
```

```
cell area *
```

— Calculates the area of the level

— Contours the resulting UD

— Lists the area of the 95% UD

KERNELPD

```
grid
```

```
setwindow sites
```

```
kernel=pointdensity(sites,spot,#,kernel,#,{smoothing parameter})
```

```
kpd = kernel * 100000
```

```
if(kpd > {value}) kpd2 = kpd
```

```
endif
```

```
kpd3 = pow(kpd2,0.5)
```

```
quit
```

```
tables
```

```
select kpd3.sta
```

```
additem kpd3.sta sd95 4 12 f 3
```

```
calculate sd95 = ( mean - ( stdv * 1.645 ) ) ** 2
```

```
list
```

```
quit
```

} Estimates the UD

— Converts the UD to an approximate bivariate normal distribution

} Calculates the upper kernel density which is equivalent to 95% of the UD

KERNELPD2

```
grid
```

```
if(kpd2 > {value from kernelpd}) kpd95 = kpd2
```

```
endif
```

```
quit
```

```
tables
```

```
select kpd95.sta
```

```
additem kpd95.sta interval 4 12 f 3
```

```
calculate interval = ( max - min ) / 7
```

```
list
```

```
quit
```

} Calculates a new grid with 95% of the UD

KERNELPD3

```
grid
```

```
if(kpd95 > 0) kpd95b = 1
```

```
endif
```

```
kpdarea = zonalarea(kpd95b) / 10000
```

```
display 9999
```

— Calculates area estimate for 95% UD

```

mapex kpd95
shadeset colorange
gridshades kpd95 value linear
kpdcontour = contour(kpd95, interval, {value from kernelpd2})
kpdwnd = gridpoly(kpd95b)
linecolor red
arcs kpdcontour
linecolor yellow
arcs kpdcontour
cell kpdarea *

```

} Contours UD

Stability

```

reselect sites pnts point
res $recno < {desired # of points}
~
n
n
grid
k5a = pointdensity(pnts,spot,#,kernel,#,{h})
k5b = k5a * 100000
k5bcon = contour(k5b,interval,{contour interval})
quit
clean k5acon k5acont # # poly
tables
select k5acont.pat
list
quit
kill k5a
kill k5b
reselect sites pnts1 point
res $recno < {desired # of points}
~
n
n
grid
k10a = pointdensity(pnts1,spot,#,kernel,#,{h})
k10acon = contour(k10a,interval,{contour interval})
quit
clean k10acon k10acont # # poly
tables
select k10acont.pat
list
quit
kill k10a
reselect sites pnts2 point
res $recno < {desired # of points}
~
n

```

Stability.aml was an attempt to develop a routine based on our mcp asymptote.aml. In each step it takes a sequential number of points and calculates a fixed kernel estimate. However, unlike asymptote.aml we could find no way of exporting the area estimate into an attribute table and so after each iteration the area is displayed on screen. We were unable to run this routine due to a lack of filespace (the grids which results are large).


```

n
grid
k15 = pointdensity(pnts2,spot,#,kernel,#, {h})
k15con = contour(k15,interval, {contour interval})
quit
clean k15con k15cont # # poly
tables
select k15cont.pat
list
quit
kill pnts1
kill k15
reselect sites pnts3 point
res $recno < {desired # of points}
~
n
n
grid
k20 = pointdensity(pnts3,spot,#,kernel,#, {h})
k120con = contour(k20,interval, {contour interval})
quit
clean k20con k20cont # # poly
tables
select k20cont.pat
list
quit
kill pnts3
kill k20

```

Thiessen

```

dirichlet sites tiles
tables
select tiles.pat
sort AREA
additem tiles.pat order 4 4 b
calculate order = $recno
reselect order < {# of data points} AND order > 0
statistics
sum AREA
sort tiles#
quit
reselect tiles tilesb
res order < {# of data points} AND order > 0
~
n
n
arcplot
display 9999

```

Thiessen.aml was an attempt to develop a new non-parametric method of identifying core-areas (Wray *et al.* 1992). This method uses a dirichlet tessellation to create a surface based on the animal fixes. Where points are dense the resulting polygons are small. Therefore, by ordering the resulting tiles in increasing area it is possible to select out proportions of these tiles which will reflect different levels of usage (50% is often used to delineate core-areas - however, see discussion).

We were unable to fully develop this method as it requires splitting the resultant tiles when animal fixes are duplicated in the data-set. We could find no easy way to do this within ArcInfo.

mapex sites
polys tilesb

3D

shadeset colorange
surface lattice kgrid
surfaceextent surface
surfacetarget 356200 177000
surfaceobserver relative 120 6 15000
surfacezscale 5
surfaceprojection perspective
surfacedrape gridshades {grid} value linear

Calculation of h using WORTON

Smooth

grid
setwindow sites
k10 = pointdensity (sites,spot,#,kernel,#, {h})
k10sc = k10 * 1000000
list k10sc.sta

smooth10

k10con = contour(k10sc, interval, {contour interval})
k9 = pointdensity (sites,spot,#,kernel,#,({h} * 0.9))
k9sc = k9 * 1000000
list k9sc.sta

smooth9

setwindow sites
k9con = contour(k9sc, interval, {contour interval})
k8 = pointdensity (sites,spot,#,kernel,#,({h} * 0.8))
k8sc = k8 * 1000000
list k8sc.sta

smooth1

k1con = contour(k1sc, interval, {contour interval})

windows

display 9999
mapex sites

3D.aml is a routine which displays a 3D representation of a grid. This is sometimes useful for visually inspecting UDs and being able to visualise where core-areas may be or where lacunae may be present.

This set of amls implements the routine of Wray *et al.* (1992) for selecting an appropriate smoothing parameter. It takes the smoothing parameter calculated by one of the methods mentioned in the methods section. UDs are estimated using this smoothing parameter and 0.1 proportions of this parameter down to 0.1. Each of these UDs is then visually inspected to see if there are a range of parameters which give a similar outer boundary and similar internal configurations. The smoothing parameter which then is represented by this 'best-fit' kernel is then chosen as the appropriate smoothing parameter.

Amls smooth, smooth10, smooth9...smooth1 (intervening amls not shown) must all be run sequentially but necessitates user-input at the end of each aml into the next to facilitate similar contouring between UDs so that comparisons can be made. The 10 UDs can then be visualised using windows.aml and windows2.aml, however only a maximum of 5 windows can be open at once.

This method, whilst giving a reasonable output, is extremely laborious and needs extensive user-input and a large amount of filespace.

shadeset colorange
linecolor red
imageview create k10
imageview create k9
imageview create k8
imageview create k7
imageview create k6
imageview k10sc value linear # # k10con k10
imageview k9sc value linear # # k9con k9
imageview k8sc value linear # # k8con k8
imageview k7sc value linear # # k7con k7
imageview k6sc value linear # # k6con k6

windows2

imageview create k5
imageview create k4
imageview create k3
imageview k5sc value linear # # k5con k5
imageview k4sc value linear # # k4con k4
imageview k3sc value linear # # k3con k3

