Time Geography and Wildlife Home Range Delineation

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ABSTRACT We introduce a new technique for delineating animal home ranges that is relatively simple and intuitive: the potential path area (PPA) home range. PPA home ranges are based on existing theory from time geography, where an animal's movement is constrained by known locations in space-time (i.e., *n* telemetry points) and a measure of mobility (e.g., maximum velocity). Using the formulation we provide, PPA home ranges can be easily implemented in a geographic information system (GIS). The advantage of the PPA home range is the explicit consideration of temporal limitations on animal movement. In discussion, we identify the PPA home range as a stand-alone measure of animal home range or as a way to augment existing home range techniques. Future developments are highlighted in the context of the usefulness of time geography for wildlife movement analysis. To facilitate the adoption of this technique we provide a tool for implementing this method.

KEY WORDS home range, time geography, potential path area, wildlife movement, GIS, error

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INTRODUCTION

Animal home ranges are used to study many aspects of wildlife ecology including habitat selection (Aebischer et al. 1993), territorial overlap (Righton and Mills 2006), and movement impacts of offspring status (Smulders 2009). Home ranges often serve as the primary spatial unit for wildlife research and represent the area to which an animal confines it's normal movement (Burt 1943). Wildlife telemetry data, typically collected with radio or GPS collars, provide a collection of space-time locations for an animal.

Telemetry data are commonly converted to home ranges to identify spatial patterns in animal movement and answer specific research questions.

In order to derive animal home ranges, wildlife scientists have used existing methods in geometric topology and spatial smoothing to transform a set of telemetry *points* into a *polygon* animal home range. The two most common methods for computing animal home ranges are the minimum convex polygon (MCP), and kernel density estimation (KDE) (Laver and Kelly 2008). MCP continues to be used extensively in wildlife movement analysis (Laver and Kelly 2008) despite considerable drawbacks, such as sensitivity to sampling intensity and outliers, convex assumption, and inclusion of large, unused interior areas (Worton 1987, Powell 2000, Borger et al. 2006). The prevalence of MCP is likely due to its ease of implementation in common GIS platforms and that it requires no input parameters. Kernel density estimation (KDE) has been influential in home range analysis since its introduction by Worton (1989). KDE remains contentious in animal movement analysis due to issues with selecting an appropriate kernel bandwidth (Hemson et al. 2005, Kie et al. 2010), which can significantly impact results (Worton 1989). Unfortunately, KDE based home ranges can be misleading when telemetry points are irregularly shaped (Downs and Horner 2008) or when animals habituate patchy environments (Mitchell and Powell 2008). A number of other lesser used methods also exist (e.g., harmonic mean, Dixon and Chapman 1980, local nearest-neighbor convex hull, Getz and Wilmers 2004, Brownian bridge, Horne et al. 2007, characteristic hull, Downs and Horner 2009), but have yet to become widely adopted.

The objective of this article is to demonstrate a new approach for integrating time attributes accompanying telemetry data when calculating animal home ranges. Drawing on concepts from time geography (Hagerstrand 1970), we develop a new approach for computing animal home ranges that explicitly considers the temporal constraints of animal movement. Time is largely ignored in existing home range techniques, and used primarily for separating data into temporal groups such as seasons (Nielson et al. 2003). The value of this method is discussed in context of existing home range research, including existing examples moving towards a time geographic approach.

METHODS

Background: Time Geography

Time determines bounds on an objects movement in space (Parkes and Thrift 1975). With time geography (Hagerstrand 1970), these constraints are represented as volumes containing all accessible locations in a three dimensional space-time continuum consisting of geographic coordinates x and y and time (t) (frequently termed the space-time cube, Kraak 2003, or space-time aquarium, Kwan and Lee 2004). If both starting and end points are known (as with a collection of telemetry fixes) then the *space-time prism* represents the set of all accessible locations to the object during that movement segment (Figure 1). The projection of the space-time prism onto the geographic plane is termed the *potential path area* (PPA), and represents all locations accessible to an object given its start and end points and assumed maximum rate of travel (Figure 1). An object's maximum traveling velocity impacts the extent of these volumes into geographic space.

< approximate location Figure 1 >

Potential Path Area (PPA): A New Measure of Animal Home Range

This work will focus on potential uses of PPA in wildlife movement analysis, specifically the calculation of a PPA animal home range. The PPA represents the set of all accessible locations between two known locations in space and time (Miller 2005). Geometrically, the PPA is an ellipse with focal points located at two known locations, the origin and destination. The spatial extent of the PPA depends on the animal's maximum velocity ($v_{\max}$) which may be explicitly known or empirically estimated from the data.

Visually, conceptualizing the creation of a PPA ellipse is best done using the 'pins-and-string' method (Figure 2a). Consider placing pins at the known start (i) and end (j) locations of an animal movement segment. A single string is then tied to each point, connecting the two pins. The length of the string is $D_{\max}$, representing the maximum distance the animal can travel given its maximum velocity ($v_{\max}$) and the time difference between points i and j (Δt).

$$D_{\max} = v_{\max} \times \Delta t \qquad [1]$$

The PPA ellipse is drawn by moving a pencil around the two points, but inside of the string, keeping the string tight at all times. Any point located along or within the PPA ellipse is reachable by the animal during this movement segment.

< approximate location Figure 2 >

Mathematically, given that in unconstrained space PPA is an ordinary ellipse, we can derive PPA using parameters of an ellipse related to animal movement in time and space. We define $v_{\max}$ and Δt as above, the maximum velocity of the animal and the time difference between known telemetry locations i and j. A PPA ellipse is defined using four parameters: a center point, a major axis, a minor axis, and a rotation angle (Figure 2b). The center point is calculated as the midway point between the spatial (x, y) coordinates of telemetry points i and j. The major axis (a) is defined as:

$$\begin{aligned} a &= D_{\max} \\ &= v_{\max} \times \Delta t \end{aligned} \qquad [2]$$

With this we can define the minor axis (*b*) as:

$$b = \sqrt{a^2 - d^2} \quad [3]$$

Where *d* is the Euclidean distance between points *i* and *j*. Rotation angle (R_θ) is the angle the ellipse is rotated from the horizontal, and defined using *x* and *y* coordinates of telemetry points *i* and *j*:

$$R_\theta = \tan^{-1}\left(\frac{y_j - y_i}{x_j - x_i}\right) \quad [4]$$

Using these parameters we can generate the PPA ellipse for any pair of known locations in space-time.

A PPA home range can be computed by generating PPA ellipses for a set of animal locations. A telemetry dataset of *n* recordings requires calculation of *n*-1 PPA ellipses which are combined to produce the PPA home range (Figure 2c). Formally this is defined as the union of *n*-1 PPA ellipses such that:

$$\mathrm{PPA}_{\mathrm{HR}} = \bigcup [\mathrm{PPA}_{i,i+1}], \quad i \text{ in } \{1, \ldots, n-1\} \quad [5]$$

The mathematical formulation of this method (represented by equations [1] through [5]) is easily implemented in a GIS.

Estimating $v_{\max}$

The PPA home range method requires a single input parameter $v_{\max}$ that has obvious biological connotations and in some cases may be explicitly known based on a fine understanding of an organism’s mobility. This parameter could be related to an organism’s maximum velocity. For example, cheetahs have a maximum speed of up to 120 km/h (Sharp 1997); however it is unreasonable to expect a cheetah to maintain that speed over longer intervals, characteristic of telemetry datasets. It is more useful to compute the maximum distance a cheetah could cover in 30 minutes and derive $v_{\max}$ from this. In practice, $v_{\max}$ should relate biologically to the temporal frequency of recordings.

In many cases however, a biologically reasonable estimate of $v_{\max}$ will not be explicitly known and a researcher will be required to estimate it from the data. For each pair of consecutive relocation fixes we can compute the segment velocity (v_i) by:

$$v_i = \frac{d_i}{t_i} \qquad [6]$$

where d_i is the distance and t_i the time difference between consecutive fixes. Computing v_i for all $n - 1$ segments will provide a distribution of v values which can be used to generate estimates for $v_{\max}$. The simplest would be to take $\max(v_i)$ – the maximum observed velocity as $v_{\max}$, however this is problematic as it produces a straight-line (degenerative ellipse) between any consecutive pair of fixes that have this maximum value. A more robust approach is to estimate a value for $v_{\max}$ based on the ordered distribution of the v_i. Following Robson and Whitlock (1964) an estimate of $v_{\max}$ could take the form:

$$\hat{v}_{\max} = v_m + (v_m - v_{m-1}) \qquad [7]$$

where v_i are in ascending order such that $v_1 < v_2 < \ldots < v_{m-1} < v_m$ and $m = n - 1$. This estimate for v_{max} has an approximate $100(1 - \alpha)\%$ upper confidence limit given by:

$$\mathrm{U}_{\mathrm{Lim}}(v_{\max}) = v_m + \frac{(1-\alpha)(v_m - v_{m-1})}{\alpha} \qquad [8]$$

Cooke (1979) and van der Watt (1980) have extended the work of Robson and Whitlock (1964) deriving estimates with lower mean squared errors and smaller confidence intervals, at the cost of added complexity. In the case where $v_m = v_{m-1}$, the result from [7] will equal $\max(v_i)$ and cause degenerate ellipses to be produced for pairs of consecutive points that have this maximum value. The method of van der Watt (1980) is advantageous as it avoids the problem of degenerate ellipses through careful selection of the parameter *k* in the equation:

$$\hat{v}_{\max} = \left(\frac{k+2}{k+1}\right)v_m - \left(\frac{1}{k+1}\right)v_{m-k} \quad [9]$$

where $1 < k < m$ representing the k^{th} ordered value of v_i. This estimate for $v_{\max}$ has an approximate $100(1 - \alpha)\%$ upper confidence limit given by:

$$\mathrm{U}_{\mathrm{Lim}}(v_{\max}) = v_m + \left(\frac{1}{1/\left(1-\alpha^{1/k}\right)-1}\right)(v_m - v_{m-k}) \quad [10]$$

In the previously stated problem scenario where $v_m = v_{m-1}$ it would be useful to take *k* to be the largest value such that $v_{m-k} < v_m$. In general [9] has been shown to be an improved estimator of $v_{\max}$ over [7] (van der Watt 1980), however it requires that the researcher select an appropriate value for *k*. Alternatively, a more conservative analysis could use the upper confidence interval limits (e.g., [8] or [10]) as an estimator for $v_{\max}$.

RESULTS

For demonstration, we simulate an animal trajectory using a correlated random walk (n = 2000). Using this data as a surrogate for animal movement data, we calculate animal home range using two common, existing techniques (MCP and KDE) and the new PPA home range approach (Figure 3 a–c). We used the Robson and Whitlock (1964) method given by [7] for estimating the $v_{\max}$ parameter from the data. The temporal sampling interval of telemetry fixes is known to influence output home range size and shape using MCP (Borger et al. 2006) and KDE (Downs and Horner 2008), but also will influence the PPA home range. To demonstrate this effect, we re-sampled our simulated animal trajectory using only ¼ (n = 500) of the points and re-estimated the v_{max} parameter using [7] (Figure 3 d–f).

< approximate location Figure 3 >

DISCUSSION

In this example, the effect of changing sampling frequency had minimal effect on home range computed using MCP (figure 3 a & d), however this will not always be the case (Borger et al. 2006). With KDE, fewer points lead to increased uncertainty in the bandwidth selection process, resulting in a wider bandwidth selection, and in general a larger output home range. With the PPA home range method uncertainty is a function of the time between consecutive known locations, rather than the number of points. As a result, PPA home ranges are comprised of fewer, larger ellipses to account for uncertainty in animal location between consecutive known points, and produce larger home range estimates. We suggest that PPA home ranges be employed only when telemetry data are collected using a relatively short sampling interval (e.g., dense GPS telemetry data). In these situations uncertainty between consecutive fixes will be relatively low. In cases where the temporal duration between fixes is substantially longer (e.g., with most VHF collars), the ellipses produced by the PPA algorithm will be large, resulting in significant overestimations of home range size. We withhold from specifying an absolute threshold on sparse telemetry data where the PPA method should not be used as it will be dependant on both the species (e.g., large vs. small mammal) and application (seasonal home range vs. migratory behavior). Comparison of the PPA home range with existing methods (e.g., KDE and MCP) should provide information as to whether or not the PPA approach is appropriate with a given dataset (see Figure 4 and the accompanying discussion below).

The conceptual and computational simplicity of the PPA home range may be its greatest asset. The PPA home range can be defined simply as: *given a set of sampled locations (telemetry points) the PPA home range contains all locations in geographic space that the animal could have visited*. PPA can be easily implemented in a GIS and requires only one input parameter, maximum travelling velocity – $v_{\max}$, that can be derived using biological knowledge or estimated directly from the data (e.g., using [7] or [9]). If telemetry data are categorized into distinct behavioral segments (e.g., Jonsen et al. 2005, Gurarie et al. 2009) where differing $v_{\max}$ would be expected, PPA home range analysis could be further enhanced.

It is interesting that given its intuitive structure, ideas from time geography are largely absent from wildlife movement research. Baer & Butler (2000) use time geographic theory for modeling wildlife movement building upon Hagerstrand’s (1970) concept of ‘bundling’, representing animals congregating in space-time. Regions where ‘bundling’ occurs can be used to identify specific ecological activity in groups of animals (e.g., locating scarce resources). Wentz et al. (2003) implement time geographic constraints for animal movement, interpolating between sampled telemetry locations to model movement paths. Time geography volumes are used by Wentz et al. (2003) to constrain random walks between sampled locations. More recently, Downs (2010) presents a novel approach for incorporating time geographic principles, specifically the potential path area (termed *geo-ellipse*), into kernel density estimation. Downs (2010) uses the geo-ellipse in place of a circular kernel in the density estimation. Several advantages of this approach are identified, such as replacing subjective selection of kernel bandwidth by an objective parameter – maximum travelling velocity. Time geographic kernel density estimation assigns zero density to regions outside of the PPA home range, creating a utilization distribution density allocated only to accessible regions.

Wildlife do not use the space within their home range evenly motivating use of an intensity surface – termed *utilization distribution*, to analyze animal space use (Jennrich and Turner 1969). Utilization distributions more adequately portray patterns of space use within wildlife home ranges and provide more reliable estimates of overlap and/or fidelity compared with discrete home range methods (Fieberg and Kochanny 2005). However, these advantages come at the cost of added complexity in deriving the utilization distribution with many researchers continuing to use discrete measures of home range over utilization distributions in analysis due to their simplicity (Laver and Kelly 2008). KDE remains the most popular method for computing utilization distributions despite considerable drawbacks with newer (temporally dense) telemetry data (Hemson et al. 2005, Kie et al. 2010). Horne et al. (2007) propose the Brownian bridge approach for computing the utilization distribution. A Brownian bridge is simply defined as the probability a random walk passes through a location given the known start and end points. Like the PPA home range, with the Brownian bridge approach telemetry data are analyzed using pairs of consecutive telemetry fixes. This method relies on a variance parameter – σ_m that is difficult to interpret but can be estimated from the data using an optimization algorithm. The PPA method is essentially the discrete equivalent of the Brownian bridge approach, but with simple, intuitive, and easy to estimate parameters that can be straightforwardly computed in a GIS. Getz and Wilmers (2004) propose the use of overlapping local convex hulls to generate a utilization distribution. A similar approach could be adopted with PPA ellipses to generate a utilization distribution based on the areas under overlapping ellipses. The derivation of an overlap-based utilization distribution for PPA ellipses remains an area for future investigation.

Wildlife researchers now routinely collect temporally dense telemetry data using sophisticated tracking technologies (e.g., GPS, Tomkiewicz et al. 2010). Such temporally dense telemetry data provide a more detailed and informative view of animal movement. Given continued advancements in technology in the future it is likely that we will be analyzing (near) continuous animal trajectories. This improved representation of animal movement necessarily results in highly autocorrelated movement data. Much attention has been given to the problems autocorrelated telemetry data pose with traditional methods for studying wildlife movement (Swihart and Slade 1985, Otis and White 1999, Fieberg et al. 2010). Many existing methods, developed for use with temporally sparse telemetry data, are ill equipped for dense telemetry data. The PPA home range method is advantageous with temporally dense telemetry data, as it is capable of including rich temporal information into the derivation of home range. With few exceptions (e.g., Horne et al. 2007) existing home range techniques ignore rich temporal information contained in telemetry datasets. Including temporal information in analysis is beneficial as points are no longer considered independent observations, but rather as a sequence of recordings taken over a time period.

Certain land cover types (e.g., dense forest, Rempel et al. 1995) can interfere with locating technologies resulting in missing recordings. Missing data points are problematic in subsequent analysis as bias towards specific cover types can occur (Frair et al. 2004). By explicitly considering the temporal sequencing of points, PPA home ranges adjust for missing telemetry recordings by way of a larger Δt value in these areas, providing an unbiased estimator of home range.

Commission errors (locations included in the home range but never visited) and omission errors (locations visited but not included in the home range) are important properties of output home range polygons that require careful consideration (Sanderson 1966). All home range methods short of a direct trace of an animal's movement path will include commission errors. Omission errors occur with most methods, but can be avoided by substantially overestimating home range size. This is equivalent to selecting an overly large bandwidth with KDE. Substantial overestimation limits utility for wildlife research as the signature of animal behavior is masked. The PPA home range method can be used in tandem with other methods to examine commission and omission errors. Consider a simple comparison, by intersecting the PPA home range with commonly employed home range techniques MCP and KDE (Figure 4). The PPA home range represents the largest spatial unit such that no omission error occurs, due to explicit consideration of the time geography constraints on animal movement. Potential omission errors are then easily represented as those areas included in the PPA home range, but not in other techniques. Areas not included in the PPA home range but included in other methods can be considered inaccessible regions and an unnecessary source of commission error. With MCP, potential omission errors are likely to occur near edges of MCP home ranges. Due to the convex assumption, MCP home ranges almost always include inaccessible areas as well (Powell 2000). KDE home range polygons are not guaranteed to even include all sampled telemetry points, therefore explicitly known errors of omission may exist.

< approximate location Figure 4 >

All measures of home range are indirect and based on specific properties of the telemetry data from which they are derived. Most existing methods use only the spatial properties of telemetry data represented as points. The PPA method provides a complementary view that not only considers spatial information but also temporal information. Using the demonstrated intersection technique, omission errors and inaccessible regions (unnecessary commission error) using existing home range methods can be mapped and quantified. This represents a significant contribution towards home range analysis that carefully considers these types of errors as has been previously suggested (Sanderson 1966). Often studies employ multiple methods when delineating wildlife home ranges to evaluate a range of possibilities (e.g., Righton and Mills 2006). The PPA home range should be included in such studies as it can be used to augment other techniques by providing information on omission and commission errors.

In this derivation of PPA home range all geographical space is considered equally navigable. In reality, environmental factors (e.g., topography, land cover, water bodies) influence an animal’s ability to traverse the landscape. As well, external factors such as inter- and intra-species competition (Schwartz et al. 2010), and habitat requirements (Sawyer et al. 2007), motivate wildlife movement, and subsequent home range delineations. Optimally, PPA home ranges would be based on the time geography constraints across an unequal surface (see Miller and Bridwell 2009), that considers competition, habitat, topography, and barriers to wildlife movement. Future work should investigate combining available environmental datasets into animal specific movement cost surfaces. Movement cost surfaces could then be integrated into time geographic analysis to compute more realistic PPA home ranges. However, incorporating movement cost surfaces may take away from the attractiveness of time geography methods due to added complexity.

MANAGEMENT IMPLICATIONS

The concept of home range remains at the core of current research on wildlife movement and habitat analysis, and is frequently adopted as a tool in wildlife management applications. In this article we have presented a new technique for deriving animal home ranges that is simple and intuitive, but also designed specifically for use with emerging temporally dense telemetry datasets, such as those now routinely collected with GPS collars. However, we suggest the PPA approach not be adopted with temporally coarser telemetry data (e.g., VHF collars) as it can lead to overestimation of home range size and misleading interpretations. The PPA home range can be used as a stand-alone measure of animal home range, or to augment existing techniques by identifying potential omission errors and inaccessible areas making it flexible for use with both novel and existing analyses. When performing PPA home range analysis the method for obtaining the $v_{\max}$ parameter (e.g., through biological reasoning or by one of the estimation approaches we provide) along with the parameter value should be explicitly stated, as it will influence the resulting home range area. To those wishing to implement the PPA home range technique in their own research we have provided access to a tool for implementing the PPA home range. For more information please go to: http://www.geog.uvic.ca/spar/tools.html.

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Figure Captions:

Figure 1: Diagram of Hagerstrand's (1970) time geography. The space-time prism contains the set of all locations accessible to an individual given telemetry fixes at t_1 and t_2, and a velocity parameter ($v_{\max}$). The projection of the space-time prism onto the geographical plane is called the potential path area (PPA), used here for delineating wildlife home ranges.

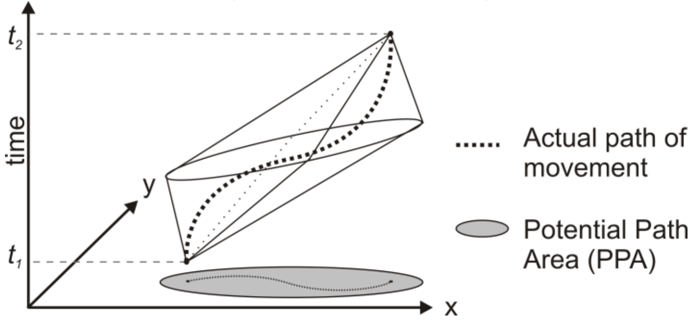

Figure 2: a) Pins-and-strings method for generating PPA ellipses. The length of the string is equal to the longest distance the animal could travel ($D_{\max}$) given parameter $v_{\max}$ and the time difference between points. b) Geometric properties of a PPA ellipse with telemetry points *i* and *j*. *CP* is the center point and *d* is the Euclidean distance between points *i* and *j*; *a* and *b* are lengths of the major and minor axis respectively; and R_θ is the rotation angle. c) Computation of the PPA home range involves combining multiple (*n*–1) PPA ellipses.

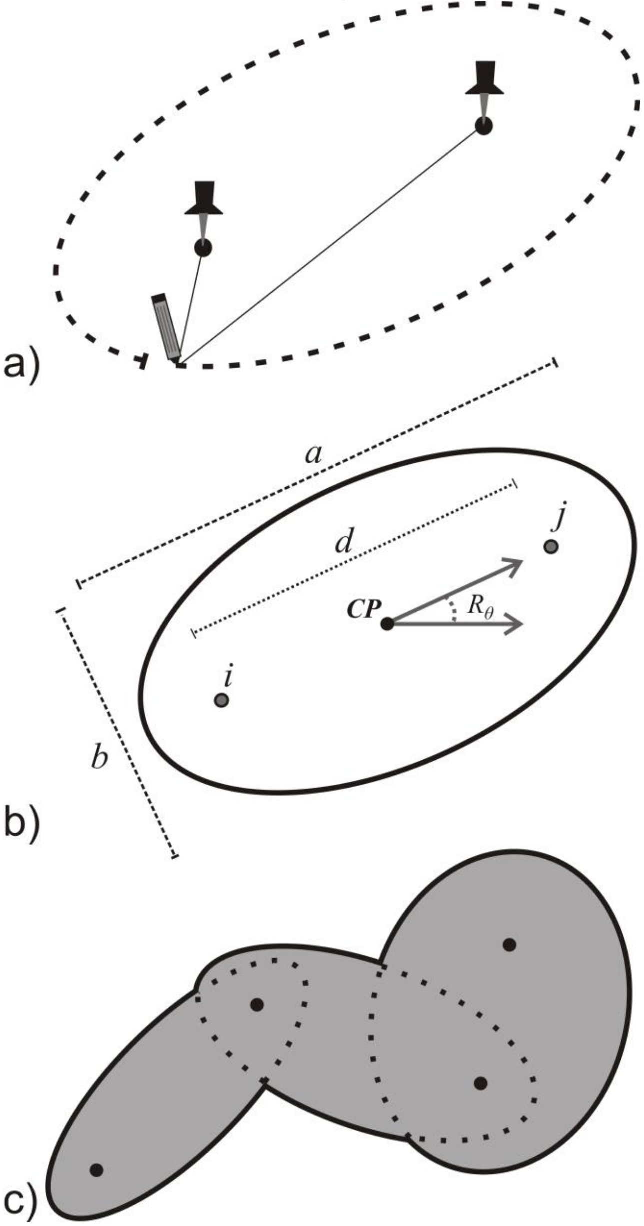

Figure 3: Home range polygons for a simulated dataset with $n = 2000$ (top) re-sampled to $n = 500$ (bottom) using MCP (a & d), KDE (b & e) and PPA (c & f).

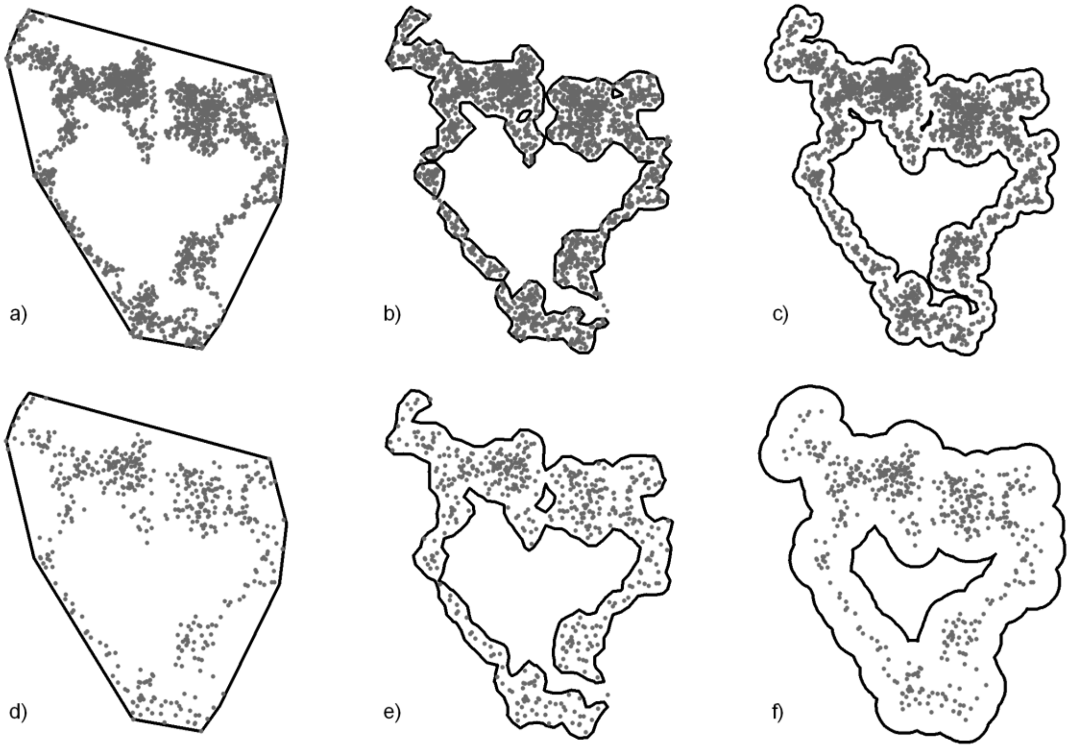

Figure 4: Intersections between a) MCP & PPA and b) KDE & PPA (for *n* = 2000); demonstrating how PPA home ranges can be used to augment existing techniques by identifying omission errors and inaccessible areas.