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Original article

A technique to estimate white-tailed deer *Odocoileus virginianus* density using vertical-looking infrared imagery

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Aerial infrared imagery is used increasingly in eastern North America to provide population counts of white-tailed deer *Odocoileus virginianus* because of the increased probability of detection compared to visual methods. To date, most work using infrared technology has been conducted using imagery from Forward-Looking Infrared (FLIR). Methods have produced counts, but density or population estimates have not been forthcoming because of problems with methodology and automation. Using standard photogrammetry techniques, Vertical-Looking Infrared (VLIR) data, GIS and distance sampling, we describe a method for estimating density. We estimated deer density in four bottomland hardwood sites in Arkansas, USA, with distance sampling using VLIR data and assessed the probability of detection of deer identified in the imagery. Uniform models were selected as the best representative models for each site, and probability of detection was similar ($\bar{x} = 0.95 \pm 0.05$ SE) across sites. Distance sampling used in conjunction with VLIR data may provide estimates of ungulate populations in ecosystems of deciduous hardwoods with little topographic relief.

Key words: density estimation, distance sampling, Odocoileus virginianus, Vertical-Looking Infrared, VLIR, white-tailed deer

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Aerial infrared imagery, used for the purposes of providing population counts and estimating population size for ungulates, has been collected most often using Forward-Looking Infrared (FLIR; Naugle et al. 1996, Bernatas & Nelson 2004, Dunn et al. 2002), but results have been mixed (Naugle et al. 1996, Dunn et al. 2002, Haroldson et al. 2003). Aerial surveys for ungulates that use infrared imagery are subject to similar confounding factors as visual aerial surveys, such as cover type (Dunn et al. 2002), time of day (Graves et al. 1972) and flying height (Wiggers & Beckerman 1993). Aerial infrared imagery surveys are also subject to the same assumptions as visual surveys. Specifically, a census is assumed for all areas sampled; otherwise an adjustment for the probability of detection (Anderson & Pospahala 1970, White 2005) is required.

Sampling designs and methods have not been consistent among studies. Early aerial infrared imagery work for deer used strip transects and collected data with the imager in a fixed, vertical position (Croon et al. 1968, Graves et al. 1972). With the emphasis placed on determining demographic data (Wiggers & Beckerman 1993), circular plots with imagers in variable, oblique positions became more common.

The inability to calculate the area surveyed and time required to provide estimates of probability of detection have been two problems limiting the use of aerial infrared imagery for density estimation.

Haroldson et al. (2003) pointed out the difficulty in using circular plots with oblique angles to calculate an area. They used multiple oblique angles and were not able to provide reliable estimates of the areas surveyed. The difficulty in calculating the area was due to changing oblique angles and lack of an automated methodology for geo-referencing the area searched. The use of vertical imagery is required to be able to easily calculate linear and areal measurements (Paine & Kiser 2003). Borrowing from the field of photogrammetry, flight lines are essentially transects and the imagery data collected, if from a vertical position, provide strip transects. A probability of detection is required to compensate for the thermal targets missed, and distance sampling may provide a solution for this limitation.

It takes time to develop sightability models using telemetry techniques; Bernatas & Nelson (2004) required three years to collect a sufficient amount of data to provide a sightability model for counting bighorn sheep *Ovis canadensis* in canyonlands based on FLIR data. Distance sampling, however, provides a measure of detection probability (White 2005). Vertical-Looking Infrared (VLIR) imagery is a source of distance data that lends itself to distance sampling and may overcome the limitation of time required to sample large areas.

Our goal was to provide a method of collecting and analyzing infrared imagery data based on established remote sensing techniques (Paine & Kiser 2003) and common data analyses (Buckland et al. 2001) to estimate population density. VLIR imagery integrated with GPS and GIS data allows for distance calculations that may be used with distance sampling. Specifically, we wanted to determine: 1) if VLIR data, as opposed to FLIR data, were suitable to estimate density of a model species, white-tailed deer *Odocoileus virginianus*, using distance sampling, and 2) if the unaltered uniform model, which would indicate perfect detectability across the imagery, was the best model for all sites examined.

Material and methods

Study area

Our study area was located in the Mississippi Alluvial Valley of eastern Arkansas, USA (Fig. 1). We collected VLIR data in four sites: Choctaw Island Wildlife Management Area (CIWMA), Cut-Off Creek Wildlife Management Area (CCWMA), Lakeside Hunting Club (LHC) and Wingmead Farms (WMF). CIWMA and CCWMA were both owned by the Arkansas Game and Fish Commission, and LHC and WMF were privately owned.

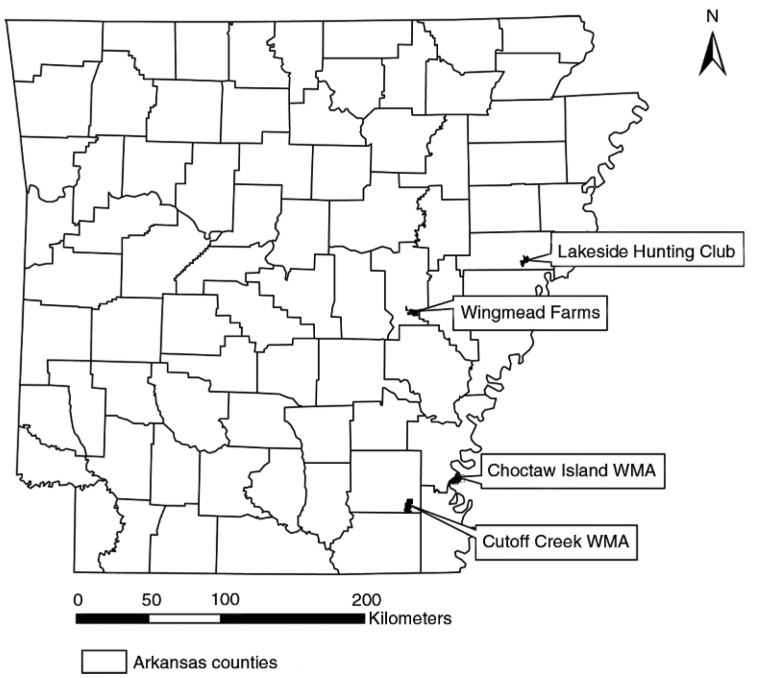

Figure 1. Location of the four study sites in eastern Arkansas where aerial thermal infrared videography data were collected for estimating white-tailed deer density during February 2004.

CIWMA is located in Desha County, Arkansas, USA, within the Mississippi River levee system and is 3,360 ha in size. It contains bottomland hardwood forests and eastern cottonwood *Populus deltoides* plantations interspersed with old fields and food plots. Dominant tree species are oaks *Quercus* spp., pecan *Carya illinoensis* and eastern cottonwoods (Kissell & Tappe 2004). Elevation ranges from 32 to 41 m and is prone to winter and spring flooding.

CCWMA is located in Drew County, Arkansas, USA, and is 3,650 ha in size. Dominant overstory species are willow oak *Quercus phellos*, overcup oak *Q. lyrata*, southern red oak *Q. falcata* and American elm *Ulmus americana* (Fowler 2004). Food plots were dispersed throughout. Elevation ranges from 35 to 52 m and the area is prone to winter and spring flooding.

LHC, located in St. Francis County, Arkansas, USA, is 2,030 ha in size, and is dominated by agricultural fields, interspersed with bottomland hardwood forests and food plots. Sweetgum *Liquidambar styraciflua*, nuttall oak *Q. nattallii*, water oak *Q. nigra*, willow oak, pecan and hickory *Carya* spp. comprise the overstory. Elevation ranges from 50 to 60 m.

WMF is 2,310 ha in size and is located in Prairie County, Arkansas, USA. Agricultural fields, interspersed with food plots, and bottomland hardwood forests are the major cover types. Bottomland hardwood forests are dominated by cherrybark oak *Q. pagoda*, sweetgum, southern red oak, sycamore *Platanus occidentalis*, water oak and green ash *Fraxinus pennsylvanica*. Elevation ranges from 57 to 67 m. More detailed descriptions of the sites may be found in Gregory (2005).

Flight information

We conducted flights along transects between 23:00 and 06:00 on 20-21, 21-22, 22-23 and 27-28 February 2004. The first transect was randomly placed at each site. All other transects were systematically placed parallel to the first transect and spaced approximately 400 m apart. We based transect orientation in each study site on the ability to maximize the area covered and to minimize the flight time. We sampled 21, 14, 13 and 12 transects in the CIWMA, CCWMA, LHC and WMF, respectively, across the four nights, and we flew the same transects each night. We flew surveys at each site using a Cessna 182 at approximately 457 m above ground level (agl) and at approximately 120 km/hour. Strip transect width and pixel size resulting from the altitude and aperture of the lens were approximately 110 m and 0.15 m, respectively. We recorded locations (latitude and longitude), flight paths, altitude, speed, date and time by an onboard global positioning system (GPS) unit and integrated GPS data into a geographic information system (GIS). We converted flight paths to a shapefile using ArcPad 6.0.3 NT to represent transect lines flown. The order in which the sites were visited was based on the most efficient route and the prevailing weather conditions. We did not conduct flights under conditions that reduced detectability of deer or were not suitable for flying, i.e. in heavy fog, rain or wind.

Camera specifications and imagery acquisition

We surveyed each site using a Mitsubishi IR-M700 thermal infrared imager (Mitsubishi Electric Corporation, Canada) equipped with a 50 mm lens mounted in the belly of the aircraft with the head oriented perpendicular to the flight path. We used mid-infrared and far-infrared wavelengths (1.2-5.9μm). The detector array size was 801 (H) x 512 (V) pixels. The imager captured 50 frames per second in a field of view 14° (H) x 11° (V). We sent output to a digital video cassette recorder (Sony GV-D1000). We routed the GPS signal through a video encoder-decoder, and recorded it on the audio portion of the tape. Flight line spacing and GPS information minimized the potential for double counting. We reviewed and analyzed recorded video using a video-editing program (Avid Xpress DV, version 3.0) and a 33 cm black and white, 1,000 line monitor (Sony PVM-137). Thermal signatures of deer were identified by their unique shape and brightness relative to the background. No other species that had similar thermal signatures occurred in any of the sites. We exported images containing thermal signatures of deer as 8-bit tagged information file format (TIFF) images. We geo-referenced TIFF images using the encoded GPS data and transferred images into a GIS. We converted locations in decimal minutes to Universal Transverse Mercator coordinates for the purpose of calculating distances (Chang 2006).

Population estimation

We collected distance sampling data from TIFF images containing thermal signatures of deer. We delineated transects on images and measured the perpendicular distance from each deer to its associated transect (Fig. 2) to the nearest meter

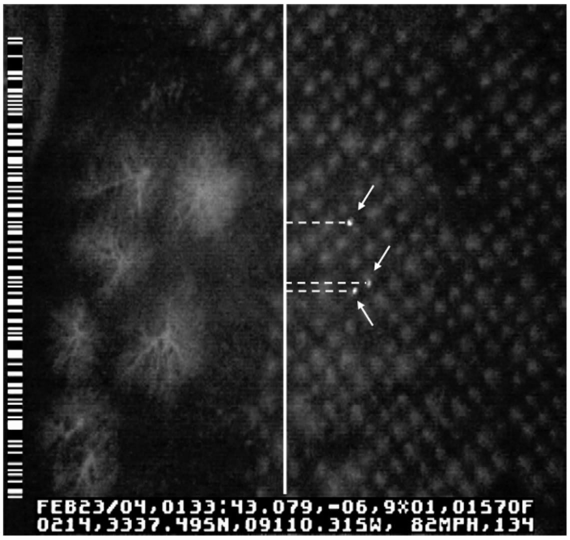

Figure 2. An example of perpendicular distances from the transect line to thermal signatures of individual white-tailed deer (arrows) that were measured for distance sampling using aerial thermal infrared imagery.

using GIS. We used individual deer instead of groups because thermal signatures of individual deer were detected independently of group affiliation. We truncated data as recommended by Buckland et al. (2001) to provide the best possible model to represent density. We determined deer density for each site using program DISTANCE 6.0, version 2 (Buckland et al. 2001, Thomas et al. 2002). We fit perpendicular distance data to uniform and half-normal key functions with no adjustments, cosine, simple polynomial and hermite polynomial adjustments. We used minimum Akaike Information Criterion (AIC; Akaike 1973) values to select the best model for each site. Based on competing models for each site, the density estimate, coefficient of variation (CV) of the density estimate and the probability of observing deer in the imagery were provided. We calculated the weight of each competing model based on AIC values.

Results

We flew a total of 185.2 km, 204.3 km, 139.5 km and 218.2 km of transects and observed 572, 213, 76 and 405 individual deer on the CIWMA, CCWMA, LHC and WMF, respectively. We found that uniform models fit data best for each site (Fig. 3). The densities ranged from 0.042 to 0.125 deer/ha across sites, and the coefficients of variation decreased with an increasing number of transects (range: 14.3-33.4%). The probability of observing a deer in the imagery ranged from 0.82 to 1.00 ($\bar{x} = 0.95 \pm 0.05$ SE) for the models from each site with the lowest AIC value; only models with ΔAIC values ≤ 2 are reported (Table 1). The probability of detection was < 1.0 for the WMF site only.

Discussion

We used a data collection method different from recent work (Dunn et al. 2002, Haroldson et al. 2003, Bernatas & Nelson 2004) in that we main-

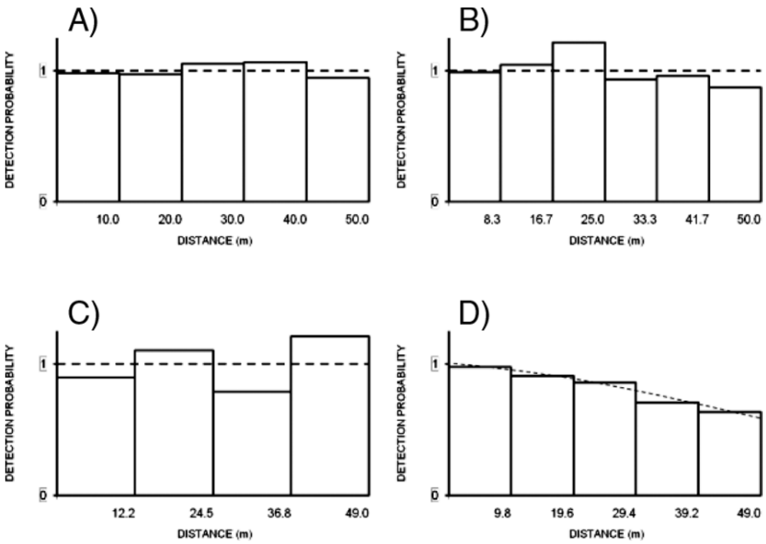

Figure 3. Detection functions used to estimate density for white-tailed deer on Choctaw Island Wildlife Management Area (A), Cut-off Creek Wildlife Management Area (B), Lakeside Hunting Club (C) and Wingmead Farms (D) in eastern Arkansas in February 2004. The dotted line represents the fitted distribution.

Table 1. Distance sampling results for white-tailed deer based on vertical looking infrared imagery data collected across four nights on four sites (CCWMA = Cut-off Creek Wildlife Management Area, CIWMA = Choctaw Island Wildlife Management Area, LHC = Lakeside Hunting Club and WMF = Wingmead Farms) in eastern Arkansas in February 2004.

				Density			Probability of observation[a]					
Site	Model[b]	AIC[c]	ΔAIC	LCL[d]	Estimate	UCL[e]	LCL[d]	Estimate	UCL[e]	GOF[f] p-value	CV[g]	Weight[h]
CCWMA	Uniform	763.290	0.000	0.065	0.104	0.168	1.000	1.000	1.000	0.782	0.222	0.592
	UniformSP2	764.349	1.059	0.069	0.112	0.183	0.809	0.930	1.000	0.827	0.233	0.205
	Half normal	764.365	1.076	0.069	0.112	0.183	0.801	0.929	1.000	0.824	0.235	0.202
CIWMA	Uniform	1841.197	0.000	0.230	0.309	0.415	1.000	1.000	1.000	0.884	0.143	0.879
	Half normal	1843.181	1.984	0.228	0.311	0.423	0.905	0.994	1.000	0.765	0.151	0.121
LHC	Uniform	389.872	0.000	0.030	0.056	0.105	1.000	1.000	1.000	0.551	0.296	0.881
	Half normal	391.872	2.000	0.029	0.056	0.108	0.775	1.000	1.000	0.349	0.325	0.119
WMF	UniformC2	1295.863	0.000	0.114	0.232	0.472	0.730	0.817	0.914	0.969	0.334	0.271
	Half normal	1295.869	0.006	0.111	0.225	0.457	0.760	0.842	0.933	0.969	0.333	0.269
	UniformSP2	1296.027	0.164	0.109	0.222	0.451	0.780	0.853	0.933	0.938	0.332	0.230
	UniformHP2	1296.027	0.164	0.109	0.222	0.451	0.780	0.853	0.933	0.938	0.332	0.230

[a] Probability of observing a deer in the defined area under the selected model.
[b] Models included Uniform, UniformSP2 = Uniform key function with a simple polynomial adjustment of 2nd order, Half normal, UniformC2 = Uniform key function with a cosine adjustment of 2nd order, UniformHP2 = Uniform key function with a hermite polynomial adjustment of 2nd order.
[c] AIC = Akaike information criterion value.
[d] LCL = Lower confidence limit (95%).
[e] UCL = Upper confidence limit (95%).
[f] GOF = Goodness-of-fit.
[g] CV = Coefficient of variation.
[h] Weight based on AIC values.

tained a vertical position of the imager throughout each flight. Much of the recent work collecting infrared imagery from an aerial platform used a forward looking or oblique approach (Haroldson et al. 2003, Bernatas & Nelson 2004). Our approach allowed us to apply standard photogrammetry techniques (Paine & Kiser 2003) for calculating distances and using distance sampling (Buckland et al. 2001), as vertical imagery is preferred over oblique imagery for calculating distance and area measurements (Paine & Kiser 2003).

Vertical data collection provides the most consistent pixel resolution across the image, and allows for distance and area calculations (Paine & Kiser 2003). Data collected at view angles other than vertical increase the area of blind spots (Addison 1972). Thermal signatures of vegetation have the ability to hide target species under the vegetation. Even in open landscapes or under leaf-off conditions, oblique angles increase the area behind which target species may be obscured, while vertical views minimize the area of the blind spots.

Much of the recent research using infrared technology to provide counts or population size used FLIR data collected in circular plots or 'orbits' (Wiggers & Beckerman 1993, Haroldson et al. 2003, Bernatas & Nelson 2004). Haroldson et al. (2003) criticized area calculation using this method because of the labour intensity and inaccuracies of plotting field of view information on aerial photos. We avoided these issues by using the imager in a vertical position, collecting data along a transect line as recommended by Reynolds et al. (1995) and Haroldson et al. (2003), and using distances as our response variable, which we calculated through an automated process using GIS.

A uniform distribution is not reasonable when group size influences visibility or if surveys are conducted under different visibility conditions (Samuel et al. 1992). We eliminated group size influence by using distances to individual animals (Buckland et al. 2001). We minimized differences in visibility conditions by surveying only under similar, favourable conditions. Additionally, we addressed visibility by using strip widths based on 5-10% truncation as recommended by Buckland et al. (2001) which resulted in reduction of the half width by approximately 5 m at each of the four sites.

Distance sampling uses transects as replicates, and the greater the number of replicates the better the precision (Buckland et al. 2001). We sampled our four sites with economics taking precedence. The site with the most transects, CIWMA, provided the greatest precision of density, and the site with the least number of transects, WMF, the poorest precision. We believe that the extra cost of flight time would justify the precision obtained.

Probability of detection has been of concern and great importance in the development and use of aerial infrared imagery. High probability of detection (> 85%) should be expected where the vegetative cover is short (Parker & Driscoll 1972, Naugle et al. 1996). Addison (1972) first examined the probability of detection of cattle and described the trade-off between altitude and clarity of the thermal signature. As expected, lower altitudes (agl) yielded better results where all animals were detected. Parker & Driscoll (1972) assessed the detection of mule deer *Odocoileus hemionus* and pronghorn antelope *Antilocapra americana* confined to pens with no overhead canopy cover. Detection of the total number of animals varied by interpreter, but were high (92-99%). Haroldson et al. (2003), by contrast, reported low detection rates (31-89%) using circular flight patterns in a landscape containing deciduous hardwoods. They attributed the low detection, in part, to observer bias and methodology. Our study sites varied in amounts and proportions of deciduous hardwoods and agricultural land. Our use of transects and VLIR likely minimized the effect of deciduous hardwoods and maximized the probabilities of detection.

We found that the probability of detecting a deer was < 1 and resulted from an 'edge effect' when identifying deer in our imagery in one site. The probability of detection at the edge of the imagery likely declined as the radial distance from the center of the image increased. Increased distances from the center of the imagery caused an increased effect of vegetation; specifically, tree bolls increased blind spots. We did not quantify this source of variation, though it may be an important component of detection probability. Given that the uniform distribution provided the best fit for the other three sites, we did not find this source of variation influential on those sites; however, it is a source of error that should be considered when using VLIR.

Population closure is an important assumption for providing population estimates (White et al. 1982). We surveyed four sites each night, replicated each survey four times, and covered a total of > 11,000 ha. The methods we used provided for efficient data collection and likely maximized the likelihood of meeting the closure assumption. Most other estimation methods, such as mark-recapture (Gould et al. 2005) or even ground-based FLIR (Collier et al. 2007), often require considerably more time for data collection and increases the likelihood of violating the closure assumption.

Three basic assumptions are required for distance sampling (Buckland et al. 2001). The assumption that all objects on the transect line were always detected (i.e. $g(0) = 1$) was assumed to be valid, but we did not explicitly test for this. There are two forms of bias, availability and perception, related to $g(0) = 1$. Availability bias occurs when animals are not available for detection, such as in VLIR when deer are under canopy and are not visible from above. Perception bias occurs when the animal is present but the observer fails to detect the animal (Borchers 2004). The product of these forms of bias provide an estimate of the probability of detection on the line (i.e. $g(0)$; Grünkorn et al. 2004). While we did not have estimates of availability bias for any site, we believe that we minimized the bias by conducting surveys during leaf-off conditions and utilizing the effect of parallax (Paine & Kiser 2003) in reviewing the imagery. We did, however, have an estimate of perception bias through a larger study (Gregory 2005) using independent double counts (Grünkorn et al. 2004). For all the observations across the CIWMA, CCWMA, LHC and WMF, we estimated the detection bias as 0.97, 0.90, 0.91 and 0.96, respectively. More importantly, the thermal signatures that were identified by the secondary observer and not the primary observer were near the edges of the imagery for each site. Thus, we believe that objects on the transect line were detected with a probability very close to 1.0, if not 1.0 (Buckland et al. 2001) at all sites. We believe the second assumption, i.e. that objects were detected at their initial location, was met because deer were not disturbed by the aircraft flying at 457 m agl. Also, the distance between transects (approximately 400 m) and the short time required to fly one transect ($\bar{x} = 1.33$ minutes, SE = 0.03 minute) minimized the chance of double counting. We believe the third assumption, i.e. that measurements were exact, was met because we used geo-referenced images and perpendicular distances from deer to transect lines computed in a GIS. The pixel size of images was approximately 15 cm; therefore, distances measured from transect lines to deer were thought to be within 1 m.

We did not have density estimates over multiple years to determine if the detection probability changed over time in a site, but we did observe site-specific detection probabilities. Site-specific probabilities for visual surveys from the air for other ungulates have been addressed using sightability models (Unsworth et al. 1990, Bodie et al. 1995), and the probability of detection using VLIR also appeared to be site-specific. Even though a uniform detection function with no adjustments was found at three of four sites in our study, the validity of the assumption of detection being independent of distance would need to be verified before it could be used on different sites.

Reliable scientific studies require a CV of ≤ 0.051 for research purposes, 0.128 for accurate management purposes and 0.255 for rough management purposes (Skalski et al. 2005). Estimates that are more precise are more useful in managing ungulate populations. Our results indicate that VLIR data analyzed with distance sampling can provide levels of precision sufficient for long-term management practices when collected in bottomland hardwood forests and agriculturally dominated landscapes in winter.

Similar to sightability in visual aerial surveys, probability of detection varied across sites and a measure of detectability should be provided specific to the site sampled. Use of VLIR data for population estimation, if not using distance sampling for analysis, requires some other measure of probability of detection such as ground verification of animals observed in the imagery (Naugle et al. 1996). We hypothesize that other ungulate species, other cover types and other aerial platforms will yield different probabilities of detection as have been observed with sightability models for visual aerial surveys (Samuel et al. 1987, Noyes et al. 2000).

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