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Search strategies for conservation detection dogs

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Monitoring rare or cryptic species can be challenging, especially with limited time and resources. Dogs are often used for this purpose, but methods are highly variable. There is a need to optimise search methods for dog teams so that time and resources are used as efficiently as possible. Some degree of standardisation is also desirable so that search results are comparable between different times and places. The discipline of search theory has developed effective methods to maximise the probability of detecting a search object and/or maximise the efficiency of a search. However, these advances have not been explicitly applied to the use of dogs to search for plants and animals in the wild. Here, we provide a brief introduction to search theory, then discuss how ideas from search theory might be used to standardise and optimise the use of conservation detection dogs. We describe approaches that have been used, discuss their strengths and weaknesses, and suggest priorities for further research. Standardised methods based on search theory could increase the effectiveness of conservation detection dogs, and make search results more comparable across different locations and times.

A major challenge in wildlife management and conservation is monitoring the abundance and distribution of cryptic species. Many plants and animals can be difficult to detect, either because they are scarce (e.g. invasive species early in an incursion; Hauser et al. 2015), or because they are intrinsically cryptic (e.g. small seedlings; Patten and Milne 2008). Monitoring cryptic species requires methods that are affordable and repeatable (Reed et al. 2011). This means there is a need to optimise search strategies for cryptic species within the limitations of budget, time and human resources. Researchers and managers must decide how many sites to search, which ones, and how much effort to allocate to each (Baxter and Possingham 2011).

Failure to detect an organism does not necessarily mean it is absent, especially when density is low. In deciding what level of search effort to apply, managers have to weigh up the costs of surveillance against the risk of missed detections (Parkes and Nugent 2011).

Dogs are increasingly being used to search for cryptic animals and plants (Long et al. 2007a, b, MacKay et al. 2008, Woollett et al. 2013, Johnen et al. 2017). Searches are conducted for a wide variety of purposes; for example, to enumerate populations, to determine presence/absence of a species, to assist in capturing animals for research, or to locate and remove invasive plants or animals. However, search methods using conservation detection dogs are not standardised, and variation in their performance is not well understood or quantified (Clare et al. 2015a). Our aim was to collate published studies relating to conservation detection dogs (hereafter 'conservation dogs'), review attributes of search theory relevant to conservation dogs, and synthesise lessons for future application by conservation managers.

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Literature search

We searched Google Scholar and the ISI Web of Science database using the keywords: 'wildlife detect* dog'; 'scat detect* dog; conservation detect* dog; plant detect* dog; weed detect* dog', and; ('search theory' AND (dog OR canine OR wildlife)). We scanned the resulting titles for references to the use of dogs to find wild plants or animals. We also searched for review articles on search theory in general. Additional articles were located from the reference lists of these publications. Our literature search yielded 152 publications (Supplementary material Appendix 1). There was an apparent taxonomic bias in published studies using conservation dogs: 63 studies related to mammals, 20 to plants, 9 to reptiles, 3 to invertebrates and 1 to birds. An additional 56 publications had no taxonomic focus; these related to methods (e.g. selection and training of dogs) or to search theory in general. A database with details of each publication is provided in Supplementary material Appendix 1.

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Search theory

Initially developed by Koopman (1946, 1980) for naval applications, search theory helps determine an optimal search strategy, taking into account environmental conditions and resource constraints. It allows the user to estimate (and maximise) the probability of detecting a search object (e.g. a plant or animal) while explicitly considering characteristics of the search object, the physical environment and the capabilities of the searcher (Frost 2000).

Search theory has applications in such diverse fields as computer science (Geem et al. 2009), mineral exploration (Kolesar 1982), search and rescue (Cooper 2005), animal behaviour (Alpern et al. 2016) and invasive species management (Cacho et al. 2007), among others. Excellent syntheses are provided by Frost (2000), Frost and Stone (2001) and Washburn (2002). Cacho et al. (2007) provide an extremely useful introduction to search theory for ecologists.

Effective sweep width

Search theory allows the user to estimate the probability of detecting an object with a given search strategy and level of effort (Cacho et al. 2006, Perkins and Lovelock 2008). A fundamental concept in this process is 'effective sweep width' (R), which is a measure of the search object's detectability (Cooper et al. 2003, Cacho et al. 2007). It is defined as the distance either side of the searcher at which the number of missed detections inside the range equals the number of positive detections outside the range (Koopman 1946, 1980).

To design an optimal search pattern, it is necessary to estimate effective sweep width. This is influenced by characteristics of the search object (how conspicuous is it?), the capabilities of the searcher (e.g. speed, sensory acuity, ability to negotiate rough terrain), and environmental conditions such as weather and vegetation type (Frost 2000, Hauser et al. 2015). Robe and Frost (2002) describe a simple method to estimate effective sweep width experimentally. Search objects are placed at locations known to the observer, but not to the searcher, in an environment similar to that of a real search. Detections and missed detections are then recorded, along with the distance of each search object from the search path. This information is used to generate cumulative detection and non-detection curves. The intersection of the two curves indicates half the effective sweep width (Robe and Frost 2002). To obtain a reliable estimate, a minimum of 250 detection opportunities is recommended. This could be achieved, for example, by 10 searchers searching for 25 objects (Robe and Frost 2002).

The concept of effective sweep width is equally applicable to searches that rely primarily on vision, or on smell. Effective sweep width is estimated in a probabilistic fashion. Estimates should therefore be robust to stochastic variations in the distance at which a target is likely to be detected (e.g. due to changes in wind speed or direction).

Coverage

The proportion of the total area of interest that is effectively searched is termed 'coverage' (c), which can be estimated as $c = STR / A$ (where S is the speed of the searcher, T is time, R is effective sweep width, and A is the area of the search zone). Factors such as remote or rugged terrain may reduce the searcher's speed, and therefore increase the time required to achieve the same coverage (Cacho et al. 2007).

Probability of detection

'Probability of detection' (POD) is the probability that a searcher will detect a target; POD declines with increasing distance from the searcher to the target. The relationship between POD and distance is described by a 'lateral range curve' (Fig. 1). The area under the curve equals the effective sweep width (Koopman 1980, Perkins and Lovelock 2008).

Probability of detection increases with additional search effort, and the cumulative POD for a search can be estimated from the effective sweep width and the search effort per unit area (Robe and Frost 2002). Cumulative POD always falls between a theoretical maximum, represented by a 'definite range sensor', and a minimum, represented by

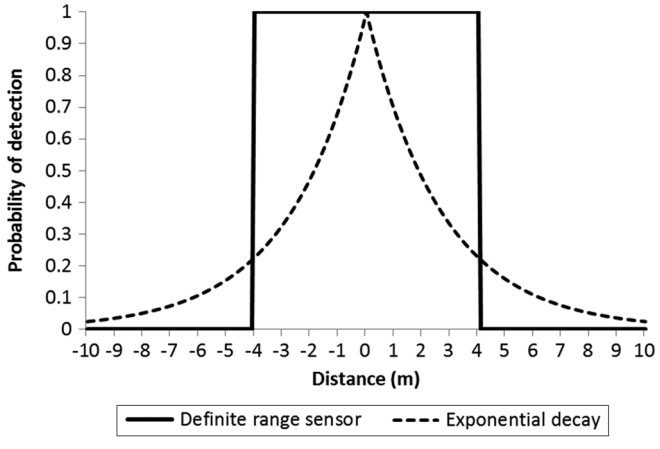


Figure 1. Two examples of lateral range curves, which describe the relationship between the distance from a searcher to a target, and the probability of detection (POD). The solid line represents a hypothetical definite range sensor: any target within the sensor's range (4 m in this example) will be detected with certainty (POD = 1), but no target beyond this distance will be detected (POD = 0). The dashed line represents a more realistic search scenario in which POD declines exponentially with increasing distance. If the target is directly in the searcher's path (i.e. distance = 0), then POD = 1. Although POD declines sharply with increasing distance, it approaches zero asymptotically. It is therefore possible (but unlikely) for a distant target to be detected (e.g. at 10 m).

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an exponential detection curve (Frost 2000) (Fig. 1). The hypothetical definite range sensor detects all search objects within a specific range but none beyond that range. By traversing the search zone along parallel tracks, a definite range sensor would detect all search objects in a single pass (Cacho et al. 2007). However, definite range sensors are merely a heuristic concept useful for explaining the idea of effective sweep width; such sensors do not exist in reality. At the opposite end of the spectrum is the exponential detection function (Koopman 1946, 1980), which is expressed as $POD = 1 - e^{-c}$ (where e is the base of natural logarithm and c is coverage). Frost (2000) argues that this curve best approximates real searches because even small variations in search parameters cause POD to drop sharply towards the theoretical minimum.

Experimental estimates of POD can be obtained by varying the survey conditions and measuring the effort required to detect the target (Hauser et al. 2015, 2016). For example, Moore et al. (2011) empirically measured the relationship between search effort and POD for the invasive plant *Hieracium aurantiacum* (see also Moore et al. 2010, Hanigan and Smith 2014).

Search strategies and search effort

The relationship between search effort and probability of detecting the target is influenced by the search pattern. For example, the searcher may follow parallel lines, a random walk, or one of many other possible search patterns (Wharton 2000, Washburn 2002, Cooper et al. 2003, Chung and Burdick 2007, Arbeit 2013). An efficient search strategy is one that has a high probability of locating the target using minimal time and resources. Search strategy must therefore consider coverage, routing and resource allocation (Wharton 2000). The optimal distribution of search effort depends on the effective sweep width, the speed of the searcher, and the probability that the search object is present in a given area (Frost 2000). When planning a search, the search zone is usually divided into cells, each with an estimated probability of containing the target (Frost 2000). These probabilities may be estimated in various ways; for example, when searching for plants or animals, a map of preferred habitat types might be used (Hauser and McCarthy 2009, Thalmann et al. 2015).

Search effort is assigned to each cell according to 'probability of area' (POA), which is the likelihood that it contains the target (Chung and Burdick 2007, Doherty et al. 2014). The effectiveness of a search is measured by 'probability of success' (POS): $POS = POD \times POA$. Searches can be designed to maximise POS with a certain level of search effort. Alternatively, if time is critical (such as in a search and rescue scenario), the objective may be to minimise the time required to find the target (Frost 2000). Cooper et al. (2003) describe two approaches to optimal allocation of search effort. 'Optimal search density' aims to optimise the distribution of search effort across all possible locations within the search zone, but ignores variation in ease of access or movement. The 'optimal searcher path' incorporates these variables, making it more realistic but computationally intensive (Cooper et al. 2003).

Hauser and McCarthy (2009) describe a model to optimise allocation of search effort for an invasive species. Their model accounts for spatial variability in probability of occurrence and detection, as well as the benefits of detection. They conclude that searches should generally target habitats where the search object is relatively easy to detect; however, more difficult habitats may be searched intensively if there is a high probability that the search object occurs there, or a high benefit in detecting the target in that habitat (Hauser and McCarthy 2009). For example, there may be increased benefit in detecting invasive predators in critical habitat of a threatened species. It may therefore be beneficial to search such areas even if predators are more difficult to detect there.

More recently, Moore and McCarthy (2016) developed a model to optimise survey effort, taking into account variation in detection probabilities and travel costs for sites. The model determines what proportion of the budget, and how many visits, should be allocated to each site. Similarly, Chung and Burdick (2007) developed a decision support model to help optimise the order in which cells are searched and the amount of effort assigned to each. Using Bayesian methods, the search plan can be continually updated with new knowledge (Chung and Burdick 2007).

Chung and Burdick (2007) also evaluated various search patterns, including: random search; sweeping search along parallel lines; 'optimal lookahead search', in which the next cell to be visited is continually updated with new information; 'saccadic search', in which search cells are visited in order of their probability of containing the search object, and; '*Drosophila*-inspired search', in which search focus follows (more or less) the shortest path from the cell just searched to the next most probable cell. The optimal lookahead search delivers the best strategy, but is computationally intensive, whereas saccadic and *Drosophila*-inspired searches are computationally simple. A saccadic approach might be useful in planning a series of discrete searches; however, it does not account for travel time between cells. The *Drosophila*-inspired search can apply to a continuous search through multiple search cells (Chung and Burdick 2007).

Baxter and Possingham (2011) assessed the tradeoffs between widespread searching (with low search intensity per site) and focused searching (high intensity per site). They found that widespread searching is preferable if the target species is widespread, or if knowledge of its likely distribution is poor. However, focused searching may be optimal if the target species' distribution is highly restricted or predictable (Baxter and Possingham 2011). Similarly, Delaney and Leung (2010) compared intensive searches of random quadrats with less intensive, widespread searching. A 95% POD required 9.5 h of intensive searching, or 2.2 h of widespread searching; however the widespread search was biased towards larger (more conspicuous) targets. Regardless of search strategy, POD was similar for mobile and sessile targets, but mobile targets took longer to detect (Delaney and Leung 2010). As well as considering mobile targets, search problems can also include situations in which the target responds to the approaching searcher, e.g. by hiding or fleeing (Frost and Stone 2001).

Tools for optimising searches

A number of authors have used search theory to develop automated tools for search planning. Models can use information from geographic information systems, as well as

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characteristics of the searcher and target, to evaluate factors such as ease of traversing the terrain, ease of detecting the target, and optimal search path (Wharton 2000, Sujit and Ghose 2004, Arbeit 2013). Allocation of effort and resources can then be optimised, and can be updated as the search progresses (Wharton 2000). Mission plans can be produced for searchers with a series of search tasks to be carried out in sequence (Flushing et al. 2012).

Examples of search planning software include the US Coastguard's Search and Rescue Planning (SARP) and computer-assisted search planning (CASP) programs, and the freely available computer-aided search information exchange (CASIE) (Frost and Stone 2001, O'Connor 2004). Similar software has yet to be developed specifically for use with conservation dogs.

Conservation dogs

Because of their speed, agility, trainability and acute sense of smell, dogs are increasingly being used to search for plants and animals (Beebe et al. 2016, Johnen et al. 2017). For example, dogs have been used to search for carnivores (Long et al. 2007a, b, Glen et al. 2016), rodents (Gsell et al. 2010), reptiles (Stevenson et al. 2010, Browne et al. 2015), birds (Cheyne 2011) and invertebrates (Ward et al. 2016), as well as rare or cryptic plant species (Goodwin et al. 2010, Cherry et al. 2016, McLean and Sargisson 2017). Dogs have been trained to detect up to 10 different target odours, and learn more quickly as they are trained for more targets (Williams and Johnston 2002).

Dogs can be useful for capturing animals, assessing population status, collecting specimens (e.g. scats or carcasses), studying animal behaviour, or managing invasive species (Cruz et al. 2009, Dahlgren et al. 2012, McGregor et al. 2016, Mumma et al. 2016). Conservation dogs are particularly useful for detecting species at low density when other methods have a low probability of detection (Cheyne 2011). On detecting a target, dogs generally alert their handler through a trained response, such as sitting, or through a change in behaviour, such as an altered search pattern (Cablk and Heaton 2006, Savidge et al. 2011, Cablk and Harmon 2013, McLean and Sargisson 2017).

The use of dogs has a number of advantages over other methods of detecting wildlife. Compared to human observers, detector dogs may have higher effectiveness. For example, a koala *Phascolarctos cinereus* scat detection dog achieved higher efficacy (proportion of available scats found) and efficiency (time to find scats) than human observers (Cristescu et al. 2015), and dogs are much more successful than humans at detecting invasive brown tree snakes *Boiga irregularis* (Savidge et al. 2011). Dogs can also locate target animals at very low density, e.g. a single rat *Rattus norvegicus* experimentally released on a small (9.5-ha) rodent-free island (Russell et al. 2008).

Some studies have reported that scat detection dog surveys were more cost-effective than camera traps for detecting various carnivores (Long et al. 2007a, Alexander 2016), although a recent study found the cost-effectiveness of detecting feral cats *Felis catus* in a New Zealand pastoral landscape was similar for camera traps and dogs. However, dog teams had some advantages over the use of camera traps: they can detect cats more rapidly, and are less prone to interference by humans or livestock (Glen et al. 2016).

Applying search theory to the use of conservation dogs

Although a variety of strategies are used when searching with dogs, principles of search theory are usually not explicitly applied. Furthermore, dogs are sometimes used to detect wildlife without assessing accuracy or considering potential sources of bias (Cablk and Heaton 2006). Here we discuss how ideas from search theory might be used to standardise and optimise the use of conservation dogs.

For any search problem, the optimal strategy will depend on the aims of the search (MacKay et al. 2008). For example, if the aim is to estimate landscape occupancy, only a moderate probability of detection may be required (MacKenzie et al. 2002). In other situations, e.g. response to an incursion, managers may wish to maximise detection probability and minimise time taken to find the target. Much greater search effort would be justified in the latter case. Search design should consider the minimum density of targets the search should be able to detect with a certain level of confidence, the sensitivity of the search effort, and cost (Kean et al. 2015).

Search theory tells us that the relationship between distance of the searcher to the search object and probability of detection is important in planning a search and interpreting the results. However, because the distance at which a scent can be detected is highly variable, it is difficult to estimate effective coverage (Reed et al. 2011). For the purposes of a dog team, we define the dog handler as the searcher; the dog may be thought of as a sensory tool used by the searcher. Detection distance might be affected by such factors as weather, habitat and topography, as well as the abilities of the dog and searcher. Characteristics of the search object (e.g. size and developmental stage of plants; size and age of scats) are also important (Wasser et al. 2004, Patten and Milne 2008, Reed et al. 2011, Dahlgren et al. 2012).

Experimental studies using dogs to search for wildlife have delivered variable estimates of detection distance (Table 1). For example, de Oliveira et al. (2012) estimated that deer (*Mazama* spp.) scats were detectable from no further than 7.2 m, while Cablk et al. (2008) found that dogs could detect desert tortoises *Gopherus agassizii* from as far as 62.8 m. In a New Zealand study, handlers reported that dogs detected rodents from an average distance of around 50–60 m (Gsell et al. 2010). Estimates of detection distance are sometimes subjective, as the handler must judge when the dog has detected a scent.

Ground cover can influence odour dispersion but does not consistently reduce the effectiveness of scat detection dogs (Arnett 2006, MacKay et al. 2008). For example, Leigh and Dominick (2015) found no effect of habitat on the distance at which dogs detected scats of a threatened carnivorous marsupial, *Dasyurus maculatus*; mean detection distances ranged from 12.9–15.4 m (Table 1).

Weather conditions can influence detection distance and detection probability. For example, detection success for brown tree snakes increased with humidity and decreased with wind speed (Savidge et al. 2011), and Shivik (2002) reported that variable winds may increase the time taken for dogs to find a target. Long et al. (2007b) found that site

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Table 1. Published estimates of detection distance for various target species using detection dogs. Target species are listed according to taxon, habit (e.g. arboreal, fossorial), and whether the dog teams searched for live subjects or scat.

Target species	Taxon	Habit	Target type	Mean detection distance*	Reference
Spotted knapweed *Centaurea stoebe* (small)†	plant	terrestrial	live subject	8.5 m[1] (SE 1.3)	Goodwin et al. 2010
Spotted knapweed (medium)†				12.8 m[1] (SE 2.8)	Goodwin et al. 2010
Spotted knapweed (large)†				12.6 m[1] (SE 1.9)	Goodwin et al. 2010
Kit fox *Vulpes macrotis mutica* and coyote *Canis latrans*	mammal	terrestrial	scat	4.8 m[2] (SE 6.7; range 0–38.4)	Ralls and Smith 2004
Desert tortoise *Gopherus agassizii*	reptile	terrestrial/fossorial	live subject	13.9 m[1] (0.5–62.8)	Cablk et al. 2008
Spotted-tailed quoll *Dasyurus maculatus*	mammal	terrestrial/arboreal	scat	12.9–15.4 m, depending on habitat[1] (SE 1.2–1.6)	Leigh and Dominick 2015
Felids *Puma concolor, Lynx rufus* and *Felis catus*	mammal	terrestrial	scat	9.6 m (0–25)	Reed et al. 2011
Foxes *Vulpes vulpes, V. macrotis* and *Urocyon cinereoargenteus*	mammal	terrestrial	scat	10.4 m[2] (0–25)	Reed et al. 2011
Human *Homo sapiens* (normal clothing)	mammal	terrestrial	live subject	40.2 m[1]	Shivik 2002
Human *Homo sapiens* (scent-adsorbing clothing)	mammal	terrestrial	live subject	29.3 m[1]	Shivik 2002
Rodents *Rattus norvegicus* and *Mus musculus*	mammal	terrestrial	live subject	50–60 m (4–150)[1]	Gsell et al. 2010
Deer (*Mazama* spp.)	mammal	terrestrial	scat	0–6 m[2]	de Oliveira et al. 2012

*Figures in brackets indicate variability in detection distance for those studies in which this was reported. Studies reported the range of values and/or standard error (SE).
†The range of detection distances for all size classes combined was 1.0–62.2 m (Goodwin et al. 2010). The range was not reported for each size class of plant.
[1]Detection distance estimated as distance from target when a marked change in search behaviour indicated the dog had detected the scent.
[2]Detection distance estimated as distance of target from defined search transect.

characteristics and weather conditions had little effect on detection probabilities, but did influence the time required to search a site. However, other studies have found weather conditions to be relatively unimportant. Cablk and Heaton (2006) reported that variations in wind speed (0–9 m s^{-1}), temperature (12–27°C) and humidity (18–88%) had no measurable effect on the efficacy and reliability of dogs. Similarly, Reed et al. (2011) conducted trials with wind speeds of 0.7–3.4 m s^{-1}, temperatures of 4–29°C and humidity 22–100%; they concluded that detection probability was more strongly influenced by distance than by environmental variables. It is likely that weather conditions affect the distance at which dogs detect a target odour. However, dogs and handlers are able to adjust their search behaviour according to the conditions. Thus, searches may take longer to complete in some conditions, but are likely to achieve similar results.

One challenge with adapting search theory for use with dogs is that scent cues may be more directional than visual cues, depending on wind direction. If the searcher is walking directly into the wind, we might expect a symmetrical lateral range curve (Fig. 1), in which POD declines equally with increasing distance on the searcher's left or right. However, if the search transect is perpendicular to the wind, we would expect a skewed curve, in which POD declines more sharply on one side than the other.

Detection parameters also vary between dog teams (Clare et al. 2015b). For comparability between sampling times and locations, the same dog team should be used where possible (Dahlgren et al. 2012). Alternatively, we suggest the identity and experience level of the dog team could be included as covariates in analyses.

Search efficacy also varies for the same dog team over time, and may increase with training and experience (Cablk and Heaton 2006). However, dogs may lose motivation if not rewarded for finding a target (e.g. if reward is withheld pending confirmation that the correct target has been identified). If the handler is uncertain whether the correct target has been identified, a 'partial reward' can be given, while reserving the 'full reward' for cases when the handler can verify the target's identity (Cablk and Harmon 2013). Search efficacy may also be influenced by fatigue and motivation level of the dog or handler (Cablk and Harmon 2013), potentially reducing POD and/or effective sweep width. For example, a dog's motivation can be reduced if few targets are encountered over a long period. Handlers can carry target objects (e.g. plant material or scats) and plant these in the search area to maintain the dog's interest and motivation when detections are rare (Wasser et al. 2004, Kelly et al. 2012).

Variation in search efficacy is not exclusive to detection dogs; other ecological survey methods have similar limitations (Neff 1968). Researchers and managers using detector dogs should report the results for each individual dog and handler so that more reliable estimates of detection parameters can be obtained (Kelly et al. 2012, Clare et al. 2015b).

Search design

Armed with estimated detection parameters, the searcher must decide where to search and how to distribute search

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effort across the area in question. Search areas are often divided into cells, with a certain amount of effort assigned to each. The size of search cells may be determined by biological factors, such as home range of the target species (Brook et al. 2012, Mumma et al. 2015, Fuller et al. 2016) or logistical considerations, such as the area a dog team can search in a given time. This will vary according to terrain and conditions, but various studies report that dogs can typically search for about 5–7 h per day (Wasser et al. 2004, de Oliveira et al. 2012, Fuller et al. 2016), covering about 3–10 km of transect (Brook et al. 2012, Clare et al. 2015b, Mumma et al. 2015, Alexander 2016). The distance covered by the dog may be much greater than the transect followed by the handler (Woollett et al. 2013).

When the search area is too large to cover exhaustively, searches can follow roads, drainage lines, or some other predefined search path (MacKay et al. 2008), although this may introduce bias towards particular habitat types. For efficiency, transects are often designed as a loop so that the dog team starts and finishes at the same point (Ralls et al. 2010, Beckmann et al. 2015, Alexander 2016). To make optimal use of wind direction, we suggest that the handler should walk perpendicular to the prevailing wind on the outward and return legs of the loop. Alternatively, loops could be traversed once in each direction. Dogs can work on- or off-leash (Savidge et al. 2011, Woollett et al. 2013), although the latter allows the dog to cover more ground, and to adjust to factors such as wind direction (Fuller et al. 2016).

Searches may follow a regular, pre-determined path, or they may be flexible. For example, Cablk and Harmon (2013) describe a 'three-pass' search strategy starting with a perimeter search, followed by a 'hasty' pass (cross-grid search along widely spaced lines) and a 'detail' pass (search lines closer together, perpendicular to those of the hasty pass). Gsell et al. (2010) used dog teams to search a 32-ha area for rodents, travelling along parallel grid lines either 50 or 100 m apart. The authors considered that a typical dog team in New Zealand would be able to search 30–40 ha per day, although larger areas could be searched in open habitat (Gsell et al. 2010). Other studies have adopted stratified search patterns, focusing on habitat features where the target species is likely to be found (Brook et al. 2012, O'Kelly et al. 2012, Alexander 2016, Fuller et al. 2016). Because individual searchers vary in their abilities, some flexibility in search strategy can be beneficial (Flushing et al. 2012). Wultsch and Kelly (2012) compared the effectiveness of linear transects, diamond-shaped transects, and 'opportunistic' (ad hoc) searches for locating scats of large felids in various habitat types. Opportunistic searches in a range of habitats on and off roads and trails revealed the highest numbers of scats.

Detection probabilities of various plants and animals have been estimated experimentally. For example, for every kilometre searched, the estimated probability of detecting bobcat scats was 0.135. Dogs searched 8.8 km day^{-1} on average, yielding a daily detection probability of 0.721. Therefore two days, or 16 km, of search effort would yield a probability $\geq$ 90% of detecting bobcat scats, if present (Clare et al. 2015b). However, detection probabilities can vary between habitats (Smith et al. 2005, Hunter 2011), and between repeated visits to the same site (Kapfer et al. 2012).

Statistical analysis

Although dog teams can achieve high detection rates, their use presents analytical challenges, particularly when attempting to estimate population size. Many methods of density estimation require fixed sampling points, such as traps for animals or sampling quadrats for plants (Thompson et al. 2012). While locations where target species are found are easily recorded, most analysis methods also need data on locations where nothing was detected. For example, capture-mark-recapture analysis uses information from traps that catch nothing, as well as those that catch animals. To address this problem, Thompson et al. (2012) modified the spatially explicit capture–recapture model of Royle et al. (2009). The survey area is divided into hexagonal grid cells, the centres of which provide locations for detection/non-detection data (Thompson et al. 2012). An alternative approach was adopted by Fuller et al. (2016): search transects were divided into 25-m sections, which were treated as 'traps' for spatially explicit capture–recapture analysis. Other analytical approaches include occupancy modelling (Clare et al. 2015b) and mark–recapture analysis based on individual identification from scat DNA (Wultsch and Kelly 2012).

Another potential problem in enumerating populations from scat detection data is the assumption of population closure (Alexander 2016). Scats can remain detectable in the field for prolonged periods (Brown et al. 2011, Hunter 2011). One solution is to search the area once, removing all scats found, then re-visit and collect scats at a later date for capture–recapture analysis (Alexander 2016). Another possibility is to discard scats that are not fresh, although the age of scats can be difficult to determine (Cristescu et al. 2012).

Future research

Of utmost priority is to quantify effective sweep widths for wildlife detector dogs. This will include variation between: individual dogs and handlers; vegetation structures; topographic features; weather conditions and; search target (Reed et al. 2011, Dahlgren et al. 2012). The condition of the search target (e.g. live or dead animal; fresh or old scat) may also contribute to variation. There is also likely to be day-to-day variability even when all of the above factors are held consistent (Cablk and Harmon 2013). Therefore it would be beneficial to determine a typical effective sweep width, plus a measure of variability, for each combination of the above factors. Tabulating effective sweep width for different types of search objects and environments would allow optimal search strategies to be identified quickly and easily for a given scenario (Cacho et al. 2007).

Although some estimates of detection distance exist, tests involving larger numbers of dogs would help gauge variability. It would also be useful to perform tests with search objects placed further off the search transect to assess the distance at which detection rate approaches zero (Reed et al. 2011). There are various approaches to estimate detection distance. For example, distance sampling methods (Buckland et al. 2005) can be used to estimate the relationship between detection probability and distance (Guthery and Mecozzi 2008, MacKay et al. 2008). Cablk et al. (2008) developed a practical method to estimate detection distance.

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Search objects were deployed at locations unknown to the dog team, and dogs were tracked by GPS. The distance to the search object from the point where the dog changed direction and moved directly towards the target was taken as the detection distance (Cablk et al. 2008).

Having estimated effective sweep widths, it would also be helpful to determine optimal approaches to stratify a search; what proportion of effort should be applied to various habitat types? This may be influenced by detectability of the target within each habitat, relative proportions of each habitat, the probability of the target occurring there, and the relative benefit of detecting the target in different habitats (Hauser and McCarthy 2009, Doherty et al. 2014, Moore and McCarthy 2016). A helpful approach using existing data may be to map locations where dogs have detected targets, then identify landscape features with the highest probability of success (Hauser and McCarthy 2009). A similar approach might be adopted to evaluate different search strategies if GPS track data are available for dogs and/or handlers.

Conclusions

Search theory has potential to increase effectiveness of conservation dogs, and to standardise methods so that results may be compared across different locations and times. However, this will require reliable data on detection parameters, including estimates of variation and the factors contributing to it.

The limited data available on detection distances suggest that most target taxa are detected by conservation dogs from an average of around 10 m (Table 1), although distance may be greater for some targets (e.g. humans; Shivik 2002). Although some detections occur from much greater distances (e.g. up to 150 m; Gsell et al. 2010), these instances are the exception rather than the rule. In the absence of detailed data specific to the target taxon and environment, we recommend that searches with conservation dogs assume an average detection distance of approximately 10 m. However, new data should be collected as searches are carried out. Using an adaptive management approach, search strategies may be modified to improve efficacy and/or efficiency as more data come to hand.

What is ultimately needed is a decision support tool to help determine optimal search strategy for one or more dog teams, given: resources; effective sweep width (which may depend on the target, habitat type and topography); desired probability of detection (which will depend on the search objectives). Such a tool would allow researchers and managers to use conservation dogs more effectively and efficiently.

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Supplementary material (available online as Appendix wlb-00393 at <www.wildlifebiology.org/appendix/wlb-00393>). Appendix 1.

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