Final Report

Burrowing Owl Population Size in the Imperial Valley, California: Survey and Sampling Methodologies for Estimation

Submitted to:

Imperial Irrigation District
333 E. Barioni Boulevard
Imperial, California
92251

Submitted by:

Bloom Biological, Inc.
13611 Hewes Avenue
Santa Ana, California
92705

For work performed under:

Imperial Irrigation District
Service Agreement #
8100000664

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April 15, 2009

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Disclaimer: The authors designed, analyzed, and interpreted the results herein to the best of their abilities. As of the date of this report, the information herein is accurate to the best of the authors' knowledge, and reflects their best recommendations for monitoring the abundance of burrowing owls in the Imperial Irrigation District's Service Area in the Imperial Valley, California USA. The authors are not responsible for problems that may arise during the implementation of the recommended protocols or for new information or interpretations that may change the understanding of the results or recommendations presented herein.

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FOREWARD

Jeffrey A. Manning produced this report under a subcontract between Bloom Biological, Inc. and Manning Biological Research, dated March 10, 2007 and in accordance with the Final Detailed Study Approach for a Burrowing Owl Population Study submitted to the Imperial Irrigation District (IID – Operational Headquarters, 333 E. Barioni Blvd., Imperial, CA 92251), dated January 31, 2007. This report was prepared as part of the IID's mitigation program for the San Diego/ IID Water Transfer project. The study was funded by the Water Transfer project Joint Powers Authority, and the study was conducted under the direction of the Water Transfer Implementation Team.

This report stems from a collaborative effort by Jeff Manning, Bloom Biological, Inc., and the Wildlife Research Institute, Inc. Having conducted more than 40 years of research on southern California Burrowing Owl populations and other raptors, Bloom Biological Inc. contributed baseline natural history information that was used to develop the original research proposal and provided the financial and administrative infrastructure for the project. Jeff Manning developed the study designs, field protocols, and methods of data collection (with reviews and recommendations by W. R. Gould, B. Manly, and others), was the principle field investigator, performed the analyses (with the collaborating coauthors of respective chapters), and authored the reports. He also selected, trained, and supervised field biologists. The Wildlife Research Institute, Inc. hired the selected field biologists, provided information on Burrowing Owl natural history during the 2006 pilot study, and assisted in the training of field biologists. Their senior biologists also assisted in the collection of data during the 2006 pilot study.

I, with Bloom Biological, Inc. and the Wildlife Research Institute, Inc., would like to especially thank Mary Coolidge, Paula Graff, and Scott Thomas for their work as Field Crew Managers, and Caren Goldberg and Stacie Robinson for their work as Statistical Analysts; they all provided recommendations that greatly improved various aspects of field activities, assisted in training field biologists, and spent endless hours to creative problem solving that contributed greatly to the success of the project. Jason Bone of CH2M Hill provided digital data on the IID's rights-of-way. Jeff Tupen of CH2M Hill provided valuable insight into interpreting aspects of the HCP and facilitating and coordinating communications with the Water Transfer Implementation Team. Caren Goldberg provided valuable comments on the general readability of earlier versions of this report. Lastly, this project would not have succeeded without the dedication and hard work of the 66 field biologists listed in Appendix I, who collected standardized survey, behavioral, and experimental field data during the 3 year-period. We thank them all.

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EXECUTIVE SUMMARY

The western Burrowing Owl (*Athene cunicularia hypugea*) is one of 18 New World Burrowing Owl subspecies, only 2 of which are found in North America (Haug et al. 1993). It is listed by the U .S. Fish and Wildlife Service as a Bird of Conservation Concern in every USFWS Region it occurs in and on the National list (USFWS 2002, Klute et al. 2003). It is listed as threatened or endangered in several U.S. states and has been listed as a species of special concern in 16 other U.S. states, including California (Remsen 1978, James and Espie 1997, Sheffield 1997, USFWS 2002). The Imperial Valley of California supports the largest concentration of Burrowing Owls in its range (Desante et al. 2004), and is the site for the Imperial Irrigation District's (IID – Operational Headquarters, 333 E. Barioni Blvd., Imperial, CA 92251) Colorado River Water Conservation and Transfer Project (Final EIR/EIS, dated June 2002). In response to requirements in the draft Habitat Conservation Plan (HCP) and other authorizations associated with the Water Conservation and Transfer Project, the IID issued a request for proposals (Qualifications Request 531) to design and implement a Burrowing Owl population investigation. The overall objective was to estimate the relative abundance and distribution of Burrowing Owls throughout the non-submerged portions of the 500,000-acre HCP Study Area, which encompasses the agricultural matrix of the Imperial Valley. These surveys for Burrowing Owls in the HCP Study Area were to focus on the IID's rights-of-way and service areas that parallel irrigation canals, drains, and ditches, including the All American Canal, and be considered as the initial phase of a 3-phase "Effective Monitoring" strategy described in section 4.5.2 of the HCP.

The proposal for this work was submitted under a partnership between Peter H. Bloom of Bloom Biological, Inc (13611 Hewes Avenue, Santa Ana, California 92705), Jeffrey A. Manning of Manning Biological Research (1868 Conestoga Rd., Moscow, Idaho 83843), and Jeff Lincer of the Wildlife Research Institute, Inc. (18030 Highland Valley Road, Ramona, California 92065). On February 1, 2006, the IID awarded Bloom Biological, Inc. a contract to further design and conduct a proposed stratified random sampling mark-recapture survey methodology for Burrowing Owls developed by Jeffrey A. Manning. The scope of that work entailed the development and implementation of detailed survey and sampling methods during 2 consecutive spring seasons, from which to provide estimates of population size and a validated method to survey for Burrowing Owls within the HCP Study Area in subsequent years. This was later amended by the Water Transfer Implementation Team (IT) on March 20, 2006 to include a pilot study during April and May, 2006, prior to implementing the originally proposed 2-year effort. The objective of the pilot study was to assess probabilities of detection and determine the best survey method (mark-recapture versus removal), times of day, and minimum number of repeat sampling occasions that would be necessary to balance accuracy of abundance estimates with effort (cost) during the 2-year population study.

This final report was developed in accordance with guidance from the IT, the requirements of the HCP and other Water Transfer related authorizations, and includes findings from a series of retrospective studies and field experiments (including a pilot study) conducted on Burrowing Owls during daylight hours in the HCP Study Area. These studies were conducted during the prehatch stage (April) of the Burrowing Owl

breeding cycle in 2006, 2007, and 2008. Retrospective studies and their associated analyses followed rigorous scientific methods based on applying the information theoretic approach with multiple working hypotheses (Chamberlin 1890, 1965; Burnham and Anderson 2002), novel techniques that were tested and validated, random sampling or complete censuses, and/or bootstrapped simulations. Field experiments involved experimental controls, randomly assigned treatments, random sampling, and replication.

All surveys were conducted by biologists with a minimum of a bachelor's degree in biology or related field, formal training in the scientific method, ≥1 years experience conducting avian surveys, or demonstrated abilities conducting wildlife population surveys. All field biologists received extensive classroom and field training in order to standardize the collection of survey data.

The topics presented here correspond to those listed in the detailed study approach titled "Final Detailed Buow Study Approach Section 5.2 of QR 531," included in the IID's Work Order No. 2 (8100000664), dated January 31, 2007, as amended.

The primary objectives were to:

1. Provide accurate annual estimates of relative Burrowing Owl abundance and distribution in the HCP Study Area over a 2-year study period.

2. Develop and validate a repeatable sampling and analysis methodology that optimizes the accuracy of annual estimates of population abundance and distribution while minimizing costs.

Amendments to the approaches used to achieve the above objectives were made after independent peer reviews were provided by Dr. W. Gould (New Mexico State University, Las Cruses; January 8, 2007) and B. Manly (West, Inc, Cheyenne, Wyoming; August 22, 2007) and as new information was made available. These amendments include:

1. Use of a grid with a standardized 3x3-Km grid cell size to evaluate spatial autocorrelation in abundance of owls in lieu of linear IID right of ways. These grid cells would also represent standardized sampling units for all subsequent analyses. This approach was approved by the Water Transfer IT on May 9, 2007, and the size of grid cells approved by Brad Norling of the IID on August 22, 2007 and also by the IT in September 2007.

2. Use of a 110-m buffer to surround point-coordinate-based Burrowing Owl locations for estimating unbiased estimates of male Burrowing Owl population sizes from point-coordinate-based closed capture-recapture data. The approach to examine the most appropriate buffer size was approved by the IT on May 9, 2007, and the 110-m buffer size was approved by Brad Norling of the IID on August 22, 2007 and (by email) by the IT on Sept 17, 2007.

3. Use of remote sensing crop data as a correlate of male Burrowing Owl territory abundance. The initial approach of analyzing remote sensing crop data was part

of the approved detailed study approach, but final approval to use the results to predict abundance was emailed by the IT on September 17, 2007.

4. Disturbance experiment approved by Bruce Wilcox of the IID, April 2008

5. Comparison of double and single drain surveys (in response to requests made by the IT and Dr. W. R. Gould's independent review and recommendation, dated 8 January 2007 and the IT's request).

6. Use of summed estimates of local population abundances to validate long-term stratified sampling monitoring design (in response to Dr. W. R. Gould's independent review and recommendation, dated 8 January 2007).

This report is divided into 20 chapters, with subsequent chapters building upon information from former chapters. Due to the numerous novel scientific approaches applied by individual experts here, the format of this report follows that widely used and accepted by the scientific community, including a listing of authors under each chapter heading (e.g., see Barclay et al. 2007. Proceedings of the California burrowing owl symposium, November 2003. Bird populations monographs No. 1. The Institute for Bird Populations and Albion Environmental, Inc., Point Reyes Station, CA).

In Chapter 1, I provide a general introduction, objectives, and description of the study area. In Chapters 2-9, I focused on the development of an efficient survey method that produced unbiased, precise estimates of abundance. Chapter 10 involved the calculation of maximum likelihood estimates of local male Burrowing Owl territory abundance for each 3x3 km grid cell across the study area in 2007. In Chapters 11-13, I identified correlates of abundance and occupancy with the intention of evaluating the efficacy of using those correlates as surrogates of abundance for stratifying the HCP Study Area prior to subsequent population surveys. In Chapters 14-19 I developed, tested, validated, and recommended a stratified random sampling methodology with the survey method embedded into it to improve precision of population estimates and reduce costs. Chapter 20 provided a brief list of recommended future research directions divided into two sections: 1) those intended to improve the accuracy and reduce costs of population monitoring, and 2) those intended to improve the understanding of the status of the Burrowing Owl population and factors that potentially limit or regulate it.

Key points from this study include the following:

1. Diurnal home ranges of male Burrowing Owls ranged from 0.01 to 2.14 hectares (to 5.30 acres), with an average of 0.32 +/- 0.09 hectare (~0.80-acre). Males restricted 97% of diurnal movements to less than 110 m from their burrow site. Diurnal home ranges were distinct and non-overlapping.

2. Availability of Burrowing Owls (which differs from the probability that an owl was detected, given that it was available for detection) was best explained by temperature, with "availability" decreasing as temperature increased.

3. We recommend single-stop car surveys over two-stop car surveys (surveying both sides of drain feature) or foot-based surveys. Surveying from one side of a drain is recommended over surveying from both drain sides, as the latter produces no substantial reductions in bias over the former (both had about 20% bias range).

4. We recommend a three-pass (e.g., 3 survey occasion) closed population capture-recapture approach over the four-pass approach used in 2007 and 2008: the fourth pass provided only limited additional power, and is not justifiable given the additional effort required. Survey passes are conducted on separate days.

5. Of many potential environmental correlates of owl abundance investigated, the best-fit model (i.e., best correlates) included number of available burrows and presence of alfalfa three years prior to the 2007 survey effort. Based on these results, we initially recommended that these two variables could be used to stratify the study area in future survey efforts. However, after additional analyses in the later chapters, we concluded that it would not be advantageous to use these two variables in stratifying the HCP Study Area, and provided an alternative.

6. Abundance of Burrowing Owls in the study area was estimated at 3,557 male owl territories (= breeding pairs) in 2008. This represented a 27% decline from the 2007 estimate of 4,879 territories. These numbers are considerably lower than prior estimates by other researchers (e.g., Desante et al. 2004 estimated approximately 6,000 territories). The decline in abundance between 2007 and 2008 was detected in most (n=206, 75%) of the 274 3x3 km grid cells used to estimate local abundances across the study area. Substantial abundance declines (>50%) between 2007 and 2008 were detected in over 20% of the grid cells.

7. We present the minimum number of grid cells (of total n=274 in Imperial Valley) to be sampled in future burrowing owl surveys to detect a targeted percent-change in abundance. For example, the abundance estimate resulting from surveying 119 randomly-selected grid cells would produce estimates that would be within 10% of the true population size. This would allow the detection of a change in abundance as small as 20% between survey periods. However, stratified random sampling improved the ability of detecting a change to as low as about 10%.

8. The stratified random sampling methodology requires that the study area be re-stratified prior to each population survey. The best method to stratify is based on BUOW abundance, which can be obtained by a valley-wide single-pass census of owls just prior to selecting a random sample to complete capture-recapture surveys. After this single census, the sample of grid cells to be surveyed (e.g., 119) could be randomly selected and surveyed with only 2 additional passes. By combining census data with the data from the 2 additional passes, a total of 3 survey passes (occasions) would occur in the randomly selected grid cells. With a sample of 119 grid cells, this could produce an estimate that would enable detection of a 10% change in between-year abundance of male Burrowing Owl territories.

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Chapter 1

GENERAL INTRODUCTION AND STUDY AREA

JEFFREY A. MANNING

GENERAL INTRODUCTION

The western Burrowing Owl (*Athene cunicularia hypugea*) is listed by the U .S. Fish and Wildlife Service as a Bird of Conservation Concern in every USFWS Region it occurs in and on the National list (USFWS 2002, Klute et al. 2003). It is listed as threatened or endangered in several U.S. states and has been listed as a species of special concern in 16 other U.S. states, including California (Remsen 1978, James and Espie 1997, Sheffield 1997, USFWS 2002). The Imperial Valley of California, USA (32° 58' N, 115° 31' W) supports the largest concentration of Burrowing Owls in its range (Coulombe 1971, Desante et al. 2004), and is the site for the Imperial Irrigation District's (IID – Operational Headquarters, 333 E. Barioni Blvd. Imperial, CA 92251) Colorado River Water Conservation and Transfer Project (Final EIR/EIS, dated June 2002). As part of that project, a draft Habitat Conservation Plan (HCP) was prepared, and the Burrowing Owl was included as a covered species in the HCP.

The HCP specified measures to avoid, minimize, and compensate for potential impacts to Burrowing Owls resulting from the IID's activities, and specified Burrowing Owl monitoring requirements. However, the status and trends in the Burrowing Owl population within the HCP Study Area are largely unknown. Only one study has estimated the size of the Burrowing Owl population in this region (Desante et al. 2004). They surveyed 6% of the Imperial Valley, and estimated the population to be between 3,405 and 7,795 pairs. Because accuracy of abundance estimates is important for species-specific monitoring plans (Atkinson et al. 2004) and making well informed adaptive management decisions, increased accuracy is needed in estimating the Burrowing Owl distribution and population size in the HCP Study Area.

Prior to initiating a long-term population monitoring program for Burrowing Owls along the IID's rights-of-way and service areas that parallel irrigation canals, drains, and ditches within the non-submerged portions of the proposed 500,000-acre HCP area (HCP Study Area), a standardized sampling design that minimizes the required sample size, optimizes the allocation of survey effort, and reduces costs while maintaining high levels accuracy at all stages of the survey is needed. Although range-wide surveys have been recommended (Holroyd et al. 2001), no statistically rigorous broad-scale Burrowing Owl population estimation has been conducted, except for a statewide survey by Desante et al. (2007). Guidelines for conducting standardized visual surveys prior to development in an area have been developed by numerous non-governmental organizations and regulatory agencies across the southwest (California Burrowing Owl Consortium 1997, Arizona Game and Fish Department 2007, New Mexico Department of Game and Fish 2007), but these guidelines are not suitable for determining the appropriate level of sampling and surveying needed to minimize cost while maintaining accuracy in a large area with a high

abundance of owls like that found in the HCP Study Area. Additionally, factors that affect detection of owls during the breeding season have been reported for populations in the northwest and central United States (Conway et al. 2008), but because the range of environmental conditions determined to be important in that study differ dramatically from that found in the Imperial Valley, these results should not be inferred to the HCP Study Area. Additionally, while Conway and Simon (2003) provide a rigorous comparison of detection probabilities among three methods of surveying for Burrowing Owls, other survey methods are available, and the applicability of using these survey methods in the HCP Study Area has yet to be evaluated.

Two sources of error that influence the precision of population estimates are measurement error and sampling error (Cochran 1977). Measurement error occurs when an observer fails to detect an animal that was available for detection during a survey, also referred to as detection probability (Diefenbach et al. 2007). This source of error can be attributed to habitat and/or environmental conditions, animal behaviors, observer fatigue, and survey methodology, among numerous other factors. Methods of estimating abundance commonly adjust raw counts by an estimated detection probability (Diefenbach et al. 2007), but lower detection probabilities coincide with lower precision of abundance estimates. Measurement error can be reduced by implementing a variety of techniques, including the use of skilled observers, application of standardized survey protocols, selection of survey times to maximize visibility and minimize misidentification of target animals, training to increase consistency and accuracy, and use of field instruments with high accuracy.

Sampling error is associated with experimental design and sampling of a population (Kuehl 1994). Time and money limitations typically constrain population surveys to a sample of areas that represent a fraction of the area occupied by the population of interest. Here, each area represents an areal sampling unit, and sampling error refers to the variability in abundance of animals among these sampling units. In these situations, a carefully selected experimental design can reduce sampling error and improve statistical power (Kuehl 1994). Designs such as cluster sampling, randomized block design, and stratified random sampling reduce sampling error by classifying sampling units according to their similarity or dissimilarity and estimating abundance in each class separately. These designs generally assume that population counts in sample units are without measurement error, which is why it is still important to reduce measurement error when using them.

Steidl et al. (1997:274) provide an elegant example that illustrates the gains in power when an efficient experimental design and appropriate statistical model for analysis are used. The remainder of this paragraph is an excerpt from that paper. "The effect of recreation on breeding bald eagles … was investigated by measuring brood behavior of eagles with people camped at distances of 500 and 100 m from nests (Steidl 1995). Assuming these data were collected with a completely randomized design, the null hypothesis of no difference in the percent day that eagles spent brooding with people camped at these 2 distances could not be rejected … However, power to detect a 20% effect with this design … was low …, indicating that the results were inconclusive.

Eagle nesting behavior changes rapidly as nestlings mature (Steidl 1995), and [the] completely randomized design [above] did not account for this known source of variability. Instead, a crossover design was used (Jones and Kenward 1989), where both treatment and control were applied in succession to the same experimental unit (nest). This design eliminated variability due to nestling age between nests. The null hypothesis of no difference in behavior between distances [people were camped] was rejected with this approach …, indicating that eagle behavior changed when people camped near nests."

Because abundance of owls is expected to be unevenly distributed across the HCP Study Area, a simple random sample of areas would likely lead to imprecise population estimates of male Burrowing Owl territories (Caughley 1977:27; Williams et al. 2002:247). An accurate estimate of population size can be obtained with sampling designs that account for the size, shape, number, and placement of sampling units across areas where abundance is unevenly distributed (Caughley 1977:27; Williams et al. 2002:247). This is a critical issue in population monitoring because increased precision translates to an increase in the ability to detect changes in population size. Imprecise estimates only allow for detection of large changes in a population.

A commonly used design to estimate the size of wildlife populations in large areas where abundance is unevenly distributed is stratified random sampling (Caughley 1977:27; Williams et al. 2002:249). The area supporting the total population of interest is subdivided into areal sampling units, and these are categorized according to their similarity in animal abundance (e.g., low, medium, and high). These categories are referred to as strata, and a random sample of units is drawn separately from each stratum. Animals are counted in the randomly sampled units and the strata abundances are summed to estimate a total population size. This stratification of units into similar abundances reduces sampling error within strata and the estimated total population estimate.

This report provides the results from a series of retrospective and experimental studies conducted over a 3-year period in the HCP Study Area, beginning with a pilot study in 2006. Our general objective was to develop and validate a repeatable stratified random sampling and analysis methodology that optimizes the accuracy of annual estimates of population abundance and distribution while minimizing costs. Secondarily, we provide unbiased estimates of local and HCP-wide Burrowing Owl abundance and distribution and demonstrate an application of these estimates in calculating annual rates of population change over the last 2 years of the study. Except where otherwise emphasized, this study focused on observations of individual owls, with inference drawn to nests and territories where appropriate. For retrospective and survey-based analyses, my general approach was to use the information theoretic approach to test multiple working hypotheses (Chamberlin 1890, 1965; Burnham and Anderson 2002); but, in some cases where inferential statistics were applied, and a P-value of <0.1 was used for determining significant differences. Field experiments used inferential statistics with a P-value of <0.05, unless otherwise stated.

This study was funded by the IID, with oversight provided by the IT. Bloom Biological, Inc. held the contract with the IID, established subcontracts with Jeff Manning and the Wildlife Research Institute, Inc., and provided information on the natural history of owls. Jeff Manning developed the study designs, field protocols, and methods of data collection (with reviews and recommendations by W. R. Gould, B. Manly, and others), was the principle field investigator, performed all analyses (with the collaborating coauthors of respective chapters), and authored all reports. He also managed purchases and the budget and selected, trained, and supervised field biologists. The Wildlife Research Institute, Inc. hired the selected field biologists, provided input during the pilot study, and assisted in the training of field biologists. Their senior biologists also assisted in the collection of data during the pilot study.

GENERAL DESCRIPTION OF STUDY AREA

This study was conducted in the agricultural matrix of the Imperial Valley of California, USA (32° 58' N, 115° 31' W), an important region for Burrowing Owls that supports the largest population in North America (Coulombe 1971, Desante et al. 2004). Specifically, the HCP Study Area included all non-submerged portions of the 500,000-acre HCP Study Area, and surveys were conducted where the IID's rights-of-way and service areas paralleled irrigation canals, drains, and ditches, including the All American Canal.

Extensive landscape change occurred in this desert ecosystem during the 20th century, with a large portion of the Imperial Valley cultivated for agricultural production with irrigation water supplied by the Colorado River (Bailey 1994). During this study, fields were intensively managed year-round for irrigated agricultural production, with alfalfa (*Medicago sativa*), Sudan grass (*Sorghum bicolor*), Bermuda grass (*Cyondon dactylon*), and wheat (*Triticum* spp.) as the dominant crops. Agricultural fields were routinely flood irrigated, irrigation drains, canals, and ditches were dredged and maintained for water conveyance, and access roads were graded. Within this agricultural landscape during the course of this study, Burrowing Owls nested almost entirely within or along irrigation drains, canals, and ditches.

Chapter 2

SPACE USE AND AVAILABILITY OF BREEDING MALE BURROWING OWLS DURING DIURNAL POPULATION SURVEYS

JEFFREY A. MANNING, CAREN S. GOLDBERG, PETER H. BLOOM, AND SCOTT E. THOMAS

ABSTRACT. Formulating a baseline understanding of Burrowing Owl space use during the day in the HCP Study Area and the implications of this information on conducting diurnal surveys is important. Here, we showed that male Burrowing Owls occupied small, spatially distinct, diurnal home ranges, restricted 97% of their activities to <110 m from the nest, and remained closest to their nest burrow during mid-afternoon while females were in the burrow. We also found that an increase in nest density coincided with a decrease in diurnal home range size and that diurnal home ranges remained spatially distinct (i.e., no change in the level of inter-home range overlap) when the density of nests increased. We also found that their availability for detection decreased on the mid-day. We concluded that these patterns in diurnal space use would minimize the risk of double counting owls or pairs during diurnal population surveys conducted in the prehatch stage of the breeding cycle and that surveys should be avoided in the mid-day until an estimator of abundance that incorporates availability becomes available.

INTRODUCTION

Like many highly mobile species, Burrowing Owls utilize various locations across their home ranges throughout a 24-hr period. This variation should be identified and accounted for to improve the accuracy of estimates derived from population surveys. For example, the probability of being available for detection (which differs from the probability that an animal is detected, given that it is available for detection) throughout the day (e.g., due to being in a burrow) is likely not to be constant; depending on when a survey is conducted, this variation can bias population estimates (Diefenbach et al. 2007). Many of the current methods used to estimate populations, like distance sampling, double-observer, and sightability (Williams et al. 2002), assume that the probability that an animal is available for detection is 1.0. Thus, information on the availability of individuals for detection and home range use and overlap can be useful in developing standardized survey protocols that increase the accuracy of population estimates, as is specified under the HCP.

Burrowing Owls use their nest burrow as a central place, with activities emanating outward like that of a central place forager (Orians and Pearson 1979, Schoener 1979). During the breeding season, male Burrowing Owls actively defend the immediate vicinity of the nest during the day (Coulombe 1971, Thomsen 1971, Martin 1973, Moulton et al. 2004) and expand their space use at night, with nocturnal home ranges measured at 45 to 184 ha (Gervais et al. 2003, Rosenberg and Haley 2004). Low detection probabilities during nocturnal surveys (Haug and Didiuk 1993, Conway and Simon 2003) may be due to these extensive movements, as owls may be absent from the area being surveyed. This

is a concern for population monitoring because low detection probabilities decrease precision of population estimates (Seber 1982).

Surveys conducted while owls are occupy small diurnal home ranges may avoid these issues and produce highly accurate population estimates if movements of individual owls are short and home ranges show little overlap. However, the probability that an owl is available for detection throughout the day may change, which can bias estimates (Diefenbach et al. 2007). For example, low availability of Burrowing Owls during mid-afternoon surveys in northern California biased population counts 90% below the known population size (Thomsen 1971). Due to these behaviors, sampling throughout the day in northern latitudes, as recommended by Conway et al. (2008), may not provide reliable estimates of population size if this variability is not accounted for.

In this chapter, we focused on formulating a baseline understanding of Burrowing Owl space use and the implications of such on conducting surveys in the HCP Study Area. We estimated the size and level of overlap of diurnal Burrowing Owl home ranges during the prehatch stage of the breeding cycle and explored how these parameters varied with nest density. We further estimated the availability of Burrowing Owls throughout the day, and demonstrated how availability can influence population estimates derived from diurnal sampling.

METHODS

Data Collection

Spatial use of diurnal home ranges

We surveyed resident male Burrowing Owls during the breeding season from 1 April to 1 May 2007. We chose these dates because they corresponded with the prehatching stage of the nesting cycle, when males move little and remain sentinel around the nest entrance while females incubate (Martin 1973, Plumpton and Lutz 1993). We randomly selected 5 linear areas along the irrigation system that contained neighboring owl nests (n = 40 nests). We counted all active burrows in each of the 5 areas that contained sign of Burrowing Owl use (e.g., an owl that retreats or flushes from burrow, regurgitated pellets, feathers, nest lining, whitewash, or footprints with an absence of cobwebs; Conway et al. 2008). We considered the burrow entrance with the greatest amount of sign in the vicinity of each male to be the primary burrow entrance, and recorded its Geographic Positioning System (GPS) location. We used the distance between nest burrows that were at each end of a sampling area to estimate the density of nest sites.

We captured 94 resident owls with noose carpets, Bal-Chatris traps, Havahart traps, and mist nets (Collister 1967, McClure 1984, Bloom 1987, Bloom et al. 2007; Federal Bird Marking and Salvage permit 20431 and California Scientific Collector's Permit 801176-02). Each owl was fitted with metal U.S. Fish and Wildlife Service and colored plastic polyvinyl chloride, alphanumeric leg bands. We used the apparent absence of brood patches to assign sex to each banded owl, and verified that the male at each nest site was

banded by conducting visual surveys the following day when we anticipated that females would be incubating eggs in the nest burrow. We used this information and that from counting active nests to derive a true number of active nests. We were unable to capture and band owls in eight nests, but we retained these for observations because they were situated between nests with banded owls, thus enabling us to distinguish them.

We continuously tracked each male for 13 consecutive hours between sunrise and sunset and mapped perch locations every 15 minutes. Observations were conducted with binoculars and a spotting scope, range finder, compass, and GPS unit. Observations were made from vehicles parked at a distance that we believed would not disturb owls (ca. 160 m). We recorded the GPS location of the observer and used the distance and bearing to the owl to map 15-minute owl locations, which were determined during a pilot study to be accurate to <3 m. The flat agricultural landscape enabled us to maintain sight of owls even when they traveled far distances. But, if an observer was unable to locate or verify identification of an owl ≤1 minute before or after a 15-minute time stamp, the location was not recorded.

Availability throughout the day

We conducted time budget surveys of resident Burrowing Owls in the vicinity of eight randomly selected, individual active nests during the prehatching stage of the nesting cycle, from 7-17 May 2006. We surveyed continuously from 06:30-19:30 (PDT), except between 12:30 and 13:30, and recorded the number of minutes within each hour when ≥1 owls were available for detection (e.g., not in a burrow). Again, due to the flat agricultural landscape, we were able to maintain continuous sight of owls even when they traveled far distances.

We examined the relative importance of ambient air temperature, wind speed, and time of day on the probability that Burrowing Owls were available for detection. We included the 2 weather variables because past authors suggested that they reduce detection probability (Shyry et al. 2001, Conway et al. 2008). We recorded ambient temperature (°C) and wind speed (km hr^{-1}) frequently throughout each survey hour with a Kestrel 3000 Pocket Weather Monitor, from which we computed hourly averages throughout the day. Ambient temperature varied from 17 to 41°C, and wind speed varied between 0 and 17 km hr^{-1}.

Diurnal population surveys

To examine how availability of owls throughout the day may affect estimates of population abundance, we counted the number of Burrowing Owl pairs in 12 randomly selected linear areas along the irrigation system between 16 April and 20 May 2006. These areas were independent from those used to assess space use in 2007. Each area was approximately 6.5 km long and was surveyed completely during each hour throughout the day (06:30-18:30 (PDT), except for 12:30-13:30). Surveys were completed by one observer and one driver in a vehicle that traveled 11 km hr^{-1}. We used the same make and model vehicle during all surveys, and positioned vehicles so the

observer had an unobstructed view of the nesting habitats. We followed the same path and direction during each hourly survey. To reduce double counting owls, the observer maintained a field of view in the direction of travel and did not look behind the vehicle. We stopped the vehicle at each owl and mapped the location with a GPS unit. Because females and males typically remain close the burrow during this period of the nesting cycle (Thomsen 1971, Martin 1973), we considered owls <12 m apart to be a nesting pair and recorded them as a single observation.

Statistical Analyses

Spatial use of diurnal home ranges

We measured the distance between an owl's primary nest burrow and its 15-minute locations using ArcGIS 9.2 (ESRI, Redlands, CA). To evaluate distance moved through time of day, we divided these values by the farthest distance an owl moved. We fit a 95% fixed kernel home range utilization distribution to each owl's set of 15-minute locations (Worton 1989), and considered these as diurnal home ranges. We used likelihood cross validation smoothing because it has been shown to be a better procedure for small sample sizes and for obtaining more accurate and consistent estimates in high use areas (Blundell et al. 2001, Horne and Garton 2006).

We assessed the proportional difference in size of diurnal home ranges relative to nocturnal use areas ($\bar{x}$ = 45.3 ± 18.2 ha) measured within our study area (Rosenberg and Haley 2004). We also computed the probability that an owl would cross into a neighboring home range as ½ of the volume of overlap between neighboring diurnal home ranges. To examine if distinct boundaries of diurnal home ranges were maintained at various densities, we used unpaired, two-tailed Student's *t*-tests to determine if the size of diurnal home ranges or the probability of crossing into a neighboring home range differed when density of home ranges increased by 114% (7 owls km^{-1} vs. 15 owls km^{-1}). Statistics were computed using R (Ihaka and Gentleman 1996), *P*-values <0.1 were considered significant, and estimates are presented ± 95% confidence limits.

Availability throughout the day

We computed the proportion of each hour that ≥1 owls were available for detection in a home range throughout the day, and applied an arcsin square root transformation. We fit seven *a priori* linear mixed effects models to these data, and used Akaike's Information Criterion (AIC) to evaluate the relative strengths of the models (Akaike 1973, Burnham and Anderson 2002; Table 2.1). Statistics were computed using R (Ihaka and Gentleman 1996).

Diurnal population surveys

We used the raw counts to compute the proportion of the largest number of nesting pairs observed in the corresponding area during each hourly survey. Estimates are presented ± 95% confidence limits.

RESULTS

Spatial Use of Diurnal Home Ranges

We recorded 1401 diurnal locations of 40 male Burrowing Owls during the prehatch nesting stage in April 2007. Diurnal home ranges (95% fixed kernel) ranged from 0.009 to 2.14 ha ($\bar{x}$ = 0.32 ± 0.09 ha; Figure 2.1), and averaged <1/100th the size of nocturnal use areas previously reported in our study area. Male Burrowing Owls moved short distances through the day, with the shortest occurring in mid-day (e.g., 12.0 ± 3% as far as the maximum diurnal distance moved) and the longest close to sundown (Figure 2.2).

The probability that an owl was present at increasing distances from its nest burrow followed the pattern of a central-place forager, and reached almost 100% at 110 m from a nest burrow (Figure 2.3). Overlap among neighboring diurnal ranges was minimal ($\bar{x}$ = <0.001 ± 0.000001 ha), and did not differ where density of burrows was doubled (Student's t_8 = 1.34, P = 0.20). However, the size of diurnal ranges where density was high (0.38 ± 0.30 ha) was only 39% of that where the density was low (0.98 ± 0.65 ha, Student's t_{18} = 1.82, P = 0.08).

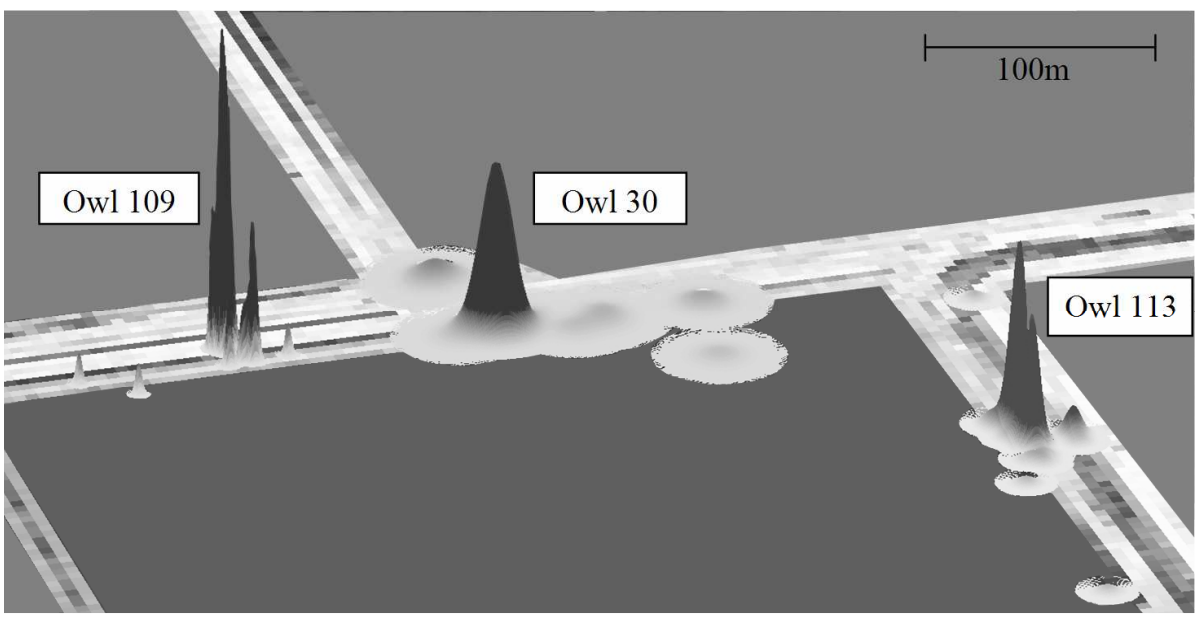

Figure 2.1. Male Burrowing Owl diurnal ranges depicted as 95% fixed kernel utilization distributions along linear irrigation drains (light grey) paralleling dirt roads (white) during the prehatch stage of the nesting cycle in the Imperial Valley, California, April 2007. Solid grey polygons represent agricultural fields.

Availability Throughout the Day

We recorded 142 time budget records in eight home ranges from 16 April 20 May 2006. The best mixed effects model predicted the probability that ≥ one owls was available for detection during a given hour of the day in a diurnal home range as a negative function of temperature [availability = $(\sin(2.13 - 0.03 \times \text{temperature}))^2$, $R^2 = 0.34$, Table 2.1]. The next best model (ΔAIC = 3.6 predicted availability as a 2nd-degree polynomial function of time of day. Availability decreased in mid-afternoon, was lowest (58%) between 1530 and 1630h, and increased to 92% by 17:30 (Figure 2.4).

Diurnal Population Surveys

We counted 93 pairs of Burrowing Owls during hourly surveys in 12 6.5-km nesting areas. Numbers of pairs declined with increasing temperature (Figure 2.4a), which also roughly corresponded with that predicted by our best model for availability throughout the day (Figure 2.4). Numbers of pairs also followed availability throughout the day, declining to the lowest numbers in the mid-afternoon (Figure 2.4b).

Table 2.1. Linear mixed models predicting the proportion of time ≥ one Burrowing Owl is available for detection at a nesting territory as a response to time of day or weather in the Imperial Valley, California April 16-May 20, 2006. Time budget surveys were based on 11-hr observations of 8 nesting home ranges, home ranges were considered random effects, and availability was arcsin square root transformed.

Model	# Parameters	ΔAIC_c
Linear trend (temperature)	2	0
2nd-degree quadratic (time of day)	3	3.6
Linear trend (time of day)	2	5.4
Linear trend (temperature + wind)	3	6.9
Linear trend (wind)	2	7.0
Linear trend (time of day + wind)	3	12.1
2nd-degree quadratic (temperature)	3	12.7

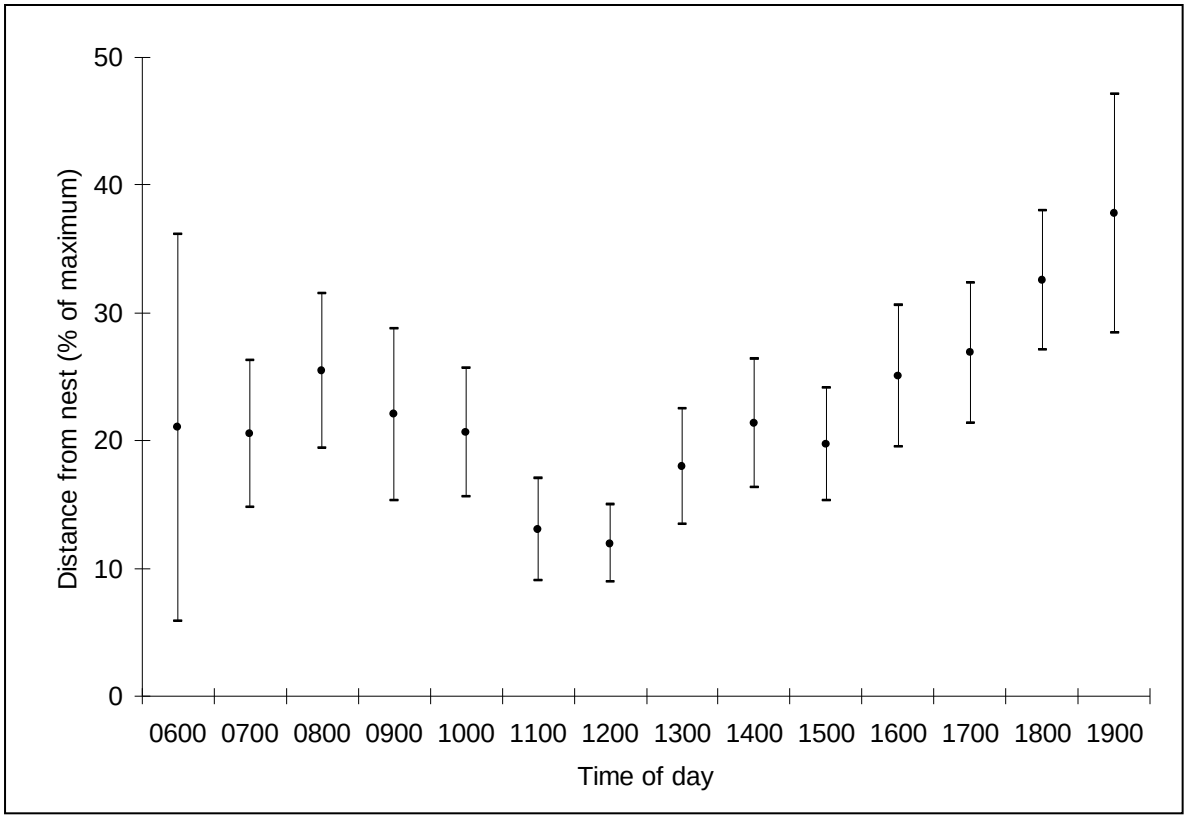

Figure 2.2. Distance (distance/maximum distance) that male Burrowing Owls moved from their nest burrows through time of day during the prehatch stage of the nesting cycle in the Imperial Valley, California, April 2007. Percentages are from 15-minute observations (*n* = 1,401) of 40 male owls recorded during 13 continuous hours (0600-1900). Error bars represent 95% CI.

CONCLUSIONS AND RECOMMENDATIONS

Spatial use of home ranges by Burrowing Owls was not uniform throughout the day. As suggested by other studies (Thomsen 1971, Moulton et al. 2004), male Burrowing Owls in our study occupied small, spatially distinct, diurnal home ranges. During the day, males restricted 97% of their activities to <110 m from the nest, and remained closest to their nest burrow during mid-afternoon while females were in the burrow. Diurnal activities were confined to <1% of nocturnal use areas as measured in a previous study on Burrowing Owls in this area (Rosenberg and Haley 2004). Our results support Moulton et al.'s (2004) findings that male Burrowing Owls during the breeding season appear to defend a relatively small portion of their nocturnal foraging areas during daylight hours. The small diurnal home ranges we observed may be due to males remaining close to their nest burrows to protect their mate from predation and from unmated males (Thomsen 1971). An alternative explanation is that nest burrows in agricultural landscapes like the Imperial Valley may function as a primary source of escape cover against aerial predators, as we occasionally observed owls entering their burrows when aerial predators (*Buteo, Falco, or Circus* spp.) were present.

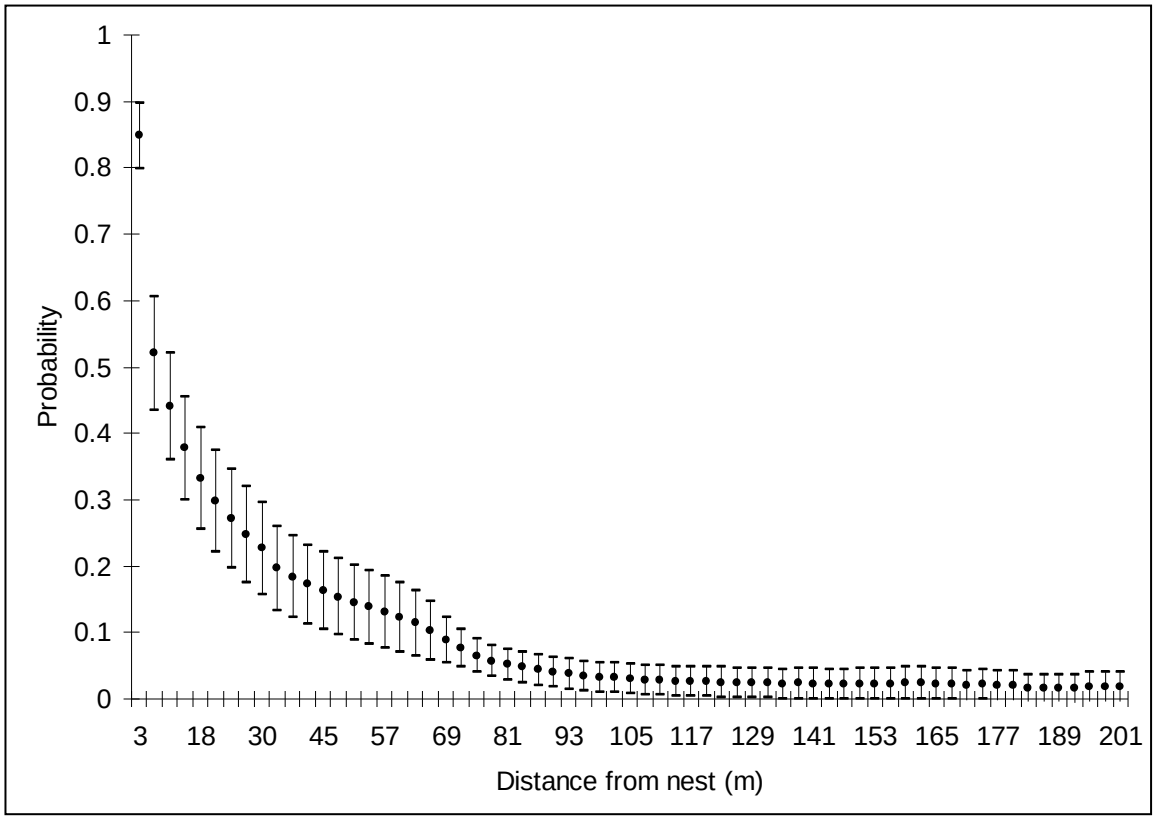

Figure 2.3. Probability that a male Burrowing Owl was present at increasing distances from its nest burrow throughout the day during the prehatch stage of the nesting cycle in the Imperial Valley, California, April 2007. Probabilities are from 95% fixed kernel estimates computed with 15-minute observations (n = 1,401) of 40 male owls recorded during 13 continuous hours (0600-1900). Error bars represent 95% CI.

Although previous studies reported that the number of neighboring nests did not account for the size of nocturnal home ranges during the breeding season (Gervais et al. 2003), we found that an increase in nest density coincided with a decrease in diurnal home range size, as suggested by Haug et al. (1993). We further found that diurnal home ranges remained spatially distinct (i.e., no change in the level of inter-home range overlap) when the density of nests increased. Similarly, Thomsen (1971) reported that Burrowing Owl pairs in northern California with the shortest distance to another nesting pair had the smallest home ranges. Although we did not investigate whether the density of breeding home ranges translated to density dependent demographic rates, we suspect that the spatially distinct diurnal home ranges and high use <110 m from nests we observed may maximize reproductive fitness, as nests <110 m from neighboring nests in Oregon were shown to have lower reproductive success than nests farther apart (Green and Anthony 1989).

Because many population estimation procedures assume that the probability that an animal is available for detection is 1.0 (Otis et al. 1978, Diefenbach et al. 2007), it is important to identify and account for probabilities of availability not otherwise accounted

for when conducting population surveys. Estimates of Burrowing Owl abundance from previous studies have been based on detection probabilities where the probability that an owl was observed was confounded with the probability that an owl was available for detection (e.g., Rosenberg and Haley 2004, Conway et al. 2008). We found that the availability of Burrowing Owls in home ranges throughout the day in the HCP Study Area was best explained by a temperature, although our next best model predicted it as a 2nd-degree polynomial function of time of day, but there was no support for wind.. Availability was highest when temperatures were low (mainly in the morning and late afternoon), and declined as the temperature increased. Availability declined to its lowest level (58%) when it reached the hottest temperatures generally in mid-afternoon. The proportion of the population counted during our independent surveys followed this pattern with temperature and time of day closely, indicating that probabilities of availability <1.0 throughout the hotter afternoon periods bias estimates of Burrowing Owl population abundance based on counts. Likewise, Thomsen (1971) reported that availability declined to its lowest level in the mid-afternoon, and that surveys during that time estimated only 10-25% of the population.

Burrowing Owls maintain small, distinct, non-overlapping diurnal home ranges at various densities during the prehatch stage, when they are most readily surveyed. However, population estimates derived from surveys conducted during the hotter afternoon period will be biased low, as owls are least available for detection during this relatively hot period. We recommend that surveys of Burrowing Owls either incorporate appropriate correction factors for this variability or be conducted in the morning and late afternoon during the prehatch stage to produce the most accurate estimates of population size.

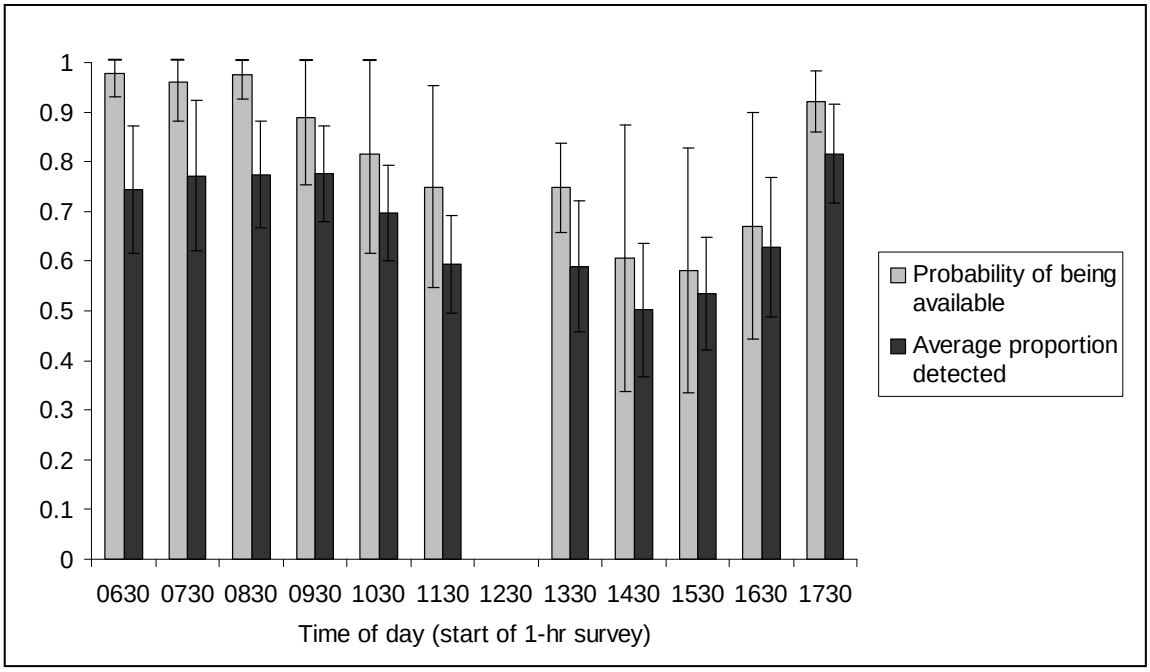

Figure 2.4a. Hourly percentage of time male Burrowing Owls (*n* = 8) were available for detection (e.g., not in their nest burrow) and hourly average number of breeding pairs (*n* = 93) detected throughout the day during the prehatch nesting stage in the Imperial Valley, California. Percentages are from time budget surveys and number detected from automobile-based survey counts. Error bars represent 95% CI.

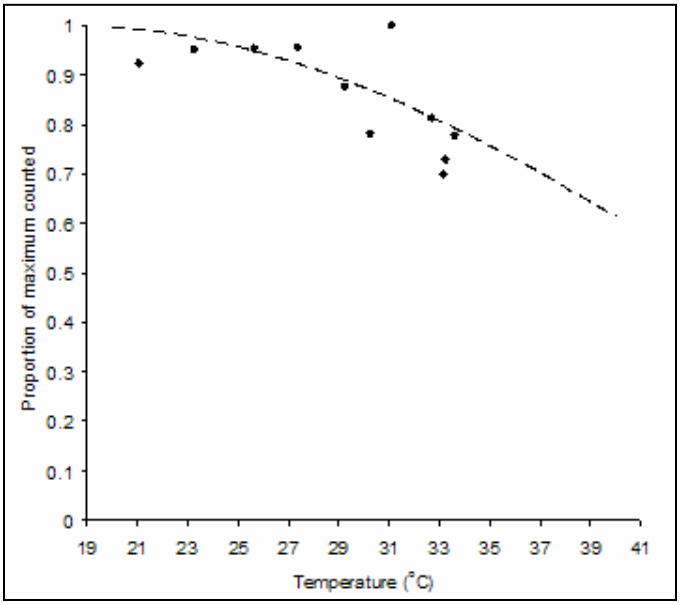

Figure 2.4b. Hourly proportion of maximum Burrowing Owl pairs (*n* = 93) counted throughout the day from automobile-based survey counts as a function of temperature during the pre-hatch nesting stage in the Imperial Valley, California. Dashed line depicts the best linear mixed model predictions of availability (availability = $(\sin(2.13 - 0.03 \times \text{temperature}))^2$) derived from independent time budget surveys. Temperature is arcsine square-root transformed.

Chapter 3

EFFECTS OF SURVEY METHODS ON BURROWING OWL BEHAVIORS

JEFFREY A. MANNING AND ROBB S. A. KALER

ABSTRACT. Information on the behavioral responses of Burrowing Owls to various methods of surveying in the HCP Study Area would be useful for the development of survey protocols. As part of Amendment 4, we compared the effects of 4 survey methods against an experimental control (no survey) on short-term behavioral responses of Burrowing Owls during the prehatch stage of the breeding cycle. The 4 survey methods included a 2 car that drove by an owl twice and stopping both times, representing the double sided drain surveys described in the HCP. Another involved a car that drove by and stopped once, representing the method we used for conducting the population surveys. We found that an owl was 5 times more likely to be displaced by a passing survey car, 15 times more likely to be displaced by a walking surveyor, 16 times more likely to be displaced by a single car survey stop, and 27 times more likely to be displaced by a double car survey stop. We recommend the single car stop for conducting population surveys across the HCP Study Area because they are more efficient than walking and may reduce short-term responses compared to double car stops, which may help minimize bias associated with double counting.

INTRODUCTION

Due to the large extent of the HCP Study Area, we proposed that surveys be conducted from slow moving (7 mph) vehicles. This approach provides an efficient sampling method because burrowing owls nest and forage near roadsides (Brenckle 1936, Ratcliff 1986, Plumpton and Lutz 1993), with the majority of nests in the HCP Study Area occurring <15 m from the banks of water conveyance structures that parallel roads (Desante et al. 2004, Rosenberg and Haley 2004). Additionally, the HCP made reference to surveying both sides of drains (essentially requiring a vehicle to pass on both sides of a water conveyance structure). However, there is some evidence that locomotion and alertness of Burrowing Owls are correlated with vehicular traffic (Plumpton and Lutz 1993). Thus, multiple passes by a vehicle could disturb owls by flushing them (Plumpton and Lutz 1993), which may increase the probability of inter-territorial overlap we reported in chapter 2. Such disturbances could lead to unintended double counting of unmarked owls, resulting in a positive bias in population estimates.

There is a paucity of studies in the literature regarding the effects of various survey methods (e.g., surveyors with or with vehicles, vehicles that stop versus not stopping when owls are detected) on behaviors of owls. Information regarding how owls respond to various population survey methods can help elucidate possible sources of bias associated with estimates of population size. Survey methods that minimize disturbance may reduce movements, which should reduce double counting and its associated influence on bias while also reducing stress and other ecologically important rates (e.g.,

predation by aerial predators or energy expenditure) for owls. This chapter presents the results from a field experiment we conducted in the HCP Study Area, where we compared the effects of 4 survey methods against an experimental control (no survey) on short-term behavioral responses of Burrowing Owls during the prehatch stage of the breeding cycle.

METHODS

Data Collection

We conducted a field experiment with 1 control (no survey) and 4 methods of surveying owls as experimental treatments (Table 3.1). Between April 25-May 1, 2008, we randomly selected 395 owls along IID-maintained water conveyance structures across the HCP Study Area and randomly assigned one of the above 4 treatments or control to each of the owls, following a balanced design (n = 79 for each treatment group and control). We chose this period because it corresponded with the prehatching stage of the nesting cycle, when females incubate and males remain sentinel outside the nest entrance (Martin 1973, Plumpton and Lutz 1993).

Eight survey teams of 3 biologists in 2 vehicles applied treatments and recorded behavioral responses. One vehicle was designated as the 'observation' vehicle and included a single observer. The second vehicle was designated as the 'treatment' vehicle and included two surveyors. With the exception of color, all vehicles were identical and were required to keep lights off and windows rolled up during treatments.

Upon locating a randomly selected owl, the observer positioned their vehicle along the right-of-way at a vantage point ~50 m from the owl and signaled (via punctuated illumination of the vehicle's taillights) to the surveyors in the treatment vehicle positioned >150 m behind to move to ~100 m behind the observation vehicle. Based on previous observations, we believed that these distances would minimize disturbance to the owl. After the treatment vehicle was in position, both vehicles remained stationary for a 5-minute pre-treatment period to allow the owl to acclimate to the observer vehicle. If during the 5-minutes pre-treatment period the target owl appeared to be disturbed by the presence of the vehicles (head bobbing, multiple flights, repeated looking in the direction of the vehicles), then that owl was excluded from the study.

At the end of the 5-minute pre-treatment period, the treatment vehicle applied the randomly selected treatment. After the survey vehicle departed, the observer remained in the other vehicle for up to 20 minutes and recorded the location of the perch that was at the maximum distance the owl was displaced from its original perch where the treatment was first applied. If the owl returned to <10 m from its original perch <20 minutes after the treatment was applied, we also recorded the time it was displaced and that it returned to its original perch. If the owl did not return within the 20-minute post-treatment period, the observer recorded the location of the perch associated with the maximum distance and time (20 minutes) displaced and ended observations. If an owl departed from the observers view during the treatment or 20-minute post-treatment period and could not be

Table 3.1. Survey methods (treatments) randomly assigned to Burrowing Owls in the HCP Study Area, May 2008.

Survey Method	Description
Control	No surveyors or vehicles present; observed owl from observation vehicle (see below).
Car pass	Vehicle traveled 7 mph and paused for 2 minutes where owl was located before traveling away at 7 mph; the engine remained on and surveyors remained inside vehicle.
Walk	A single surveyor walked along the right-of-way surveying for owls with binoculars.
Single car stop	Survey vehicle traveled 7 mph along right-of-way, stopped at owl, and two surveyors exited the vehicle to record location data for 2 minutes, then resumed driving away from the owl.
Double car stop	This treatment represented the double survey pass initially proposed in the HCP; survey vehicle traveled 7 mph along right-of-way, stopped at owl, and 2 surveyors exited the vehicle to record location data for 1 minute, followed by the departure of the vehicle with the surveyors and the subsequent return of the vehicle within a few minutes to repeat the above for 1 minute (regardless of the owl had moved), at which time the vehicle and surveyors resumed driving away from the owl.

resighted, the observation was abandoned and excluded from the study. If the owl traveled out of the observer's view by going into a burrow, the observation continued until the owl (if ever) reappeared from the burrow, or to 20 minutes, whichever was shorter. For the control, there was no treatment vehicle and the observer recorded the maximum displacement location of the owl during a 20-minute observation period. In addition to above-ground locations, we considered standing on the ground, at burrow entrances, or in burrows as perch locations. All location data were recorded using a Trimble GeoXM, range finder, and compass, with <3-m accuracy.

Statistical Analyses

We used ArcGIS 9.2 (ESRI, Redlands, CA) to measure the maximum distances that owls were displaced. We used a logistic model with a binomial response (displaced, no response) to assess whether the probability that an owl was displaced differed among survey methods. We used the area under a receiver operating characteristic (ROC) curve to assess how well the model parameters predicted when an owl would be displaced (Hanley and McNeil 1982, Heagerty et al. 2000). We used odds ratios to compare how much more likely it was for an owl to be displaced by one survey method over another (Hosmer and Lemeshow 1989).

We used analysis of variance (ANOVA) to assess if the duration of time or distance that an owl was displaced differed among treatments and our control. We $\log_e (x + 0.1)$ transformed distance displaced. When the ANOVA indicated a $P<0.1$ difference among treatments, we used Tukey-Kramer HSD multiple comparison tests based on alpha = 0.05 to determine which treatments differed between each other or the control.

We also conducted a post-hoc analysis to assess if car color had a differential affect on the distance or time an owl was displaced by a car survey pass. We $\log_e (x + 0.1)$ transformed both variables.

All statistical analyses were performed using Program JMP 7.0.1 (SAS Institute, Inc., Cary, N.C.).

RESULTS

The probability that an owl being displaced during a survey differed among survey methods (whole model test: $\chi^2_4 = 82.2$, $P<0.0001$). The model performed fairly well at predicting when an owl would be displaced (area under the ROC curve = 0.74). Odds ratios indicated that, compared to the control group, an owl was 5 times more likely to be displaced by a passing survey car, 15 times more likely to be displaced by a walking surveyor, 16 times more likely to be displaced by a single car survey stop, and 27 times more likely to be displaced by a double car survey stop. A double car survey stop was 1.7 times more likely to displace an owl than a single car survey stop, a single car survey stop and walking surveyor were equivalent, but 3 times more likely to displace an owl than a passing survey car. Raw data for the proportion of owls displaced during each treatment are shown in Figure 3.1.

The time an owl was displaced differed between survey methods ($F_{4,390}=10.84$, $P<0.0001$), with owls responding to the control and car pass equally and at a shorter duration than that due to the remaining 3 survey methods that involved the presence of a surveyor (Tukey-Kramer HSD, $P<0.05$; Figure 3.2).

The distance an owl was displaced also differed between one or more treatments ($F_{4,390}=19.63$, $P<0.0001$), with owls responding to the control and car pass equally, but at a shorter distance than that moved in response to the remaining 3 survey methods (Tukey-Kramer HSD, $P<0.05$, Figure 3.2).

Car color did not have a differential affect on the time or distance an owl was displaced ($F_{4,74} = 2.26$, $P = 0.07$, $F_{4,74} = 2.41$, $P = 0.06$, with Tukey-Kramer HSD not detecting any differences at $P<0.05$).

CONCLUSIONS AND RECOMMENDATIONS

Compared to the control and car pass, the presence of a surveyor outside of a vehicle was the common factor among the 3 survey methods that led to significant increases in the

probability of owls being displaced as well as the distance traveled and time spent while displaced. Double car stops increased the probability that owls would be displaced, as well as the median distance traveled by the displaced owl (although the latter was not a statistically detectable difference due to high levels of variation). Surveys based on the car pass method could minimize disturbance and decrease bias associated with accidental double counting of due to movements, however, accurately recording an owl's location and surroundings from inside of the vehicle would be problematic. We recommend single car stops for conducting population surveys across the HCP Study Area because they are more efficient than walking and may reduce short-term responses compared to double car stops, which may help in minimizing bias associated with double counting.

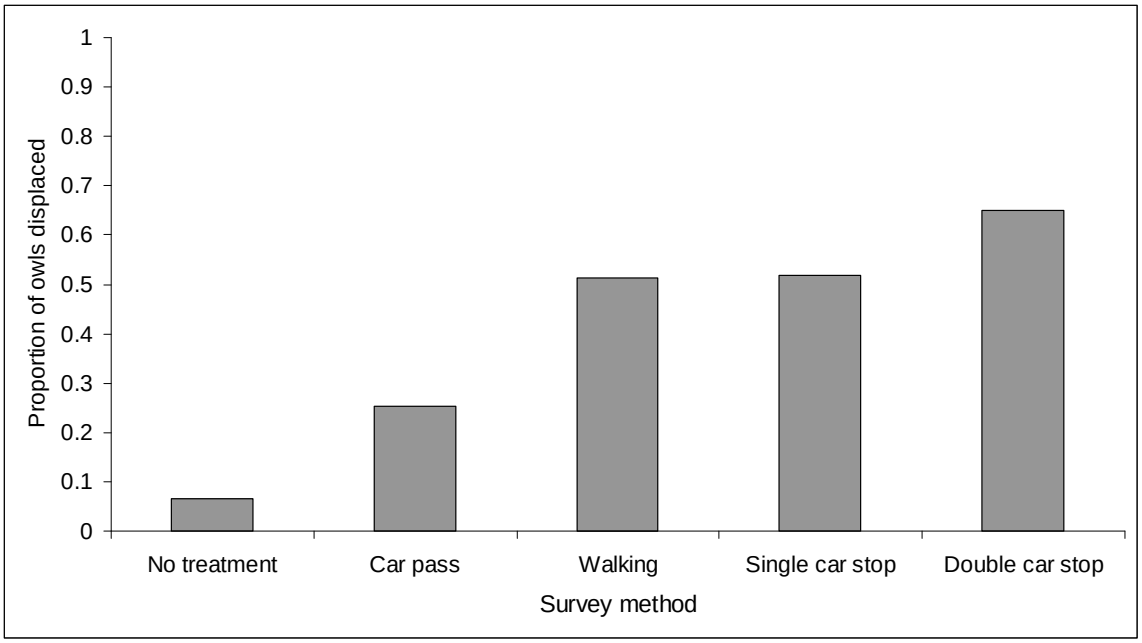

Figure 3.1. Proportion of owls displaced from a perch <20 minutes after a survey method was applied during the prehatch stage of the breeding cycle; no treatment represented an experimental control, Imperial Valley, California 2008.

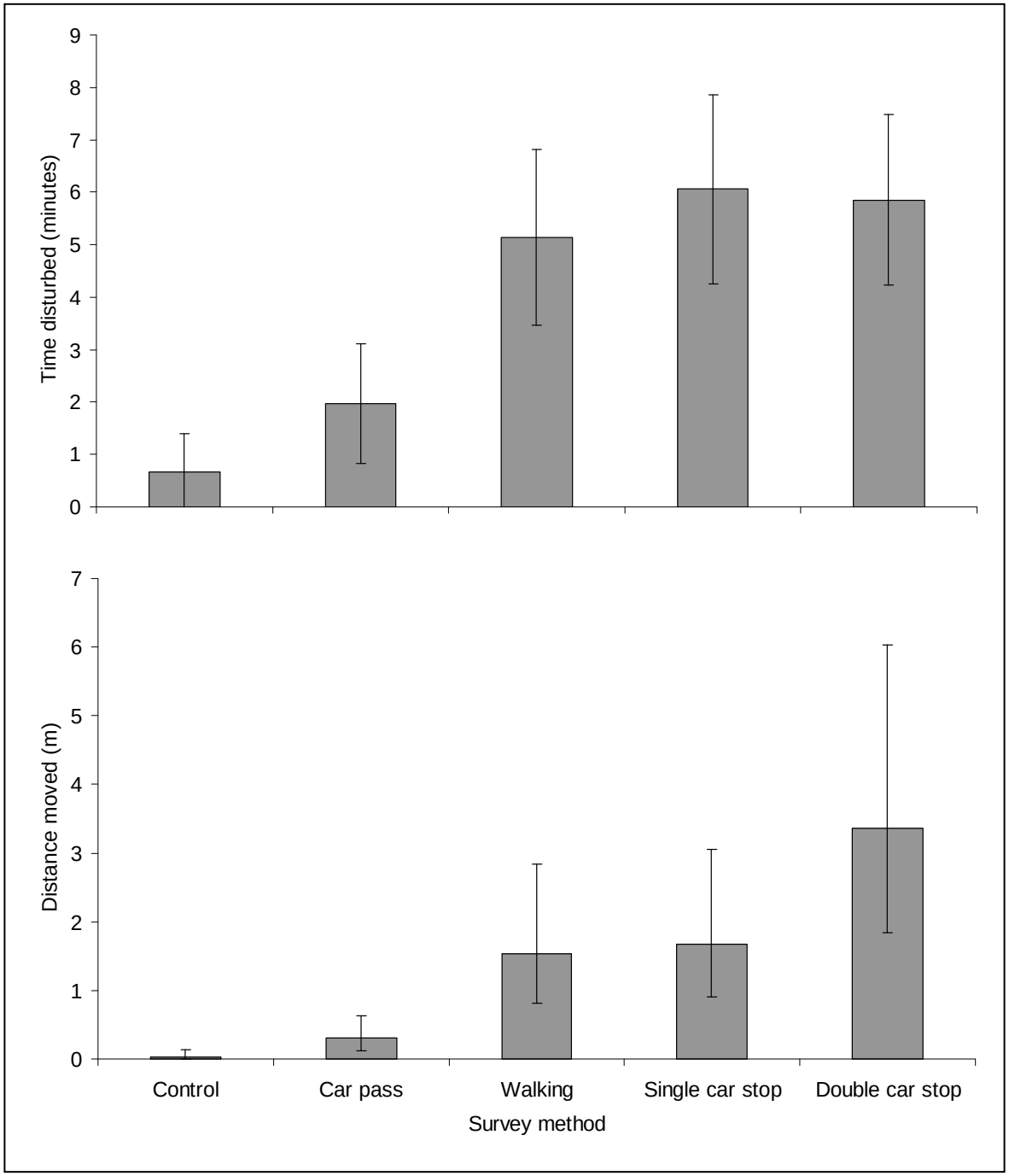

Figure 3.2. Average time and median distance that owls were displaced by a survey method during the prehatch stage of the breeding cycle, Imperial Valley, California 2008. Vertical bars are 95% confidence intervals.

Chapter 4

SINGLE VERSUS DOUBLE SURVEY PASSES

JEFFREY A. MANNING

ABSTRACT. Information on the reliability of surveys conducted from single versus double survey passes can aid in making decisions that balance cost and accuracy of population estimates. In response to Amendment 5, I present the results from a study that compared estimated population sizes, magnitudes of bias, and levels of precision between single and double pass surveys along water conveyance structures containing a known number of active Burrowing Owl territories in the HCP Study Area. I showed evidence that there is no appreciable difference in detection rates or abundance estimates between 1 versus 2 survey passes. Because the cost of 2 survey passes would be nearly twice that of a single survey pass and restricted access to both sides of numerous drains and canals across the HCP Study Area would lead to unequal levels of effort when using the 2 survey pass method, which would introduce an unknown level of error in population estimates that may fluctuate between grid cells and years based on access and maintenance, I concluded that 1 survey pass provides an adequate and consistent method of surveying for male Burrowing Owl territories in the HCP Study Area.

INTRODUCTION

The IT requested that we evaluate the differential effects of single versus double survey passes on bias and precision of population estimates. In chapter 3, Manning and Kaler compared short-term behavioral responses by Burrowing Owls to 4 methods of surveying owls and an experimental control. In that study, we used double car stops along the same side of the drain as a surrogate for two survey passes where each would occur on either side. We found that although not statistically significant, double car stops at Burrowing Owls during the prehatch stage of the breeding cycle were shown to increase the probability and distance of displacement. We concluded that these increases could lead to accidental double counting of owls, which can bias population estimates high. In this study, single and double pass surveys along water conveyance structures containing a known number of active Burrowing Owl territories were conducted during the prehatch stage of the breeding cycle. From these data, I computed population estimates, magnitude of bias, and level of precision between these 2 survey methods.

METHODS

I randomly selected 4 irrigation drains (Rice, Central, Strout, and Date drains) in the southern portion of the HCP Study Area (Figure 4.1), and conducted point-coordinate capture-recapture surveys (see chapter 7 for detailed description of survey method) along a randomly selected 4-km length (route) of IID rights-of-way along each drain. I focused on that portion of the HCP Study Area due to logistical constraints, but believe that the results can be inferred to irrigation drains throughout the HCP Study Area because

environmental conditions, habitat characteristics, and owl numbers and distribution appear to be similar along drains in the north and south portions. Surveys were completed during the prehatch stage of the breeding cycle, between 26 April and 2 May, 2007, which lies within the period previously recommended for conducting population surveys.

Each drain route was surveyed on both sides along IID rights-of-way in opposing directions 3 times (occasions), following the survey methods described in chapter 7 along the same path. When a survey was completed on one side, the surveyors waited >15 minutes at the end of the survey route to allow owls to resume normal behaviors and perching that may have been disturbed by the first survey pass. This produced the first, third, and fifth survey passes in the same direction on the same side of a drain, and the second, fourth, and sixth passes on the opposing side and direction of the corresponding drain.

I combined the first, third, and fifth survey pass data (which were in the same direction) along a route, and considered these to represent 3 single pass survey occasions. I further combined the first and second passes that were in opposing directions along each route, and considered these as the first double pass survey occasion, and applied this to the remaining 2 groups of opposing passes to produce the 2nd and 3rd double pass survey occasions. These groupings enabled me to develop capture-recapture encounter histories from single pass surveys and separately for double pass surveys along the same randomly selected drains.

I used estimated the abundance of owls from single and double pass surveys in each drain separately. I fit 2 maximum likelihood, multinomial, closed-population models to these data with a sin link function using Program MARK (Otis et al. 1978, White et al. 1982, Cooch 1999, White and Burnham 1999). One assumed constant detection probabilities and the other assumed that detection varied among survey occasions. I applied an information theoretic framework (Burnham and Anderson 2002) to select the best model for each drain separately because the goal was to obtain the most reliable estimates of abundance.

Additionally, I pooled the 4 routes into 16 km of surveyed irrigation drain, and pooled the resulting encounter histories into 2 groups based on single and double pass surveys. I fit maximum likelihood, multinomial, closed-population models with a sin link function available in Program MARK (Otis et al. 1978, White et al. 1982, Cooch 1999, White and Burnham 1999) to these data, and applied an information theoretic framework (Burnham and Anderson 2002) to assessing differences between single and double pass surveys. I developed an *a priori* set of multiple working hypotheses that involved similarities and differences in detection probabilities and/or abundances between single and double pass surveys, and constructed a separate model for each hypothesis. I used Akaike's Information Criterion adjusted for small samples (AIC_c) with a cutoff of 2.0 and the principle of parsimony to determine the best model (Akaike 1973, Burnham and Anderson 2002). I assessed the lack-of-fit of the best model here and in the prior closed-population analyses to the data by examining a plot of its deviance residuals. A

symmetric and narrow pattern of deviance residuals close to zero would suggest a good fit to the data, whereas a wide pattern around zero would suggest poor fit due to extra-binomial variation.

To estimate the true number of male Burrowing Owl territories along the survey routes, I used all nest locations from the surveys that were located >40 m apart. I chose this distance because owls occupy non-overlapping diurnal home ranges and spend >80% of the time within 40 m of their nest (as shown in Chapter 2). I assumed that nest locations closer together than 40 m represented additional burrows in a complex occupied by a single pair.

RESULTS

Based on our count of owl nests that were >40m apart, there were a total of 57 male Burrowing Owl territories in the 4 drain routes. A single survey pass produced estimates of abundance for each drain route that was 5 to 25% biased below the true number of territories believed to be present (Figure 4.2), whereas the bias associated with 2 survey passes ranged from -7 to 12% (Figure 4.2). Population estimates from 2 survey passes produced less bias in each of the 4 drain routes, the single survey pass was consistently below the true number, and both survey methods were similar in their precision (i.e., the range in bias for the 1 survey pass was 20% and that of 2 survey passes was 19%).

The comparison of multiple closed-population models fit to the larger dataset that was created by pooling the 4 replicate drain routes led to 3 competing models that best explained the variation in the data (ΔAIC_c<2.0; Table 4.1). Based on the principle of parsimony, the simplest of those 3 models [p=c(.) N(.)] represented the hypothesis that capture and recapture probabilities did not differ between 1 and 2 survey passes and the estimated abundances also did not differ between them. Based on AIC_c weights, that model had the highest level of support, and there was 50% more evidence for it being the best model over replicated datasets compared to the next best model (Table 4.1). This model fit the data well (deviance residuals followed a narrow and symmetric pattern surrounding zero), and the model estimated capture and recapture probability for both methods to be 0.77 (SE = 0.03) and the abundance estimates were 49 (95% CI: 48-56) for 1 survey pass and 55 (95% CI: 55-59) for 2 survey passes.

CONCLUSIONS AND RECOMMENDATIONS

The comparison of multiple working hypotheses with the information theoretic approach over the combined dataset provided evidence that there is no appreciable difference in detection rates or abundance estimates between 1 versus 2 survey passes. When the data was analyzed individually for each survey route, 2 survey passes produced less bias in estimated abundance for each of the 4 drain routes. The 2 survey pass method produced estimates that were sometimes positively and sometimes negatively biased, while the single survey pass was consistently below the true number when drains were analyzed surveyed.

One explanation for the difference in bias between the 2 levels of survey effort when examining the data at the level of short drain routes may be due to the poor performance of capture-recapture models with small sample sizes like those present in each drain route. In this situation, the estimator did not correct for visibility bias efficiently with the small observed samples to adequately correct estimated abundance. This is especially important for the single pass data because the assumption is that all territories are not counted in every pass, but that this will be corrected for by the capture-recapture model. For the 2 survey pass method, the number of counted territories should be closer to the true number present, and the capture-recapture model should not inflate the estimate as much. The analysis with the pooled data is likely more representative of the results that may be obtained when sampling 3x3 km grid cells or larger areas in the HCP Study Area. The similar levels of precision from 1 and 2 survey passes suggests that both may be adequate for monitoring changes in the size of the population or relative differences among grid cells in the HCP Study Area.

Some other differences between conducting 1 and 2 survey passes that were not examined here include cost and consistent levels of effort across the HCP Study Area in order to obtain comparable estimates of abundance among local areas or grid cells. Cost would approximately double if two survey passes were conducted instead of one. Additionally, restricted access to both sides of numerous drains and canals across the HCP Study Area would lead to unequal levels of effort. This would introduce an unknown level of error in population estimates that may fluctuate between grid cells and years based on access and maintenance. For these reasons, it is reasonable to conclude that 1 survey pass provides an adequate and consistent method of surveying for male Burrowing Owl territories in the HCP Study Area during the prehatch stage of the breeding cycle. Although this method may slightly underestimate the number of territories along large drains, this bias should be small and consistent between years, allowing for accurate detection of changes in population size.

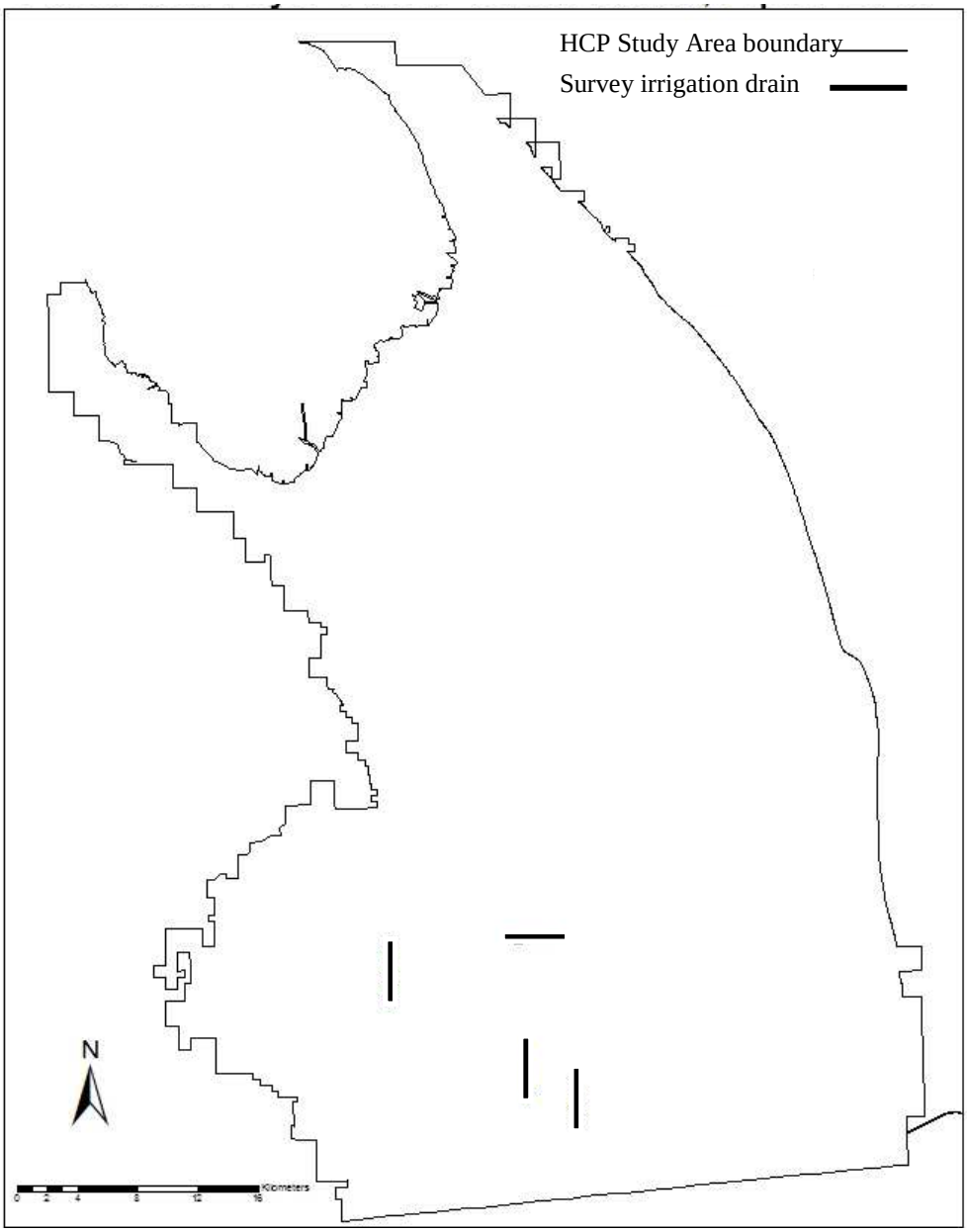

Figure 4.1. Locations of four randomly 4-Km lengths of irrigation drain where point-coordinate capture-recapture surveys were conducted for male Burrowing Owl territories using 1 and 2 survey passes in the HCP Study Area, Imperial County, California, 26 April - 3 May, 2007.

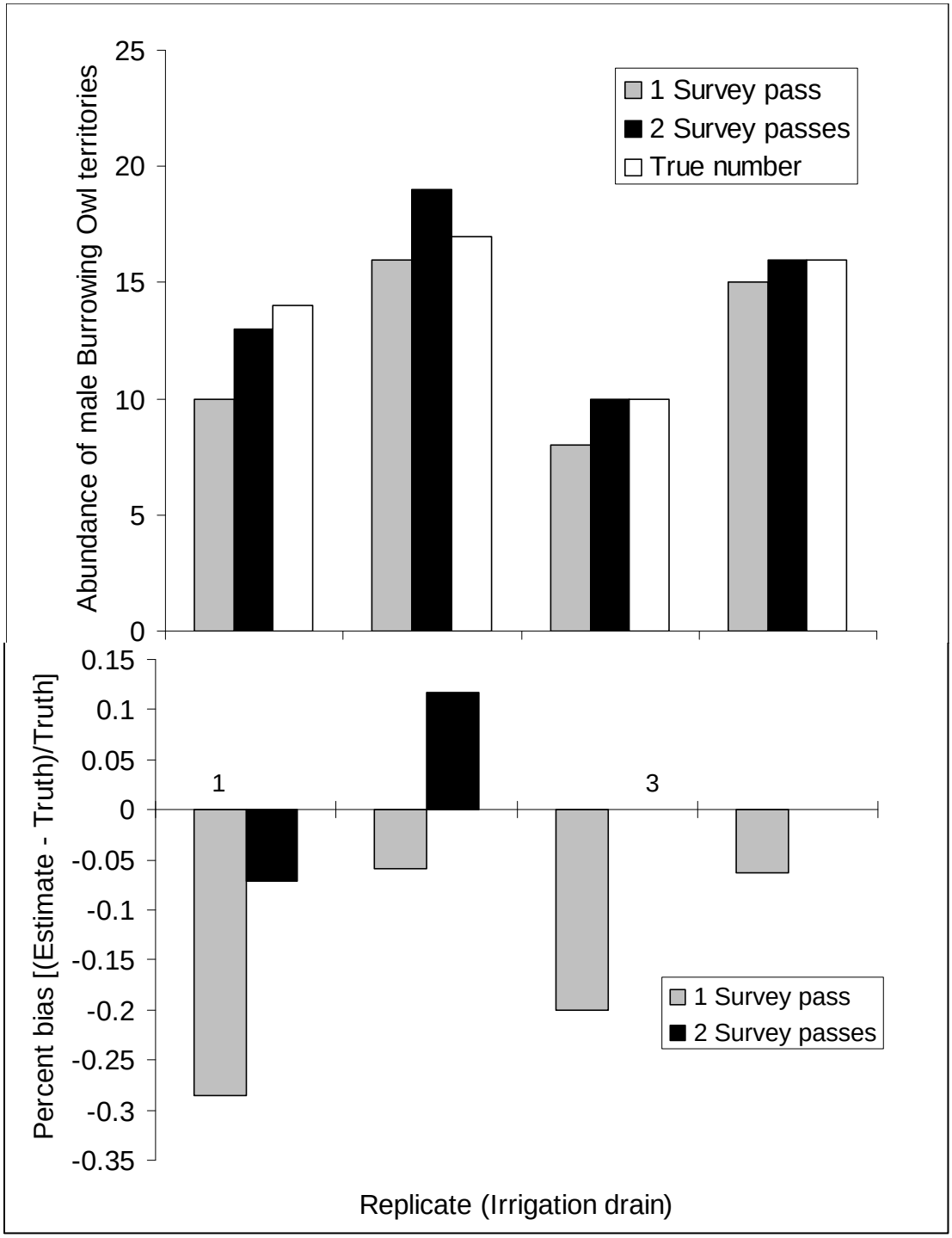

Figure 4.2. Abundance (A) and associated percent bias (B) of estimated male Burrowing Owl territories from 1 or 2 survey passes along 4 randomly selected 4-Km lengths of irrigation drain in the HCP Study Area, Imperial County, California, 26 April - 3 May, 2007.

Table 4.1. Maximum likelihood closed-population models applied to point-coordinate capture-recapture data of male Burrowing Owl territory encounter histories to assess differences in detection [capture (p) and recapture (c)] probabilities as well as abundance between single and double survey passes during the prehatch stage of the breeding cycle in the HCP Study Area, Imperial County, California, 26 April - 2 May, 2007. Models were constructed with the sin link function in Program MARK, and model syntax followed Otis et al. (1973) and White and Burnham (1999).

Model	ΔAICc	AICc Weight	Likelihood	No. of Estimated Parameters	Deviance
N(.) p=c[1](.)	0.00	0.31	1.00	2	21.70
N(survey type) p=c(survey type)	0.72	0.22	0.70	3	20.38
N(.) p=c(survey type)	0.84	0.21	0.66	3	20.50
N(survey type) p=c(.)	2.03	0.11	0.36	3	21.69
N(.) p=c(t)	2.36	0.10	0.31	4	19.97
N(survey type) p=c(t)	4.42	0.03	0.11	5	19.96
N(survey type) p=c(survey type × t)	7.12	0.01	0.03	7	18.49
N(.) p=c(survey type × t)	7.23	0.01	0.03	7	18.60

[1] capture and recapture probabilities were modeled to be equal

Chapter 5

POINT-COORDINATE CAPTURE-RECAPTURE TECHNIQUE TO PRODUCE UNBIASED CLOSED CAPTURE-RECAPTURE ESTIMATES OF MALE BURROWING OWL TERRITORY ABUNDNANCE

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. Due to the extent of the distribution and high abundance of Burrowing Owls in the HCP Study Area, an efficient and reliable method of surveying is needed. Here, we address Amendment 2, and present the results from developing a closed-population capture-recapture survey technique that relied on a swift recording of each Burrowing Owl's location. We developed this method to provide a cost effective method of surveying owls in the HCP Study Area, where other methods of surveying could be costly or hampered by the high density of owls. We formalized, tested, and validated the technique, showing that it produced unbiased estimates of male Burrowing Owl territory abundance.

INTRODUCTION

Many methods used to obtain abundance estimates for wildlife populations involve some form of closed-population capture-recapture sampling (Williams et al. 2002). Capture-recapture methods stem from a strong statistical and theoretical foundation and long history involving mobile animals (Petersen 1896, Otis et al. 1978, Williams et al. 2002). The general principle of capture-recapture methods is to uniquely tag individuals in a first capture occasion and record the proportion of tagged individuals in subsequent recapture occasions, with information about the detectability of organisms obtained from the recapture information of individuals (Williams et al. 2002). However, the intensive effort required to capture and tag individual animals (e.g., see Seber 1982:93 for a list of methods) can render capture-recapture methods cost prohibitive in some cases (Otis et al. 1978, Pollock et al. 1990, Petitt and Valiere 2006). Moreover, these techniques may be impractical in instances where tagging is difficult or when the population is widespread or abundance spatially variable, and the disturbance of capture activities may be incompatible with conservation strategies for sensitive species (Royle and Nichols 2003, Royle 2004). Alternatives to physically capturing and tagging animals in capture-recapture studies may reduce effort and cost, thus enabling conservation and management programs, such as that proposed for the Burrowing Owl in the HCP Study Area, to conduct annual population monitoring.

As an alternative to physically marking Burrowing Owls in the HCP Study Area, we proposed collecting point coordinates of burrowing owls during multiple occasions to generate capture-recapture encounter histories (Section 5.2 of Qualification Request #531: Final Detailed Study Approach for a Burrowing Owl Population Study). This novel approach does not require that individual owls be physically marked, but rather their point coordinates recorded and used to generate 'new' captures and recaptures. A

primary concern with this technique is the effect of misidentifying individual owls because owls move within their home ranges among survey occasions. Here, misidentification consists of 2 types of error: intrusion by neighbors and misidentifying recaptures as 'new' individuals. However, Kendall (1999) found that closed-population methods are robust to completely random movement by individuals in and out of a study area, and that estimates remain unbiased under this scenario. Equivalently, if the types of misidentification associated with using point coordinates are random, unbiased estimates of burrowing owl abundance may be attainable from encounter histories generated from point-coordinate-based survey data in the HCP Study Area.

We assessed the effects of these sources of misidentification on population estimates obtained from capture-recapture analyses computed from point-coordinate-based encounter histories. The objective of this study was to assess the probability that a 'recapture' was recorded when a pair was not seen in the buffer and effects of buffer size, detection probabilities, and owl density on the bias and precision of population estimates computed using encounter histories developed from point-coordinate data. We were particularly interested in identifying a standardized buffer width that could be used to surround each point coordinate to generate capture-recapture encounter histories.

We thank Dr. Bryan Manly (West, Inc., 2003 Central Avenue, Cheyenne, WY 82001, bmanly@west-inc.com) for his review and suggestions to perform simulations, which greatly improved the analysis. He also provided a letter to Brad Norling of the Imperial Irrigation District, dated August 22, 2007, concluding that the recommendations provided in this chapter represent the best approach.

METHODS

1. Collected field data between April 11-May 2, 2007
2. 40 individual burrowing owls from 40 breeding territories (Figure 5.1).
3. Individuals were believed to be males because they were visible much of the time during the peak period when females were anticipated to be on eggs.
4. Leg-banded most, but not all, individuals with unique numbers before April 11.
5. Conducted 13-hr continuous observations (0600-1900)/individual.
6. Recorded point coordinates of owl perch locations every 15 minutes when visible (n=1,400) using a Trimble GeoXM GPS, rangefinder, and compass with <3m accuracy. The flat agricultural landscape enabled us to maintain sight of owls even when they traveled far distances.
7. Considered the burrow entrance with the greatest amount of sign (e.g., excrement, pellets, feathers, tracks) in each territory to be the primary burrow entrance, recorded its GPS location, and used ArcGIS 9.2 (ESRI, Redlands, CA) to measure the distance between each owl's location and its primary nest burrow entrance.
8. Computed 95% fixed kernel home range utilization distributions for each owl, based on likelihood cross validation smoothing because likelihood cross-validation has been shown to be a better procedure for small sample sizes and for obtaining more accurate estimates in high use areas then other methods (Horne

and Garton 2006). This was intended to assess the level of overlap among neighboring owls.

9. Created 15 Monte Carlo datasets (each containing 4 survey occasions) by bootstrapping the original field sample to mimic our actual 4-occasion survey effort across the HCP. We decided on using 15 subsamples rather than the originally proposed 30 because variances with 15 were sufficiently small. We applied a constant detection probability (0.7), based on the average probability during diurnal periods (see Chapter 2), by randomly removing 12 of the 40 observations from each occasion.
10. These bootstrapped data were used to create capture-recapture encounter histories by buffering point coordinates with various buffer radii, generating centroids for each individual, and using the buffer radius specified to assign the latter occasion's point coordinates as existing or new individuals by the following rules:
    a. Owl point coordinate locations recorded on occasion 1 were considered as new individuals.
    b. Owl locations from occasion 2 were determined to be recaptures if they were the closest location of a location in occasion 1 and buffers from each location overlapped. All other owls from occasion 2 were considered as new individuals.
    c. We computed a center location (centroid) for owls that were observed in both occasions.
    d. Owl locations from occasion 3 were determined to be recaptures if they were the closest location to a centroid or a location from occasions 1 or 2 that were captured only once and buffers from the previous and new location overlapped. All other owls were considered to be new individuals.
    e. We computed a centroid for all owls that were captured in 2 or more occasions.
    f. Owl locations from occasion 4 were determined to be recaptures if they were the closest location to a centroid or location from occasions 1, 2, or 3 that were captured only once and buffers from the previous and new location overlapped. All other owls were considered to be new individuals.
11. Calculated the probability that encounter histories would contain misidentified owls (owls identified as their neighbor due to their location and neighbor's non-detection).
12. Computed closed-population, capture-recapture estimates of population size ($\hat{N}$) for each bootstrapped sample using the standard model structure [N(subsample) p=c(.)]; models were developed using the closed captured model with the sin link function available in Program MARK (Cooch 1999, White and Burnham 1999).
13. Computed mean estimates of population size and 95% confidence intervals for each buffer size and compared them to true (known) numbers.
14. Conducted additional simulations to test for the effects of detection probability on population estimates given the optimal buffer size.
15. Tested the effects of owl density on point-coordinate capture-recapture population estimation using additional Monte Carlo simulations with the same parameters as

for the full dataset for 2 survey routes of different densities (7 owls/km and 15 owls/km).

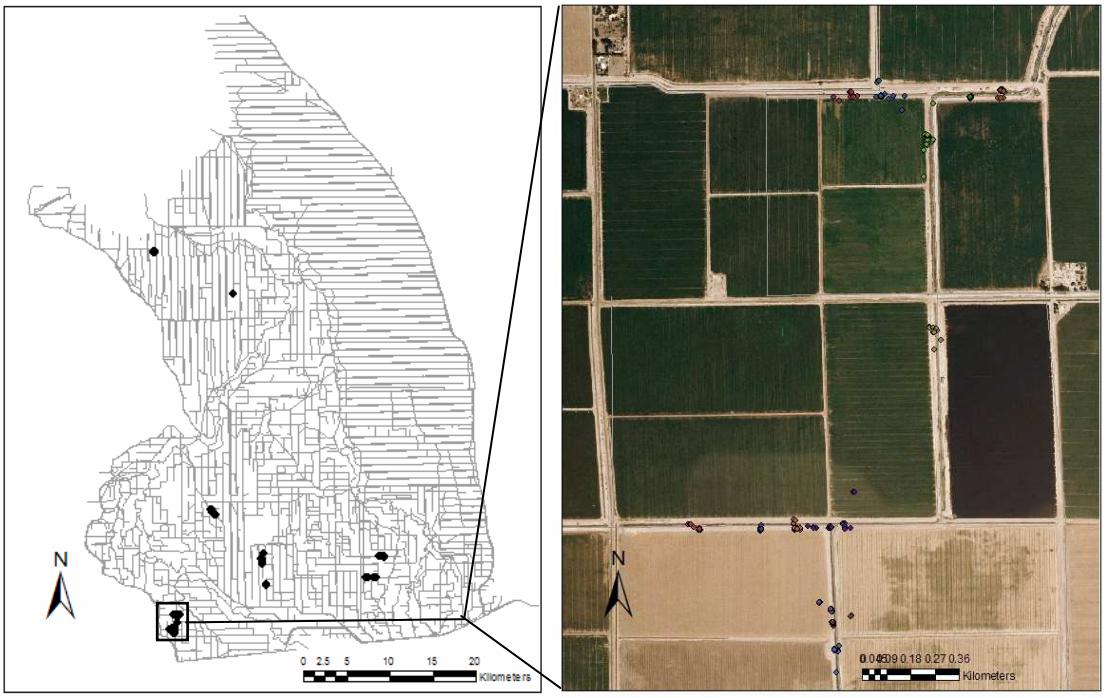

Figure 5.1. Point coordinate locations (n=1,400) of 40 individual burrowing owls at 8 randomly selected locations, Imperial Valley, California 2007.

RESULTS

The mean maximum distance between all locations of each owl was 89.2 m (95% CI: 66.9 to 111.5 m), the mean maximum distance moved (MMDM) from a nest was 58.4 m (95% CI: 46.2 to 70.5), and densities ranged from 7-15 nests/km.

Likelihood Cross Validation Fixed Kernel Home Range Sizes of Burrowing Owls and Volume of Overlap by Neighboring Owls

We used the 15-minute diurnal locations to compute fixed kernel home ranges, from which we assessed volume of home range overlap for neighboring owls. We found that on average, the amount of overlap that occurs between neighboring territorial Burrowing Owls is negligible (Mean = 0.8%, 95% CI = 0-1.9%). Such a low level of overlap suggests that misidentification of neighboring owls while using the point-coordinate-based closed capture-recapture approach used here may not occur often in the Imperial Valley agricultural matrix.

However, portioning the 2 sources of misidentification out into its constituent parts showed that the probability that a correct owl (i.e., the owl actually occupying the territory being sampled) is present for detection rapidly decreased with distance from its nest burrow, and that probability approximated zero at 110 m from the burrow (Figure

5.2). As expected, the probability that a wrong owl (i.e., neighboring owl) is present for detection in the territory being sampled increases with distance from the correct owl's nest (Figure 5.2). In other words, the closer an owl was to an active burrow when detected, the higher the probability that it was the correct owl and the lower the probability that the owl was the wrong owl, as suggested by the utilization distributions presented in chapter 2.

This expected interaction between these 2 sources of misidentification with buffered point-coordinates was the impetus for the following bootstrapping analyses.

Probability that a Recapture is Recorded when the Breeding Pair is Unavailable for Detection in the Buffer

Given a constant buffer radius approximately equal to the MMDM (55 m), a constant detection probability (0.7), 4 encounter occasions, and 40 original owls, there were 48 instances in each Monte Carlo simulation where a breeding pair was unavailable for detection.

Monte Carlo simulations indicate that the mean probability that a 'recapture' would be recorded when a pair is not available for detection, given the simulation conditions, is 0.085 (N = 15, SE = 1.1). This occurred when the correct owl was not observed, but a neighboring owl was falsely identified as the missing owl. Overall, for a survey under these conditions, the probability of this form of misidentification occurring is 0.025 (N = 15, SE = 0.3) for each observation.

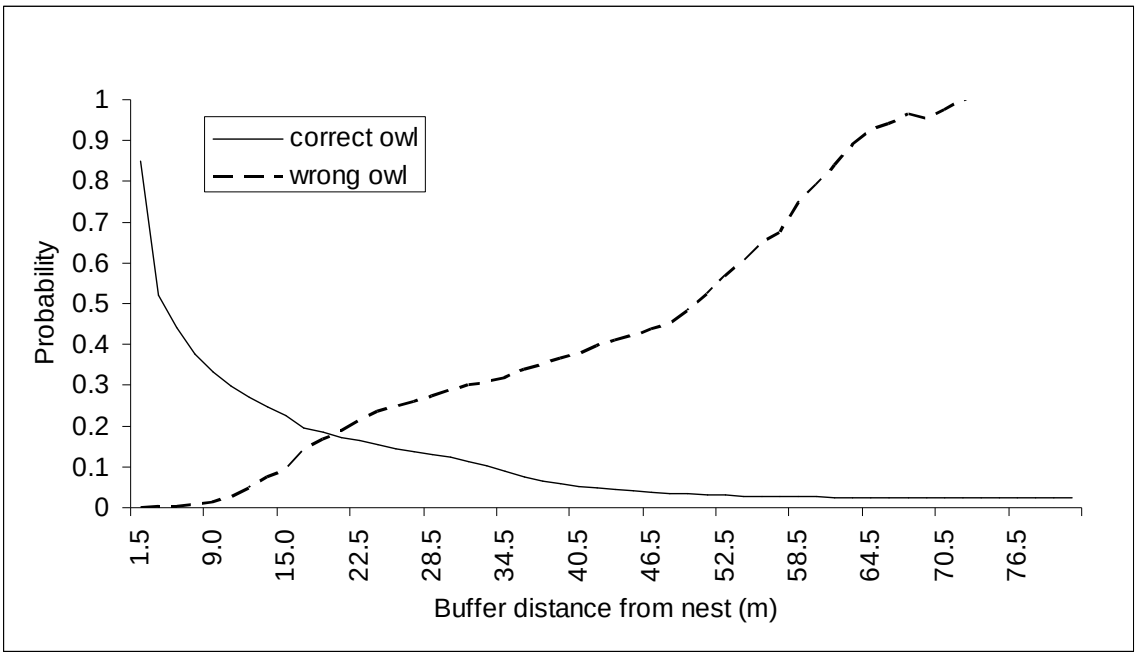

Figure 5.2. Probabilities that the correct and wrong male Burrowing Owls are present and available for detection at increasing distance from the correct owl's nest, Imperial Valley, California, April 2007.

Effects of Buffer Size on Population Estimates

Monte Carlo simulations with a constant detection probability of 0.7 indicated that the buffer radius that produced highly precise and unbiased population estimates was 55 m, approximately equal to the MMDM (Figure 5.3). These results also suggest that the effect of misidentification of individual owls as neighbors is minimal on population estimates relative to effects of misidentifying a recapture as a 'new' individual.

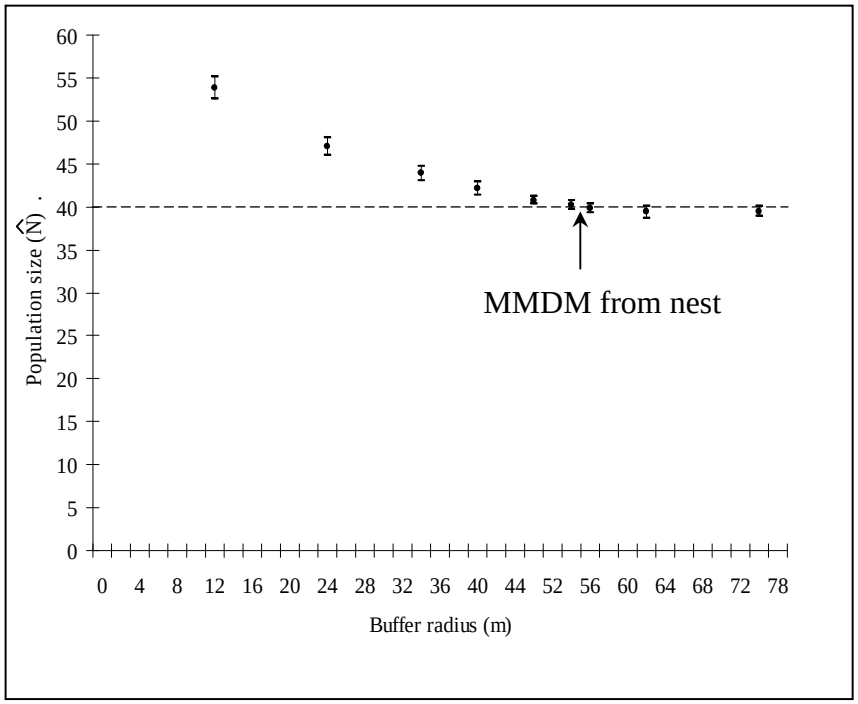

Figure 5.3. Effects of buffer size (radius) surrounding burrowing owl capture-recapture point coordinates on closed-population estimates, Imperial Valley, California. Dotted line represents true N. Vertical bars are 95% CI. Estimates are from closed-capture models [N(rep) p(.)=c(.)]; data bootstrapped from 15-min locations (with p-hat=0.7) recorded consecutively from 0600-1900 for 40 male breeding burrowing owls from April-May, 2007.

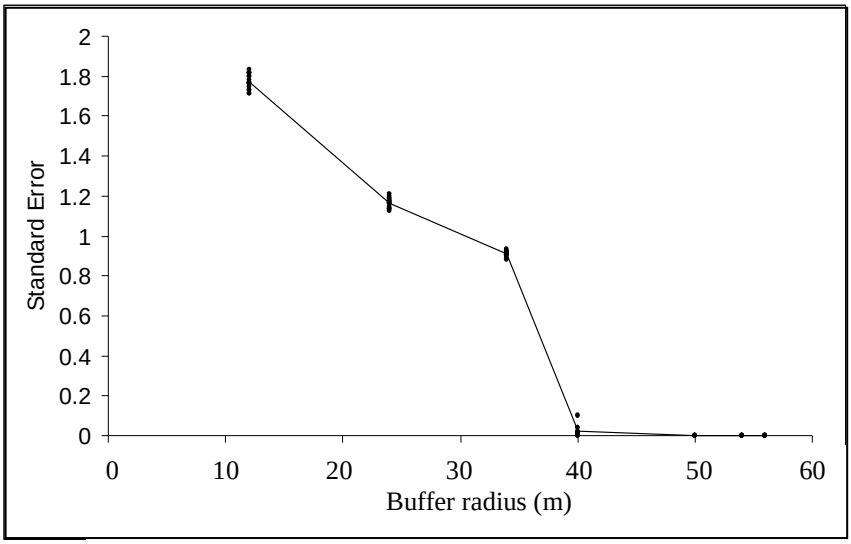

Figure 5.4. Effects of buffer size (radius) surrounding capture-recapture point coordinates of male Burrowing Owls on the standard error of closed-population estimates, Imperial Valley, California. Vertical bars are 95% CI. Estimates are from closed-capture models [N(rep) p(.)=c(.)]; data bootstrapped from 15-min locations (with p-hat=0.7) recorded

Effects of Detection Probabilities on Population Estimates

We found that the high level of accuracy obtained by buffering point coordinates with a buffer radius equal to the MMDM was robust to varying detection probabilities between 0.6 and 0.9, yielding relatively unbiased, precise estimates of male Burrowing Owl territory abundance (Figure 5.5). Detection probabilities near 0.6 may produce slightly biased low (~1%) population estimates and 0.9 slightly biased high (~1%) from the true number, but the true number fell within all 95% CIs (Figure 5.5).

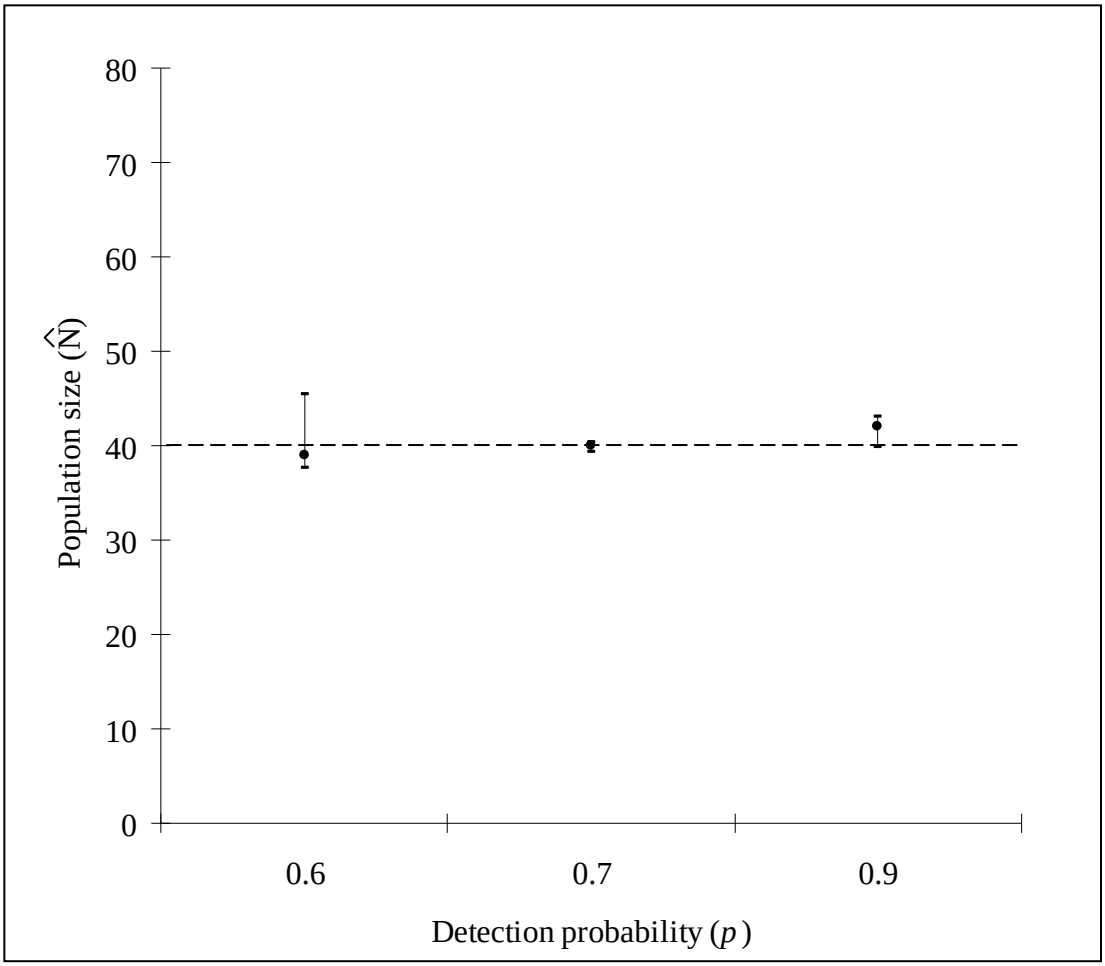

Figure 5.5. Effects of detection probabilities on burrowing owl population estimates based on a 55 m buffer surrounding capture-recapture point coordinates, Imperial County, California 2007. Dotted line represents true N. Vertical bars are 95% CI.

Effects of Density on Population Estimates

The following results are based on a fixed buffer = 55 m and a constant detection probability (0.7) and used a Monte Carlo simulation as above to create datasets representing 4 capture survey occasions along these 2 routes.

Low density (6 adjacent owls where the linear density = 7 owls/km)

Mean $\hat{N}$ = 6.1, 95% CI: 5.8 to 6.5

This $\hat{N}$ approximates the true N = 6 with reasonably good precision that encompasses the true N.

High density (7 neighboring owls where the linear density = 15 owls/km)

Mean $\hat{N}$ = 7.1, 95% CI: 6.8 to 7.5

This $\hat{N}$ approximates the true N = 7 with reasonably good precision that encompasses the true N.

CONCLUSIONS AND RECOMMENDATIONS

We found that buffering burrowing owl point coordinates with a 55 m radius circle yielded relatively precise, unbiased estimates of burrowing owl abundance that we believe are adequate for estimating annual burrowing owl abundances across the HCP on an annual basis. The 55 m radius circle essentially enabled us to identify locations from subsequent survey occasions that were the closest within 110 m from previous locations as recaptures, which corroborates with the results presented in figures 2.3 and 5.2. Our results suggest that the misidentification errors due to using point-coordinate-based encounter histories in capture-recapture analyses are random and therefore do not introduce bias into estimates of population abundance (Kendall 1999). This is because when a neighboring owl is misidentified as a recapture in its neighbor's buffer when its neighbor is undetected, the misidentified pair receives a 'zero' in its encounter history, thereby maintaining the constant probability of detection for the cohort in that occasion.

This technique produces encounter histories that provide unbiased, precise population estimates from currently available capture-recapture models. Consequently, in combination with the low level of measurement error associated with acquiring point-coordinate locations (see Appendix II for details), we believe this approach is well suited for population-level analyses. However, use of point coordinates recorded by observing vagile species like owls leads to shifting of encounters among neighboring individuals in an occasion, which can lead to unreliable estimates of detection probabilities at the level of individual animals. Thus, we (and Dr. Bryan Manly, personal communication) do not advocate the use of point coordinate capture-recapture encounter histories for estimating parameters in individual-based analyses (e.g., use of individual covariates).

This point coordinate technique is suitable for surveying Burrowing Owls in the HCP because it:

1. produces: A. unbiased, precise estimates of abundance,

2. is robust to: A. variable probabilities of detection among encounter histories and
   B. variable densities, and

3. assumes: A. high probabilities of detection (>0.6)

The Imperial Valley agricultural matrix supports conditions that meet these assumptions. Thus, we believe that the point-coordinate capture-recapture technique is an efficient technique to obtain unbiased estimates of male Burrowing Owl territory abundance in that area.

Chapter 6

NUMBER OF SURVEY OCCASIONS

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. Cost benefit information is always beneficial in designing population monitoring programs. We evaluated the minimum number capture-recapture survey occasions needed in the HCP Study Area to calculate accurate estimates of population size. We found clear evidence that a minimum of 3 survey occasions were necessary when using the point-coordinate capture-recapture technique to achieve an acceptable level of accuracy in estimating the abundance of male Burrowing Owl territories. Three survey occasions nearly doubled the precision of population estimates compared to using only 2 occasions, and a retrospective power analysis showed that ≥4 occasions provided little improvement over the 3, indicating that an increase in the number of surveys beyond 3 did not appreciably improve power, and doing so would only be at an unnecessary expense.

INTRODUCTION

To ensure accuracy of estimated owl abundances in the HCP Study Area while minimizing costs, it is essential that detection probabilities, level of effort, and sampling/analysis methods be carefully selected prior to starting the formal population-level study. To reduce cost while maintaining accuracy, it is important to determine the minimum amount of effort necessary to achieve an acceptable level of accuracy.

One type of field sampling effort associated with the approach we proposed for estimating abundance relates to the number of repeated surveys (occasions) needed to obtain accurate estimates of population size each year. As described in the original proposal, repeated survey occasions are a necessary part of the proposed closed population capture-recapture method. The original proposal called for 2 occasions. However, further insight into the existing literature on Burrowing Owls led to recommending alternatives to using only 2 occasions, as described in the letter from Bloom Biological Inc. to Bruce Wilcox dated February 24, 2006, one of which was the addition of a pilot study.

We conducted a pilot study of point-coordinate capture-recapture surveys of Burrowing Owls across approximately 412 randomly selected km of IID right-of-way in the HCP Study Area to assess the minimum number of sampling occasions required to obtain accurate estimates of population size. This was followed by prospective power analyses to elucidate the statistical power behind the minimum number of repeat sampling occasions that we identified. We assessed the accuracy of population estimates ($\hat{N}$) by their corresponding coefficients of variation ($CV(\hat{N})$). The $CV(\hat{N})$ reflects precision, and an acceptable level of precision for reliable scientific studies is considered to be 0.1 (White et al. 1982).

These initial analyses were based on 20-m buffer around each owl location to generate capture-recapture encounter histories, followed by fitting maximum-likelihood, closed-population models (Cooch and White 2006) to each capture-recapture encounter history dataset. These preliminary analyses led us to initially conclude that 4 capture-recapture survey occasions were necessary to achieve reasonably accurate estimates of male Burrowing Owl territory abundance. However, an independent peer reviewer raised several concerns regarding this buffer size, which instigated our development of the Monte Carlo simulations of the point-coordinate capture-recapture technique in 2008, as described in Chapter 5.

In order to determine the minimum number of repeat sampling occasions required to achieve accurate estimates of population size, in this chapter, we reanalyzed the 2006 data using the new analytical point-coordinate capture-recapture technique, with the mean maximum distance moved (55m) as the buffer radius (see Chapter 5 for details).

METHODS

Field Surveys

We conducted diurnal, capture-recapture surveys for Burrowing Owls from April 16-May 20, 2006 using the following detailed methods:

1. Randomly selected 64 replicate survey routes (each approximately 6.4 km in length; Figure 6.1).
2. Conducted surveys for approximately 1-hour in each replicate route at approximately the same time of day (between 0630-1830, excluding 1230-1330) for 6 consecutive days (occasions).
3. Used 1 vehicle/route (each having a driver and observer) to conduct visual surveys at 7 mph. Vehicle was positioned so observer was closest to drain/canal, observer surveyed passenger side of vehicle, and driver provided incidental observations from in front of vehicle.
4. Stopped at every ≥1 Burrowing Owl(s), and recorded the following information:

    A. Date
    B. Time
    C. Location, based on:
        i. GPS coordinates (Trimble GeoExplorer XM with GPS slider set halfway to balance productivity with precision and postprocessed differential correction)
        ii. Compass heading to owl/nest from observer (Suunto Handheld Directional Compass)
        iii. Distance to owl/nest from observer (Opti-Logic Laser Rangefinder with ±1 m accuracy)
    E. Type of location (nest burrow, no nest, flying, perched)
    F. Number of owls (1, 2, 3, …n)

5. Avoided errors in detection by not looking past the vehicle after stopping at an owl (except to track an owl that moved in order to avoid double counting) and not backtracking route.

Data Processing and Analyses

Processing and analyses of Burrowing Owl closed-population capture-recapture data entailed 3 general steps:

1. Development of capture-recapture encounter histories

    A. We used the point coordinate technique with a 55m radius buffer (which corresponds to the mean maximum distance moved (see Chapter 5))
    B. Created 5 individual encounter histories from the 64 routes:
        i. Encounter history dataset 1: First 2 occasions
        ii. Encounter history dataset 2: First 3 occasions
        iii. Encounter history dataset 3: First 4 occasions
        iv. Encounter history dataset 4: First 5 occasions
        v. Encounter history dataset 5: First 6 occasions

2. Closed population modeling

    A. Fit maximum-likelihood, closed-population models (Cooch 1999) to each capture-recapture encounter history dataset.
    B. Used the sin link function to link model coefficients to matrices because it allows for better estimation of the number of estimable parameters and of the shape of the log-likelihood function at its maximum, while constraining its parameter to be within 0-1 (White and Burnham 1999).
    C. Used deviance plots to heuristically assess model fit.

3. Minimum number of repeat sampling occasions needed to achieve accurate estimates of population size

    A. Computed coefficients of variation (CV) for each population estimate and plotted them against the number of survey occasions (Figure 6.2).
    B. Determined the minimum number of repeat survey occasions necessary for obtaining reliably precise estimates by identifying the number of survey occasions needed to achieve a $CV(\hat{N}) \leq 0.1$. We chose this cutoff because "reliable scientific studies … should try for a $CV(\hat{N}) \leq 0.1$" (White et al. 1982:50).
    C. Performed retrospective power analyses (Kuehl 1994, Steidl and Thomas 2001) with a specified range of effect sizes (changes in annual population size) to assess the relative statistical power of detecting a change in population size between the 5 encounter history datasets (2, 3, 4, 5, and 6 occasions). We used a one-tailed test (because adaptive management would be triggered only when the population would decline), an α=0.05,

and empirically based estimates of population size associated with the 5 encounter history datasets. We chose a range in population changes to yield power curves that would illustrate differences among sampling design scenarios and various changes in annual population sizes since an acceptable level of population change has yet to be determined for the demographic study (section 4.5.3 of the HCP Plan, dated June 2002).

RESULTS

Capture-recapture Results

We successfully computed CV($\hat{N}$)s and $\hat{N}$s for 300 of the 320 possible encounter histories (1 encounter history file for 2, 3, 4, 5, and 6 repeat sampling occasions x 64 routes). The 20 that were not estimated were generally those corresponding to low numbers of occasions (and hence low effective sample sizes), preventing the convergence of model likelihoods. The average detection probability was 0.63.

Minimum number of repeat sampling occasions needed to achieve accurate estimates of population size

1. Minimum number of repeat survey occasions to achieve a CV($\hat{N}$) $\leq$1 was 3.
2. Statistical power of detecting a change in the Burrowing Owl population increases with an increase in survey occasions; there was a marked increase in power from >2 occasions (Figure 6.3A).
3. Statistical power began to asymptote at 3 occasions (Figure 6.3B).

CONCLUSIONS AND RECOMMENDATIONS

We found clear evidence that a minimum of 3 survey occasions are necessary when using the point-coordinate capture-recapture technique in order to achieve an acceptable level of accuracy in estimating the abundance of male Burrowing Owl territories in the HCP Study Area. Three survey occasions nearly doubled the precision of $\hat{N}$ compared to using only 2 occasions. This high level of precision stemmed from our using 3 capture-recapture occasions on a species with high detection probabilities. For example, given the average detection probability/occasion we found here (0.63), the probability of that we <u>did</u> <u>not</u> detect a territory $\geq$1 times during the 3 occasions was 5.0% [i.e., $(1\text{-}0.63)^3$]; thus, the probability that we <u>did</u> detect a territory $\geq$1 times over the 3 occasions was 95.0% [i.e., $1\text{-}(1\text{-}0.63)^3$].

Our prospective power curve analyses showed that 3 occasions provided a marked increase in statistical power to detect a change in the annual Burrowing Owl population size compared to using 2 occasions. For example, the power curve associated with 2 occasions consistently provided the least power to detect a change at any level, and the addition of 1 more survey occasion increased power by as much as 11%. Coinciding with this increase, $\geq$4 occasions provided little improvement over 3, indicating that an increase in the number of surveys beyond 3 did not appreciably improve power, and

doing so would only be at an unnecessary expense (effort). Additionally, we advise against the use of only 2 occasions because that level of effort does not allow for the complex testing of assumptions and subsequent selection of a model from which to obtain unbiased estimates. Furthermore, the power curves began to asymptote at 3 occasions, substantiating the minimum number required to obtain the highest power to detect a change in abundance.

Prospective power analyses like these can aid in the development of future Burrowing Owl capture-recapture sampling designs because they provide a probability that a specified change in annual population change could be detected (Peterman 1990). Based on our results, we conclude that all vehicle-based point-coordinate capture-recapture surveys of Burrowing Owls (following our protocols) in the HCP should conduct 3 consecutive occasions. Fewer than 3 may provide poor accuracy and more than 3 may be an unnecessary expense.

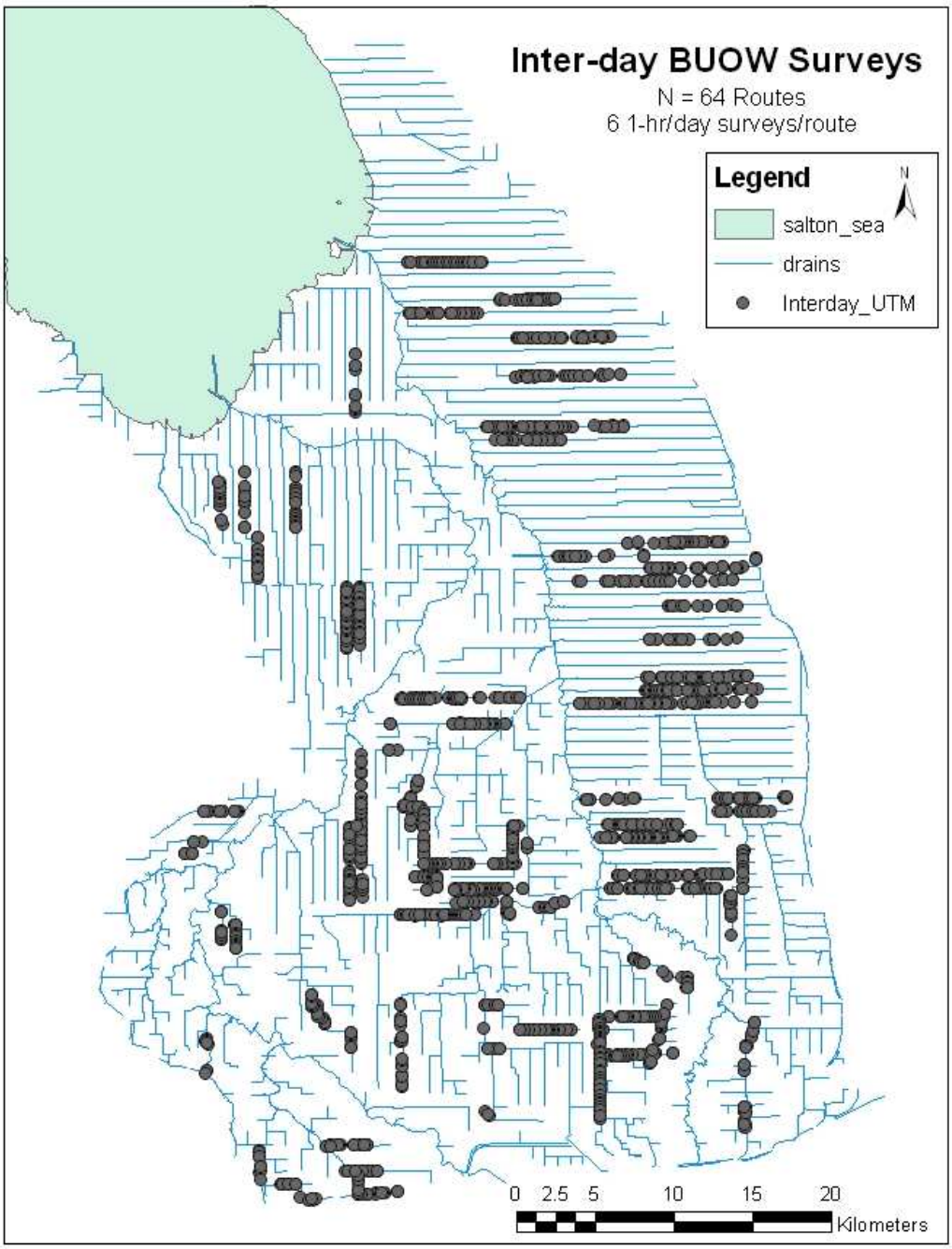

Figure 6.1. Routes where 6 consecutive days of diurnal, capture-recapture surveys were conducted for Burrowing Owls in the HCP Study Area, Imperial County, California. Points represent individual owl locations, April 16-May 20, 2006.

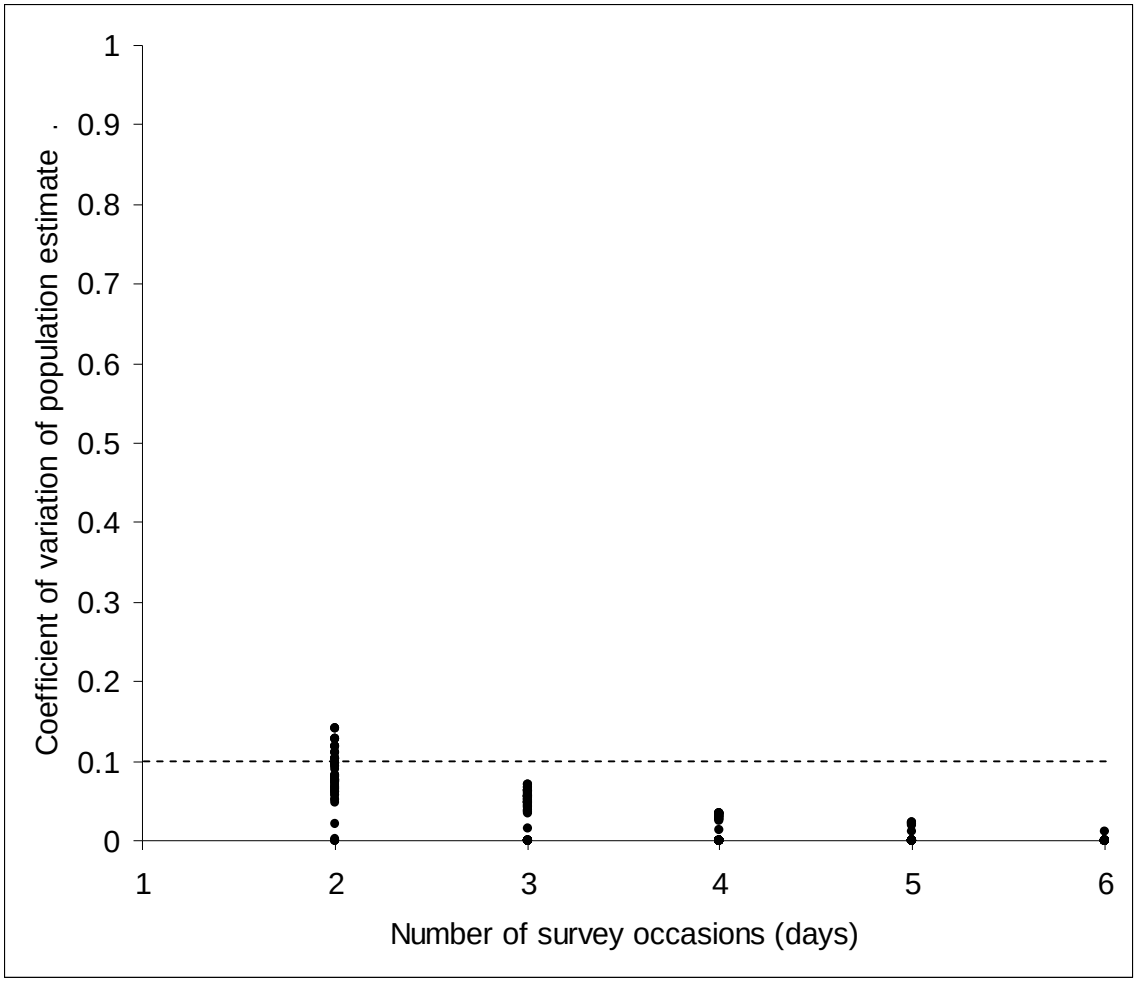

Figure 6.2. Coefficients of variation of population size as a function of the number of repeat survey occasions for male Burrowing Owl territories in the HCP Study Area, Imperial County, California, April 16-May 20, 2006. "Reliable scientific studies … should try for a $CV(\hat{N}) \leq 0.1$" (White et al. 1982:50).

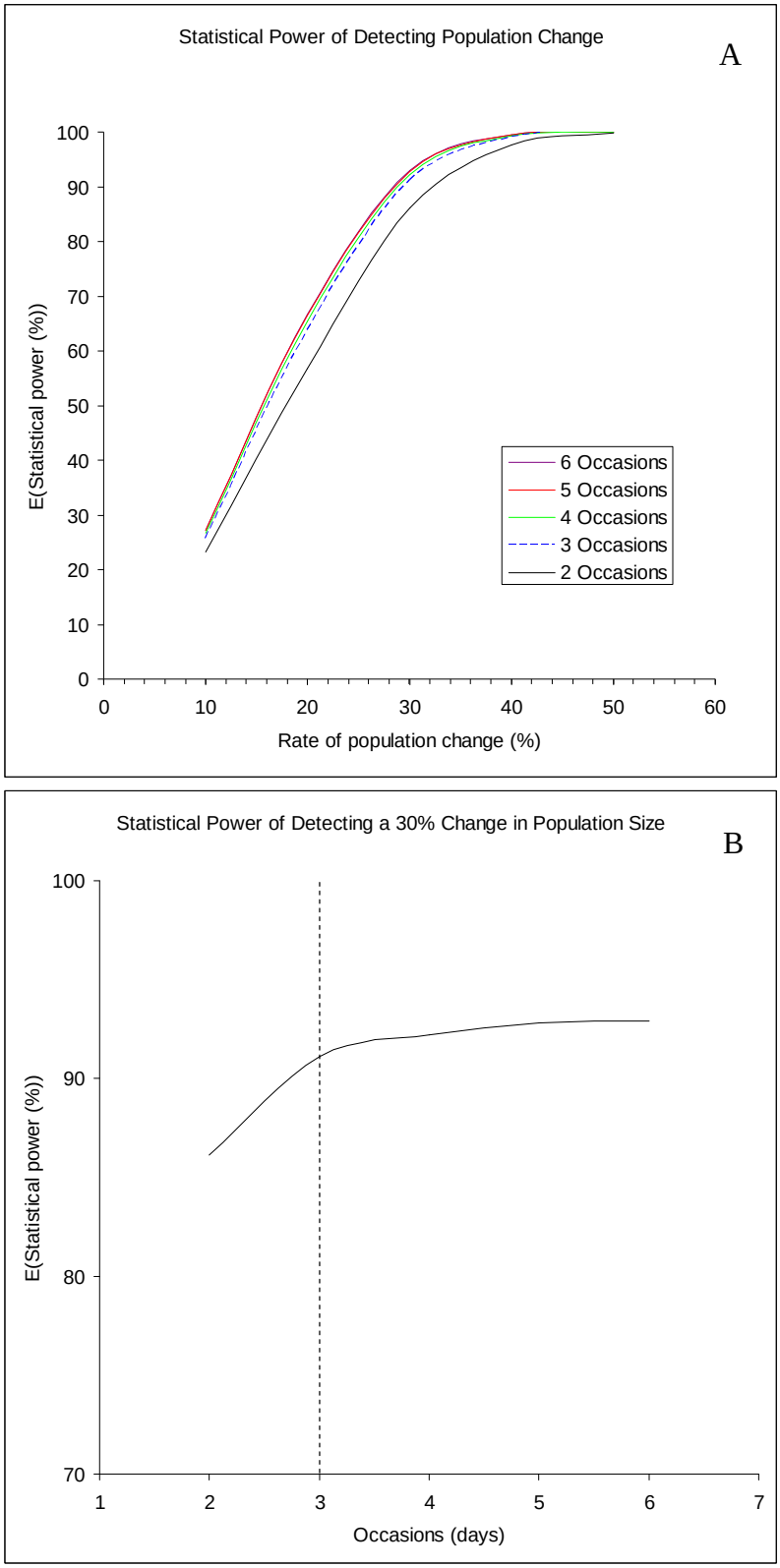

Figure 6.3. Retrospective power curves for various rates of Burrowing Owl population change (indexed by changes in population size) in the HCP Study Area, Imperial County, California, April 16-May 20, 2006. Power curves are in vertical order listed in legend.

Chapter 7

CLOSED-POPULATION CAPTURE-RECAPTURE SURVEYS IN 2007

JEFFREY A. MANNING

ABSTRACT. In this chapter, I present the results from conducting a complete census of male Burrowing Owl territories in the HCP Study Area during the prehatch stage of the breeding cycle in 2007 using the point-coordinate capture-recapture technique.

INTRODUCTION

Closed-population, capture-recapture methodology is a powerful approach for estimating the abundance of male Burrowing Owl territories in the Imperial Valley. This technique is based on marking and recapturing animals during repeated survey occasions. Repeated surveys are required to increase probabilities of detecting male owl territories and accuracy of population estimates (Otis et al. 1978). Generally, greater numbers of survey occasions increase the accuracy of population abundance (Otis et al. 1978, White et al. 1982). There is an optimal number, beyond which additional surveys would not improve accuracy appreciably and thus would constitute wasted effort. Based on preliminary analyses from a pilot study in 2006, we initially suggested that 4 occasions were appropriate; we therefore completed 4 survey occasions in 2007. However, as we reported in Chapter 6, a recent reanalysis of that data led us to recommend that the application of the point-coordinate capture-recapture survey technique to estimate the size of the owl population in the HCP Study Area requires only 3 survey occasions to achieve an optimal level of effort when following our survey protocols.

Achieving accurate population estimates from closed-population sampling methods depends on meeting the critical assumption of population closure (no emigration, immigration, births, or deaths) (White et al. 1982). We met this assumption demographically by conducting point-coordinate surveys in a brief period (≤30 days from April 2-May 3), which coincided with the prehatch stage of the breeding cycle, when females incubate and males remain sentinel outside the nest entrance (Martin 1973, Plumpton and Lutz 1993). This period began after migrant owls were thought to have departed from the Imperial Valley, ended prior to resident owls fledging young, and coincided with minimal movements of resident males away from burrows. The majority of resident females should have already been pair-bonded with males by the start of this period, and have been spending the majority of their time in the burrow. Thus, we minimized the risk of biasing estimates of male owl territories in the HCP Study Area by avoiding migrant and fledgling owls and surveying when males were expected to exhibit minimal movements away from nest burrows while females were unavailable for accidental double counting.

METHODS

We conducted diurnal, capture-recapture surveys for Burrowing Owls from April 2 – May 3, 2007 using the following detailed methods:

1. Conducted 4 point-coordinate survey occasions (1 occasion/day) along every IID right-of-way that paralleled an aboveground water conveyance structure (canal and/or drain) in the HCP Study Area. During each survey occasion, the vehicle traveled one side of an isolated drain or canal. Where ≥2 water conveyance structures paralleled multiple access roads within a single right-of-way and the field of view could be compromised by distance between the water conveyance structures (roughly ≥60 m) or topography, a survey was conducted on >1 of the roads to ensure complete survey coverage of the right-of-way while care was taken to not survey the same water conveyance structure twice (i.e., each water conveyance structure was surveyed from only one side).
2. Conducted diurnal, visual surveys by traveling the same direction during all 4 surveys.
3. Conducted the 4 surveys at approximately the same time of day (½-hr after sunrise to 1130 and 1600 to ½-hr before sundown) to avoid issues with reduced availability of owls during midday:

April 2-11:	0700-1130 and 1600-1830
April 12-23:	0650-1130 and 1600-1845
April 24-May 3:	0640-1130 and 1600-1850

4. Randomly partitioned the HCP Study Area into 6 routes (where a consecutive number of survey occasions completed along a route was considered to be a survey session; Figure 7.2), and completed each session with 1 vehicle (each having a driver and observer) traveling 7 mph in 4 days (e.g., 4 survey occasions/route). Vehicles were positioned so the observer was closest to drain/canal, observer surveyed passenger side of vehicle, and driver provided incidental observations towards the front of vehicle.
5. Stopped at every ≥1 Burrowing Owl(s), and recorded the following information (in ≤2 minutes) for the 1st owl detected at that stop and separately for any owl(s) >20 m from the first owl detected or in addition the first 2 owls seen:

   A. Date
   B. Time
   C. Location of burrow entrance <20m from the owl(s) that contained the highest number of signs of activity (e.g., an owl that retreats or flushes from burrow, regurgitated pellets, feathers, nest lining, whitewash, or footprints with an absence of cobwebs; Conway et al. 2008) or the closest burrow if multiple burrows revealed an equal amount of signs of activity. Location of owl, if no burrow is evident within 20 m.
      i. GPS coordinates (Trimble GeoExplorer XM with GPS slider set halfway to balance productivity with precision and postprocessed differential correction)

ii. Compass heading to owl/nest from observer (Suunto Handheld Directional Compass)
iii. Distance to owl/nest from observer (Opti-Logic Laser Rangefinder with ±1 m accuracy)

D. Detection method
E. Observed behavior (Flush/flying)
F. Fate
G. Type of location (nest burrow, no nest, flying)
H. Number of owls (1 or 2)
I. Type of perch:

i.	At burrow entrance	-- within the burrow entrance
ii.	On bare ground	-- on bare ground (with no veg or debris)
		-- on cement liner (with no veg or debris)
iii.	Flying only	-- never seen on the ground (wings flapping)
iv.	On pppwdfh	-- on fence post or stake
		-- on horizontal pipe
		-- on utility pole
		-- on utility or fence wire
		-- on debris pile (cement, dirt, gravel, other)
		-- on farm equipment
		-- on head gate
v.	In or on vegetation	-- in live or dead vegetation
		-- on live or dead vegetation
vi.	In agricultural field	-- in vegetated agricultural field
vii.	On hay bale(s)	-- on hay bale(s)
viii.	Other	-- any other structure or substrate, described

J. Texture within an approximated 8-degree radius circle centered on the detected owl from observer's view. This was based on a 6-m radius circle surrounding an owl at 21 m from the observer because many vantage points for detecting owls were approximately 21 m from where owls often perched (across the water conveyance structure).
K. Vegetation cover in the same circle used for measuring texture:
   i. 0%
   ii. 1-25%
   iii. 26-50%
   iv. 51-75%
   v. 76-100%
   vi. No vegetation because owl was silhouetted above horizon
   vii. No vegetation because owl was detected in flight
L. Leg band status:
   i. Banded
   ii. Unbanded
   iii. Unknown
M. Number of squirrels detected since previous owl location

6. Avoided errors in detection by not looking past the vehicle after stopping at an owl (except to track an owl that moved in order to avoid double counting) and not backtracking route in order to obtain detections primarily from the moving vehicle. If an owl was detected while not in the moving vehicle, the above information was recorded and a note that it was not detected from the moving vehicle.
7. Standardized observations by having the vehicle lights off, windows rolled up, come to a stop after passing detected owl to avoid flushing it forward into areas yet to be surveyed, and engine turned off upon stopping; also required all field biologists to participate in extensive training and field exercises; did not use cell phones, radio, and cameras while surveying.

This survey method essentially 'marked' or 'captured' each territory on the first date observed using global positioning system (GPS) coordinates. 'Recaptures' were successive recordings of GPS coordinates during subsequent sampling occasions, identified using the method described in Chapter 5.

RESULTS

We conducted 4 capture-recapture survey occasions along 3,960 Km of IID right-of-way that paralleled an above-ground irrigation canal and/or drain. We observed 3,461 male Burrowing Owl territories on the first capture-recapture occasion; on the second, we observed 3,685, the third 3,737, and the fourth had 3,748 (Figure 7.1). Owl locations by survey session are portrayed in Figure 7.2.

Obstacles that led to delays in our traveling along the IID right-of-ways included locked gates, farm equipment, piled hay bales, erosion, mud, sand, and restricted access to private property.

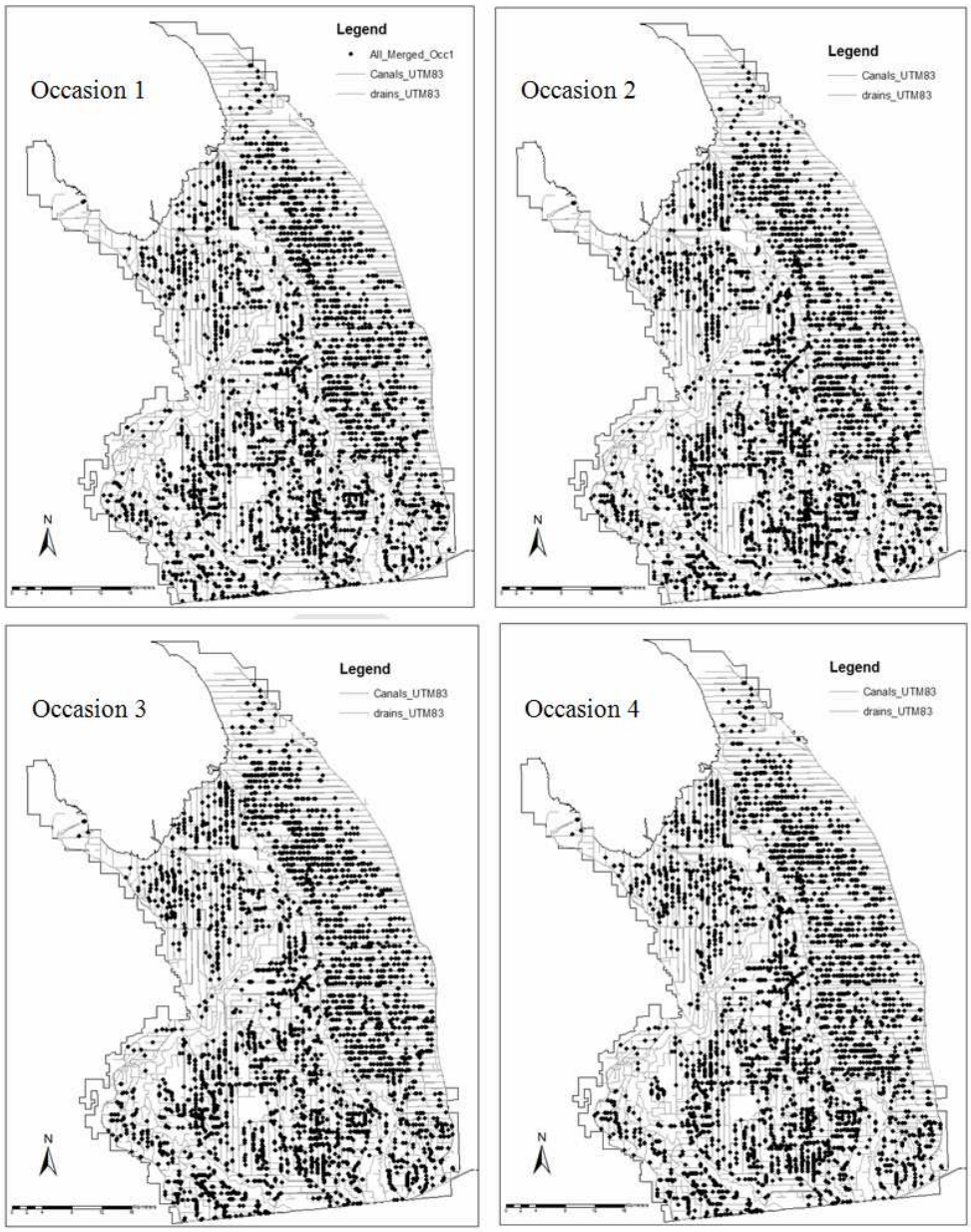

Figure 7.1. Point coordinate locations of male Burrowing Owls during capture-recapture survey occasions 1, 2, 3, and 4 from April 2-May 3, 2007.

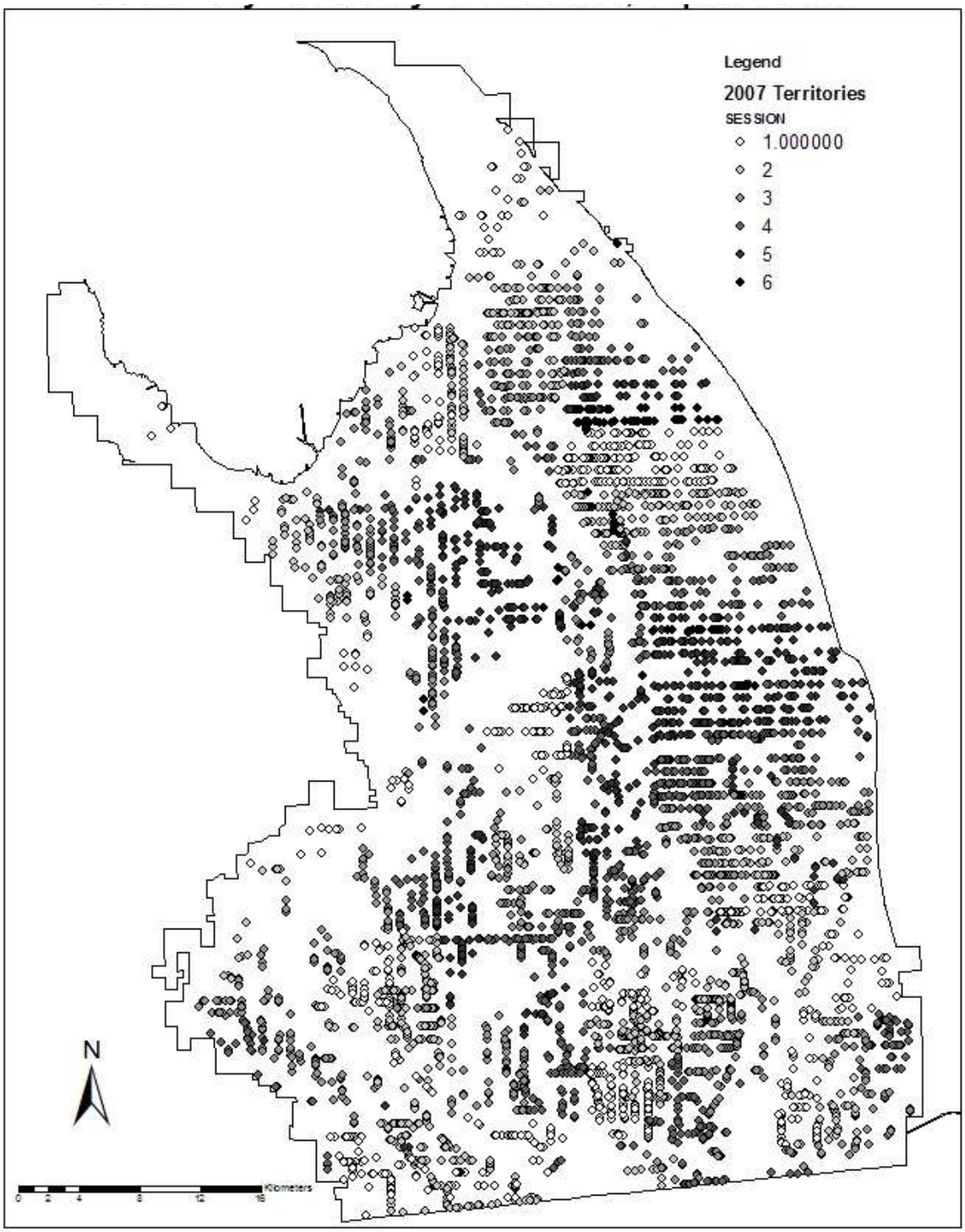

Figure 7.2. Locations of male Burrowing Owl territories coded according to 6 separate 4-occasion survey sessions during the prehatch stage of the breeding cycle across the HCP Study Area, Imperial County, California, 2007.

CONCLUSIONS AND RECOMMENDATIONS

These surveys of 3,960 Km of IID right-of-way that paralleled above-ground water conveyance structures during 6 4-day survey sessions over a 30-day period demonstrates that a complete census of the HCP Study Area during the prehatch stage of the breeding cycle is possible. The successful completion of these surveys was largely due to the absence of significant delays or postponements through intensive preplanning and training, and the cooperation and support of the IID staff. The IID staff informed private landowners in advance and during our surveys of the survey effort, provided gate keys upon our encountering locked gates, and shared additional support. Such collaboration would be essential for the success of any future HCP-wide census.

We conducted these 4 survey occasions prior to the new information we presented in chapter 6, which suggested that only 3 survey occasions are necessary to compute reliable estimates of population size in the HCP Study Area. The first 3 survey occasions of Burrowing Owl point-coordinates presented here provide the basis for constructing point-coordinate capture-recapture encounter histories, as described in Chapter 5, that will be used in chapter 8 to compute maximum likelihood estimates of male Burrowing Owl territory abundance in the HCP Study Area.

Chapter 8

MAXIMUM LIKELIHOOD ESTIMATE OF MALE BURROWING OWL TERRITORY ABUNDANCE IN THE HCP STUDY AREA IN 2007

JEFFREY A. MANNING

ABSTRACT. Maximum likelihood estimates of population size are widely considered to be the most reliable estimates attainable by wildlife scientists. Here, I present a maximum likelihood estimate of male Burrowing Owl territory abundance in the HCP Study Area using the data presented in Chapter 7. The data were pooled into a single capture-recapture encounter history and categorized according to six separate periods when the 3 survey occasions occurred. In the absence of sampling error or sampling units, this analysis estimated the population to be 4,998 (95% CI=4,946-5,081).

INTRODUCTION

The HCP specified the need to obtain annual estimates of the population of male Burrowing Owl territories in the HCP Study Area. One approach to achieve this would be to sample the HCP Study Area and extrapolate those results to the remainder of the area that was not sampled. Alternatively, a complete census could be used to estimate a single estimate. The latter approach is not cost effective on an annual basis. But, because our approach to develop a validated survey method relied on 2 consecutive years of complete censuses, we had the unique opportunity to utilize those data to compute annual estimates for those years. This chapter presents the estimated population size of male Burrowing Owl territories during the prehatch stage of the breeding cycle along the IID's rights-of-way in the HCP Study Area in 2007.

METHODS

I combined the encounter histories from all male Burrowing Owl territories across the entire HCP into a single encounter history dataset, and stratified it by 6 survey sessions, as described in Chapter 7. I used the closed-capture capture-recapture models with the sin link function available in Program MARK to fit 6 maximum likelihood models to these data (Table 8.1, Otis et al. 1978, White et al. 1982, Cooch 1999, White and Burnham 1999). All models estimated abundance for the portion of the HCP Study Area that was surveyed in each session, and assumed that detection and recapture probabilities were equal and either constant [$\hat{p} = \hat{c}$ (.)], vary across occasions [$\hat{p} = \hat{c}$ (t)], vary among sessions [$\hat{p} = \hat{c}$ (session)], or vary by the interactive effects of session and occasions ($\hat{p} = \hat{c}$ (session x t)). I used Akaike's Information Criterion adjusted for small sample sizes (AIC_c) to determine the most parsimonious model and considered this to be my best model (Akaike 1973, Burnham and Anderson 2002). I obtained estimates of abundance for each session $(\hat{N}_s)$ from this model, and considered the sum of the abundance

estimates for the sessions ($\sum_{i=1}^{6} \hat{N}_s$) as the approximate true population size of male Burrowing Owl territories in the HCP Study Area in April 2007. I assessed the lack-of-fit of this model to the data by examining a plot of its deviance residuals. A symmetric and narrow pattern of deviance residuals close to zero would suggest a good fit to the data, whereas a wide pattern around zero would suggest poor fit due to extra-binomial variation.

Although I had initially proposed to include individual covariates (e.g., percent vegetation and texture) into the models, our approach of using buffered point coordinates restricted their use at this stage of analysis, as described under the conclusions and recommendations in Chapter 5.

RESULTS

The most parsimonious model showed that detection probabilities varied through time differently within each session (Table 8.1). This model fit the data well (deviance residuals followed a narrow and symmetric pattern surrounding zero), and estimated a total of 4,998 (95% CI=4,946-5,081) male Burrowing Owl territories in the HCP (Table 8.2).

Table 8.1. Closed-population capture-recapture models fit to male Burrowing Owl Territory encounter histories and their corresponding ΔAIC_c-values, Imperial Valley, California, April 2007.

Model Syntax	ΔAIC_c	AIC_c weight	No. of Parameters	Deviance
$\hat{p} = \hat{c}$ (session x time[1])	0	1.00	24	298.628
$\hat{p} = \hat{c}$ (session)	234.53	0.00	12	557.218
$\hat{p} = \hat{c}$ (time)	276.98	0.00	9	605.68
$\hat{p} = \hat{c}$ (.)	294.78	0.00	7	627.487

[1] Time refers to days (n=3), as a survey occasion occurred on each of 3 days.

Table 8.2. Estimates of detection and abundance of male Burrowing Owl territories during the prehatch stage of the breeding cycle in the HCP Study Area, Imperial County, California, 2007. Estimates are from the best closed-population model in Table 8.1.

	Detection and recapture probabilities (p=c) (SE)			
Session[1]	Occ. 1	Occ. 2	Occ. 3	$\hat{N}_s$ (95% CI)
1	0.71 (0.02)	0.67 (0.02)	0.79 (0.01)	897.4 (890.3 - 909.2)
2	0.68 (0.01)	0.69 (0.01)	0.77 (0.01)	1161.4 (1152.5 - 1175.1)
3	0.58 (0.02)	0.62 (0.02)	0.72 (0.01)	1102.1 (1088.2 - 1121.5)
4	0.64 (0.02)	0.78 (0.01)	0.52 (0.02)	985.7 (974.1 - 1002.6)
5	0.70 (0.02)	0.68 (0.02)	0.68 (0.02)	758.4 (749.9 - 771.8)
6	0.60 (0.05)	0.71 (0.05)	0.70 (0.05)	92.8 (90.7 - 100.4)
Entire HCP Study Area				4998.0 (4948 - 5081)

[1] Refers to 3 consecutive survey occasions in 6 different geographic portions of the HCP Study Area.

CONCLUSIONS AND RECOMMENDATIONS

Based on the closed-population point-coordinate capture-recapture estimation procedure used there, the estimate of 4,998 (95% CI=4,946-5,081) best approximates the true population size of male Burrowing Owl territories in the HCP Study Area in April 2007.

Chapter 9

EVALUATION OF SPATIAL AUTOCORRELATION IN MALE BURROWING OWL TERRITORY ABUNDANCE AND THE DETERMINATION OF A STANDARDIZED SAMPLING GRID

JEFFREY A. MANNING AND STACIE ROBINSON

ABSTRACT. A standardized sampling grid across the HCP Study Area would standardize a population of sampling units that could be sampled annually for estimating and comparing Burrowing Owl population sizes. We present the results on an analysis of spatial autocorrelation in owl abundance to identify an appropriate resolution of a standardized sampling grid intended for use in sampling the HCP Study Area for Burrowing Owls in subsequent years. In accordance with Amendment 1, and based on the needs of the analytical survey and sampling methods, we determined that a 3x3 km grid cell resolution was appropriate for establishing a standardized grid.

INTRODUCTION

The original HCP document required that the relative abundance and distribution of owls be determined (section 4.5.2.2). In order to evaluate relationships between correlates and abundance, a standardized unit to measure abundance is needed. Such sampling units should be independent from one another. Since levels of Burrowing Owl abundance are believed to vary across the HCP Study Area, we suspect that abundance may be spatially auto-correlated, in which case independence has a spatial component to it. Fortunately, spatial statistics can be used to evaluate at what resolution spatial independence of male Burrowing Owl territory abundance may occur in the HCP Study Area. We initially proposed using the linear distance of the IID's rights-of-way for this analysis, but later proposed and received approval for an amendment to this (see executive summary), which entailed the evaluation of grids of various grid cell sizes to evaluate spatial autocorrelation. The intent of such an analysis would be to determine a standardized sampling grid.

A standardized sampling grid would standardize a population of sampling units that serve the purpose of making comparisons between annual population estimates over the 75-year permit of the HCP. Data currently available and suitable for an evaluation of grid cell sizes comes from the owl surveys presented in the previous chapter. These data are from a census of the HCP Study Area, the methods were thorough and standardized, and they provide an opportunity to assess possible relationships in spatial patterns of owl abundance. Because these data are empirical, their use comes with the assumption that they are from a population of owls that exhibit an approximate distribution and pattern of local abundances typical to that expected to be present over the life of the HCP.

Spatial patterns provide information about the processes that affect ecological communities (Fortin and Dale 2005), as well as information to best model systems where

data are not spatially random (Haining 2003). Assessing spatial autocorrelation is a basic, but critical, step in assessing data structure and describing spatial patterns. Spatial autocorrelation describes the degree to which similarity in data values is dependent on spatial proximity (Haining 2003). The extent of spatial dependence can be used to describe ecological structure and define the extent of biological communities (Fortin and Dale 2005, Heywood 1991). The definition of ecological neighborhoods based on the extent of spatial autocorrelation has even been used to define units for conservation and reserve design (Diniz-Filho and Telles 2002).

Sampling designs and distributions of selected sampling units can affect the spatial pattern observed in the data, and may influence a researcher's ability to infer the true spatial structure in an ecological system (Tobin 2004). This is especially true of complex ecological systems like the Imperial Valley, where numerous environmental factors may combine to affect the spatial distribution of Burrowing Owls (Legendre and Fortin 1989). The census of owls across the HCP Study Area that were conducted in the IID's rights-of-way (see previous chapter) does not represent a sample and therefore should not affect the spatial pattern we observe. We are confident that the data enables us to capture the true patterns in the distribution of male Burrowing Owl territories.

In looking at the abundance of male Burrowing Owl territories across the Imperial Valley, we needed to decide on an areal unit of analysis in which to compute abundance. The definition of analysis units and the scale of spatial analysis can substantially affect the extent and intensity of spatial pattern observed (Turner et al. 1989, Wiens 1989). The manner in which we divide the study area into sampling units to assess abundance could therefore influence the spatial patterns (i.e. the degree of spatial autocorrelation) we observe. We chose square sampling units because they have smaller perimeter lengths per unit area than rectangular units and therefore less potential for error in including individuals in a unit. Square units are generally easier to map out than rectangular ones. Square units can also be used to easily subdivide a study area into non-overlapping areas without excluding areas, which is not the case with circular units.

It has long been established that spatial analyses should be carried out at multiple scales to get the most accurate picture and to detect confounding influences of scale on spatial patterns (Mead 1974). In order to assess scale effects and decide upon an areal unit of analysis for computing owl abundance, we performed spatial analyses at multiple resolutions using variable grid cell sizes to partition the study area.

METHODS

Autocorrelation – Moran's *I* Correlogram

1. Used the maximum number of owls observed during the 4 occasions for grid cell counts.
2. Grid cell sizes were 1x1 km, 2x2 km, 4x4 km, 8x8 km, 10x10 km, 11x11 km and 12x12 km.
3. Computed density of owls in grid cells as count/km of IID linear right of way.

4. Constructed Moran's *I* correlogram.
    A. Moran's *I* provides an autocorrelation measure that is similar to a Pearson's correlation coefficient, and ranges from -1 to 1 (Moran 1950).
    B. A negative Moran's *I* would suggest that similar densities were over-dispersed, or spread farther than expected at random.
    C. A positive Moran's *I* would indicate that similar densities were clustered or closer together than expected at random.
    D. The correlogram is a graph of the Moran's *I* coefficient calculated at multiple distance thresholds (i.e. Moran's *I* is first calculated according to all pairs of nearest neighbors, then all pairs of 2nd order neighbors, then 3rd, 4th etc.). In this way we graphed the decay of spatial dependence between neighbors as the distance separating them increased (Fortin and Dale 2005, Haining 2003, Rangel et al. 2006).
5. Used program SAM – Spatial Analysis for Macro-ecology (Rangel et al. 2006)
    A. Number of distance classes used coincided with 80 km [the approximated longest distance across the HCP divided by grid cell size (i.e., the number of neighbors expected to span the maximum distance across the HPC)].
    B. Used Queen's adjacency scheme (included neighbors on all sides and corners)

Autocorrelation - Variogram

1. Constructed semivariograms (refered to as variograms)
2. The variogram plots variance between sampled pairs against distance
3. The variogram can be seen as a compliment or inverse of the correlogram – where as the correlogram shows the breakdown in correlation at increasing distance, the variogram graphs the increase in variance between sampled pairs as the distance between them increases (Cressie 1991, Fortin and Dale 2005, Haining 2003, Ribeiro et al. 2003)
4. The variogram curves upward as long as the variance between samples increases with distance, at some point the curve levels off where distance no longer influences the variation between samples – this point is called the sill
5. Calculated variograms using geoR (Ribeiro et al. 2003), a package in the R statistical environment (Ihaka and Gentleman 1996)
6. Both classical and modulus models were used for completeness (Cressie 1991)

Determination of a Standardized Sampling Grid

We received a joint assessment of our results from the above analyses by Dr. Manly (WEST, Inc., Laramie, WY). His assessment required the further analyses at intermediate grid cell sizes (Figure 9.2). In light of the need to establish a grid that would be appropriate for stratified random sampling, this assessment was based on the following issues:

1. Large enough to support reasonably sized numbers of owls for capture-recapture modeling.

2. Large enough to support a range of abundances (including zero) for estimation purposes.
3. Small enough to support a large population of cells necessary for stratified random sampling.
4. Small enough to reduce washing out variation in covariates of abundance.

We developed a standardized sampling grid in ArcGIS 9.2 (ESRI, Redlands, CA) based on the assessment from Dr. Manly and laid it over the HCP Study Area. In doing this, some grid cells along the border of the HCP Study Area encompassed non-HCP Study Areas; to avoid inclusion of these areas, we refined the geographic extent of that grid by clipping it to the boundary of the HCP Study Area. However, clipping led to non-square cells along the boundary. In order to maintain grid cells of approximately equal size (which is advantageous for survey logistics and with the stratified random sampling framework described in Chapter 15), we combined some of these individual cell fragments that contained IID water conveyance structures to approximate the size of the standardized cell size. We removed cells that lacked any IID water conveyance structures, as these were not surveyed during this study.

RESULTS

We found that the abundance of male Burrowing Owls was spatially autocorrelated across the HCP at all grid cell resolutions we examined (Figure 9.1). Based on the subsequent assessment with Dr. Bryan Manly (Figure 9.2), it was determined that the 3x3 km grid cell provided a fairly large number of cells (n = 274), which contained reasonable numbers of owls for capture-recapture modeling and should be sufficient for stratified random sampling. This size reflected a balance of assessed issues; larger cell sizes reduced the number of cells available for stratification and smaller cells reduced sample sizes for capture-recapture modeling. The final, refined, standardized sampling grid produced 274 grid cells, with some clipped and combined cell fragments along its border approximating the 9 km^2 cell size (Figure 9.3).

CONCLUSIONS AND RECOMMENDATIONS

Based on the presence of spatial autocorrelation in the abundance of male Burrowing Owl territories across the HCP Study Area, we did not find a grid cell size that eliminated the autocorrelation among sampling units. Recognizing the need to establish a standardized grid from which to sample owls from so comparable estimates can be made in subsequent years, we chose to focus on the additional needs to adequately stratify the HCP Study Area. Based on Dr. Manly's assessment, we conclude that a 3x3 km grid cell would be appropriate for performing the current analyses and future surveys and analyses of male Burrowing Owl abundance.

This grid is intended for use in future surveys through the 75-year period of the HCP, from which a new random sample of grid cells should be obtained each year. This conclusion is based on our analyses of empirical owl data collected in 2007, and assumes that the data represent the typical distribution and abundance of owls across the HCP in

subsequent years. As recommended by Dr. Manly, because spatial autocorrelation is inevitable, it needs to be assessed and accounted for the final model used to estimate abundance of male Burrowing Owls in the HCP Study Area.

Figure 9.1. Spatial autocorrelation Moran's I, correlogram, and variogram results.

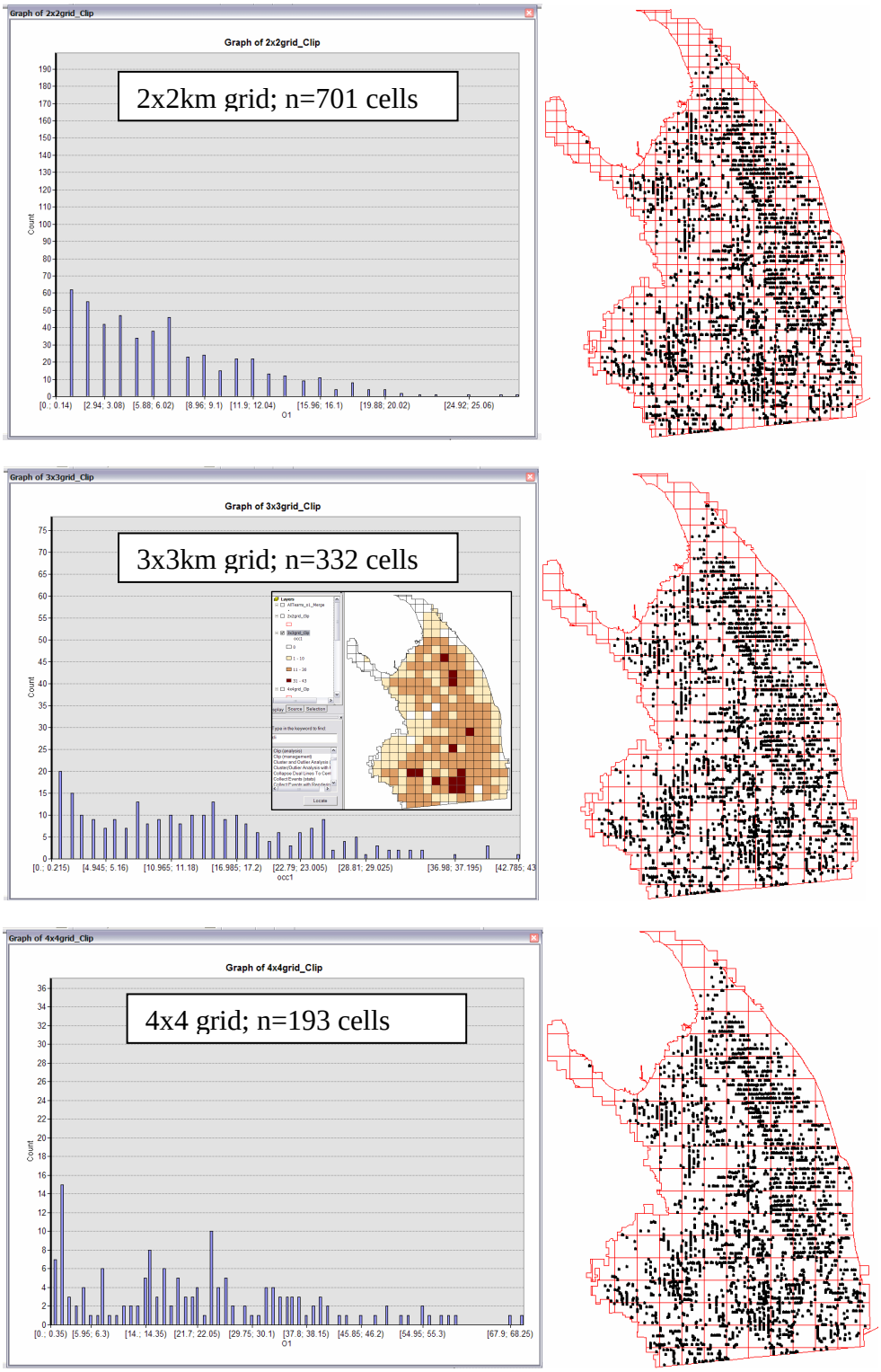

Figure 9.2. Histograms and figures of owl abundance at various grid cell sizes included as part of an assessment of results by Dr. Bryan Manly (WEST, Inc., Laramie, WY).

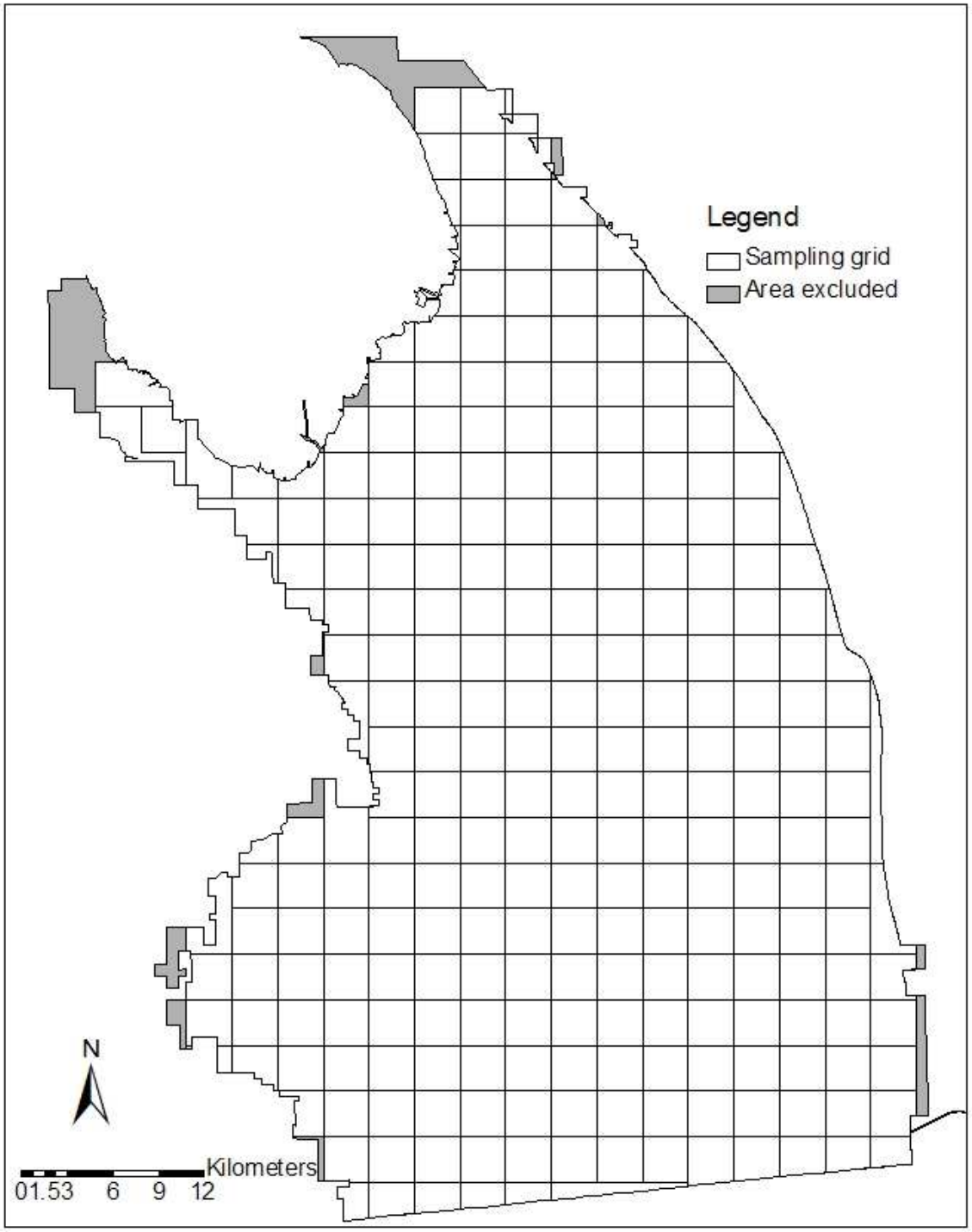

Figure 9.3. Standardized grid of 274 3x3 km sampling units for surveying Burrowing Owls in the HCP Study Area, Imperial County, California. Excluded areas are those where IID water conveyance structures were absent at the time of this survey, April 2007. Some cells along the boundary approximate 9 km^2 due to clipping and combining.

Chapter 10

MAXIMUM LIKELIHOOD ESTIMATES OF LOCAL MALE BURROWING OWL TERRITORY ABUNDANCE IN 2007

JEFFREY A. MANNING

ABSTRACT. Individual grid cells across the HCP Study Area can be used to adequately represent local Burrowing Owl territory abundances for comparisons across the area and annually. I calculated maximum likelihood estimates of local male Burrowing Owl territory abundance for each 3x3 km grid cell in 2007. To satisfy Amendment 6 and provide a total population estimate that could be compared as an approximation to the true population size to estimates calculated from sampling the data (as done in later chapters), I summed the abundances among the grid cells. Local abundances varied from 0-54 territories, and the approximated true population size was 4,879 (95% CI: 4,847 - 5,387).

INTRODUCTION

The HCP specified the need to obtain annual population estimates of male Burrowing Owl territories in the HCP Study Area. A complete census conducted annually could be used to obtain annual population sizes. However, such an extensive annual effort would be cost prohibitive and would still have to account for errors attributable to detection below 100%. A more practical and cost effective approach commonly applied by wildlife scientists would be to randomly sample portions of the HCP Study Area and extrapolate those results to the remainder of the area that was not sampled. This is because a random selection of sample units from an available population of units can yield statistically and biologically reliable population estimates. It is important to note that the population of Burrowing Owls is not the same as the population of grid cells referred to here for sampling. In order to have a population of sampling units to draw random samples from and compute local abundances annually, we developed the grid of 3x3 km cells in the previous chapter.

The goal to develop a validated long-term survey methodology (as proposed in Tasks 5 and 6 under Objective 2 of the final detailed study plan, dated January 31, 2007) relied on the acquisition of empirical estimates of population abundance (i.e., local abundance) in each grid cell. I intended to repeatedly draw random samples of cells from the 2007 census of grid cells to determine an optimal level and allocation of sampling that could be used in subsequent surveys to achieve a population estimate that would approximate that which could be obtained from a census of all grid cells (as presented in Chapter 15).

The power of such a sampling approach depends on the successful reduction in measurement error while surveying for owls in grid cells. This is because the analytical tools available for analyzing stratified random sampled data assume perfect counts in sampling units (no error in counts). Those tools, however, do account for the variation in abundance among grid cells, which is referred to as sampling variance. Thus, an important objective in surveying owls for the purpose of determining local abundances

must be to minimize measurement error during surveys. Fortunately, the field methods presented in Appendix II can be used with the point-coordinate capture-recapture analytical technique presented in Chapter 5 to achieve negligible levels of measurement error in estimates of local abundance. Here, I present maximum likelihood, point-coordinate, capture-recapture estimates of local male Burrowing Owl territory abundance in 3x3 km grid cells across the HCP Study Area and discuss their associated estimates of measurement error. Per amendment 6, I also used these data to calculate an approximate true number of Burrowing Owl territories in the HCP Study Area that is appropriate for comparing HCP Study Area-wide abundance estimates derived from random samples drawn from the population of grid cells.

METHODS

I considered a single survey pass along an IID right-of-way on a single day as a survey occasion, and consecutive occasions as a survey session (e.g., see Chapter 7). Thus, each of the 6 survey sessions described in Chapter 7 were comprised of a distinct set of survey occasions (i.e., 6 survey sessions, each in a distinct portion of the HCP Study Area, comprised of 4 single-day occasions = 24 days of surveys). Because the 6 sessions also corresponded with 6 different portions of the HCP Study Area that were surveyed at different days, I tested for time effects separately in grid cells according to each session.

Because the stratified random sampling approach to developing a long term survey protocol for owls is reliant on reducing measurement error when survey for owls inside grid cells, I used the point-coordinate capture-recapture technique (presented in Chapter 5) in analyzing owls survey data. I used the following methods to compute local, maximum likelihood, closed-population estimates of male Burrowing Owl territory abundance:

1. Applied the point-coordinate capture-recapture technique to the first 3 survey occasions, using the 55 m radius MMDM buffer recommended in Chapter 5. My use of only the first 3 occasions was based on the results presented in Chapter 6. This technique developed centroids associated with individual, point-coordinate-based, capture-recapture encounter histories.

2. To meet the HCP's requirement to estimate the abundance of breeding male territories and because I showed that owls in the HCP Study Area have a high probability of being detected during our surveys (95%; Chapter 6), I removed individual encounter histories from the dataset where a single owl was observed on only 1 of the 3 occasions and without a nest (Table 10.1). This is because owls had a high probability of being detected near their nests (see results, this chapter), and I assumed that such observations were of non-breeding owls that were not maintaining breeding territories at the time of our survey, or owls that were away from their territories at the time of observation. I considered the remaining centroids established above to be those of territorial males.

3. Overlaid the grid of 274 cells (see Figure 9.3 for grid details) onto the centroids of male Burrowing Owl territories and associated capture-recapture encounter histories determined above, and assigned each encounter history to its corresponding grid cell. I therefore used the 3x3 km grid cell as the areal unit to calculate local abundance estimates.

4. Determined in which of the 6 sessions the majority of a grid cell was surveyed, and grouped grid cells by the 6 sessions, and applied closed-population models with the sin link function available in Program MARK (Otis et al. 1978, White et al. 1982, Cooch 1999, White and Burnham 1999) to each grid cell and tested for time effects (among occasions) separately among the 6 survey sessions. Within each session, I fit models to each cell's set of encounter histories that assumed that detection and recapture probabilities were equal and constant [$\hat{N}$ (grid cell) $\hat{p} = \hat{c}$ (.)] or varied through time [$\hat{N}$ (grid cell) $\hat{p} = \hat{c}$ (time)], where time referred to occasions 1, 2, and 3. I used Akaike's Information Criterion (AIC_c; Akaike 1973, Burnham and Anderson 2002) to determine the most parsimonious model for a grid cell, and considered it to be the best model for that cell. I assessed the lack-of-fit of the model to the data by examining a plot of its deviance residuals. A symmetric and narrow pattern of deviance residuals close to zero would suggest a good fit to the data, whereas a wide pattern around zero would suggest poor fit due to extra-binomial variation.

5. Added the associated estimates of abundance and standard error from the best models into the corresponding grid cell in the GIS grid layer. Here, the standard error was a measure of precision that represented the error attributed to the point-coordinate capture-recapture surveys, which can be appropriately referred to as measurement error.

Although I initially proposed the inclusion of individual covariates (e.g., percent vegetation and texture) in models, the point-coordinate capture-recapture technique restricted their use at this stage of analysis, as described under the conclusions and recommendations in Chapter 5.

In order to have an estimate of the total population for comparisons with estimates obtained from sampling, I summed the local estimates from all 274 sample grid cells.

RESULTS

Raw counts during single survey occasions ranged from 3,451-3,726 (Table 10.1). The best capture-recapture models for most survey sessions represented the hypothesis that detection probabilities varied through time (day; Table 10.2), and most of these models fit the data fairly well (deviance residuals followed a fairly narrow and symmetric pattern surrounding zero). Estimates of male Burrowing Owl territory abundance ranged from 0 to 53.96/3x3 km grid cell (SE = 1.26), and those with a lower estimated abundance tended to be from smaller samples of owls and models having relatively greater spread in the deviance residuals. The mean abundance of the 274 cells was 17.8 owl territories (St

Dev = 13.2), and 18 cells were estimated to not contain owls during our surveys (Figures 10.1 and 10.2).

The majority of local abundance estimates had small standard errors, indicating small measurement errors. Nearly half of the grid cells, those cells where abundance was estimated to be ≤20 territories, contained very low standard errors, suggesting either negligible measurement error or poor performance of the capture-recapture models fit to those cells (Figure 10.1).

By summing the local abundances obtained from this method, we estimated the total population of male Burrowing Owl territories in the HCP Study Area in 2007 at 4,879 (95% CI: 4,847 - 5,387).

Table 10.1. Number of Burrowing Owl detections by survey occasion during the prehatch stage of the breeding cycle in the HCP Study Area, Imperial County, California, 2007. Owls detected once and without a nest were removed from the data.

	Survey Occasions		
Type of detection	1	2	3
Once without nest	165	221	232
All other detections	3,286	3,447	3,494
Mean/cell[1]	9.8	10.7	10.6
Standard deviation/cell[1]	12.6	13.4	13.6

[1] Calculated with total detections from all 274 3x3 km grid cells.

Table 10.2. Best closed-population capture-recapture models and detection estimates by session. These best models have ΔAIC_c-values = 0; their AIC_c-values that are not comparable to each other because AIC_c was used to select each of them from another model separately for each session, and those models are not included here.

		Survey Occasion		
Session	Best model	1	2	3
1	$\hat{p} = \hat{c}$ (time[1])	0.71 (0.02)	0.70 (0.02)	0.79 (0.01)
2	$\hat{p} = \hat{c}$ (time)	0.69 (0.01)	0.70 (0.01)	0.78 (0.01)
3	$\hat{p} = \hat{c}$ (time)	0.61 (0.02)	0.67 (0.02)	0.73 (0.01)
4	$\hat{p} = \hat{c}$ (time)	0.67 (0.02)	0.76 (0.01)	0.58 (0.02)
5	$\hat{p} = \hat{c}$ (.)	0.70 (0.01)	0.70 (0.01)	0.70 (0.01)
6	$\hat{p} = \hat{c}$ (.)	0.76 (0.06)	0.76 (0.06)	0.76 (0.06)

[1] Time refers to days, as a survey occasion occurred on each of 3 days.

CONCLUSIONS AND RECOMMENDATIONS

The use of 3 closed-population point-coordinate capture-recapture survey occasions resulted in a high probability (97.6%) of detecting a male Burrowing Owl territory ≥1

times over the 3 occasions, which is similar to that reported in Chapter 6. Specifically, given the average detection probability over occasions and sessions ($\hat{p}$ = 0.71), the probability that a territory was detected ≥1 times over the 3 occasions was 97.6% [i.e., 1-$(1-0.71)^3$].

This approach did not allow for modeling effects of individual covariates (e.g., amount of vegetation or type of drain or canal bank) on detection probabilities (see Chapter 5 for further details). However, given the high overall high detection probability from 3 survey occasions, such an analysis, if possible, may not have provided a marked improvement in bias or precision.

The low standard errors associated with estimates where territories numbered <20/grid cell (Figure 10.1) were likely due to the performance of the closed-population capture-recapture models that were fit to the data in Program MARK. Although this may lead to slightly biased low abundances when the number of owls is small within a grid cell, capture-recapture methods produce encounter histories for each individual owl, even if they are missed on all but one of the occasions, leading to a 97.6% chance that each territory will be accounted for. Unlike capture-recapture, which utilizes these repeated occasions to increase the number of individuals detected and thereby account for imperfect probabilities of availability when numbers are high enough, other survey methods which can minimize measurement error due to visibility bias (e.g., distance sampling, point counts, and sightability) do not correct for availability bias. This is problematic with species where availability may vary throughout the day like the Burrowing Owls in the HCP Study Area (i.e., see Figure 2.4). Variation in availability among days can also be a problem, as we found that the raw counts associated with the capture-recapture occasions conducted here were variable among days. Given the standardized and constant levels of effort applied only days apart during the owl surveys, it is unlikely that the 6% difference in counts among the 3 occasions was due primarily to visibility bias, but rather also imperfect availability of individuals among the days. Currently, capture-recapture is one of the more powerful methods to estimate abundance from species like the Burrowing Owl where visibility and availability bias affects measurement error, and hence population estimates. Until advances are made with methods that rely on a single survey occasion that will correct for imperfect availability as well as detectability while producing precise, unbiased estimates, capture-recapture methods are recommended for estimating local abundances in the HCP Study Area.

Closed-population models in Program MARK are widely accepted in wildlife science, and they allow for evaluating variable detection probabilities. The program also incorporates the ability to compare models using the information theoretic approach. One alternative to using Program MARK while maintaining the use of capture-recapture methods with such small sample sizes would be to use the model developed by Chao (1989). This model is unavailable in Program MARK. Currently, I am unaware of any statistical-based closed-population platforms that include the Chao estimator, other than Program CAPTURE, which does not have a reliable model selection procedure. Thus, applying the Chao (1989) model would preclude modeling variable detection probabilities or comparing multiple working hypotheses, which in itself could lead to

imprecise, biased estimates. It also does not perform as well as other closed-population models with larger samples.

In order to accomplish the proposed objective of evaluating the level of bias associated with various sampling methods and randomly drawn samples (to be completed in Chapters 15 and 17), an estimated abundance that best approximates the true total population size in the HCP Study Area is needed. Although we provided a maximum likelihood estimate of male territories in the HCP Study Area in Chapter 8, that estimate was calculated by pooling the complete census data into a single dataset and partitioning and analyzing it by survey session without considering the standardized sampling grid. Those data and analytical methods differ from those that will be used in future surveys, which will rely on surveys in grid cells that are to be randomly drawn from the standardized sampling grid. As suggested by Dr. W. R. Gould (New Mexico State University, Las Cruses) in his independent review, dated January 8, 2007, those differences preclude using the estimated population total from Chapter 8 as a basis for comparing estimates obtained from sampling the HCP Study Area. Because the sampling grid is intended for future surveys and will be the basis for drawing random samples in simulations intended to test different sampling methods and levels of random sampling in Chapters 15 and 17, the sum of the local 2007 abundances in grid cells [4,879 male Burrowing Owl territories (95% CI: 4,847 - 5,387)] is an appropriate estimate of the true population size for comparing with the simulated sample estimates.

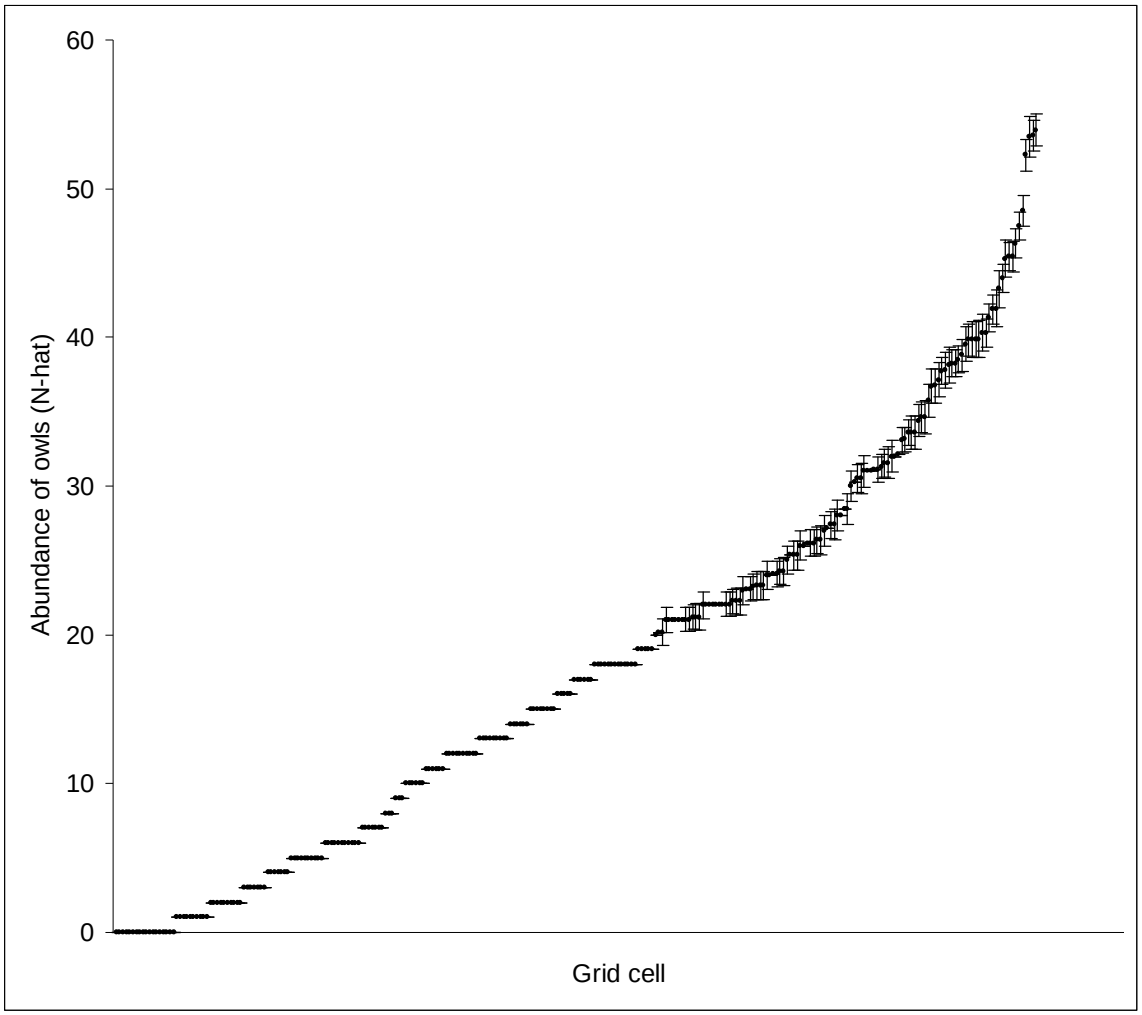

Figure 10.1. Estimates of local male Burrowing Owl territory abundances in 3x3 Km grid cells in the HCP Study Area, Imperial County, California, 2007. Data are presented according to increased abundances. Vertical bars are standard errors.

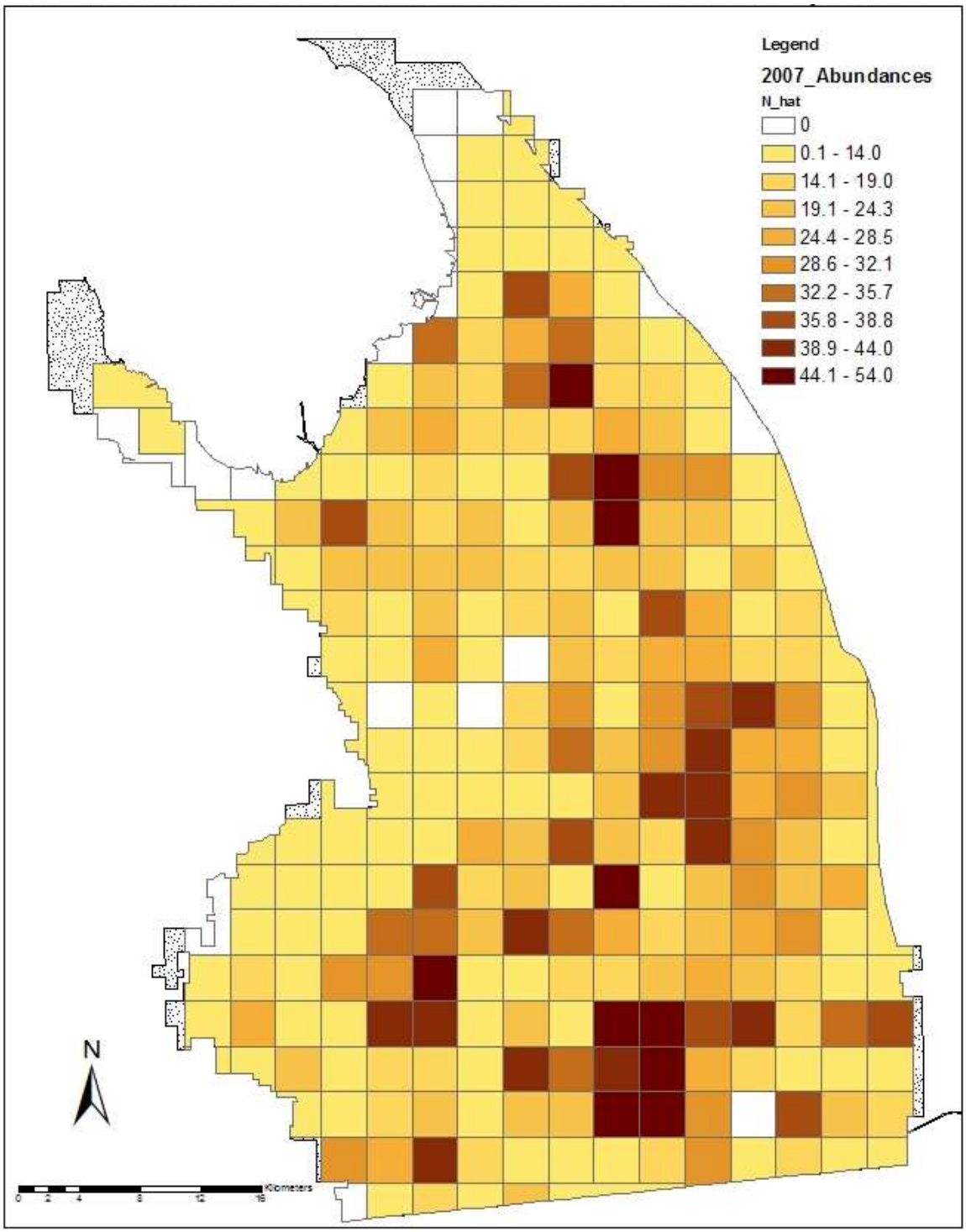

Figure 10.2. Closed-population point-coordinate capture-recapture estimates of local male Burrowing Owl territory abundance in 3x3 km grid cells in the HCP Study Area, Imperial County, California, April 2007. Stippled areas were not surveyed due to the absence of above-ground water conveyance structures.

Chapter 11

DATASETS OF POTENTIAL CORRELATES OF LOCAL MALE BURROWING OWL TERRITORY ABUNDANCE IN 2007

JEFFREY A. MANNING

ABSTRACT. Knowledge of potential environmental correlates of Burrowing Owl abundance is important in the development of survey protocols because using such correlates to stratify the HCP Study Area prior to future surveys could reduce logistical effort and costs by improving the precision of population estimates. Here, I describe spatial datasets of environmental and biological variables intended for comparing their individual and additive potential as correlates of local male Burrowing Owl territory abundance. These datasets included soils, IID maintenance activities, number of suitable nesting burrows, type of water conveyance structure, and agricultural crops.

INTRODUCTION

The identification of factors (i.e., habitat characteristics and IID maintenance activities) that may be suitable correlates of Burrowing Owl abundance was based on existing biological information and on availability of data that extends across the HCP Study Area. The latter basis was important because the intended purpose of suitable correlates was to stratify the HCP Study Area in order to optimally allocate future annual survey efforts. Thus, suitable correlates must be measurable and available across the entire HCP Study Area each year prior to conducting owl surveys.

Several factors have been hypothesized as important correlates of Burrowing Owl nest burrows, and hence possibly abundance of male territories. These include soils, maintenance activities, sympatric fossorial (burrowing) mammals, surrounding vegetation (in the HCP Study Area, this referred largely to agricultural crops), and type of bank (cement-lined or earthen) along water conveyance structures. We obtained data on each one of these factors in order to incorporate them into our analyses to test for their relative importance in predicting owl abundance

METHODS

Soils

Soft, friable, loamy soils have been hypothesized to be an important correlate of Burrowing Owl nest burrows (MacCracken et al. 1985, Green 1983). Thus, soils that deviate from this soil type are anticipated to coincide with fewer numbers of owls.

Soil information was obtained from the USDA Natural Resource Conservation Service (NRCS) geodatabase of soils (NRCS 2005). These data were derived from a digital soil survey developed by the National Cooperative Soil Survey, and was the most detailed

level of soil geographic data available. It was prepared by digitizing maps, compiling information onto a planimetric-correct base and digitizing from it, and/or revising digitized maps using remotely sensed information (NRCS 2005). National Cooperative Soil Survey standards and procedures were used in the classification of soils, design and name of map units, and location of special soil features in this dataset (NRCS 1993, NRCS 1995, NRCS and NSS undated current issue).

These data were clipped from: "Categorical ranking of soils in the Imperial Valley," California according to their suitability for burrowing owls. We measured the following soil classes in each 3x3 km grid cell for use as correlates (Figure 11.1):

1. proportion of poorly suited soils (continuous variable)
2. proportion of suitable soils (continuous variable)
3. proportion of well suited soils (continuous variable)
4. proportion of suitable and well suited soils (continuous variable)
5. dominant soil class (poorly suited, suitable, well suited; ordinal variable)

Imperial Irrigation District's maintenance activities

Section 4.5.2.2 of the HCP specified that "the Burrowing Owl population data will be linked to or combined with spatial information on the IID's maintenance activities..." This is because maintenance of water conveyance structures (i.e., dredging) is believed to possibly affect nest burrows. Thus, the location, year, and type of maintenance activities should also be assessed as possible determinants of owl abundance.

I met with maintenance personnel at the IID in April 2007 and obtained Microsoft Excel spreadsheets and GIS vector features of maintenance activities that occurred over the past 4 years. In most cases, the data were not detailed (e.g., not specific to a location on a canal, but rather named the entire canal, or a general definition for a maintenance activity was used). I counted the frequency of specific maintenance activities performed by the Imperial Irrigation District along irrigation canal and drain right-of-ways within each 3x3 km grid cell by year. Original drain and canal data were obtained by CH2M Hill, Sacramento, California. These data were further reduced to 12 general types of maintenance activity that were anticipated to possibly impact burrowing owls (as classified by the IID):

1. W03 = Concrete lined channel repair
2. W04 = Concrete lined channel brush and weed control by machine
3. W06 = Drain brush and weed control by machine
4. W08 = Earth channel machine clearing
5. W11 = Concrete canal structure maintenance
6. W12 = Drain structure maintenance
7. W13 = Earth canal structure maintenance
8. W17 = Concrete channel bank maintenance-road grading
9. W18 = Drain bank maintenance-road grading
10. W19 = Earth channel bank maintenance-road grading

11. W28 = Flood control
12. W29 = Pipeline maintenance

These general types of activities were summed for each canal or drain (vector), and divided by the total length of that water conveyance structure (across grid cells); this was multiplied by the total length of that structure in each cell, and summed across all water conveyance structures in the cell to produce grid cell-level estimates (Figure 11.2).

Availability of potential nest burrows

The presence of sympatric, fossorial mammals has been identified as an important correlate of Burrowing Owl nests (Thomsen 1971, Martin 1973, Zarn 1974, Wedgwood 1978, Haug 1985, Haug et al. 1993, Klute et al. 2003). This is because Burrowing Owls depend on the burrows from these mammals for nesting. Various species of fossorial mammals occupy the HCP Study Area, including the California ground squirrel (*Spermophilus beecheyi*), round tailed ground squirrel (*Spermophilus tereticaudus*), and Antelope ground squirrel (*Ammospermophilus leucurus*). The number of burrows dug by these mammals along the IID's right-of-way may be suitable for predicting the abundance of owl territories.

A complete count of burrows that were 'potentially suitable' as nest burrows for Burrowing Owls was conducted along the IID's rights-of-way. A burrow/hole was considered to be potentially suitable if it entered into an earthen surface, space within a debris pile, or pipe with an entrance between 3.5-15 inches in diameter that was flush with the ground. All burrows/holes that met this criteria were counted, even if occupied by a small mammal, and burrows/holes <20 m apart were considered as a single count because these data were intended to predict the number of male Burrowing Owl territories, and a single Burrowing Owl can occupy such a complex.

Vehicle-based surveys for potential burrows were completed from March 23-27, 2007, days before capture-recapture surveys were conducted for Burrowing Owls, following these procedures:

1. An observer and driver surveyed by vehicle
2. Vehicles were positioned so observers were closest to drains/canals
3. Traveled at 10 mph
4. Observers visually detected burrows while traveling in the vehicle, and used a handheld tally counter to record the number of burrows/complexes.
5. Observers set the Trimble GeoExplorer XM to record continuous vectors in order to map linear segments of the IID's right-of-way traveled in association with burrow counts.
6. Vehicles stopped every 0.5 miles to discontinue recording each previous vector, recorded the number of tallied burrows in the Trimble GeoExplorer XM data dictionary for each vector.

I summed the tallied number of burrows in each 0.5-mile within each 3x3 km grid cell in the GIS layer (Figure 11.3), and considered this summed count as a continuous variable in our correlative analyses of Burrowing Owl abundance.

Surrounding agricultural crops

The type of vegetation surrounding Burrowing Owl nest burrows may be correlated with abundance of male territories (Rich 1986, Green and Anthony 1989, Haug and Oliphant 1990, Plumpton and Lutz 1993), and thus may aid in predicting the abundance of owls across the HCP Study Area. For example, an intensive radio-tracking study of a small sample of owls in the Imperial Valley found 9 crop types were used, and that owls selected for barren ground near (<1,980 ft) and hay far (>1,980 ft) from nests (Rosenberg and Haley 2004). Furthermore, section 4.5.2.2 specified that "the burrowing owl population data will be linked to or combined with spatial information on … crop types in the HCP Study Area."

Relating crops to Burrowing Owl abundance is challenged by how and when owls tend to establish and maintain territories. Like many raptors, Burrowing Owls tend to establish territories and then occupy them for years, barring no major disturbances or nest failures. This complicates using current crop information to predict the current distribution of owl abundance because abundances may have been due to crop types present in the past. For example, older owls in the current population likely selected their territories farther back in the past than younger owls. If older owls represent the larger age class in the current population, and may have selected sites based on crops that are not currently present at those sites, a pattern between current crops and current owl abundance across the HCP Study Area may not emerge. In the absence of demographic data, methods to ascertain patterns between crops and current estimates of owl abundance warrant a multiple working hypotheses (Chamberlin 1890, 1965) approach based on comparisons of annual crop information (e.g., over the previous 5 years) and local estimates of abundance across the current Burrowing Owl population.

I took a retrospective approach to determine what crop(s) and how many years in the past the dominant age class in the current owl population may have selected their territories. If successful, this method could also possibly provide an indirect measure of the dominant age class in the Burrowing Owl population during the 2007 owl surveys. It may also be valuable in identifying the type of crop and how many years previous from a proposed population survey crops should be examined in order to adequately stratify the HCP Study Area and efficiently allocate survey efforts over the 75-year HCP permit.

This remote classification of the agricultural crops is presented separately in Appendix III. Here, those results were further used to assign a crop-related value to each 3x3 km grid cell separately each year. I computed the richness (number) of unique crops in a grid cell, and the proportion of each grid cell in the following cover types (Figure 11.4):

1. Level II grass
2. Level II bare ground and fallow

3. Level II broadleaf
4. wheat
5. fallow
6. Sudan
7. alfalfa
8. Bermuda
9. bare ground

These specific cover types were chosen because of their suggested importance in the literature (e.g., Rosenberg and Haley 2004) or expected similarity to those suggested to be important.

Type of water conveyance structure bank

Abundance of owl nests is anticipated to differ between canals, drains, and interceptors (Rosenberg and Haley 2004). Because a single or combination of these water conveyance structure(s) can occur within any stretch of the IID's rights-of-way, I had initially proposed to assign one of up to 10 different categories to each right-of-way. After reviewing the IID's canal and drain GIS feature layers, I was able only to assign only 2 categories (cement lined or earthen). I used these data to assign the proportion of cement-lined right-of-way to each 3x3 km grid cell (Figure 11.5).

RESULTS

The following figures display the GIS-based spatial datasets of selected environmental variables intended for use in assessing their potential as correlates of Burrowing Owl abundance.

CONCLUSIONS AND RECOMMENDATIONS

The resulting datasets were used in the following chapter to assess their relative importance as correlates of male Burrowing Owl territory abundance.

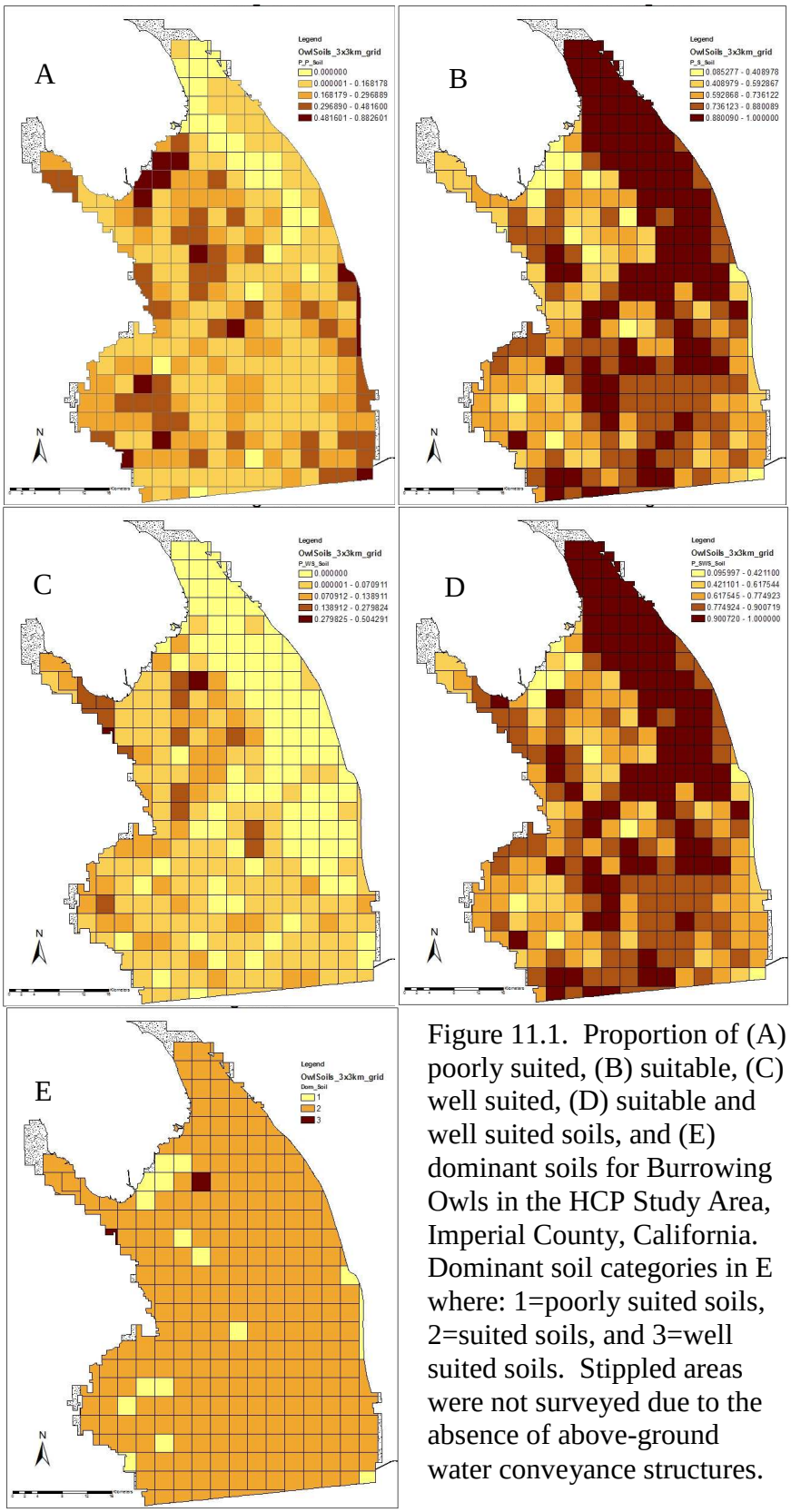

Figure 11.1. Proportion of (A) poorly suited, (B) suitable, (C) well suited, (D) suitable and well suited soils, and (E) dominant soils for Burrowing Owls in the HCP Study Area, Imperial County, California. Dominant soil categories in E where: 1=poorly suited soils, 2=suited soils, and 3=well suited soils. Stippled areas were not surveyed due to the absence of above-ground water conveyance structures.

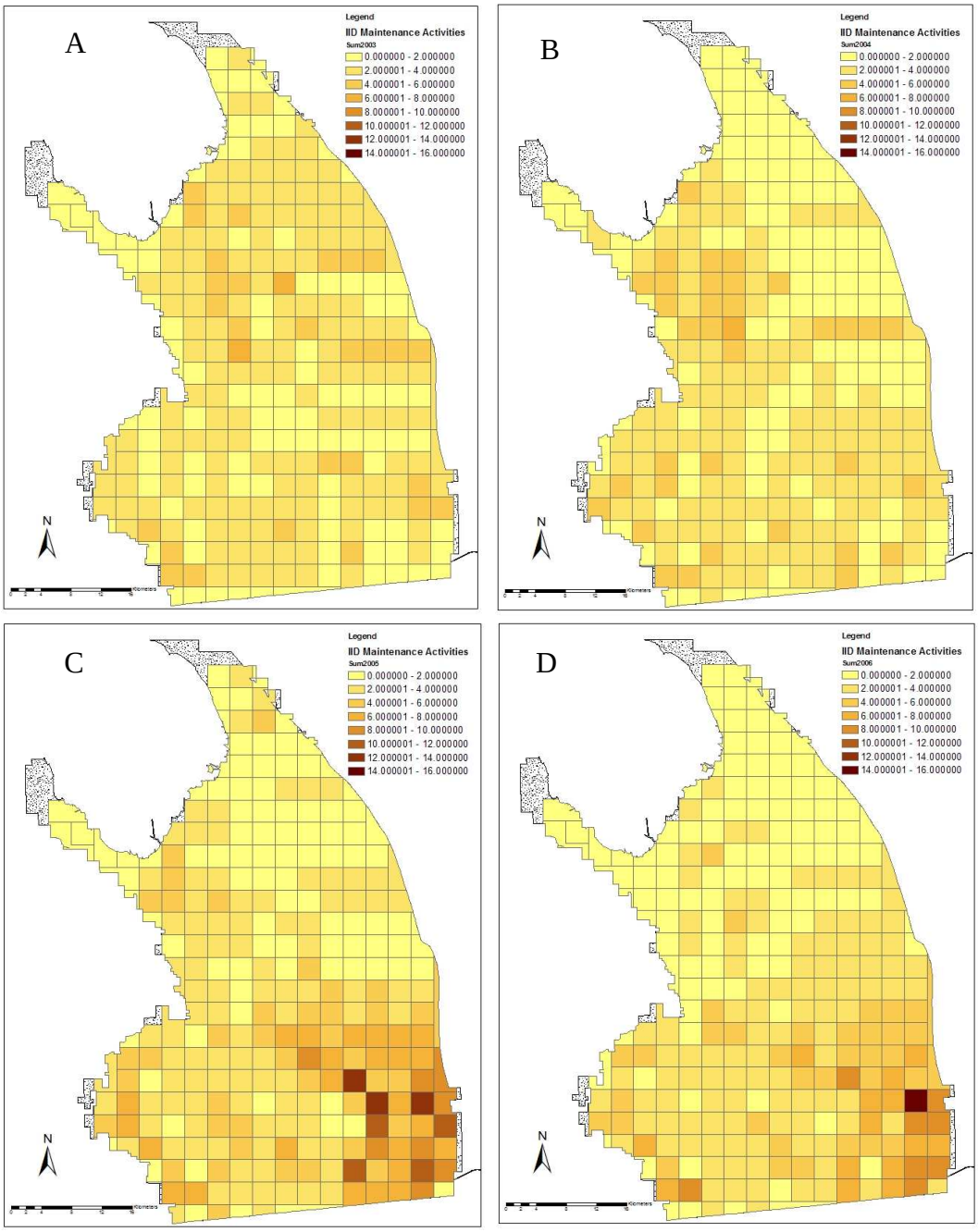

Figure 11.2. Frequency of the IID's maintenance activities in (A) 2003, (B) 2004, (C) 2005, and (D) 2006, Imperial County, California. Stippled areas were not surveyed due to the absence of above-ground water conveyance structures.

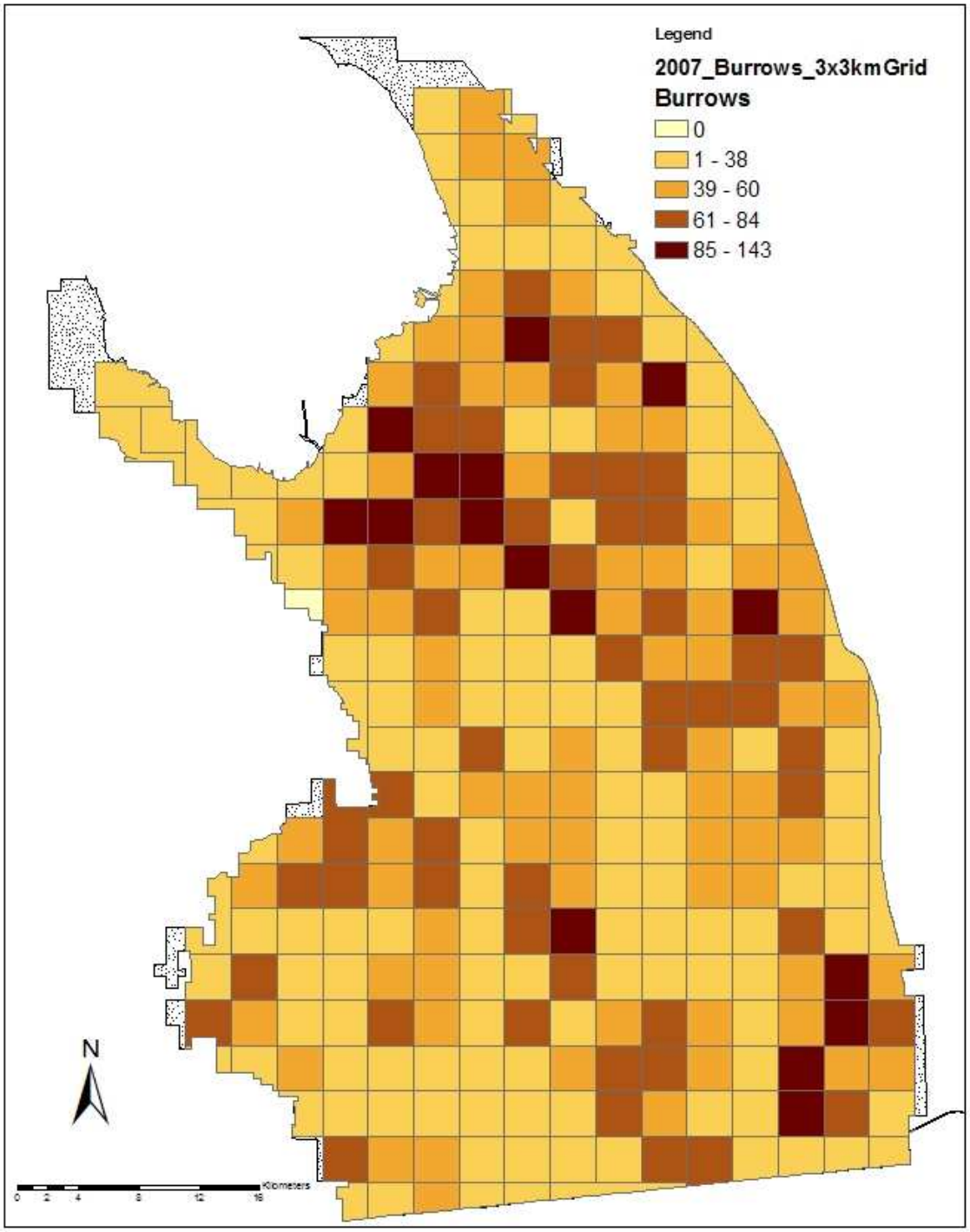

Figure 11.3. Number of potential Burrowing Owl nest burrows in the HCP Study Area, Imperial County, California, April 2007. Stippled areas were not surveyed due to absence of above-ground water conveyance structures.

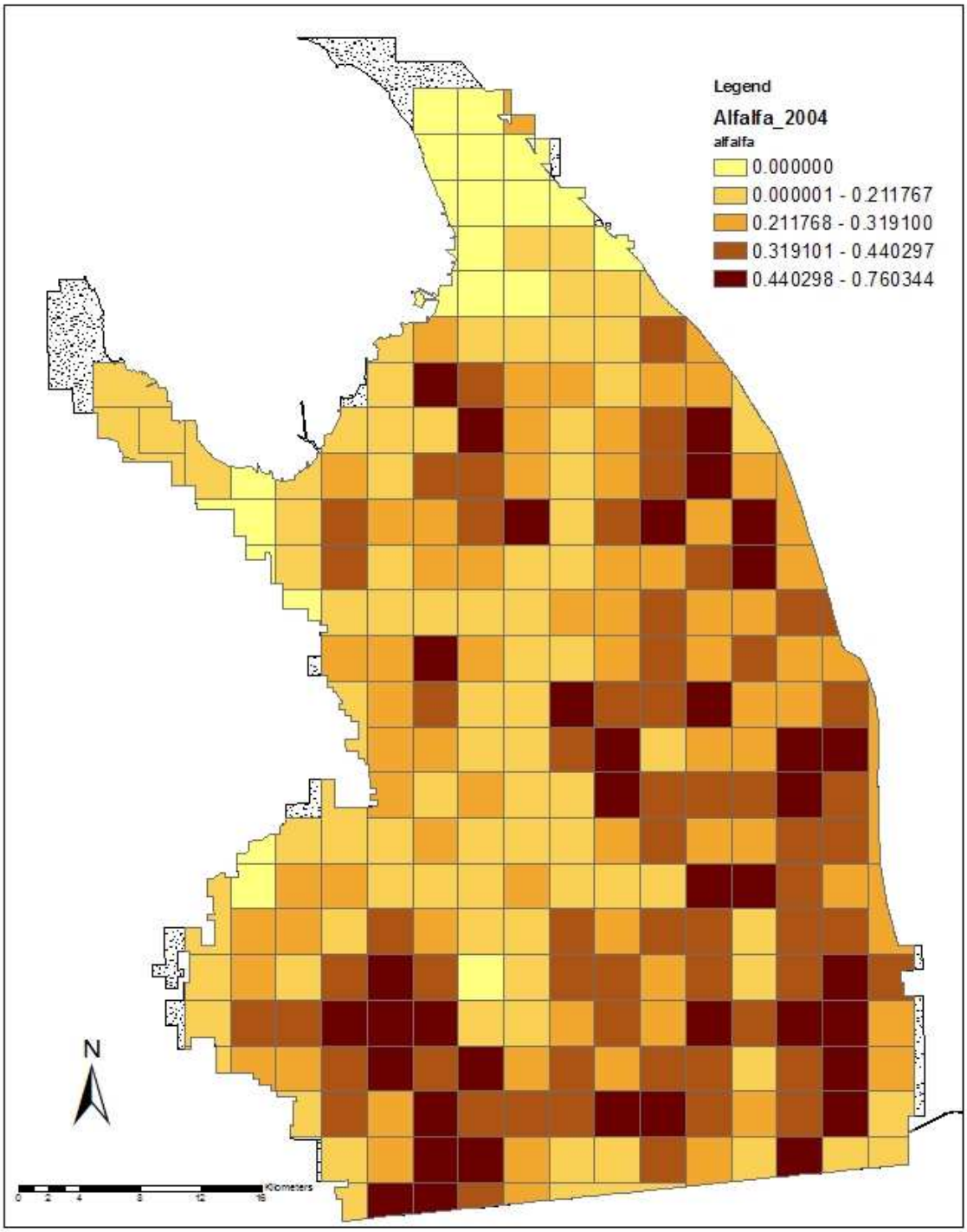

Figure 11.4. Proportion of crop class level III alfalfa in the HCP Study Area, Imperial County, California, 2004. This figure also is representative of the numerous other crop datasets generated. Stippled areas were not surveyed due to absence of above-ground water conveyance structures.

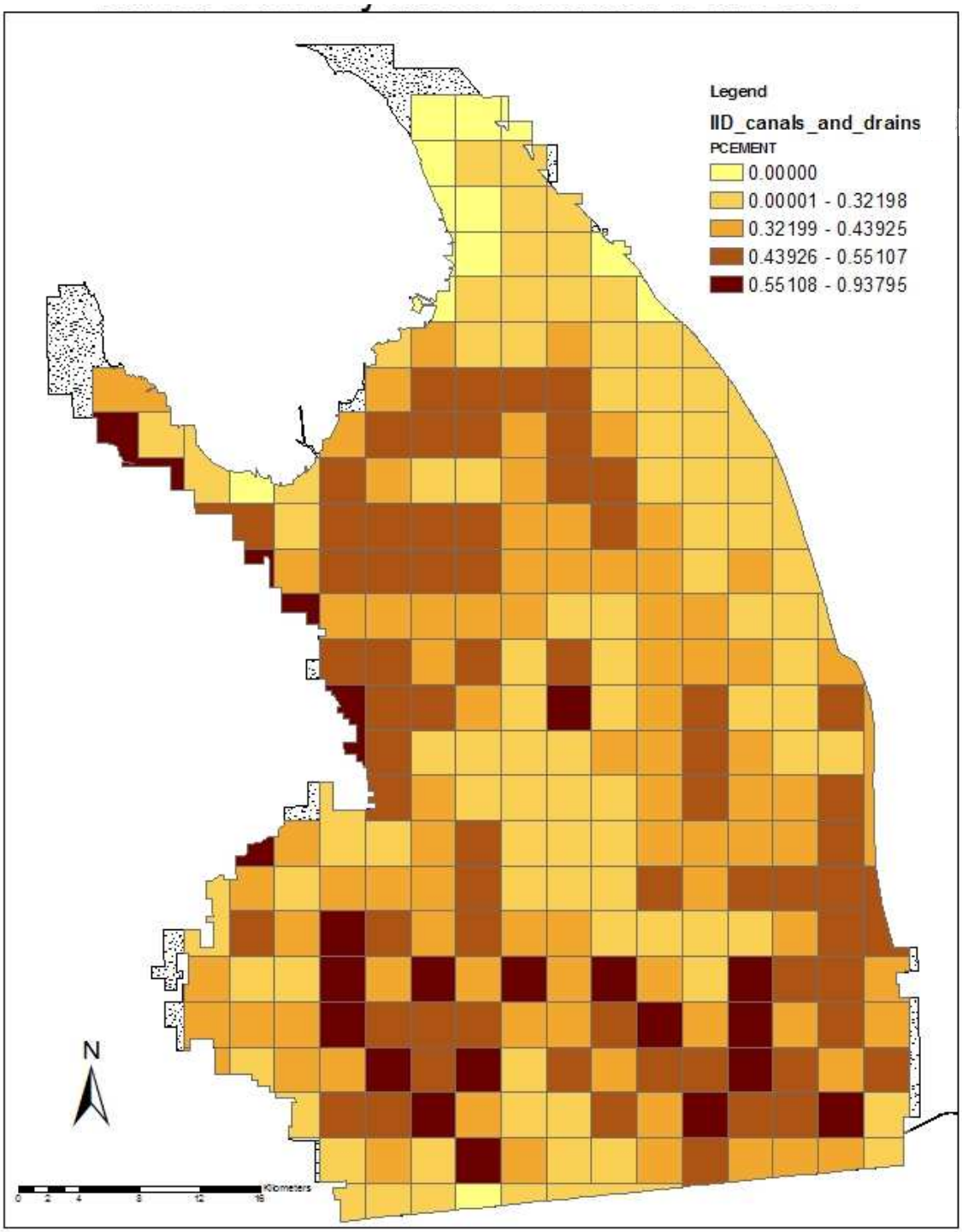

Figure 11.5. Percent cement-lined IID water conveyance structures, Imperial Valley, California, 2007. Stippled areas were not surveyed due to absence of above-ground water conveyance structures.

Chapter 12

THE RELATIVE IMPORTANCE OF POTENTIAL CORRELATES OF MALE BURROWING OWL TERRITORY ABUNDANCE

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. Given the large number of potential correlate datasets of Burrowing Owl abundance presented in the previous chapter, it is advantageous to assess their relative importance as correlates in order to consider only the strongest correlate(s). Here, we present modeling results from evaluating the relative importance of the potential correlates of male Burrowing Owl territory abundance in 2007. We intended that the resulting correlative model could be used to estimate the abundance of owls from its surrogate variable(s) reasonably well enough to stratify the sampling grid according to broad ranges of abundance because stratification would aid in improving the accuracy of sample estimates of abundance. We used the information theoretic approach with multiple-working hypotheses to compare 74 models, where each model represented one of the working hypotheses. The best model predicted male Burrowing Owl territory abundance as a function of the linear length of IID water conveyance structure, available burrows in 2007, and the proportion of agricultural crops in alfalfa production in 2004. We found that spatial autocorrelation was significant up to 2 nearest grid cell neighbors out, and a spatial covariate term added to the model improved the model's predictive ability.

INTRODUCTION

An important part of the long-term stratified random sampling survey method we proposed is to produce a model with environmental variables that can be used in subsequent years to determine which strata (low, medium, and high abundances of male Burrowing Owl territories) a grid cell belongs to prior to a given population survey. This stratification would be used to randomly select grid cells to be surveyed. Due to the dynamic nature of the system in the HCP Study Area, the use of this model to assign grid cells to specific strata is designed for re-stratifying grid cells each year.

Our objective here was to develop a model, using the environmental variables gathered and presented in Chapter 11, of the relative best correlates of male Burrowing Owl territory abundance in the HCP Study Area. We chose to use the estimate of local abundance in each independent sampling unit from Chapter 10 as the response variable in linear models outside of a closed-population statistical platform (e.g., program MARK; Cooch 1999, White and Burnham 1999) because the optimal allocation of effort proposed under our stratified random sampling approach required a large number of standardized sampling units (274 grid cells). This large number of units would lead to over-parameterized models in such platforms. Furthermore the extrapolation of results from future stratified random sampling to a full population estimate is currently unavailable within such a platform.

METHODS

Each single or combination of correlate(s) constituted a hypothesis represented by a statistical model, with owl abundance as the response, based on the 3x3 km grid as sampling units. Because the error surrounding each abundance estimate was expected not to be constant, we fit weighted least square regression models (Cleveland 1979, Cleveland and Devlin 1988) to the data. Weighted least squares regression is an efficient method to provide easily interpretable statistical intervals for estimation, prediction, calibration and optimization. In addition, the main advantage that the weighted least squares method has over other methods is the ability to handle regression situations where the data points vary in quality. If the variance of the random errors in the data is not constant across all levels of the explanatory variable(s), the use of weighted least squares can yield relatively precise parameter estimates.

Model structures followed that of simple linear regression (Table 12.1). We restricted additive structures to those factors that have been shown or suggested to be important for Burrowing Owls (e.g., alfalfa, bare ground, and fallow fields; Rosenberg and Haley 2004). Because the Burrowing Owl abundance data in each cell were dependent on the linear length of IID-maintained water conveyance structures, we standardized this effect by including a term for linear length of these structures as the baseline in every model we fit to the data. The inclusion of this variable in all models precluded the need to scale other explanatory variables by linear length of water conveyance structures.

We compared the relative fit of each model following a multiple-hypothesis testing framework, based a model-selection procedure with AIC (Akaike 1973). This information theoretic approach (Burnham and Anderson 2002) was intended to determine the best correlates of male Burrowing Owl territory abundance that we measured by identifying the most parsimonious model. Such correlates are necessary to develop strata classes associated with low, medium, and high abundances of male Burrowing Owl territories in the HCP Study Area for the development of a long-term sampling methodology.

We tested for spatial autocorrelation in the residuals of the best model using the Moran's *I* spatial statistic in Program Geoda95 (Spatial Analysis Laboratory, University of Illinois, Urbana-Champaign, IL). This test was used to assess spatial autocorrelation in owl abundance that explanatory variables did not account for in the model. We used a weight matrix based on Queen's adjacency scheme to identify how far out from a given cell (i.e., to what degree of neighboring cells) abundance was autocorrelated. We then accounted for this spatial covariance structure by using this distance to incorporate a term in the best model, thereby allowing the model to estimate the spatial coefficient, which is similar to methods used with mixed models (Laird and Ware 1982). This approach was recommended by Dr. Bryan Manly in his letter, dated June 5, 2007. We considered this model, which included the spatial autocorrelation term, as our 'best' model.

We validated the assumptions underlying the best model by performing graphical analyses of residuals. We plotted the innermost fitted values from the best model against

observed values of the response variable to provide an overall summary of explanatory power of the model, how much variation is explained, how much remains, and evidence of lack of fit. We also plotted the innermost fitted values against the innermost residuals to assess the assumption of correct model structure.

We also used a version of *k*-fold cross validation [leave-one-out cross validation; Devijver and Kittler (1982)] to validate how well the model parameters from our best model could predict abundance in a grid cell. This validation approach involved using a single observation from the original sample as the validation data, and the remaining observations as the training data. This was repeated such that each observation in the sample was used once as the validation data. We performed these analyses in Program R (Ihaka and Gentleman 1996).

Table 12.1. Linear regression models (presented as program R code). Model names are to the left of '<-' and refer to a model's explanatory variables. Definitions of model syntax are provided at the bottom of the table.

```
03grass.lm <- lm(Nhat ~ TotLength + 03grass, data=buow, weights=Nhatwt)
03barefallow.lm <- lm(Nhat ~ TotLength + 03barefallow, data=buow, weights=Nhatwt)
03broadleaf.lm <- lm(Nhat ~ TotLength + 03broadleaf, data=buow, weights=Nhatwt)
04grass.lm <- lm(Nhat ~ TotLength + 04grass, data=buow, weights=Nhatwt)
04barefallow.lm <- lm(Nhat ~ TotLength + 04barefallow, data=buow, weights=Nhatwt)
04broadleaf.lm <- lm(Nhat ~ TotLength + 04broadleaf, data=buow, weights=Nhatwt)
05grass.lm <- lm(Nhat ~ TotLength + 05grass, data=buow, weights=Nhatwt)
05barefallow.lm <- lm(Nhat ~ TotLength + 05barefallow, data=buow, weights=Nhatwt)
05broadleaf.lm <- lm(Nhat ~ TotLength + 05broadleaf, data=buow, weights=Nhatwt)
06grass.lm <- lm(Nhat ~ TotLength + 06grass, data=buow, weights=Nhatwt)
06barefallow.lm <- lm(Nhat ~ TotLength + 06barefallow, data=buow, weights=Nhatwt)
06broadleaf.lm <- lm(Nhat ~ TotLength + 06broadleaf, data=buow, weights=Nhatwt)
07grass.lm <- lm(Nhat ~ TotLength + 07grass, data=buow, weights=Nhatwt)
07barefallow.lm <- lm(Nhat ~ TotLength + 07barefallow, data=buow, weights=Nhatwt)
07broadleaf.lm <- lm(Nhat ~ TotLength + 07broadleaf, data=buow, weights=Nhatwt)
03wheat.lm <- lm(Nhat ~ TotLength + 03wheat, data=buow, weights=Nhatwt)
03fallow.lm <- lm(Nhat ~ TotLength + 03fallow, data=buow, weights=Nhatwt)
03sudan.lm <- lm(Nhat ~ TotLength + 03sudan, data=buow, weights=Nhatwt)
03alfalfa.lm <- lm(Nhat ~ TotLength + 03alfalfa, data=buow, weights=Nhatwt)
03bermuda.lm <- lm(Nhat ~ TotLength + 03bermuda, data=buow, weights=Nhatwt)
03bareground.lm <- lm(Nhat ~ TotLength + 03bareground, data=buow, weights=Nhatwt)
04wheat.lm <- lm(Nhat ~ TotLength + 04wheat, data=buow, weights=Nhatwt)
04fallow.lm <- lm(Nhat ~ TotLength + 04fallow, data=buow, weights=Nhatwt)
04sudan.lm <- lm(Nhat ~ TotLength + 04sudan, data=buow, weights=Nhatwt)
04alfalfa.lm <- lm(Nhat ~ TotLength + 04alfalfa, data=buow, weights=Nhatwt)
04bermuda.lm <- lm(Nhat ~ TotLength + 04bermuda, data=buow, weights=Nhatwt)
04bareground.lm <- lm(Nhat ~ TotLength + 04bareground, data=buow, weights=Nhatwt)
05wheat.lm <- lm(Nhat ~ TotLength + 05wheat, data=buow, weights=Nhatwt)
05fallow.lm <- lm(Nhat ~ TotLength + 05fallow, data=buow, weights=Nhatwt)
05sudan.lm <- lm(Nhat ~ TotLength + 05sudan, data=buow, weights=Nhatwt)
05alfalfa.lm <- lm(Nhat ~ TotLength + 05alfalfa, data=buow, weights=Nhatwt)
05bermuda.lm <- lm(Nhat ~ TotLength + 05bermuda, data=buow, weights=Nhatwt)
05bareground.lm <- lm(Nhat ~ TotLength + 05bareground, data=buow, weights=Nhatwt)
06wheat.lm <- lm(Nhat ~ TotLength + 06wheat, data=buow, weights=Nhatwt)
06fallow.lm <- lm(Nhat ~ TotLength + 06fallow, data=buow, weights=Nhatwt)
06sudan.lm <- lm(Nhat ~ TotLength + 06sudan, data=buow, weights=Nhatwt)
06alfalfa.lm <- lm(Nhat ~ TotLength + 06alfalfa, data=buow, weights=Nhatwt)
06bermuda.lm <- lm(Nhat ~ TotLength + 06bermuda, data=buow, weights=Nhatwt)
06bareground.lm <- lm(Nhat ~ TotLength + 06bareground, data=buow, weights=Nhatwt)
```

```
07wheat.lm <- lm(Nhat ~ TotLength + 07wheat, data=buow, weights=Nhatwt)
07fallow.lm <- lm(Nhat ~ TotLength + 07fallow, data=buow, weights=Nhatwt)
07sudan.lm <- lm(Nhat ~ TotLength + 07sudan, data=buow, weights=Nhatwt)
07alfalfa.lm <- lm(Nhat ~ TotLength + 07alfalfa, data=buow, weights=Nhatwt)
07bermuda.lm <- lm(Nhat ~ TotLength + 07bermuda, data=buow, weights=Nhatwt)
07bareground.lm <- lm(Nhat ~ TotLength + 07bareground, data=buow, weights=Nhatwt)
03CrpRch.lm <- lm(Nhat ~ TotLength + 03CrpRch, data=buow, weights=Nhatwt)
04CrpRch.lm <- lm(Nhat ~ TotLength + 04CrpRch, data=buow, weights=Nhatwt)
05CrpRch.lm <- lm(Nhat ~ TotLength + 05CrpRch, data=buow, weights=Nhatwt)
06CrpRch.lm <- lm(Nhat ~ TotLength + 06CrpRch, data=buow, weights=Nhatwt)
07CrpRch.lm <- lm(Nhat ~ TotLength + 07CrpRch, data=buow, weights=Nhatwt)
03IIDMnt.lm <- lm(Nhat ~ TotLength + 03IIDMnt, data=buow, weights=Nhatwt)
04IIDMnt.lm <- lm(Nhat ~ TotLength + 04IIDMnt, data=buow, weights=Nhatwt)
05IIDMnt.lm <- lm(Nhat ~ TotLength + 05IIDMnt, data=buow, weights=Nhatwt)
06IIDMnt.lm <- lm(Nhat ~ TotLength + 06IIDMnt, data=buow, weights=Nhatwt)
TotIIDMnt.lm <- lm(Nhat ~ TotLength + TotIIDMnt, data=buow, weights=Nhatwt)
PPSoil.lm <- lm(Nhat ~ TotLength + PPSoil, data=buow, weights=Nhatwt)
PSSoil.lm <- lm(Nhat ~ TotLength + PSSoil, data=buow, weights=Nhatwt)
PWSoil.lm <- lm(Nhat ~ TotLength + PWSoil, data=buow, weights=Nhatwt)
PSWSoil.lm <- lm(Nhat ~ TotLength + PSWSoil, data=buow, weights=Nhatwt)
DomSoil.lm <- lm(Nhat ~ TotLength + DomSoil, data=buow, weights=Nhatwt)
07Brrws.lm <- lm(Nhat ~ TotLength + 07Brrws, data=buow, weights=Nhatwt)
PCementlined.lm <- lm(Nhat ~ TotLength + PCementlined, data=buow, weights=Nhatwt)
TotLength.lm <- lm(Nhat ~ TotLength, data=buow, weights=Nhatwt)

07Brrwsplus03alfalfa.lm <- lm(Nhat ~ TotLength + 07Brrws + 03alfalfa, data=buow, weights=Nhatwt)
07Brrwsplus04alfalfa.lm <- lm(Nhat ~ TotLength + 07Brrws + 04alfalfa, data=buow, weights=Nhatwt)
07Brrwsplus05alfalfa.lm <- lm(Nhat ~ TotLength + 07Brrws + 05alfalfa, data=buow, weights=Nhatwt)
07Brrwsplus06alfalfa.lm <- lm(Nhat ~ TotLength + 07Brrws + 06alfalfa, data=buow, weights=Nhatwt)
07Brrwsplus07alfalfa.lm <- lm(Nhat ~ TotLength + 07Brrws + 07alfalfa, data=buow, weights=Nhatwt)

07Brrwsplus03barefallow.lm <- lm(Nhat ~ TotLength + 07Brrws + 03barefallow, data=buow, weights=Nhatwt)
07Brrwsplus04barefallow.lm <- lm(Nhat ~ TotLength + 07Brrws + 04barefallow, data=buow, weights=Nhatwt)
07Brrwsplus05barefallow.lm <- lm(Nhat ~ TotLength + 07Brrws + 05barefallow, data=buow, weights=Nhatwt)
07Brrwsplus06barefallow.lm <- lm(Nhat ~ TotLength + 07Brrws + 06barefallow, data=buow, weights=Nhatwt)
07Brrwsplus07barefallow.lm <- lm(Nhat ~ TotLength + 07Brrws + 07barefallow, data=buow, weights=Nhatwt)
```

Bareground referred to the proportion of a grid in a bare ground condition (i.e., no vegetation), barefallow was the proportion of a grid cell in a bare ground and fallow conditions, CrpRch was crop richness (count) in a grid cell, Brrws was the number of suitable burrows counted in a grid cell in 2007 immediately prior to the population surveys, PCementlined was the proportion of above-ground water conveyance structure in a grid cell that was cement-lined, TotLength was the total length of above-ground water conveyance structure in a grid cell, and IIDMnt was the frequency of IID's maintenance activities in a grid cell (as calculated in the previous chapter). Numeric values preceding model names referred to year.

RESULTS

The best model predicted male Burrowing Owl territory abundance as a function of available burrows in 2007 and the proportion of agricultural crops in alfalfa production in 2004, with the next model having a ΔAIC = 1.62 ($r^2 = 0.37$, $F_{3,270} = 53.7$, $p<0.001$; Tables 12.2 and 12.3). The difference between this model and a competing one was the year of alfalfa production. Because both models had the same number of parameters and alfalfa production between any 2 years is likely to be correlated, we considered the model with the smaller ΔAIC as the best for stratification purposes.

We used the residuals from the best model above to assess spatial autocorrelation in Burrowing Owl abundance, and found that spatial autocorrelation was significant up to 2 nearest grid cell neighbors out (Table 12.4).

We constructed an additional model that included a spatial covariate term that accounted for the mean abundance of male Burrowing Owl territory abundance out to 2 nearest grid cell neighbors away (Table 12.5). The addition of this spatial autocorrelation term improved the fit of the model, with the original model having a ΔAIC = 59.74. The adjusted r^2 for this model was 0.51 ($F_{4,269}$ = 67.22, p<0.001; Table 12.5), and *k*-fold cross validation indicated that the correlates in the model were not biased (slope in Figure 12.1 = 1) and explained 53% of the variation in grid cells used for validation, which were independent from the cells used for training the model.

Table 12.2. Models of abundance in grid cells and ΔAIC values. All models included the total length of IID water conveyance structure in addition to the parameters listed.

Model Parameters	ΔAIC
Burrows in 2007, alfalfa in 2004	0
Burrows in 2007, alfalfa in 2003	1.62
Burrows in 2007, alfalfa in 2006	5.38
Burrows in 2007, alfalfa in 2005	6.21
Burrows in 2007, bare and fallow in 2007	9.82
Burrows in 2007, bare and fallow in 2006	10.09
Burrows in 2007, bare and fallow in 2003	10.54
Burrows in 2007, bare and fallow in 2004	12.48
Burrows in 2007, alfalfa in 2007	13.16
Burrows in 2007	27.53
Grass in 2006	27.94
Burrows in 2007, bare and fallow in 2005	29.31
Bare/fallow in 2004	30.06
Bermuda grass in 2007	30.46
Alfalfa in 2004	31.03
Alfalfa in 2003	33.29
Fallow in 2007	35.71
Fallow in 2006	40.07
Fallow in 2003	40.19
Grass in 2007	40.70
Alfalfa in 2006	40.92
Bare/fallow in 2007	42.13
Fallow in 2005	43.90
Sudan grass in 2006	43.92
Alfalfa in 2005	44.21
Proportion cement-lined water conveyance structures	44.57
Bare/fallow in 2006	45.14
Bare/fallow in 2003	46.28
Grass in 2004	47.05

Bermuda grass in 2003	47.14
Bare/fallow in 2004	48.13
Grass in 2003	49.01
Broadleaf in 2003	50.27
Bermuda grass in 2004	52.69
Bermuda grass in 2005	52.83
Alfalfa in 2007	52.90
Bermuda in 2006	53.19
Broadleaf in 2004	55.69
Grass in 2005	57.38
IID Mainenence in 2006	58.56
Proportion suitable soils	59.59
Broadleaf in 2006	59.82
Broadleaf in 2007	60.06
Sudan grass in 2004	60.22
Total IID Maintenance activities, 2004-2007	61.14
Proportion suited and well-suited soils	61.39
Wheat in 2004	61.96
Crop richness in 2006	62.03
Wheat in 2003	62.50
Crop richness in 2005	62.52
IID Maintenance in 2005	62.70
Proportion well-suited soils	62.75
Wheat in 2005	63.04
Bare/fallow in 2005	63.87
Crop richness in 2003	64.34
Proportion poorly-suited soils	64.37
Length of water conveyance structures	64.40
Bare ground in 2004	64.60
Dominant soil category	64.69
Crop richness in 2004	64.74
Wheat in 2006	65.01
IID Maintenance in 2004	65.44
Sudan grass in 2003	65.67
Broadleaf in 2005	65.72
Bare ground in 2005	65.72
Sudan Grass in 2007	65.79
Bare ground in 2007	65.83
Wheat in 2007	65.97
IID Maintenance in 2003	66.23
Bare ground in 2006	66.32
Crop richness in 2007	66.35
Bare ground in 2003	66.39

Table 12.3. Summary of best linear regression model without a spatial covariate. TotLength is the total length of IID water conveyance structure (km) in a grid cell, 07Brrws is the number of available burrows counted in a grid cell in 2007, and 04Alfalfa is the proportion of a grid cell covered by alfalfa in the spring 2004.

Parameter	Estimate	Std. Error	*t*-value	Pr(>|t|)
Intercept	-3.63719	2.19056	-1.66	0.09
TotLength	0.45289	0.13106	3.456	<0.001
07Brrws	0.16371	0.02784	5.881	<0.001
04Alfalfa	22.87477	4.12668	5.543	<0.001

Table 12.4. Results from Moran's *I* analysis of spatial autocorrelation, using program GeoDa.

Nearest Neighbors	Moran's *I*	*p*-value
1	0.3011	0.001
2	0.1314	0.001
3	0.0040	0.355

Table 12.5. Summary of best linear regression model with a spatial covariate. TotLength is the total length of IID water conveyance structure (km) in a grid cell, 07Brrws is the number of available burrows counted in a grid cell in 2007, 04Alfalfa is the proportion of a grid cell covered by alfalfa in the spring 2004, and MNhat2NN is the mean abundance of male Burrowing Owl territories out to 2 nearest neighboring grid cells (Queen's rule).

Parameter	Estimate	Std. Error	*t*-value	Pr(>|t|)
Intercept	-12.5436	2.23862	-5.603	<0.001
TotLength	0.27721	0.11923	2.325	0.0208
07Brrws	0.16018	0.02492	6.427	<0.001
04Alfalfa	10.46895	3.9885	2.625	0.009
MNhat2NN	0.83916	0.10177	8.245	<0.001

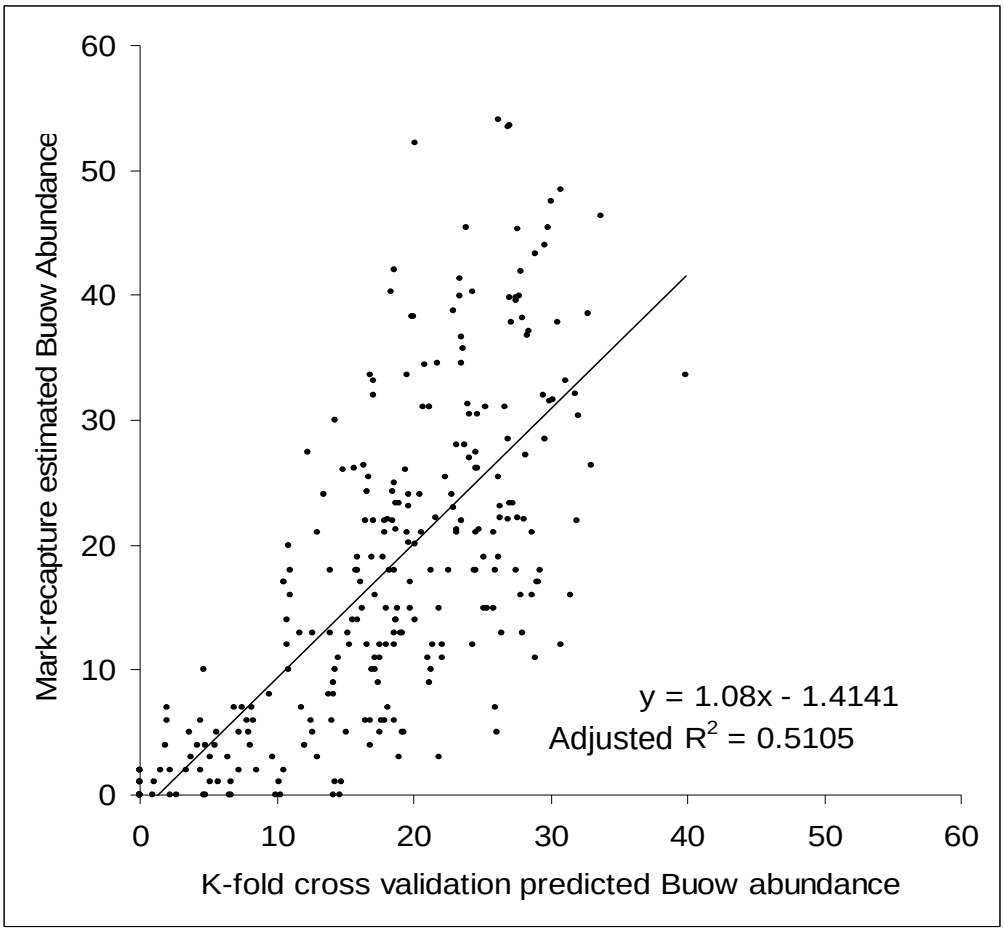

Figure 12.1. Results from *k*-fold cross validation of the best least squares weighted regression with a spatial covariate of owl abundance (Owl territory abundance = TotLength + 07Brrws + 04alfalfa + MNhat2NN) for predicting abundance of male Burrowing Owl territories, Imperial Valley, California 2007.

CONCLUSIONS AND RECOMMENDATIONS

The model representing the best correlates of male Burrowing Owl territory abundance in the HCP Study Area contained the number of available burrows and the proportion of alfalfa in grid cells three years prior to the owl survey. The competing model in our initial analysis contained alfalfa four years prior to the survey, and the four models containing only alfalfa and burrows had the best AIC rankings of all the models tested. This was not surprising given that the type of vegetation surrounding Burrowing Owl nest burrows has been suggested by others to be a possible predictor of owl abundance (Rich 1986, Green and Anthony 1989, Haug and Oliphant 1990, Plumpton and Lutz 1993). Of the 9 crop types found to be used by a small sample of radio-tagged Burrowing Owls in the Imperial Valley (Rosenberg and Haley 2004), owls selected for barren ground near (<1,980 ft) and hay far (>1,980 ft) from nests. Our results provide evidence of the importance of alfalfa as a correlate of owl abundance in the HCP Study Area.

Although the addition of a spatial covariance term improved the fit of our best model, this model explained only 51% of the variability in local owl abundance across the HCP Study Area. This may be due to a variety of factors, including the resolution of the standardized grid cells, temporal variation in the correlates themselves (e.g., crops were rotated during our owl surveys), accuracy of the remote sensing analyses that we used to derive the crop estimates, and quality of the other correlates we used. For example, the IID's maintenance data were only available for each canal or drain as a whole, with no specific location. Because some of these structures were very long and maintenance activities are often locally concentrated (Ty Mull, pers. comm.), the spatial resolution of the data was not fine enough to determine with high accuracy the amount of maintenance each grid cell received. The categorization of maintenance activities also necessitated that we pool among categories because specific activities were often referred to in the database under more general terms. Because recent information suggested that maintenance activities can directly influence Burrowing Owl survival and dispersal (e.g., Catlin and Rosenberg 2006), we suspect our generalization of that data may have diluted its accuracy, which in turn reduced our ability to adequately assess the relative importance of the IID's maintenance as a correlate of abundance. Based on our initial objective to identify the best correlates of owl abundance for use in stratifying the HCP Study Area prior to future population surveys, further investigations into correlations between specific IID maintenance activities and owl abundance may prove beneficial.

The best model identified the variables that were most correlated to owl abundance, which is a widely accepted method of choosing variables that can be used to construct strata for stratified random sampling (Cochran 1977:128). Because it did not explain all of the variation in owl abundance and its correlative power may not be stable over time (e.g., farming practices change or local owl abundances become limited by other factors), the efficacy of using this model for constructing strata needs to be tested. A validation of this correlative model with an independent dataset is essential because if the correlation between these variables and owl abundance does not remain constant or increase over time, then the stratification will become inefficient and the precision of the resulting population estimates will be reduced (Cochran 1977:100-102). In light of these concerns, chapter 17 provides a comparison of this model against alternatives to stratifying the HCP Study Area, and a recommended alternative is provided.

Chapter 13

POTENTIAL CORRELATES OF AREA OCCUPANCY BY MALE BURROWING OWLS

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. The Burrowing Owl population surveys described in previous chapters could provide information on rates of occupancy in local grid cells, which could provide valuable information for conservation and management and elimination of areas from future surveys. In this chapter, we focused on identifying potential correlates of area occupancy by male Burrowing Owls. We used the information theoretic approach to compare the fit of various logistic occupancy models to the data, where each model structure included a different potential correlate and/or assumed variable or constant detection probabilities. We found that >95% of the 3x3 grid cells in the HCP Study Area were occupied, and that none of the models fit the data well, preventing us from identifying a correlate of occupancy.

INTRODUCTION

In our detailed study plan, dated 18 January 2007, we proposed to use the Burrowing Owl survey data and datasets of potential correlative factors collected for Tasks 1 and 4 under Objective 1 to estimate the probability that sampling units (grid cells) were occupied by ≥1 owl territories. This information was intended to supplement the distribution of owl point locations obtained from conducting the complete census under Objective 1 of the study plan. It was also to provide a GIS polygon layer of independent sampling units with probabilities of occupancy categorized according to either low and high probabilities of occupancy. This GIS layer could also be viewed as a probabilistic distribution map, and was anticipated to be generated each year, based on the correlative factor(s) determined to be the most strongly correlated to probabilities of occupancy. Here, we present the findings from this approach.

METHODS

For this study, we used the original territory locations derived from the 3 point-coordinate capture-recapture survey occasions determined from the 2007 census of 3x3 km grid cells in the HCP Study Area. We used these data to construct a multinomial occupancy encounter history for each grid cell, where a given grid cell was considered occupied (1) on a given survey occasion if ≥1 owl territories were detected and unoccupied (0) if no territories were detected. We applied these binomial decisions for each survey occasion.

We fit occupancy models to the occupancy encounter history using Program PRESENCE 2.2 (Hines 2006), with the goal of determining the corrected estimate of the proportion of 3x3 km grid cells occupied in the HCP Study Area. We applied an information theoretic framework to testing multiple working hypotheses (Burnham and Anderson 2002), developed a set of 28 *a priori* hypotheses, and constructed an occupancy model for each

hypothesis. Our base model [ψ (.) p(.)] represented the hypothesis that the proportion of occupied grid cells (ψ) did not vary according to an environmental covariate and the probability of detecting occupancy (*p*) was constant among occasions. We further constructed models that differed in the environmental variable (soils, fallow land, alfalfa, maintenance activities, water conveyance structure length and type, burrows, and crop richness) hypothesized to be a potential correlate of occupancy of grid cells. We constructed simple linear models, and included only single covariates that we suspected may be important or previously reported in the literature to be important for Burrowing Owls. Because our sampling methodology involved surveying different portions of the HCP Study Area at different times over the 30 days (e.g., we would conduct 4 consecutive occasions in one portion before conducting 4 occasions in another portion, and we divided the area into 6 separate portions), we pooled the data across the different portions to create our 4-occasion encounter histories. To avoid problems with the possible confounding of time and portion of the HCP Study Area surveyed, we assumed that detection was constant in our models. We used Akaike's Information Criterion (Akaike 1973) to determine the most parsimonious model and considered it to be our best model. We assessed the fit of our global model to the occupancy encounter history data using 1,000 bootstraps for Mackenzie and Bailey's Goodness-of-fit test (Mackenzie and Bailey 2004).

RESULTS

We observed ≥1 male Burrowing Owl territories during ≥1 survey occasions in 261 (95%) of the 274 grid cells in the HCP Study Area during the 2007 surveys. We did not detect territories in the remaining 5% (13) of the grid cells, making the naïve (empirical) estimate of ψ = 0.95, which differs from the modeled estimate of ψ and can be interpreted as the probability that any grid in the HCP Study Area is occupied. The model with the smallest ΔAIC hypothesized that occupancy was a function of the dominant type of soil in grid cells, and there were no competing models (the next best model had a ΔAIC = 181). This model estimated a very high detection probability (*p*) of 0.97 (SE = 0.18).

Our best model (equivalent to a global model in its number of parameters) fit the data poorly (Goodness-of-fit X^2 = 57.2, P = 0.001), predicting an unconditional ψ that was equal to the naïve estimate (0.95, SE = 0.01) in the 13 grid cells where we did not observe territories. When conditioned on the encounter histories, this model predicted no occupancies that we did not detect.

Given the poor performance of this model and the absence of competing models, we also examined the fit and ability to correctly predict occupancy from various models with covariates that we constructed and found similar problems, with none passing the Goodness-of-fit test. Although there was little support for our base model containing no covariates (ΔAIC = 1058.94), its estimated *p* was also high (0.97, SE = 0.005), and it also predicted the proportion of occupied sites equal to the naïve estimate (ψ = 0.95, SE = 0.01).

CONCLUSIONS AND RECOMMENDATIONS

Given the high probability of detecting the presence of male Burrowing Owl territories in grid cells, and the high rate of occupancy, most of 274 grid cells in the sampling grid were occupied. The discrepancy between the 18 grid cells found in chapter 10 to contain zero territory centroids and the lower number (13) found here to be unoccupied was due to our use of owl locations in estimating occupancy. Because of the 2-dimensional nature of owl territories, locations of owls that occupy territories straddling grid cell boundaries can occur in ≥2 grid cells, and this edge effect led to classifying 5 of the grid cells without territory centroids as occupied during these analyses.

The failure of our global model to fit the data may stem from a variety of sources, including: 1) that the size of our grid cells, coupled with high detection probabilities, ensured a high rate of observed occupancy, particularly given the density of the owl population in 2007, 2) the owl population was saturated (but see Chapter 19), 3) our set of hypotheses were not comprehensive enough which could have incidentally led us to not measure the biologically correct correlative variable(s), 4) or our model structures may not have adequately accounted for additive or multiplicative biological processes that influenced occupancy. A reduced owl population or smaller grid cells would produce more variability among grid cells and may have yielded a different result, but our objective was to use the existing standardized grid intended for drawing random samples from prior to subsequent surveys.

The prediction of high occupancy rates (0.95) by the best model in grid cells where territories were not detected was likely due to the high rate of occupancy that essentially produced a homogeneous sampling grid of occupied cells. This extremely low number of unoccupied grid cells, compared to the large number of occupied cells, provided an extremely imbalanced dataset from which to estimate occupancy rates with our models, and explains the source of the poor fit. Furthermore, this may also explain why dominant soil type was the best correlate. Dominant soils were classified into only 3 types, and suitable soils was the dominant soil type in grid cells across the HCP Study Area (Figure 7.1E), including all of the grid cells where we did not detect owls, producing a nearly homogeneous distribution similar to that of occupancy rates. Thus, the response and correlate variables lacked adequate variability necessary to model a range of occupancy rates, and unoccupied grid cells were assigned the global (naïve) probability of occupancy.

Chapter 14

ELIMINATION OF AREAS DURING FUTURE SURVEYS DUE TO THE UNLIKELIHOOD OF BEING OCCUPIED BY MALE BURROWING OWL TERRITORIES

JEFFREY A. MANNING

ABSTRACT. Balancing cost and logistical effort is always a priority in developing long-term wildlife population monitoring programs. Here, I provide a brief discussion on how to prioritize survey efforts towards grid cells in the HCP Study Area with high probabilities of being occupied to reduce costs. During the establishment of the standardized sampling grid, several grid cells were removed because they lacked any above-ground IID water conveyance structures. There removal was necessitated by our conducting surveys only along water conveyance structures. Due to the high rate of occupancy among the remaining grid cells, dynamic changes in numbers of owls that can occur, and the robust ability of the sampling methodology developed in the following chapter to account for cells that are unoccupied during a given survey, no other cells were removed.

INTRODUCTION

I originally proposed to use the 2007 census data to determine if any and which grid cells in the HCP Study Area should be eliminated from the sampling grid (see detailed study design, dated 8 January 2007). I proposed to make such a determination on a cell by cell basis using the estimated local abundance from Chapter 10 and occupancy rates from Chapter 13. The approach involved eliminating grid cells where estimated abundance and occupancy rates were simultaneously low. This was intended to prioritize survey efforts towards areas with high probabilities of being occupied and coincidently improve the accuracy of population estimates.

As part of the development of the standardized sampling grid of 3x3 km cells in Chapter 9, several grid cells were removed because they lacked any IID water conveyance structures. The remaining grid cells contained a range of abundance estimates from 0 to 57 male Burrowing Owl territories, as reported in Chapter 10. The discrepancy between the 18 grid cells we reported in Chapter 10 to contain zero territory centroids and the 13 reported to be unoccupied during our occupancy modeling in chapter 13 was due to our use of owl locations in estimating occupancy rather than centroids. Because of the 2-dimensional nature of owl territories, the locations of owls along grid cell boundaries can occur in multiple grid cells, and this edge effect can lead to classifying cells without territory centroids as occupied. Nonetheless, as was shown in chapter 13, occupancy rates were consistently high across the HCP Study Area. The absence of variability in occupancy rates compromised the originally proposed effort to use them for making decisions on the selective elimination of cells from the sampling grid.

Several of the 18 grid cells where we did not detect territory centroids in 2007 were dominated by urban developments, but they did contain above-ground water conveyance structures maintained by the IID. Such structures near other urban areas in the HCP Study Area did support territories during this study period. For these reasons, grid cells dominated by urban development that contain above-ground water conveyance structures may still contain suitable nesting habitat and could be occupied in future years. In light of the dynamic changes in the numbers and distribution of territories during the breeding season (see Chapter 19), it would not be prudent to permanently remove these grid cells from future surveys. Furthermore, because the stratified random sampling methodology presented in the following chapter is reliant on low, medium, and high owl abundances among grid cells, the few grid cells where we surveyed and did not detect occupancy in 2007 can be appropriately included into the low abundance stratum, thereby making them available for random selection in future surveys. When these grid cells are randomly selected, the resulting abundance estimates at that time can be used to appropriately calculate the overall estimate and sampling error for the low abundance stratum.

Chapter 15

DEVELOPMENT OF A STRATIFIED RANDOM SAMPLING METHODOLOGY TO SURVEY FOR AND ESTIMATE MALE BURROWING OWL TERRITORY ABUNDANCE

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. As with any long-term population monitoring program, a standardized sampling design that minimizes the required sample size, optimizes the allocation of survey effort, and reduces costs while maintaining high levels accuracy at all stages of the survey is needed for surveying Burrowing Owls in the HCP Study Area. Here, we present a stratified random sampling methodology for estimating the abundance of male Burrowing Owl territories. The method involved identifying a range of minimum required sample of grid cells needed to achieve estimates with specified levels of precision. It also determined the optimal allocation of grid cells to the corresponding strata by accounting for differential variances in owl abundance and costs associated with surveying each strata (i.e., based on our standardized sampling protocols, more owls equated to more stops that required more time and higher costs). We demonstrated how this sampling methodology greatly improved precision, and recommended its use.

INTRODUCTION

Prior to initiating a long-term population monitoring program for Burrowing Owls in the HCP Study Area, a standardized sampling design that minimizes the required sample size, optimizes the allocation of survey effort, and reduces costs while maintaining high levels accuracy at all stages of the survey is needed. Wildlife monitoring programs such as these generally involve choosing a desired level of detectable change in the population. Many decisions made in the early planning stages influence the power and cost of conducting surveys intended to detect that desired level. A well designed sampling approach can reduce costs while maintaining the ability to detect the desired level of population change. As described in the general introduction, reducing measurement and sampling errors can increase the accuracy of total population estimates. Reducing these errors essentially increases statistical power, and sampling design is an important mechanism by which to accomplish this objective. Statistical power can be increased by (1) establishing homogeneous strata, (2) measuring concomitant information, and (3) selecting an efficient sampling design (Kuehl 1994).

With the proper sampling design, empirical estimates of population size can be used to compute finite rates of annual population growth (λ) with a level of precision needed to achieve a desired level of detecting a change in the Burrowing Owl population. Because the HCP specified that "the appropriate significance level for … [λ] will be determined by a statistician," a range of sample sizes that would be required to achieve a desired level of precision surrounding population estimates (or distance from the true population

mean) would be advantageous prior to making such a determination. The desired precision is important because it is a function of sample size (or visa versa) which corresponds to the level of survey effort and cost. Larger sample sizes (e.g., more grid cells surveyed) are more precise, which increase the ability to detect a smaller change in the population between years than from smaller samples, but at a greater financial cost. Because management actions involve a balance between cost and reliability of biological data, determining how many grid cells would be required to attain a particular level of precision (and detectable level of population change), is a practical and efficient method to establish the annual level of survey effort in the HCP Study Area. This method of computing a population growth rate would also enable the IT to immediately assess the stability of the Burrowing Owl population and determine if adjustments to the Burrowing Owl Conservation Strategy are needed prior to the onset or completion of the demographic study referenced in section 4.5.3 of the HCP.

Time and money limitations typically constrain population surveys to a sample of areas that represent a fraction of the area occupied by the population of interest. Here, each area is represented by a 3x3 km grid cell, and sampling error refers to the variability in abundance of male Burrowing Owl territories among these sampling units. In these situations, a carefully selected sampling design can reduce sampling error and improve statistical power (Kuehl 1994). Designs such as cluster sampling, randomized block, and stratified random sampling reduce sampling error by categorizing sampling units according to their similarity or dissimilarity and estimating abundance in each class separately.

Because abundance of owls was shown to be unevenly distributed across the HCP Study Area (see Chapter 10), a simple random sample of areas would likely lead to imprecise estimates of the total size of the population (Caughley 1977:27, Williams et al. 2002:247). An accurate estimate of population size can be obtained with sampling designs that account for the size, shape, number, and placement of sampling units across areas where abundance is unevenly distributed (Caughley 1977:27, Williams et al. 2002:247).

A commonly used design to estimate the size of wildlife populations in large areas where abundance is unevenly distributed is stratified random sampling (Caughley 1977:27, Cochran 1977:87, Williams et al. 2002:249). The area supporting the total population of interest is subdivided into areal sampling units, and these are categorized according to their similarity in animal abundance (e.g., low, medium, and high). These categories are referred to as strata, and a random sample of units is drawn separately from each stratum. Animals are counted in the randomly sampled units and the strata abundances are summed to estimate a total population size. This stratification of units into similar abundances reduces sampling error among strata and the estimated total population estimate (Cochran 1977:88). As with the other designs mentioned above, this sampling design assumes that population counts in sample units are without measurement error. Because measurement error probably cannot be completely eliminated (Steenhof and Kochert 1982, Fraser et al. 1983) and is not accounted for in these methods, it is very important to reduce measurement error when using one of these designs.

In this chapter, we present the results from a stratified random sampling design we developed for sampling and estimating the total population size of male Burrowing Owl territories in the HCP Study Area. As part of this effort, we calculated a range of sample sizes that would be required to achieve a desired level of statistical precision surrounding

population estimates (or distance from the true population mean), from which a determination of the desired level of change can be based. We accomplished this with the local abundance estimates from 2007, and the design relies on survey methods that minimize measurement errors, such as the point-coordinate capture-recapture survey technique presented in Chapter 5 and used in producing the local abundance estimates.

METHODS

Minimum Required Sample Size

We determined the size of random samples of grid cells that would be required to be surveyed in the HCP Study Area to achieve an estimated population mean at specified levels of precision (or distance away from the true population mean; Williams et al. 2002:64). Here, the population refers to the 274 grid cells from which a random sample would be drawn from and surveyed each year, and the mean refers to the mean owl abundance in grid cells. We based this analysis on sampling without replacement (e.g., a grid cell would be surveyed once per population survey), with an adjustment for the influence of the finite population of 274 grid cells available for sampling, using the following equations:

$$n = \left(\frac{z_{\alpha/2}}{d} CV \right)^2 \qquad \text{Equation 15.1}$$

where n is the sample size needed, α is the level of statistical significance, $z_{\alpha/2}$ is the upper $\alpha/2$ point of the standard normal distribution, d is the specified distance in multiples of the population mean, and CV is the population coefficient of variation, which we calculated from the estimated abundance in each 3x3 km grid cell. The finite population adjusted n was then computed with

$$n' = n/(1 + n/N) \qquad \text{Equation 15.2}$$

where N is the total population of grid cells (274) available for sampling.

This approach is commonly used in wildlife science to determine a minimum required sample size, and negates the bootstrapping that we originally proposed.

Stratum Boundaries

Stratification of a study area into relatively homogeneous subunits can improve the precision of population estimates (Cochran 1977). Stratification increases efficiency in sampling effort and is commonly used to improve the precision of wildlife population estimates. We determined the numerical boundaries of 3 strata (low, moderate, and high owl abundances) using the cumulative of the square-root of the frequency method, which should provide an efficient stratification (Cochran 1977:127-132). For this analysis, we used frequencies of owl abundance in increments of 5. We then used these numerical

stratum boundaries to post-stratify each grid cell across the HCP Study Area by the estimates of Burrowing Owl abundance in 2007. Using this same method, stratum boundaries can be recalculated prior to each subsequent survey using owl abundance or a correlate of it, and should yield relatively precise estimates.

Optimal Allocation of Survey Effort among Strata

Optimal allocation of the minimum required sample size among the predefined strata improves precision and survey efficiency. We determined the optimal allocation of effort among strata by taking into account stratum variances, sampling costs, and stratum size (Williams et al. 2002:65-67). Sampling costs were based on cost constraints in each stratum according to the mean length of survey route and mean number of owls per grid cell in a stratum. This approach allocated samples to each stratum in a manner that minimized stratum variances given an overall cost constraint C that equaled $C_1 n_1 + ... + C_i n_i$ for $n = n_1 + ... + n_i$ available samples of grid cells. This constrained optimization had an optimum solution of

$$n_i = n\left(\frac{(N_i \times \sigma_i)/\sqrt{C_i}}{\sum_{i=1}^{I}(N_i \times \sigma_i)/\sqrt{C_i}}\right) \quad \text{Equation 15.3}$$

where N_i is the total number of grid cells, σ_i is the standard deviation, and C_i is the cost constraint [($\bar{x}$ km of survey route $\times$ 0.19 minutes/km) + ($\bar{x}$ number of owls $\times$ 2 minute stop/owl)] associated with stratum *i*.

Precision of Burrowing Owl Territory Abundance Estimates by Stratified Random Sampling

When applied appropriately, stratified random sampling nearly always results in greatly improved precision of estimated means or totals than that obtained from a comparable simple random sample (Cochran 1977:98). To demonstrate how well stratified random sampling improved the precision of our estimates over simple random sampling with the same level of survey effort, we repeatedly sampled the estimates of abundance in the 274 grid cells from the entire 2007 dataset, thereby developing a series of simulated sample datasets from the original data. For each sampling method, we conducted 1,000 simulations by subsampling the grid cells, without replacement. For these simulations, we chose to use the minimum required sample size to be within 10% of the true population size that was approximated in Chapter 10 by summing the local abundance estimates from the 2007 census. For stratified random sampling simulations we also applied optimal allocation of effort among the 3 strata determined above.

Unbiased simple random sampling estimates of population size $(\hat{X}_{SR})$ for the HCP Study Area were calculated by multiplying the total number of grid cells by the ordinary sample mean $(\bar{x}_{SR})$ in the HCP Study Area:

$$\hat{X}_{SR} = N \times \bar{x}_{SR} = N \times \sum_{j=1}^{n} \hat{x}_j / n_j \qquad \text{Equation 15.4}$$

where $\hat{x}$ is the abundance estimate associated with the *j*th randomly selected grid cell *n*.

We calculated the variance of each simple random sampling estimate ($\hat{\sigma}^2_{\hat{X}_{SR}}$) with a finite population adjustment:

$$\hat{\sigma}^2_{\hat{X}_{SR}} = N^2 \times \frac{s^2}{n}(1 - n/N) \qquad \text{Equation 15.5}$$

where s^2 is the usual sample variance. We then used this variance to calculate 95% confidence intervals.

Following Steel et al. (1997:595-597), we calculated unbiased stratified random sampling estimates of population size $(\hat{X}_{ST})$ as:

$$\hat{X}_{ST} = \sum_{i=1}^{n} N_i \times \bar{x}_i \qquad \text{Equation 15.6}$$

where N_i is the total number of grid cells in the *i*th stratum and $\bar{x}_i$ is the mean abundance estimate associated with the *i*th stratum.

The variance of the estimated population mean from a stratified random sample was calculated as:

$$\hat{\sigma}^2_{\bar{x}_{ST}} = \frac{1}{N^2} \sum_{i=1}^{3} N_i (N_i - n_i) \times \frac{s_i^2}{n_i} \qquad \text{Equation 15.7}$$

We used this variance to calculate 95% confidence intervals surrounding the mean of each simulated stratified random sample and multiplied the upper and lower bounds by *N* to obtain the intervals surrounding each population estimate.

To compare between the two sampling methods, we calculated the 95% confidence interval width (CI) for each bootstrapped population estimate, computed the mean of those confidence interval widths $(\overline{CI})$ separately for each sampling approach, and

assessed the difference in this measure of precision. All analyses were performed in R (Ihaka and Gentleman 1996).

RESULTS

We present a range of minimum required numbers of 3x3 km grid cells to be randomly sampled and surveyed to achieve specified levels of precision (Table 15.1). A minimum of 119 grid cells (43% of the HCP Study Area) would need to be surveyed using a simple random sampling approach to ensure that the population estimate is within 10% of the true population size, and 44 grid cells would be required for 20% (Table 15.1; Figure 15.1). These levels of precision also specify the minimum detectable level of annual population change under simple random sampling by multiplying them by 2; but, stratification and optimal allocation of effort can further improve these levels of precision and narrow the statistically detectable level of population change.

Our analysis of numerical boundaries for the 3 strata we selected determined the following ranges in abundance: 0 - 14.9 in the low abundance stratum, 15.0 - 29.9 in the moderate, and 30 - 54.9 in the high (Table 15.2; Figure 15.2). Based on these stratum boundaries, there were 123 grid cells in the low abundance stratum, 95 in the moderate, and 56 in the high.

The optimal allocation of effort among the 3 strata was 50.4% of the low, 32.6% of the moderate, and 48.2% of the high abundance strata (Table 15.3).

For our assessment with the simulated samples bootstrapped from the census of all grid cells, we used the minimum required sample size required to be within 10% of the true population size (119 grid cells; Table 15.1). For this selected sample size, the optimal allocation was determined to be 62 grid cells in low abundance stratum, 31 in the moderate, and 27 in the high. Based on these simulations, the precision of estimated Burrowing Owl territory abundance was improved by stratified random sampling [$\overline{CI}$ = 352.7 male owl territories (95% CI: 351.8 - 353.7)] compared to simple random sampling [($\overline{CI}$ = 977.6 (95% CI: 975.0 - 980.2)]. The $\overline{CI}$ obtained from simple random sampling represented almost 20% of the true total population size of 4,879 estimated in chapter 10 (or 10% on either side of the estimate), whereas that from stratified random sampling was 7% of the true total population size.

CONCLUSIONS AND RECOMMENDATIONS

The minimum required sample of grid cells to achieve specified levels of precision and rates of change in population size we present here were based on the survey protocols and analytical methods presented in Chapters 5, 7, and 10. Our results provide basic information needed to choose a desired level of detectable change in the population by considering the statistical precision of the population estimates. Once a minimum level of change is chosen, the minimum required sample size can be determined from Table 15.1. The smallest rate of change that can be detected with 95% certainty from simple random sampling is approximately 20% (2 x 10% of the distance each sample estimate

would be from its true population size) by sampling 43% of the HCP Study Area. As an example of such a change, a 20% decline would reflect the loss of 999 of the 4,998 male territories detected in 2007. However, stratified random sampling can improve this level of precision and narrow the level of detectable rate of change.

To apply the stratified random sampling methodology, the optimal level of effort in each stratum would need to be determined for the minimum required sample size chosen. Once an optimal level of effort was determined, optimal allocation would be recalculated following the re-stratification of the sampling grid prior to each population survey. Based on our assessment with our simulated samples, that same sample size (119; but, stratified, optimally allocated, and surveyed following our methods) should provide estimates of population size that lie ≤ 3.5% from the total population size that would have been estimated if all grid cells in the HCP Study Area were surveyed. This represents a 186% gain in precision over an equal level of simple random sampling.

In theory, a stratified random sample of 119 grid cells would enable the IT to detect a ≥7% change in λ with 95% statistical confidence. However, our stratified random sampling methodology assumed no measurement error during surveys in our grid cells, although we believe our standardized survey protocols and number of point-coordinate capture-recapture occasions minimized it to a negligible level (Steenhof and Kochert 1982, Fraser et al. 1983). Furthermore, this sampling methodology was based on the construction of strata from the empirical frequency of owl abundance, which was the ideal variable for stratification (Cochran 1977:100). Although this currently was the best biological information available to construct strata, its application in subsequent surveys would assume that local owl abundances would change little. The next best alternative to using owl abundance would be to use a variable that is closely correlated to it (Cochran 1977:128), which is why we developed the correlative model in Chapter 12. That model determined the group of variables that were most correlated with abundance of owls in 2007, and in Chapter 17, we compare its use to stratify the HCP Study Area prior to an independent survey to other possible methods of stratification. Because that correlative model did not explain all of the variation in owl abundance and its correlative power may not be stable over time (e.g., farming practices change or local owl abundances become influenced by other factors), we expect that the precision presented here may be higher than realized in subsequent surveys (Cochran 1977:100-102). Thus, it is important to consider the results in Chapters 17 and 18 before selecting the final method to stratify the HCP Study Area prior to each subsequent survey and choosing the minimum required sample size for a specified level of detectable rate of change.

Table 15.1. Size of a simple random sample (no. of grid cells) required to ensure a population size within a specified distance from the true number of owls.

Distance from true mean (%)	Finite adjusted sample size
0	274
10	119
20	44
30	22
40	13
50	8
60	6
70	4
80	3
90	3

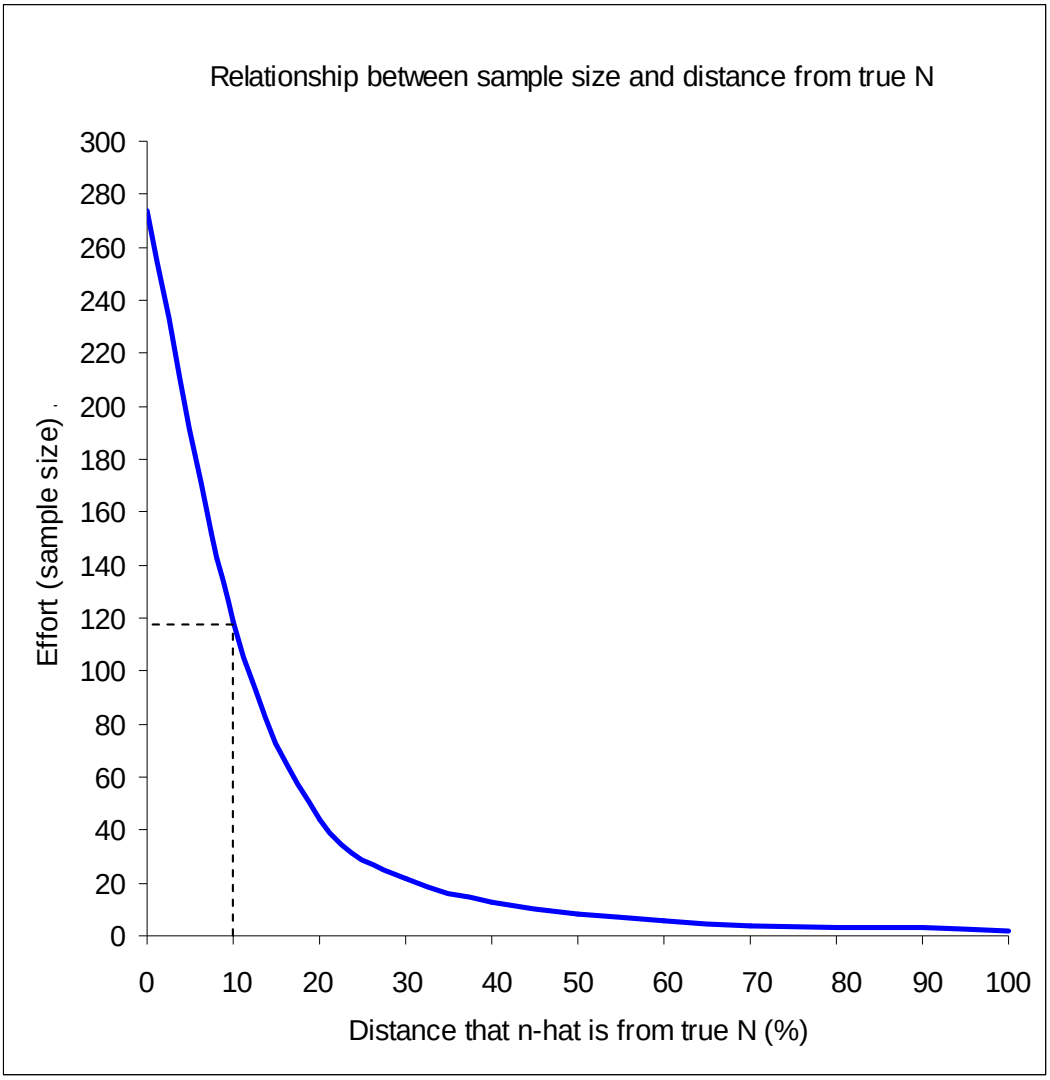

Figure 15.1. Graphical representation of Table 15.1: size of a simple random sample (no. of grid cells) required to ensure a population size within a specified distance from the true number of owls and minimum detectable population change. Dotted lines demarcate the level of simple random sampling effort (number of 3x3 km grid cells) required to detect a minimum change of 20%, which can be improved through stratification and optimal allocation.

Table 15.2. Determination of sampling strata boundaries of Burrowing Owl abundance during the prehatch stage of the breeding cycle using the cumulative square root method (Cochran 1977:127-131), Imperial Valley, California, 2007. These strata were developed as part of a long-term stratified random sampling survey method.

Abundance range	No. of cells $f(y)$	$\sum\sqrt{f(y)}$	Strata	Range	Cells (N)
0-4.99	52	7.21			
5-9.99	34	13.04			
10-14.99	37	19.12	1 (low)	0-14.99	123
15-19.99	37	25.21			
20-24.99	39	31.45			
25-29.99	19	35.81	2 (moderate)	15-29.99	95
30-34.99	23	40.61			
35-39.99	16	44.61			
40-44.99	7	47.25			
45-49.99	6	49.70			
50-54.99	4	51.70	3 (high)	30-54.99	56

Stratum Boundaries	
max $\sum\sqrt{f(y)}$ / 3 =	17.23
2xmax $\sum\sqrt{f(y)}$ / 3 =	34.47
3xmax $\sum\sqrt{f(y)}$ / 3 =	51.70

Table 15.3. Optimal allocation of survey effort among 3 strata of estimated local abundance for estimating the annual population size of male Burrowing Owl territories in the HCP Study Area, Imperial County, California, based on data from 2007. $\bar{x}$ indicates mean.

Strata	Number of owls ($\bar{x}$)	Average length of survey route ($\bar{x}$ km)	Cost constraint ($\bar{x}$ minutes)	Total cells	Optimal sample size of Total cells (%)
Low	6.03	12.24	76.46	123	50.4
Moderate	21.07	15.82	125.39	95	32.6
High	38.13	16.96	165.56	56	48.2

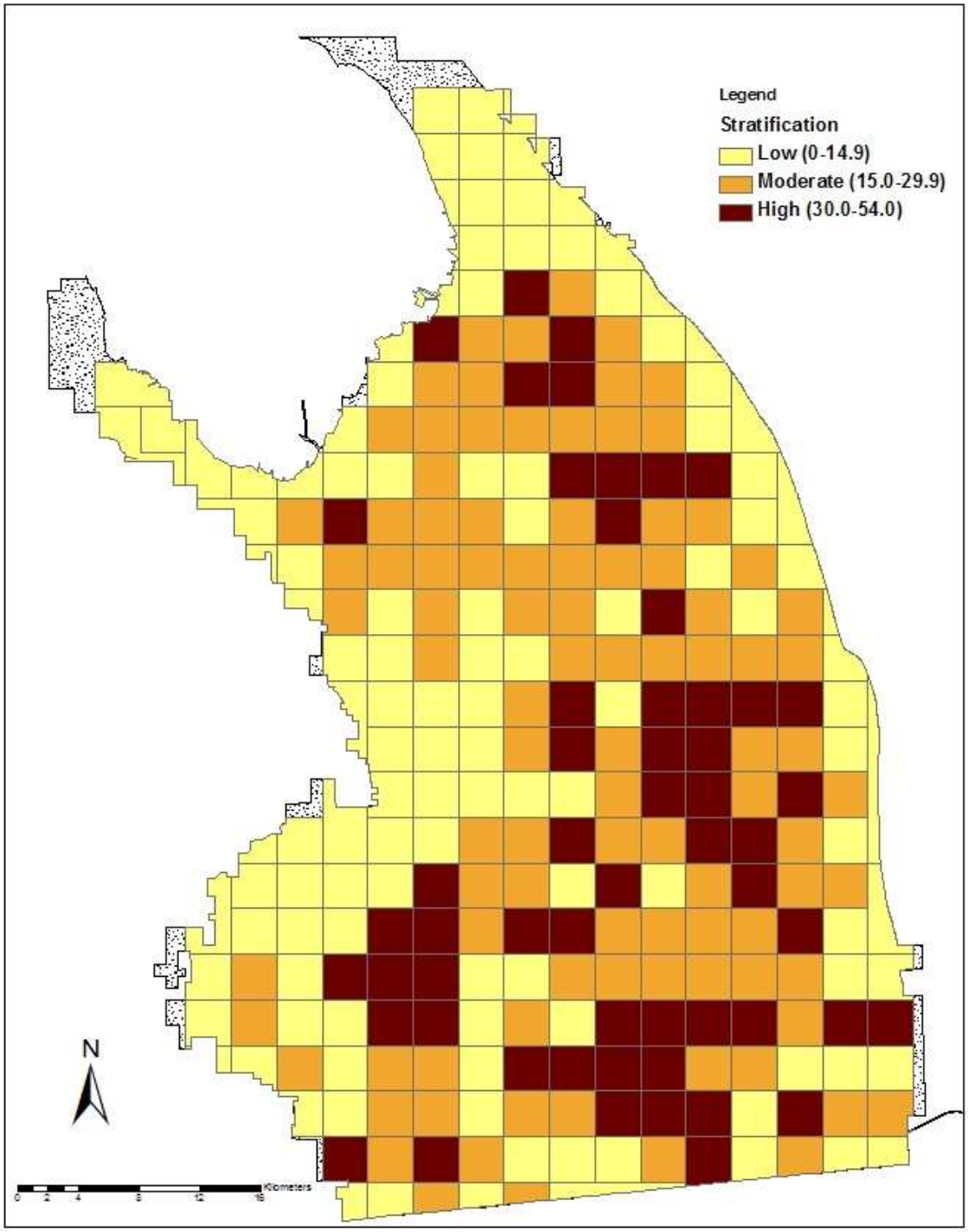

Figure 15.2. Post-stratification of Burrowing Owl abundance during the prehatch stage of the breeding cycle, Imperial Valley, California, 2007. These strata were developed as part of a long-term stratified random sampling survey method.

Chapter 16

MAXIMUM LIKELIHOOD ESTIMATES OF LOCAL MALE BURROWING OWL TERRITORY ABUNDANCE IN 2008

JEFFREY A. MANNING

ABSTRACT. Validation of models or statistical methods often includes testing those resulting tools with a dataset that is independent from the original data used to develop the tool. To validate the stratified random sampling strategy for Burrowing Owls in the HCP Study Area and the correlative model constructed for constructing sampling strata, an independent dataset was needed. I computed maximum likelihood estimates of local male Burrowing Owl territory abundance in 3x3 km grid cells from an independent dataset collected in 2008. These estimates were from point-coordinate capture-recapture survey occasions completed along the same IID rights-of-way surveyed in 2007, and following the same survey and analytical methods. By summing the grid cells, the approximated true population size in 2008 was 3,557 territories (95% CI: 3,218-3,895).

INTRODUCTION

To validate the sampling methodology developed in Chapter 15, an independent and comparable dataset was needed. In this chapter, I present the estimated local abundances calculated from a complete census of the IID's rights-of-way in the HCP Study Area in 2008.

METHODS

Between 28 March - 30 April, 2008, four point-coordinate capture-recapture survey occasions were completed along the same IID rights-of-way surveyed in 2007. Surveys and analytical methods followed those described in Chapters 5, 6, 7, and 10. The resulting male Burrowing Owl territory data from this census was used to compute local abundance estimates across the same standardized 3x3 km-resolution sampling grid applied to the 2007 census data. The sum of these grid cells was used to provide an approximated true population size in 2008.

RESULTS

Raw counts during single survey occasions ranged from 2.403-2.966 (Table 16.1), and the number of single detections without nests was similar to that found in 2007. Based on a sum of the population estimates in grid cells, a total of 3,557 (95% CI: 3,218-3,895) male Burrowing Owl territories was estimated to be present in the HCP Study Area during the prehatch stage of the breeding cycle in 2008. Local abundances within grid cells ranged from 0-55 territories, and the number of grid cells where no territories were detected increased to 21 (3 more) compared to 2007 (Figure 16.1).

Local abundances were lower on average than that found in 2007 (Figure 16.2), with 75% of the cells containing an estimated ≤20 territories (Figure 16.3). These low estimates of abundance coincide with counts in those cells and associated low standard errors that approximate zero (Figure 16.3), suggesting negligible measurement error or poor performance of the capture-recapture models fit to those cells.

CONCLUSIONS AND RECOMMENDATIONS

I estimated the population size in 2008 to be 3,557 (95% CI: 3,218-3,895) male Burrowing Owl territories. This estimate was derived by summing the local abundances, and can be used as the approximated true population size for comparing against sampled estimates in the following chapter.

This population size represented a marked decline compared to that estimated from the 2007 census. This coincided with slightly lower local abundances on average than that found in 2007 (see Chapter 10), and an increased number of apparently unoccupied grid cells.

Our survey protocols, level of survey effort, and analytical methods were standardized in both years, and all but one survey team in 2008 had at least 1 member from the survey teams used to complete surveys in 2007. Therefore, this difference was not due to differences in measurement error between the 2 years. Because a census was completed both years, this difference also cannot be attributed to sampling error. Furthermore, field biologists were asked to provide anecdotal reports on the presence of owls detected outside of the IID's rights-of-way in both years, and that information suggested that very few owls were outside of our survey areas during both years. Thus, this difference is largely due to a change in the total number of male Burrowing Owl territories present in the HCP Study Area.

The intended use of the 2008 census data was as an independent dataset for validating the survey methodology developed from the census data collected in 2007. That methodology was derived from a standardized grid of sampling units that were predominantly 3x3 km. This resolution was chosen, after communications with Dr. Bryan Manly, to balance the needs for an adequate number of territories in grid cells for capture-recapture modeling and a sufficient number of sampling units from which to draw random samples from each year. That decision was based from the best biological information available at that time, the census data from 2007. By using that empirical data with the intention of developing a standardized grid to be used for sampling in subsequent years, the sampling grid that was established assumed that the population data from 2007 was representative of that anticipated to be present in subsequent years. Thus, the unanticipated marked change in the total population size and local abundances between the 2007 and 2008 breeding seasons may compromise the validation of that methodology.

Table 16.1. Number of Burrowing Owl detections by survey occasion during the prehatch stage of the breeding cycle in the HCP Study Area, Imperial County, California, 2007. Owls detected once and without a nest were removed from the data.

	Survey Occasions		
Type of detection	1	2	3
Once without nest	123	233	203
All other detections	2,279	2,733	2,731
Mean/cell[1]	8.8	10.9	10.8
Standard deviation/cell[1]	7.5	8.9	9.1

[1] Calculated with total detections from all 274 3x3 km grid cells.

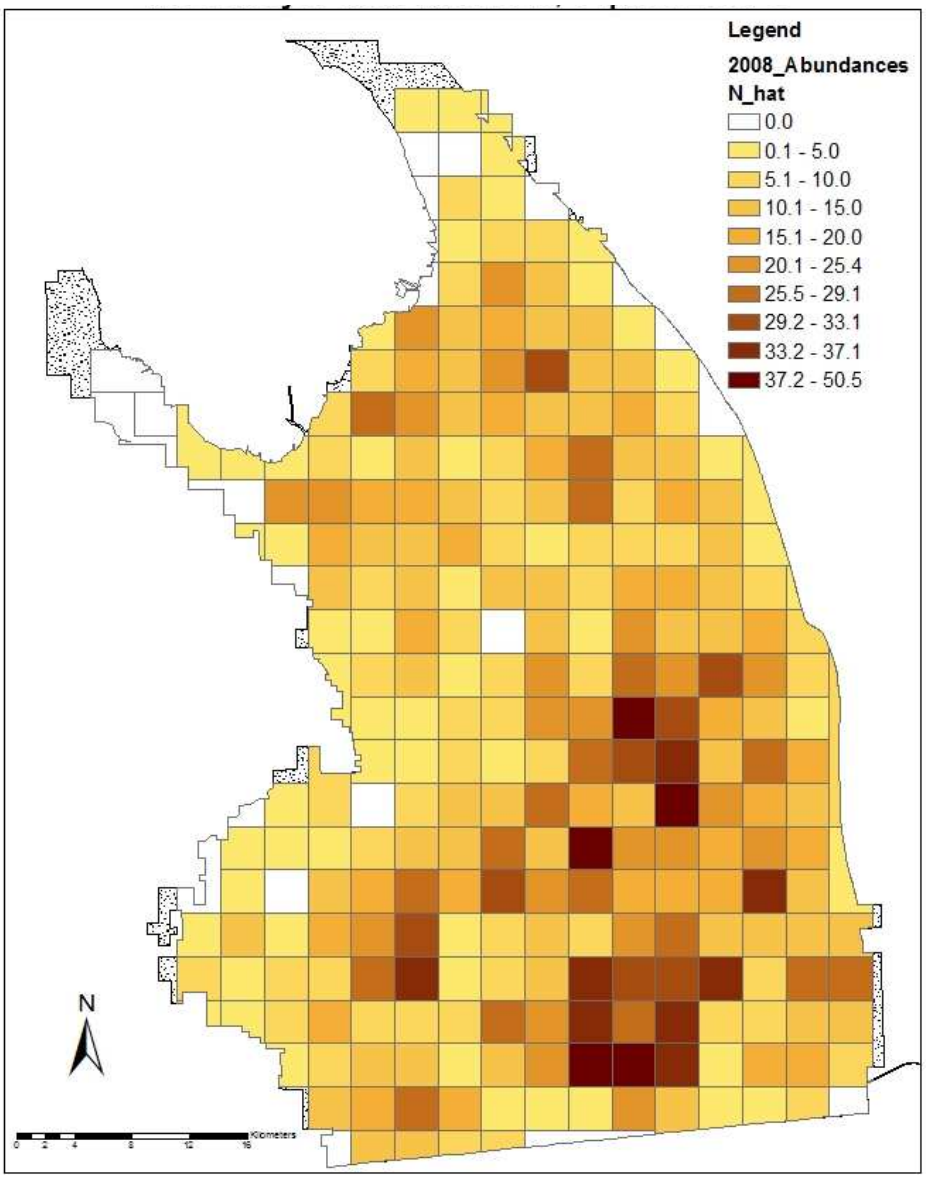

Figure 16.1. Closed-population point-coordinate capture-recapture estimates of local male Burrowing Owl territory abundance in 3x3 km grid cells in the IID's HPC area, Imperial County, California, April 2008. Stippled areas were not surveyed due to the absence of above-ground water conveyance structures.

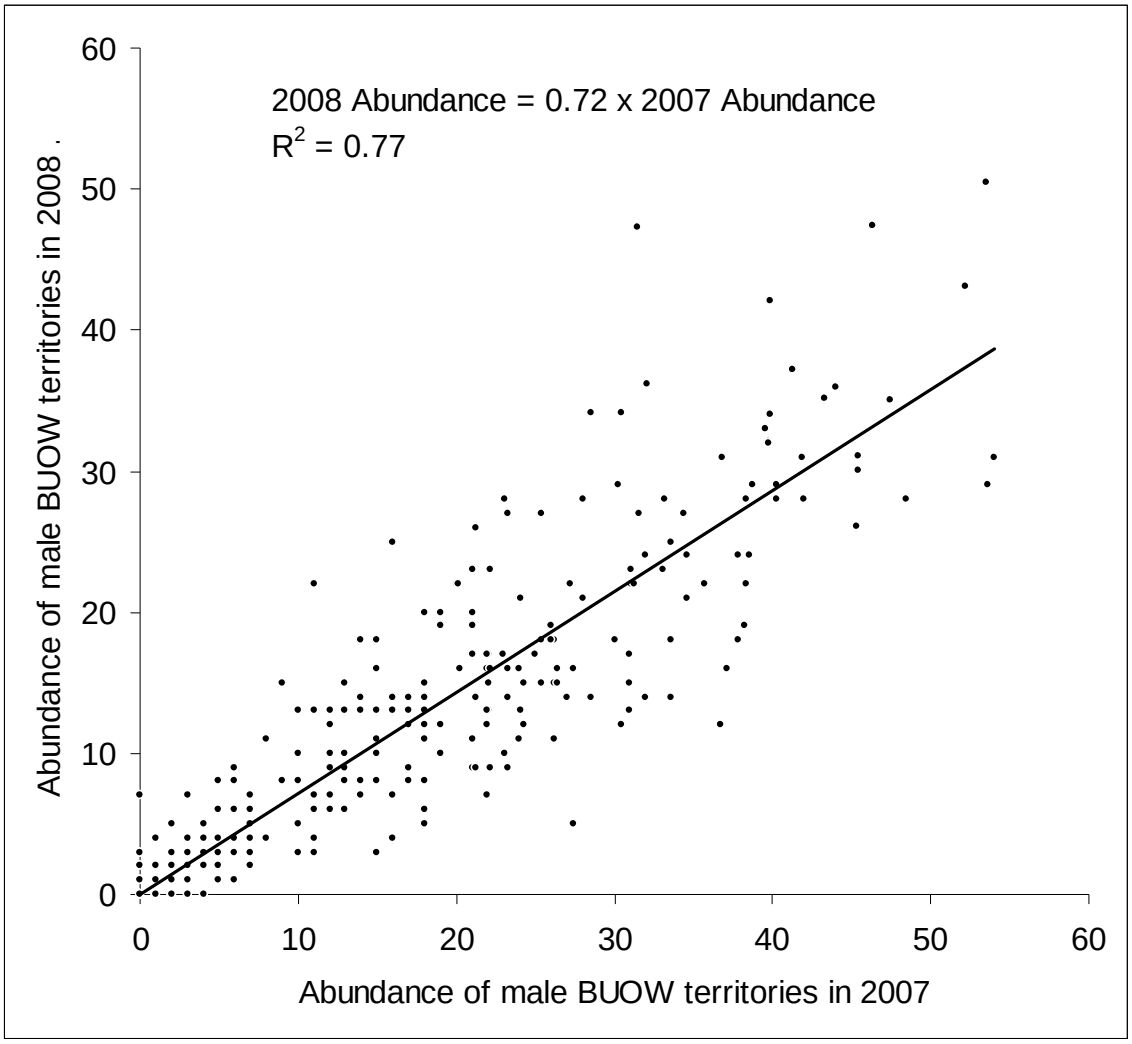

Figure 16.2. Linear relationship in the abundance of male Burrowing Owl territories in 3x3 km grid cells during the preatch period of the breeding cycle between 2007 and 2008 in the HCP Study Area, Imperial County, California.

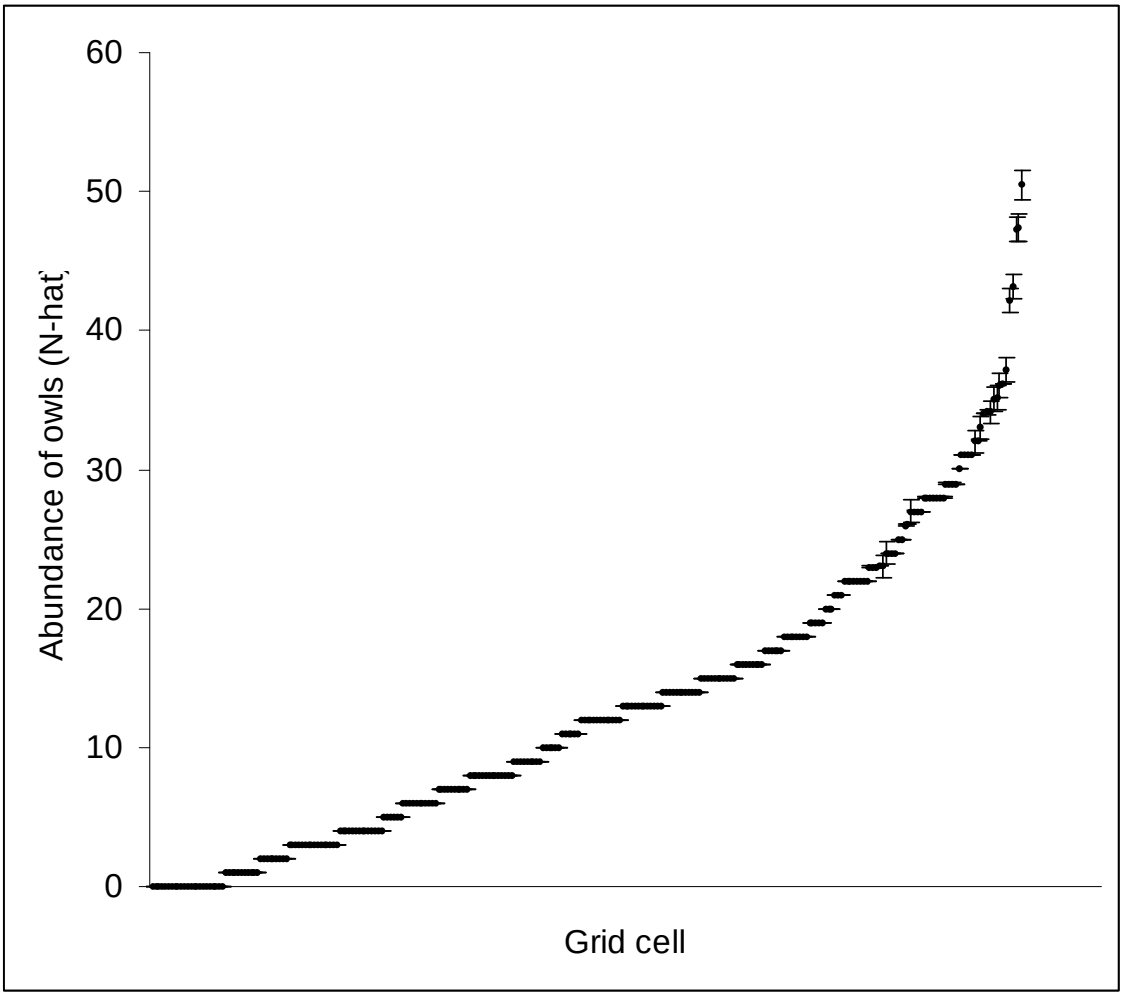

Figure 16.3. Estimates of local male Burrowing Owl territory abundances in 3x3 km grid cells in the HCP Study Area, Imperial County, California, 2008. Data are presented according to increased abundances. Vertical bars are standard errors.

Chapter 17

VALIDATION OF STRATIFIED RANDOM SAMPLING METHODOLOGY TO SURVEY FOR AND ESTIMATE MALE BURROWING OWL TERRITORY ABUNDANCE

JEFFREY A. MANNING AND CAREN S. GOLDBERG

ABSTRACT. Long-term population sampling methods should be validated to assess reliability in estimating population size. Here, we validate our stratified random sampling methodology and compare the performance of our correlative model (intended for constructing strata) against alternative methods of stratifying the HCP Study Area. Our sampling methodology was validated nicely with the independent population data in 2008. We found that the correlative model was not efficient at constructing strata. However, a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle provided a relatively efficient method of stratifying and greatly improved the precision of the stratified random sampling methodology.

INTRODUCTION

A primary reason for sampling a population is to avoid the relatively high cost of conducting a complete census. We developed the optimally allocated stratified random sampling methodology in Chapter 15 using the frequency distribution of empirical abundance estimates from our census in 2007. Based on those empirical data, we also showed that our methodology can improve the precision of population estimates 186% from that which could be obtained from an equal effort using simple random sampling. In Chapter 12, we developed a model that determined the group of variables that were most correlated with abundance of owls in 2007. Such a model could be used to stratify the HCP prior to conducting subsequent stratified random sampling of the owl population by completing a census of the surrogate variables prior to each survey. Prior to considering this model for such use, it needs to be validated with an independent dataset and its performance compared to other potential sources of information that could be used to construct strata.

There are various sources of information that may be considered for constructing strata, and we focused on those that may prove to be readily available, affordable, and statistically efficient (e.g., providing high precision). In Chapter 15, we discussed why the ideal variable for constructing strata is the variable itself (Cochran 1977:100), and in our case, that was the abundance of owls. If abundance remained spatially stable through time, at least for several years, then a practical alternative to using our model from Chapter 12 would be to use local abundance estimates from a prior census (Cochran 1977:100-101). However, if the population does not remain stable, the stratification would become inefficient and precision of population estimates would decrease (Cochran 1977:100-102). We originally proposed to develop a stratified random sampling

methodology from data collected during the 2007 breeding season, so it assumed a stable population. Given the changes in the owl population we reported in Chapter 16, abundance from a prior census may be an inefficient variable to stratify the HCP Study Area (Cochran 1977:100-102). Thus, a comparison of population estimates derived from constructing strata with this source of information to those from our correlative model may elucidate the relative efficiency of our model.

A third source of information that should be considered for constructing strata in the HCP Study Area comes from a full single survey at the beginning of the breeding season, immediately prior to sampling. As the population would likely be stable between this census and the subsequent sampling, this alternative could produce an extremely efficient method to construct strata from each year, possibly providing the most precise estimates of abundance (Cochran 1977:100-102). After this information is used to stratify the area, a cost-effective approach would involve conducting only 2 subsequent point-coordinate capture-recapture occasions in the randomly selected grid cells. Those 2 occasions could be combined with the original survey information in those cells, and this would constitute the 3 occasions recommended in chapter 6.

Our objectives here were to use an independent dataset to validate our stratified random sampling methodology and to compare the performance of our correlative model against these alternative methods of stratifying the HCP Study Area.

METHODS

To determine the most effective method of stratifying the HCP Study Area prior to future population sampling, we compared the precision of abundance estimates derived from simple random sampling and 3 methods of stratification applied with our stratified random sampling methodology across the HCP Study Area. We accomplished this using an independent dataset of local abundance estimates from a subsequent census of the population of grid cells in 2008 presented in Chapter 16. The 2008 census took place during the same period of the breeding cycle and followed the same survey routes, protocols, and analytical methods used to estimate abundance in grid cells in 2007. The methods of constructing strata that we considered were:

1. Our correlative model -- this model was the linear regression model with the spatial correlation coefficient that we determined to be best at predicting abundance from ancillary environmental variables (see Table 12.5), and was used in our development of a stratified random sampling methodology in Chapter 15. We used this model to assign 3x3 km grid cells into the 3 strata (low, medium, and high owl abundance) reported in Chapter 15. To mimic how this model could be applied to stratify grid cells for future surveys, we predicted abundance in each cell by applying the best model in Table 12.3 (which does not have a spatial covariate term) to the data on required data (i.e., total length of IID water conveyance structures, proportion of a grid cell in 2005 in alfalfa production, and number of burrows immediately prior to the intended survey in 2008). Next, we used those predicted abundances to estimate the mean number abundance out to 2

neighboring grid cells from each grid cell, and included this as the spatial data for fitting the best model with the spatial autocorrelation coefficient in Table 12.5.

2. A prior year's capture-recapture abundance estimates -- we used the point-coordinate capture-recapture estimates of local abundance from the 3 survey occasions to assign grid cells to the 3 strata.
3. A census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle -- we used the first survey occasion from our 2008 census of owls across the HCP Study Area to stratify individual grid cells to the 3 strata.

For simple random sampling and each method of constructing strata, we simulated random sampling of grid cells by bootstrapping 1,000 datasets from the complete population grid cells containing abundance estimates from the 2008 census without replacement. The total sample size for each simulation was 119, which was based on the minimum number of grid cells required to obtain an estimate <10% from the true population estimate. For each method of stratification, we used the method of determining strata boundaries and optimal allocation applied in Chapter 15. For the 3rd method of stratifying the HCP Study Area listed above, we mimicked how this method can be applied in future population surveys by using the first occasion to stratify and as the first of the three occasions in the randomly sampled grid cells.

For each method, we calculated the average and 95% confidence interval for each simulated population estimate. We compared the average of these simulated abundance estimates among the 4 methods and to the approximated true population size [3,557 (95% CI: 3,218-3,895)] reported in Chapter 16. We also compared the 95% confidence widths from each method to that surrounding the approximated true population size.

RESULTS

Simple random sampling and all 3 methods of constructing strata produced equivalent and unbiased estimates of the approximated true population size calculated from the independent census in 2008 (Figure 17.1). Stratified random sampling of strata constructed from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle, produced the most precise population estimates (Figure 17.1). The precision from this method of stratification (average 95% CI: 3,380-3,737) corresponded to a sampling error of 5% (approximately 178 territories) on either side of an unbiased population estimate, and translated to a 10% minimum detectable change in the population.

The precision of population estimates from stratified random sampling of strata constructed with a prior year's capture-recapture abundance estimates was lower than that of the previous stratification method (average 95% CI: 3,325-3,788; Figure 17.1). This level of precision represented a sampling error of 7% on either side of an unbiased population estimate and a 15% minimum detectable change in the population.

Stratified random sampling from strata constructed with our correlative model that used alfalfa, available burrows, and spatial structure provided the poorest precision among the 3 methods of stratification (average 95% CI: 3,202-3,911). The 10% precision on either side of the unbiased population estimate would allow a 20% minimum detectable change in the population.

Simple random sampling provided the poorest precision (Figure 17.1). Its level of precision (95% CI: 3,174-3,949) represented 11% error on either side of an unbiased population estimate, which would provide a 22% minimum detectable change in the population.

Strata constructed from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle or from a prior year's capture-recapture abundance estimates provided a marked improvement in precision over that attainable from simple random sampling or using the correlative model to determine strata membership (Figure 17.1).

CONCLUSIONS AND RECOMMENDATIONS

Our results validate our optimally allocated stratified random sampling methodology developed in Chapter15. We demonstrated that this methodology can greatly improve the precision of unbiased population estimates of male Burrowing Owl territories in the HCP Study Area, given the use of an efficient method of constructing strata. We also showed that this precision improved the statistical power of detecting a change in the population, thereby allowing a smaller minimal level of detectable change.

We further demonstrated that the performance of our stratified random sampling methodology is dependent on the efficiency of the strata constructed prior to a population survey. A prior year's capture-recapture abundance estimates provided 15% minimal detectable change in the population. Although this level of change may appear reasonable, it is unrealistic to expect that data from capture-recapture surveys would be available for all grid cells from the year preceding each annual survey when the overall objective is to conduct capture-recapture surveys in only a sample of the grid cells each year. Additionally, given the change in the population that we reported in Chapter 16, it would be unreasonable to consider information from such a census from ≥ 2 years prior to a population survey.

The poor performance of our correlative model for constructing strata may have been due in part to the low amount of variation in owl abundance that the model explained (see Chapter 12). The inefficiency of this stratification method indicated that the variables in the model inadequately predicted local owl abundances in the 2008. This was surprising given its predictive ability we demonstrated with the k-fold cross validation procedure in Chapter 12. One reason for this poor performance may have been the marked change in the population, which was of a degree that likely violated the assumption of a relatively stable population. Nonetheless, its poor performance with the independent dataset suggests that factors other than those in the model may be regulating or limiting the local

abundances of Burrowing Owls. Thus, given the lack of information on this subject at this time, we also suggest that it is currently inappropriate to consider surrogates of owl abundance for stratifying the HCP Study Area.

Strata constructed from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle, provided the most precise estimates and smallest level of detectable change in the population (10%). As we described in the introduction, the information needed to achieve this efficient method of constructing strata would originate from a full single survey, constituting a census, prior to, but during the same breeding season of the anticipated sampling. We believe this would provide the most reliable population estimates in the most cost-effective manner because the results from a prior census could be used in the following ways: 1) to stratify the HCP Study Area, as no other methods of stratifying are as reliable or efficient, 2) as the first of 3 required occasions (see Chapter 6) in the randomly selected grid cells, 3) to calculate the growth rates of local populations described in Chapter 19, as no other data would be available for calculating such rates, 4) as the basis for estimating the relative distribution and abundances across the HCP Study Area, and 5) to map out the exact locations of nests throughout the HCP Study Area. In the absence of the complete survey, our optimally allocated stratified random sampling methodology will become less efficient each year, lowering the minimum detectable level of change. Because it would represent the only source of information to produce the results described under points 3-5, its absence would prevent the acquisition of these results which are important for understanding where to direct adaptive management activities across the HCP Study Area.

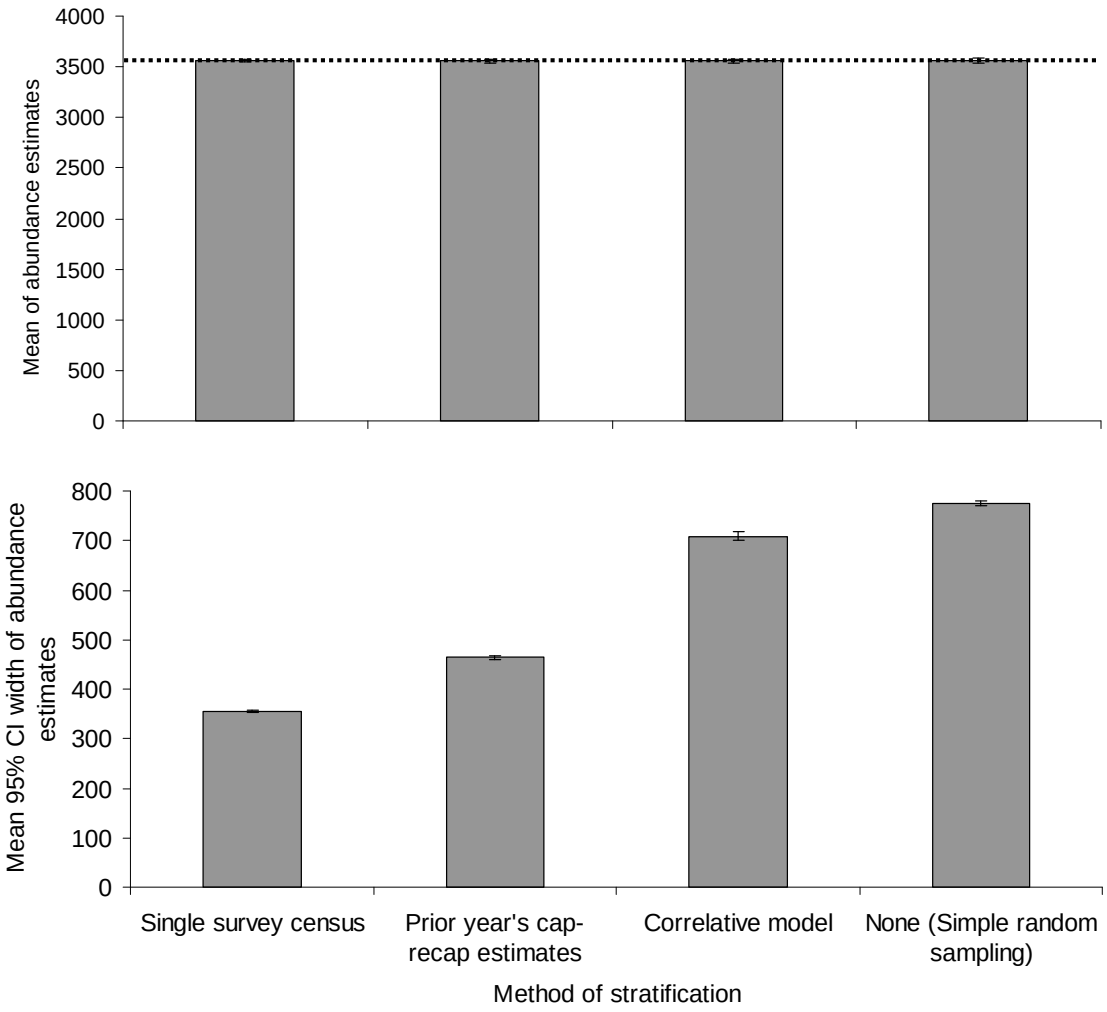

Figure 17.1. Mean simulated population (A) and 95% confidence interval width (B) estimates under 3 methods of stratifying grid cells and simple random sampling in the HCP Study Area. Datasets were simulated samples bootstrapped from the complete 2008 survey data. Dotted line represents true population size approximated by summing the point-coordinate capture-recapture abundance estimates from the entire the population of 274 grid cells. All estimates assume negligible measurement error.

Chapter 18

RECOMMENDED SAMPLING METHODOLOGY WITH OPTIMAL ALLOCATION OF EFFORT TO SURVEY FOR AND ESTIMATE MALE BURROWING OWL TERRITORY ABUNDANCE

JEFFREY A. MANNING

ABSTRACT. In this chapter, I provide recommendations for the sampling methodology with optimal allocation of effort to survey for and estimate male Burrowing Owl territory abundance. For conducting surveys in grid cells, I recommended that: 1) the point-coordinate capture-recapture technique should be used, 2) point locations of owls should be recorded following the methods previously described while avoiding the relatively hot afternoon period, 3) three point-coordinate capture-recapture survey occasions should be completed, and 4) a single survey pass on one side of all above-ground drains and canals should be conducted during each point-coordinate capture-recapture occasion. For sampling, I recommended that: 1) sampling should follow the optimally allocated stratified random sampling methodology developed in Chapter 15 and validated in Chapter 17, 2) samples should be drawn from the standardized sampling grid of 274 grid cells, 3) strata should be constructed from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle, 4) a minimum required sample size should be determined from Table 15.1, and 5) stratum boundaries and optimal allocation of sampling units should be determined based on equations in Chapter 15 once a sample size is chosen and the single survey census completed. The construction of strata from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle was shown to produce the most precise estimates and smallest level of detectable change in the population (10%) compared to other methods. The information needed to achieve this efficient method would not only provide the most reliable population estimates, but could also be used: 1) to stratify the HCP Study Area, as no other methods of stratification are as reliable or efficient, 2) as the first of 3 required occasions (see Chapter 6) in the randomly selected grid cells, 3) to calculate the growth rates of local populations described in Chapter 19, as no other data would be available for calculating such rates, 4) as the basis for estimating the relative distribution and abundances across the HCP Study Area, and 5) to map out the exact locations of approximately 70% of nests throughout the HCP Study Area.

INTRODUCTION

The success of a long-term population monitoring program depends on an efficient sampling design that minimizes the required sample size, optimizes the allocation of survey effort, and reduces costs while maintaining high levels accuracy at all stages of the survey. Monitoring programs across large landscapes generally involve sampling areas from a larger population of areas suitable for or occupied by the species of interest and surveying for the species in each of the selected areas. Sampling error occurs when areas are randomly sampled from the population of available areas (e.g., a different

random sample of areas at the same time could yield a different estimate and level of precision) and measurement error occurs during a survey of a selected area (e.g., animals were available but undetected or present but unavailable). Only monitoring programs that are based on known levels of measurement error and sampling error can yield reliable population estimates for making informed management decisions.

In the previous chapters, I considered these important aspects of monitoring programs. I developed retrospective studies, field experiments, simulations, and validations with independent datasets to elucidate various aspects of Burrowing Owl natural history in the HCP Study Area and to examine the statistical properties of population estimates from various survey and sampling methods. Based on the results from those studies, I provide the following recommended sampling methodology for monitoring the Burrowing Owl population in the HCP Study Area.

CONCLUSIONS AND RECOMMENDATIONS

Surveys

An accurate estimate of population size can be obtained with sampling designs that account for the size, shape, number, and placement of sampling units across areas where abundance is unevenly distributed (Caughley 1977:27; Williams et al. 2002:247), like that of owls in the HCP Study Area. These designs generally assume that population counts in sample units are without measurement error. Because measurement error probably cannot be completely eliminated (Steenhof and Kochert 1982, Fraser et al. 1983), it is critical that measurement error is minimized during surveys. Measurement error can be reduced by using standardized protocols, trained and skilled observers, reliably accurate survey methods, careful timing to reduce problems with availability, and reliable analytical methods.

Based on the importance of minimizing measurement error, I recommend the following:

1. The point-coordinate capture-recapture technique should be used to conduct surveys and construct encounter histories in grid cells. In Chapter 5, this technique was shown to produce accurate estimates of population size and be cost effective when many owls are present. However, as discussed in Chapter 10, the performance of capture-recapture is slightly reduced with small sample sizes (small numbers of owls within grid cells). A cost-effective alternative that may not have this problem would be a single survey technique that corrects for visibility and availability biases, but such a technique has not yet been developed for Burrowing Owls. Until such techniques are developed and proven to produce reliable population estimates, the point-coordinate capture-recapture technique is the most cost-effective method of producing estimates with negligible error.

2. Point locations of owls should be recorded following the methods described in Chapter 7 and Appendix II, including the avoidance of surveying during the relatively hot afternoon period and surveying from a vehicle of same make and model (Ford Escape). The methodology assumes that that this is the only make and model of vehicle used for conducting surveys. This is because the number of

occasions, and other aspects of the survey methods, is based on empirical information derived from observations from the view shed afforded by that vehicle. Use of an alternative vehicle for conducting surveys may compromise the accuracy and reliability of population estimates and their associated levels of precision.

3. Three point-coordinate capture-recapture survey occasions should be completed in each grid cell to estimate abundance of male territories. In Chapter 6, this number of occasions was demonstrated to the minimum number needed to produce unbiased estimates. As shown in Chapter 10, applying 3 survey occasions with this technique should detect approximately 98% of the owls. The capture-recapture models should correct for the remaining 2%.

4. A single survey pass on one side of all above-ground drains and canals should be conducted during each point-coordinate capture-recapture occasion. This is based on the findings in Chapters 3 and 4. However, where ≥2 water conveyance structures parallel multiple access roads within a single right-of-way and the field of view could be compromised by distance between the water conveyance structures (roughly ≥60 m) or topography, a survey pass should be conducted on >1 of the parallel roads to ensure complete survey coverage of the right-of-way while care is taken to not survey the same water conveyance structure twice (i.e., each water conveyance structure should be surveyed from only one side). Care should also be taken to note the location of owls detected on the first pass to ensure that the same owl is not double counted during the 2nd pass in the right-of-way.

Sampling

Because abundance of owls is expected to be unevenly distributed across the HCP Study Area, an accurate estimate of population size can be obtained using sampling designs that account for the size, shape, number, and placement of sampling units (Caughley 1977:27; Williams et al. 2002:247). This is a critical issue in population monitoring because increased precision translates to an increase in the ability to detect changes in population size among years. Imprecise estimates only allow for detection of large changes.

Based on the needs to minimize sampling error and reduce costs, I recommend the following sampling methodology for each population survey:

1. Sampling should follow the optimally allocated stratified random sampling methodology developed in Chapter 15 and validated in Chapter 17.

2. Samples should be drawn from the same standardized sampling grid of 274 grid cells established in Chapter 9.

3. Strata should be constructed prior to sampling by using the equations in Chapter 15 with data from a census comprised of a single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle. In Chapter 17, this method of stratification was shown to provide the most precise estimates and smallest level of detectable change in the population

(10%) compared to other methods. As described in that chapter, the information needed to achieve this efficient method would not only provide the most reliable population estimates, but it may also represent the most cost-effective source of information that could be used to answer numerous questions that need to be answered to achieve accurate population estimates. As such, this single dataset could be used: 1) to stratify the HCP Study Area, as no other methods of stratifying are as reliable or efficient, 2) as the first of 3 required occasions (see Chapter 6) in the randomly selected grid cells, 3) to calculate the growth rates of local populations described in Chapter 19, as no other data would be available for calculating such rates, 4) as the basis for estimating the relative distribution and abundances across the HCP Study Area, and 5) to map out the exact locations of approximately 70% of nests throughout the HCP Study Area. The use of this information as the first of 3 occasions will lead to a few-week time lag between the first and second occasions, and this differs from how the data were collected originally in developing the point-coordinate capture-recapture technique. Although we suspect that this technique should be robust to this, such time lags may introduce changes in the space use of individuals over the course of surveys, and may introduce an unknown level of error into the derived estimates, although we expect that this error would be small.

4. Due to edge effects (i.e., Burrowing Owls occupy home ranges that can be bisected from grid cell boundaries), the 2nd and 3rd surveys must be extended 110 m beyond the boundary of all sampled grid cells.

5. Minimum required sample size should be determined from Table 15.1. Because the choice of a minimum detectable level is a value judgment that defines an acceptable level of risk and determines the cost of surveys, it is difficult for a statistician to make such a recommendation. In lieu of providing a recommended level, I provided a range of statistically reliable estimates of minimum detectable levels of population change related to levels of sampling across the HCP Study Area. These statistically reliable estimates enable the IT to determine the appropriate level of sampling for their chosen minimum detectable level of population change. As long as the sampling effort corresponding to a chosen level of change is completed the same way each time, the results between population surveys should be comparable and statistically reliable (as described in Chapter 17). If that level of change is maintained in all subsequent population surveys, regardless of the level of change that is decided on, the methodology recommended above will still be valid.

   An important assumption associated with using the information in Table 15.1 to determine the minimum required sample size for a chosen level of population change is that the variability in abundance among the 274 grid cells in the following population survey is equivalent to or smaller than that found in 2007 (see Chapter 10). This is because the calculations used to

create that table were derived from the empirical data collected in 2007. If this assumption is not met (i.e., the variability on a given year is larger), the finite adjusted sample sizes listed in Table 15.1 will produce population estimates that can be farther from the true mean than the distances listed in the table. Essentially, increased variability will lower the power of a given finite adjusted sample size.

The assumption described above should be tested prior to the next population survey by calculating a measure of variability. An assessment of the variability before the next population sampling can be attained from the single survey occasion prior to sampling, but during the same prehatch stage of the breeding cycle (referenced under C above). Since the population of grid cells will always remain constant at 274 cells, a standard deviation is sufficient, which was also provided for the 2007 data in Table 10.1 (high St. Dev during a single survey occasion = 10.7). The single survey prior to the next population survey can be used to estimate the standard deviation among grid cells and comparing it to from 2007. If the standard deviations remain relatively similar, the relationships between finite adjusted sample sizes and distance from the true mean in Table 15.1 will be correct and the sample size chosen for 2007 can be applied to that sampling effort. If the variability is greater, than new a table of minimum required sample sizes will have to be created by recalculating those estimates using the calculation presented in Chapter 15. If the standard deviation does increase for any subsequent population survey, the sample size would have to be determined from either a newly created table or one of the previously constructed tables associated with an equivalent standard deviation. This should be carried out prior to each subsequent survey, thereby adjusting the sample size whenever the variance changes.

Applying this important part of the sampling methodology prior to each subsequent population survey will result in sample sizes that may vary some among years, but the power of detecting a desired level of change between population estimates would remain constant. This latter point is critical to ensure reliable and comparable estimates for detecting changes in the population.

6. Once the sample size and stratum boundaries are determined, the optimal allocation of sampling units should be based on the equations in Chapter 15.

The above recommendations should be implemented in the following sequence:

1. Single survey of entire HCP Study Area

2. Strata determined from 1

3. Determine the minimum required sample size. To do this, first calculate the standard deviation determined from 1. if the st dev is similar to that from a previous survey, use the table from that survey. If not, recreate table.

4. Determine optimal allocation based on new strata, new sample size, and new strata-specific variances

5. Randomly sample grid cells according to 4

6. Conduct surveys

7. Create point-coordinate capture-recapture encounter histories for all randomly selected grid cells using:

    a. All 3 survey occasions (including the first one consisting of the complete survey
    b. The point-coordinate capture-recapture analytical procedures described in Chapter 5, including the use of the 55-m radius MMDM as the buffer, to construct territory centroids and encounter histories
    c. The sampling grid to assign centroids to their corresponding grid cells (only for those centroids that lie within the boundary of a sampled grid cell)

8. Compute stratified random sampling estimates of population size and associated level of precision

The above recommendations for sampling should be applied for each population survey e.g., each year). They also are based on using the point-coordinate capture-recapture technique, which is dependent on completing 3 survey occasions to attain a single population estimate. This multiple number of survey occasions provides the opportunity to conduct a complete single occasion as the basis for constructing strata (as described above), from which to draw a stratified random sample from the standardized sampling grid. However, if a reliable survey technique is developed that can correct for visibility and availability bias from a single survey occasion, it could be embedded into these methods in lieu of the point-coordinate capture-recapture technique. If this is done, the stratification method presented here will be unavailable because a prior complete survey will not be available for constructing strata. Thus, in order to ensure that such an alternative approach would continue to be able to detect the desired minimum level of population change, it would warrant revisiting the sampling methodology.

2007 and 2008 Population Estimates for Comparison Purposes

Although we conducted complete censuses of the HCP Study Area in 2007 and 2008, future surveys are anticipated to be completed by sampling the population. To provide

estimates for these previous years that are comparable to those from future surveys, I provide estimates of abundance with measures of variance based on the recommended sampling and survey methods. The two estimates, which were obtained from the bootstrapped stratified random sampling of the 274 grid cells, are:

2007: 4,879 territories (95% CI: 4,692-5,065)
2008: 3,557 territories (95% CI: 3,370-3,743)

This sampling used the recommended minimum required sample size and optimal allocation. These abundance estimates were closest to the approximated true population size derived from summing all 274 grid cells, and thus represent sufficient samples. But, they provide confidence intervals that were estimated from the sampling variance that is comparable to those to be obtained from future sampling.

Chapter 19

DEMONSTRATED USE OF ABUNDANCE ESTIMATES FOR CALCULATING LOCAL FINITE RATES OF POPULATION CHANGE

JEFFREY A. MANNING

ABSTRACT. I provide a demonstration on the use of local abundance estimates for calculating local finite rates of population change that could be used to direct adaptive management actions to specific areas in the HCP Study Area.

INTRODUCTION

Two fundamental goals of the HCP are to determine the abundance and distribution of Burrowing Owls and to monitor the population's annual growth rate in order to make decisions on when adaptive management actions should take place. In the event that a marked decline is detected, it is equally important to determine where to strategically apply management actions in the HCP Study Area. One approach would be to strategically target local areas in the HCP to attain the highest ecological benefit to the Burrowing Owl population for a given expenditure of effort and cost.

Here I propose such an approach that capitalizes on abundance estimates and the spatial variability in owl abundance across the HCP Study Area rather than demographic information. When a marked decline is detected, a beneficial use of local estimates of abundance would be to evaluate Burrowing Owl population growth rates in local areas across the HCP. Population growth rates are typically estimated using demographic (fecundity and survival) or census data over time (Sibly et al. 2003:12). Censuses of high-density populations have greater statistical power of detecting a population decline than demographic studies (Taylor and Gerrodette 1993). Because these two methods of estimation can give similar values, as shown in studies of the spotted owl (*Strix occidentalis caurina*; Lande 1988, Burnham et al. 1996), the use of Burrowing Owl abundance estimates can satisfy the need to monitor the population's rate of change during the interim until the results from the demographic study required under the HCP become available. I demonstrate how abundance estimates from point-coordinate capture-recapture estimates of local abundance (or a single survey occasion as recommended in Chapter 18) can be used to calculate local population growth rates for Burrowing Owls in the HCP Study Area and discuss how such local rates can be used for identifying priority areas within the HCP Study Area to strategically direct adaptive management actions.

METHODS

Given the data collected in 2007 (Chapter 10) and 2008 (Chapter 16), it is evident that the local abundances have shifted in the HCP Study Area (Figure 19.1). Such temporal

variation among local areas between the 2007 and 2008 breeding seasons can be used to calculate and compare local growth rates. I computed a finite rate of change (λ) in the population of male Burrowing Owl territories between the 2007 and 2008 breeding seasons in local areas (3x3 km grid cells) in the HCP Study Area. Following Caughley (1977:51), I calculated λ as:

$$\lambda = \frac{N_{t+1}}{N_t}. \qquad \text{Equation 18.1}$$

RESULTS

Under the hypothetical example that a marked decline in male territory abundance was detected in the HCP Study Area, I calculated finite rates of change across the HCP Study Area to assess the local changes, and these ranged from 0 to 7.0 (Figures 19.2 and 19.3). The abundance of male Burrowing Owl territories declined in 75% (206) of the 274 local grid cells, with 23% (62) of them declining >50% (Figures 19.3 and 19.4).

CONCLUSIONS AND RECOMMENDATIONS

The reliable estimates of abundance that can be obtained from the recommended survey and sampling methodology can provide accurate rates of local population changes in the HCP Study Area. By using the local 3x3 km grid cells to calculate local rates of change, I demonstrated how to identify differences in that important demographic rate across the HCP Study Area. Such spatially explicit information can help facilitate the application of management actions by quickly identifying geographic areas according to a specific rate of change. I provided the example of identifying where local population rates declined >50%. If that cutoff was chosen for targeting management actions, the locations for such priority areas would be readably attainable from the previously collected population abundance data.

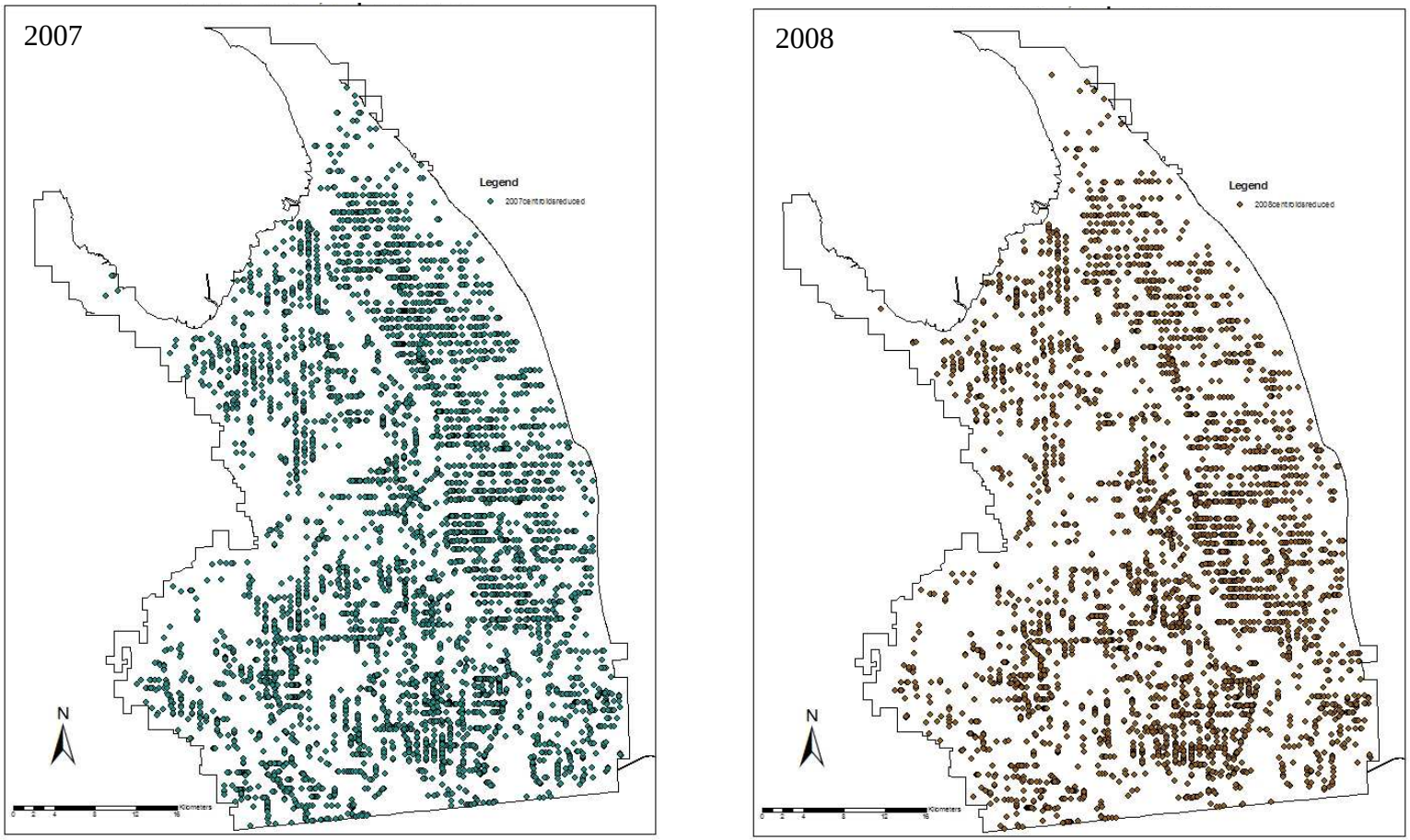

Figure 19.1. Locations of male Burrowing Owl territories in the 2007 and 2008 breeding seasons, determined from 3 point-coordinate capture-recapture survey occasions in the HCP Study Area, Imperial County, California.

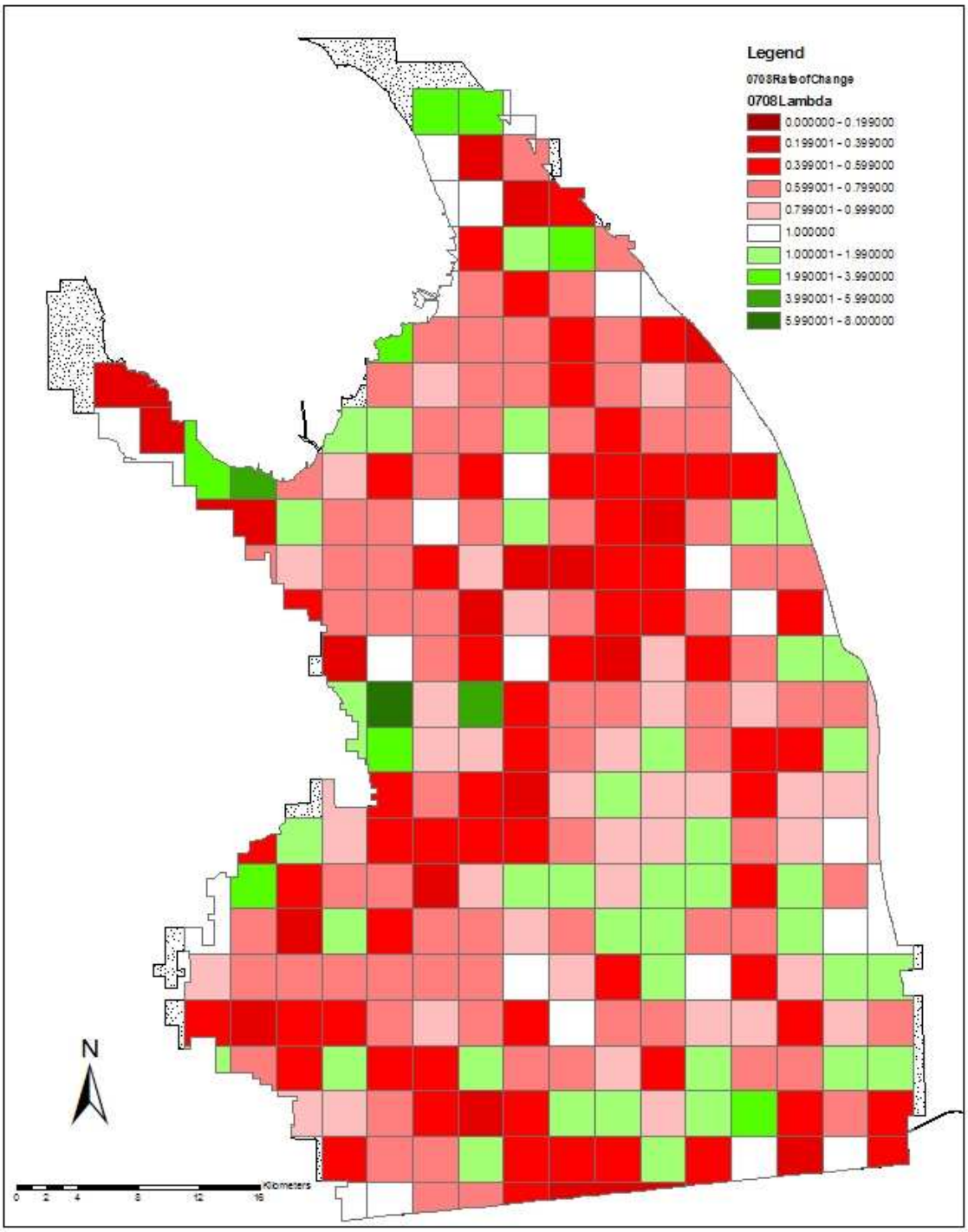

Figure 19.2. Finite rates of annual change (λ_{local}) in abundance of male Burrowing Owl territories in local areas (3x3 km grid cells) of the HCP Study Area between the 2007 and 2008 breeding seasons. Stippled areas were not surveyed due to absence of above-ground water conveyance structures.

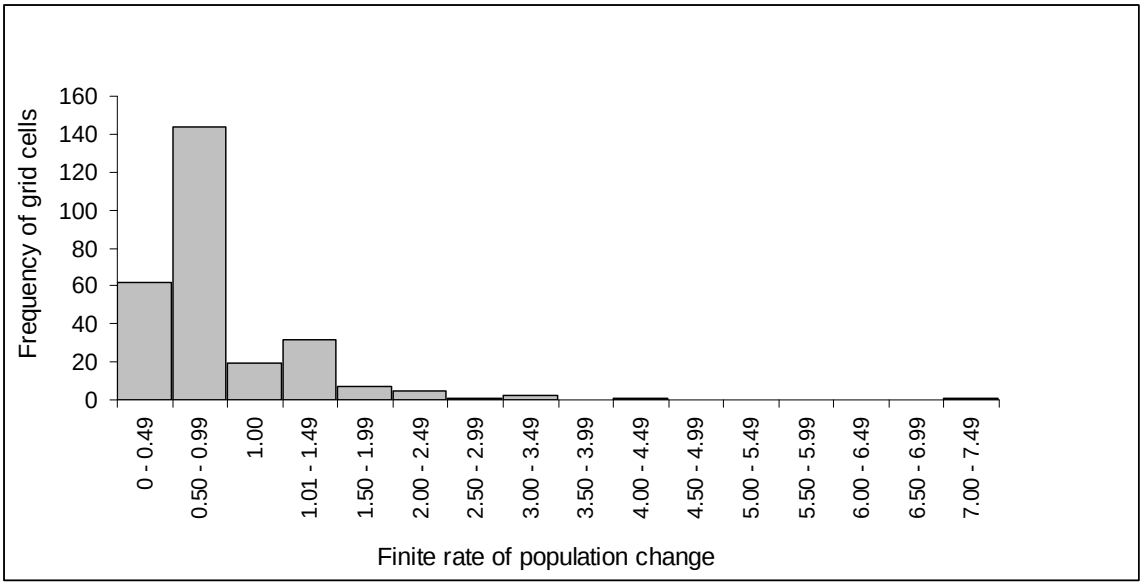

Figure 19.3. Frequency of local grid cells according to their finite rate of change (λ_{local}) in the population of male Burrowing Owl territories between the 2007 to 2008 breeding seasons in the HCP Study Area.

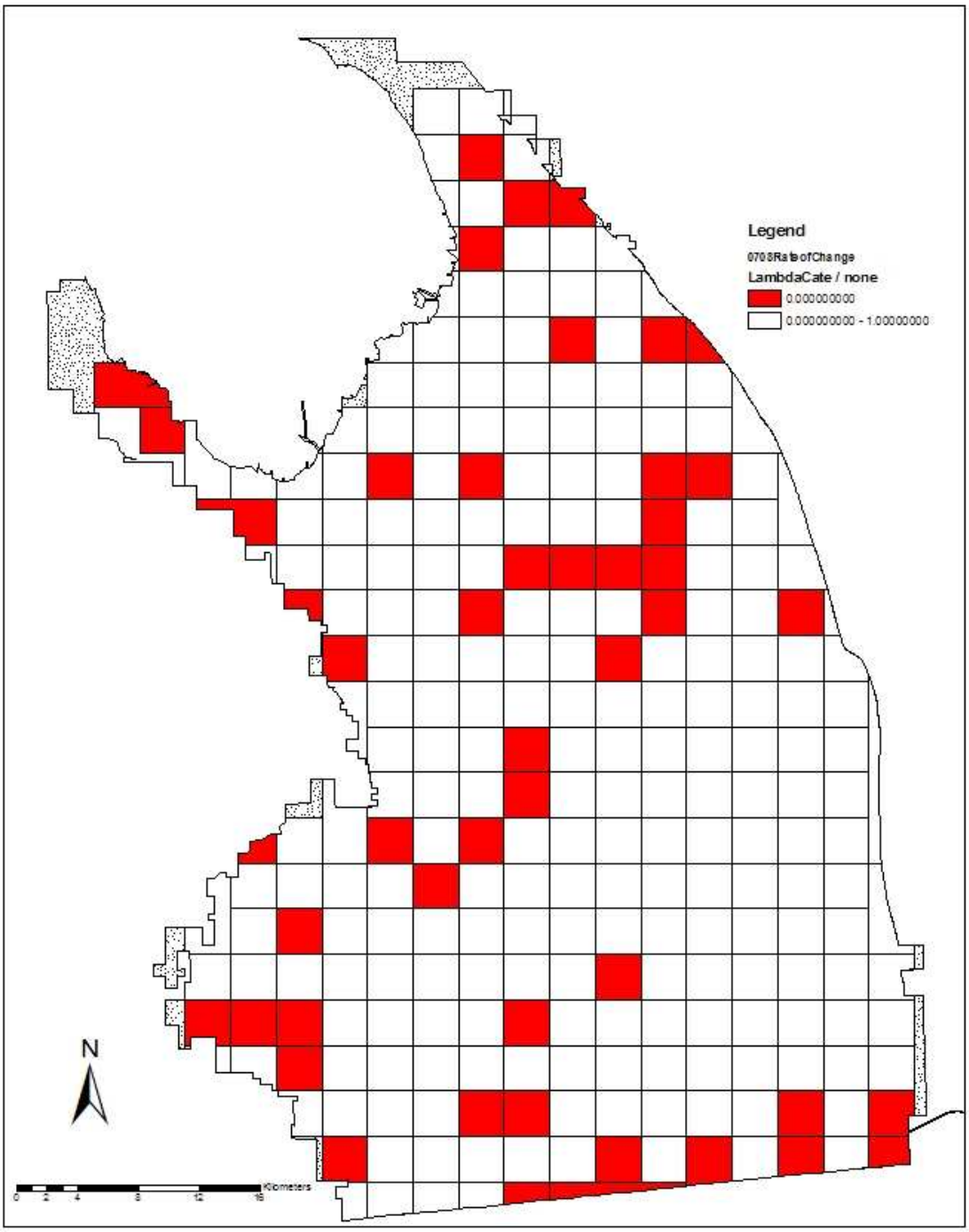

Figure 19.4. Example of finite rates of change with a cutoff = 0.5, demonstrating the locations of local areas where the lowest negative rates occurred between the 2007 and 2008 breeding seasons in the HCP Study Area, Imperial County, California. Stippled areas were not surveyed due to absence of above-ground water conveyance structures.

Chapter 20

RECOMMENDED FUTURE RESEARCH DIRECTIONS

JEFFREY A. MANNING

INTRODUCTION

The following is a brief list of recommended future research directions divided into two sections: 1) those intended to improve the accuracy and reduce costs of population monitoring, and 2) those intended to improve the understanding of the status of the Burrowing Owl population and factors that potentially limit or regulate it.

Recommended Research to Improve the Accuracy and Reduce Costs of Population Monitoring

1. Design and validate a single-survey method that accounts for visibility and availability bias (e.g., sightability) and can produce precise, unbiased estimates of male territory abundance in the HCP.

2. Investigate the effects of variable space use over time between the single survey census at the beginning of the season and subsequent capture occasions on the accuracy of point-coordinate capture-recapture estimates.]

3. Investigate more refined predictors of abundance for stratification purposes
    a. More accurate and specific maintenance data
    b. More accurate crop data

Recommended Research to Improve the Understanding of the Status of the Burrowing Owl Population and Factors that Potentially Limit or Regulate it

1. Continued annual monitoring, particularly given the change in owl abundance we identified between 2007 and 2008.

2. Investigate age-specific demographic rates (mortality, productivity) in the HCP Study Area, to direct adaptive management (Currently, the population estimates presented in this report can only direct management to a specific grid cells, but not to a targeted age class or causal factors of local declines).

3. Determine what portion of the breeding population is migratory.
    a. If migrants comprise a biologically significant component of the breeding population, a study of mortality in their wintering and migration areas is needed.

4. Determine the southern extent of this breeding population (e.g., does it extend across the International Border with Mexico).

a. If the breeding population extends into Mexico, determine the rate of exchange across the International Border.

5. Investigate spatial and temporal patterns in the numerical response of owls to crop activities and IID's maintenance activities.

6. Investigate the effects of changes in agricultural practices (due to reduced water sources) on the fitness of owls.

Recommended citation:
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APPENDICES

Appendix I

FIELD BIOLOGISTS

Name	Position	Name	Position
Aaron M. Viducich	Field biologist	Julia Harnad	Field biologist
Alexa DeJoannis	Field biologist	Kara Butler	Field biologist
Amy Musante	Field biologist	Kate Dalley	Field biologist
Andrew Davenport	Field biologist	Katie Kauffman	Field biologist
Andrew Stephens	Field biologist	Kevin Dickinson	Field biologist
Anne Bloomfield	Field biologist	Kevin O'Brian	Field biologist
Ashley C. Persinger	Field biologist	Laurel Anne Ferreira	Field biologist
Beth Dirksen	Field biologist	Laurel Genzoli	Field biologist
Bill Trione	Field biologist	Lauren MacFarland	Field biologist
Carla Mingione	Field biologist	Leah Kenney	Field biologist
Caroline Poli	Field biologist	Malcolm Grant	Field biologist
Cassidy Gratten	Field biologist	Malia Volke	Field biologist
Cassie Waters	Field biologist	Matthew Dresser	Field biologist
Chris Chutter	Field biologist	Melinda Conners	Field biologist
Craig Moran	Field biologist	Michele Kuter	Field biologist
Dan Burnett	Field biologist	Nate Richardson	Field biologist
Daniel G. Burnett	Field biologist	Pierre J. Goulet	Field biologist
Dave Bittner	Field biologist	Robb S. A. Kaler	Field biologist
Deborah Sharpe	Field biologist	Robert C. Fowler	Field biologist
Elias A Elias	Field biologist	Samantha Burrell	Field biologist
Elizabeth Donadio	Field biologist	Sarah Malick	Field biologist
Emily Kackorek	Field biologist	Sarah Sells	Field biologist
Gabrielle Gareau	Field biologist	Sean Row	Field biologist
Gabrielle Robinson	Field biologist	Shawn Carroll	Field biologist
Greg Levandoski	Field biologist	Shelly Vogel	Field biologist
Inger Marie Laursen	Field biologist	Sherri Kies	Field biologist
Jacob Cowan	Field biologist	Steve Borrego	Field biologist
James M. Field	Field biologist	Steve Tucker	Field biologist
Jeff Lincer	Field biologist	Tara Eisenhower	Field biologist
Jim Luttrell	Field biologist	Valerie Eurs	Field biologist
John Konecny	Field biologist	Whitney Menu	Field biologist
John Warzybok	Field biologist	William R. Trione	Field biologist
Julee Shamhart	Field biologist	Zachary Wallace	Field biologist

Appendix II

ACCURACY OF POINT LOCATIONS AS LOCATIONS OF BURROWING OWLS

JEFFREY A. MANNING

INTRODUCTION

Closed-population methods provide a powerful tool to obtain accurate estimates of annual Burrowing Owl population sizes in the HCP. These methods require that every newly captured animal is uniquely 'marked,' recaptured animals are recorded as 'recaptures,' and sampling be completed in a brief period to ensure the population is closed during sampling (White et al. 1982). However, capturing, handling, marking, and recapturing animals is labor intensive, thus making these methods difficult to accomplish for studies of large populations across vast areas. Because the HCP encompasses the vast agricultural matrix of the Imperial Valley, and is anticipated to support an estimated 5,600 pairs of breeding Burrowing Owls, and as many as 7,795 (Desante et al. 2004), we developed the point-coordinate capture-recapture method (presented in Chapter 5) to allow surveys to be accomplished in a timely manner in order minimize violations of the assumptions associated with close-population theory.

The point-coordinate capture-recapture technique relies on owl locations (coordinates) as 'marks' and 'recaptures.' Each time an owl was observed, its coordinates were recorded. The first time a coordinate was recorded during visual surveys, it was considered the first mark of an individual Burrowing Owl, and subsequent coordinates were considered recaptures. This novel approach to mark-recapture sampling minimizes time spent marking and recapturing individuals, thus making it a cost effective method for sampling the large population of Burrowing Owls across the HCP. It also eliminates behavioral responses elicited by using bait and/or capturing and handling (Otis et al. 1978, White et al. 1982). However, using this technique leads to sources of measurement error described in Chapter 5. To minimize the intrusion of field measurement error into the analytical and sampling errors (which scale up to the overall error that bounds a population estimate), it is important to record accurate field measurements of owl locations.

Here, I assessed the accuracy of our field equipment and method of recording point coordinate locations. My objective was to assess the accuracy of our methods to ensure that they met the 3-m accuracy we proposed in our original proposal and complied with Section 4.5.2.2 of the HCP, which specified that owl territories were to be recorded ≤30m.

METHODS

I followed the field protocols used to record owl locations in Chapter 7. Those methods included obtaining a hand-held global positioning system (GPS) location of where observers stood, and using compass directionality, and range finder distance to estimate

the coordinates of each individual or pair of owl(s) observed. Because we anticipated that numerous field crews would be required to conduct surveys each year, I arranged for 10 different biologists to collect the data. The biologists:

1. used a Trimble GeoExplorer XM GPS with ±1m accuracy and with the GPS slider set halfway to balance productivity with precision and postprocessed differential correction to acquire GPS coordinates at 105 randomly selected locations across the HCP (Figure II.1). These were considered as 'known' points,
2. randomly selected ≥5 positions/known point at various distances (<140m) from the known points (totaling 630 positions), and
3. used a Trimble GeoExplorer XM, Suunto Handheld Directional Compass, and Opti-Logic Laser Rangefinder with ±1m accuracy to compute new coordinates that estimated each 'known' location from the random points where observers stood.

I used the distance between known and estimated locations as the dependent variable and the distance (the observer was) from the known location as the independent variable in a simple linear regression model. I considered distance between estimated and known points as an index of accuracy, where shorter distances reflected higher accuracy. I used the resulting linear model equation to predict the maximum distance an observer can be from an owl when measuring/recording owl locations to attain an average error of 3 m.

Results

1. Distances from the known point that were sampled ranged from 0.12-15.2 meters from known point (Figure II.1).
2. The observer distance from a known point when the distance between the estimated and known points was the required maximum (3 m) was 36.3 m (3/0.0826) (Figure II.2).
3. Distances <36.3m produced estimated locations with average errors <3 m (Figure II.2).

CONCLUSIONS AND RECOMMENDATIONS

My results showed that hand-held GPS locations, compass directions, and range finder distances are suitable for estimating locations of objects like Burrowing Owls with reasonable accuracy. With increased distance between observers and known points, estimated distances were less accurate (i.e., farther from known points). These field methods are sufficient for use in producing average estimated coordinates ≤3 m of Burrowing Owls or their nests as long as observers are ≤36.3 m from their target.

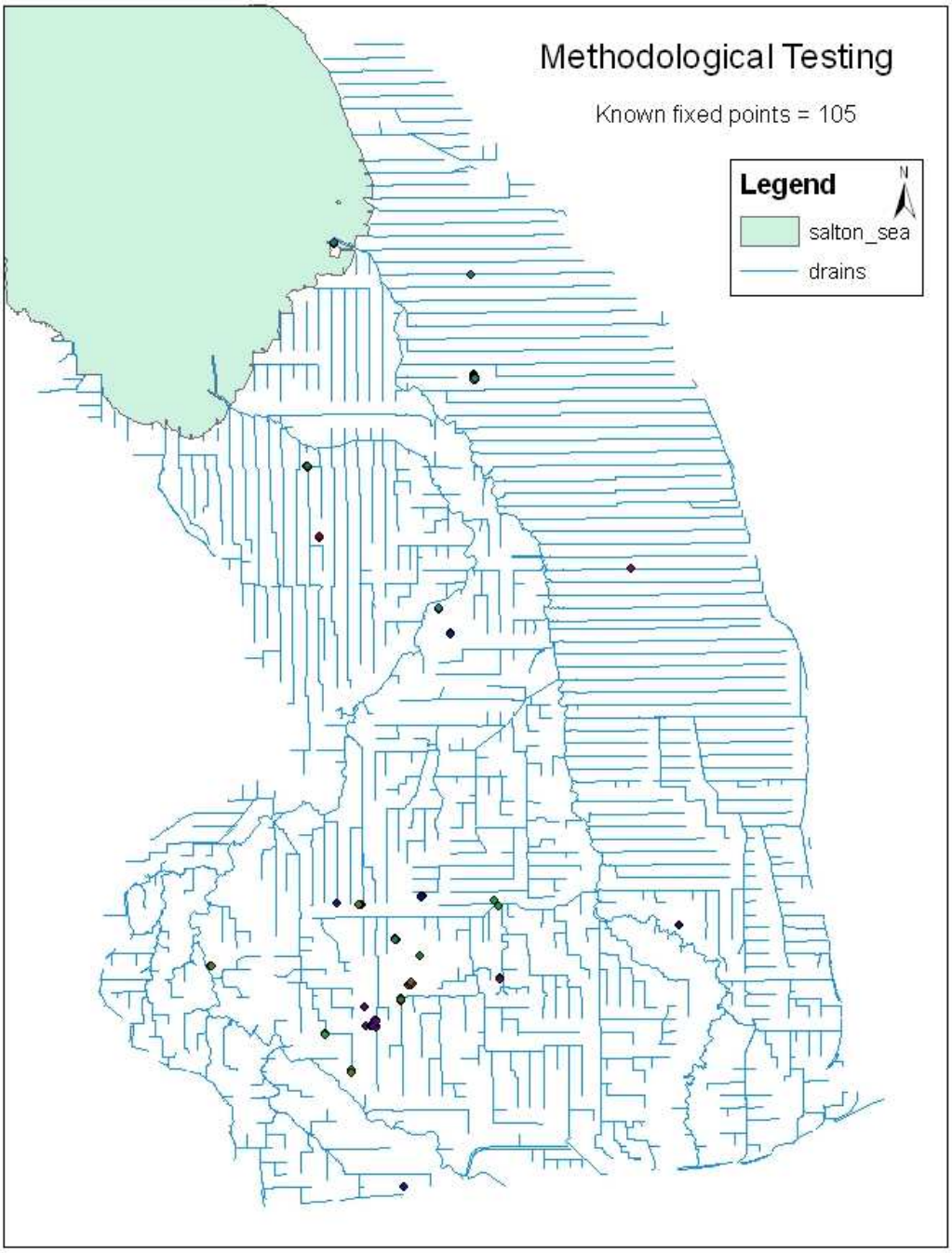

Figure II.1. Locations of known fixed points used to test the accuracy of field sampling techniques to estimate Burrowing Owl locations (derived from a combination of GPS, range finder, and directional compass) in the HCP Study Area, Imperial County, California, April 16-May 20, 2006.

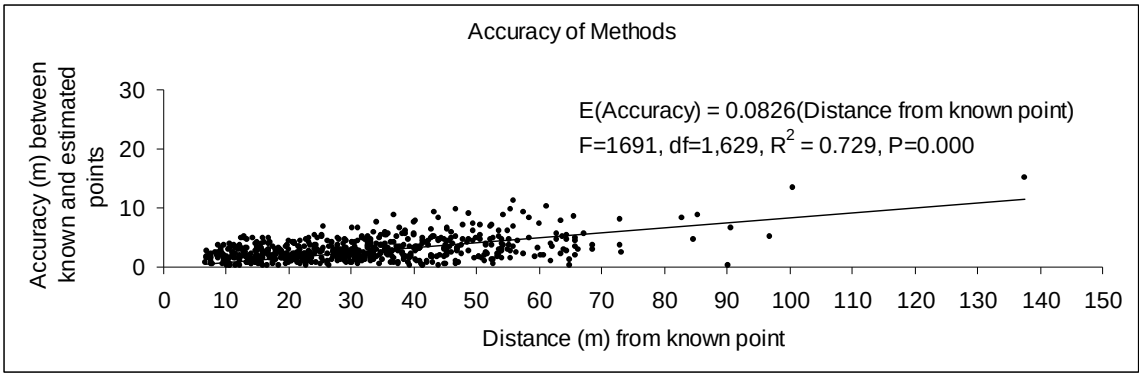

Figure II.2. Distance between estimated and known points as a function of observer's distance from a known point in the HCP, Imperial County, California.

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Appendix III

REMOTE CLASSIFICATION OF CROP AND LAND COVER TYPES

JEFFREY A. MANNING AND MIKE FALKOWSKI

INTRODUCTION

Burrowing owls have been reported to use specific types of crops in Imperial County, California (Rosenberg and Haley 2004). Knowledge of relationships between owl abundance and specific types of crops would be helpful in developing survey protocols for burrowing owls in this region, but such knowledge is dependent on availability of crop and owl data. Owls were surveyed across the Imperial Irrigation District's (IID) right-of-ways in the spring of 2007, but data (in a usable format) on when, where, and what types of crops are present are currently unavailable. This is due to the large extent of the Imperial Valley and high number of property owners, diversity of crops, and frequency of crop rotation. In particular, the large extent and numerous landowners pose challenges for mapping crops during brief periods (i.e., spring). Furthermore, in order to test hypotheses regarding relationships between owl abundance and crops, a spatial, time series dataset of crops is required, and such data are complex and impractical to attain from ground surveys. We evaluated the efficacy of satellite remote sensing for large-area crop type classification in the IID's Habitat Conservation Planning (HCP) Area and mapping crop assemblages and individual crop types with the intent that these data may be suitable for assessing relationships between owls and crops.

For the past 20 years, satellite remote sensing has been used to map, inventory, and monitor land cover types (*e.g.*, Haack 1987, Vogelman *et al.* 2001, Falkowski *et al.* 2006), including agricultural crops (Bauer 1985, Ortiz *et al.* 1997). Remotely sensed data acquired by space-borne sensors are ideal for gathering, mapping, and monitoring information on land surface and vegetation characteristics across large regions such as the agricultural matrix comprising the HCP. The Landsat family of sensors was designed specifically with such information needs in mind (Beck and Gessler, In Press).

There are numerous benefits to using satellite remote sensing data for such a task. For instance, remotely sensed data provide a time-efficient approach for mapping crops because it can be automatically processed in a timely manner. Landsat imagery can produce maps measuring a variety of landscape features like land cover and crop type. Compared to traditional field-based mapping techniques, maps produced via remotely sensed data require a relatively small amount of field data, resulting in reduced sampling effort. Lastly, it provides complete coverage across large areas as well as a long-term data archive.

Methods of using Landsat imagery to classify landscape features and vegetation continue to evolve, leading to increased accuracy. For example, individual crop types have been successfully classified from single date Landsat imagery. But, recent studies found

increased accuracy through the incorporation of multi-date imagery (Oetter, *et al.* 2000). This is because different crops have unique phenologic trajectories (e.g., stages of development and growth patterns) that can be detected via a time series of remotely sensed data (Oetter, *et al.* 2000). Thus, multi-date imagery series would be a preferred approach to classifying crops across the HCP.

Another approach that can improve accuracy is object-based classification. Typically, remote sensing classifications are pixel-based, meaning that each pixel is classified as a specific type of land surface or vegetation independent of conditions in neighboring pixels. Because landsat image pixels are 30 x 30m, agricultural fields are comprised of numerous pixels. Variable crop conditions (e.g., stages of development) and soil types among pixels within a field leads to variation in the classification of pixels in a field. This variably is represented by a salt and pepper appearance in pixel-based classification maps (Figure 1A). This within-field variably can reduce accuracy of classifying fields correctly. A solution is to use fields as objects in an object-based classification, which quantitatively groups similar contiguous pixels (Figure 1B), thereby using within-field frequency distributions to classify individual agricultural fields. Object-based classifications have been successfully applied to other large-scale areas such as forested environments (Desclee *et al.* 2006). Because object-based techniques may improve the accuracy of classifying crops at the resolution of agricultural fields rather than pixels within fields (Desclee *et al.* 2006), this approach is preferred for the agricultural matrix comprising much of the HCP.

OBJECTIVES

The overall objective was to produce reasonably accurate maps of crop types intended for use in assessing relationships between owl abundance and crops and developing future burrowing owl population surveys. Specific objectives were to:

1. Incorporate a time series of Landsat data to classify vegetation and crops types each Spring from 2003 to 2007.

2. Assess the efficacy and accuracy of an object-based classification technique in the Imperial County agricultural environment.

3. Produce a GIS polygon layer of agricultural fields with attribute information specifying crop type in each polygon each spring from 2003 to 2007.

METHODS

Ground Reference Data Collection

Ground reference data were collected at 420 randomly located agricultural crop fields across the 500,000-acre HCP from March 31-April 22, 2007. At each random field, a point location was randomly selected, and the type and stage of development (bare ground, sprout, mid-stage, mature, abandoned, grazed, stubble) were visually identified

by a crop specialist and recorded at that point. Field data were recorded using a Trimble GeoXM GPS. Sample sizes for each crop type ranged from 3 to 52 (Table 6.1).

Landsat Image Acquisition and Processing

We acquired 3 Landsat images (30 x 30 m resolution) for each spring from 2003 to 2007 (totaling 15 images) from the United States Geological Survey (USGS). The image acquisition dates (Table 6.1) coincided with the collection of ground reference data.

We originally proposed to classify crops with Landsat 5 imagery. However, due to large amounts of cloud cover during March and April it was necessary to use a combination of Landsat 5 and Landsat 7 data to avoid contamination of the data by clouds (i.e., if a particular Landsat 5 image was contaminated by clouds, we used a cloud free Landsat 7 image acquired within a similar time frame). This strategy provided imagery coverage during the desired time frame for each of the 5 years between 2003 & 2007, inclusive.

Although there was a potential disadvantage of using Landsat 7 data for this study (e.g., the Landsat 7 sensor scan line corrector (SLC) failed on July 14th, 2003, resulting in the raw imagery having systematic gaps in the data (Figure 2a)), remedies were available. For example, the USGS has developed an interpolation methodology to fill in missing data values based upon neighboring scan lines (Figure 2b). Also, the SLC error is more pronounced toward the edges of a Landsat scene (USGS 2007), but since the Imperial Valley Region is approximately at the center of a Landsat scene, the interpolated products produce seamless data for the HCP. Lastly, the object-based classification approach implemented in this project (described below) should be relatively unaffected by any interpolated values within a Landsat 7 scene since the classification rules rely upon distributional statistics within each individual agricultural field. Therefore, we believe this Landsat processing approach is comparable, if not superior, to the originally proposed approach.

We systematically processed each image to correct for radiometric and geometric errors via a streamlined image processing methodology developed by Beck and Gessler (In Press). This was accomplished by geo-reregistering the April 2007 image to high-resolution digital orthophotos, acquired by the National Agriculture Imagery Program (NAIP), spanning the HCP. The remaining 14 Landsat images were then co-registered to the April 2007 image. This geo-registration process ensured that each Landsat scene had a geo-location accuracy of < 15 m on the ground.

Following geometric correction, each image was radiometrically calibrated and converted from raw digital number to percent reflectance via equations and coefficients developed by Markhan and Barker (1986), Chander and Markham (2003), and Williams (2004). This process removed radiometric errors and ensured that each image was directly comparable to another image within the time series, regardless of acquisition date and/or radiometric differences between the Landsat 5 and Landsat 7 sensors (*i.e.*, this process allows the direct comparison of Landsat 5 and Landsat 7 images). Following radiometric

calibration, we also removed atmospheric effects (*e.g.*, haze and dust) via the COST atmospheric correction model (Chavez 1996).

Creation of Image Objects for Object-based Classification

We initially proposed using a technique referred to as image segmentation to create a GIS polygon layer that would outline individual agricultural fields for an object-based classification. However, we later chose to use Common Land Units (CLUs; U.S. Department of Agriculture, Farm Service Agency, Aerial Photography Field Office, Salt Lake City, Utah; www.apfo.usda.gov) as objects. Each CLU represents an agricultural field. Thus, the CLU layer was intersected with each Landsat image to create groups of pixels representing image objects (hereafter referred to as agricultural fields).

Distributional statistics (*e.g.*, mean, standard deviation, range, minimum values and maximum value of pixels) were calculated for each Landsat band within each agricultural field. This process created a GIS layer containing the aforementioned distributional statistics for each agricultural field across the HCP for each of the 5 years in the Landsat time series (Figure 3). The resulting GIS layer contained approximately 7,000 individual polygons (representing agricultural fields within the HCP), each containing 35 different data attributes quantifying the distributional statistics of Landsat pixels within each agricultural field. Following this process, fields sampled during data collection were separated out of the 2007 GIS layer and used as training data in the classification, as described below.

Distributional statistics were also calculated for the Normalized Difference Vegetation Index (NDVI), which is sensitive to living plant biomass (Tucker 1979). These metrics provided an opportunity to improve our classification of individual crops in the HCP because individual crops display distinct variation in their spectral responses over time (phonologic trajectories; e.g. http://rst.gsfc.nasa.gov/Sect3/Sect3_1.html). For example, Sudan grass fields in our study area showed low mean NDVI values in late March, and these rise through April, corresponding to plant establishment and growth during this time period (Figure 4). Sugar beet fields displayed a decreasing trend in the mean NDVI, which is mostly likely related to a gradual senesce of this crop (Figure 4), and the NDVI for alfalfa fields remained relatively constant through the time series (Figure 4).

Image Classification

Crops were hierarchically classified as groups (Level II crops) and individual species (Level III crops, Table 6.2) and using the Breiman Cutler classification (BCC) algorithm (Breiman 2001), also known as randomForest. The BCC algorithm is a classification and regression tree (CART) technique that has achieved excellent results in classifying remotely sensed imagery (Lawrence et al. 2006). The BCC algorithm develops classification rules by growing numerous (> 1,000) classification trees from random subsets of training data, and randomly selects which predictor variables (e.g., percent reflectance) to use for each decision rule. The correct classifications, or predictions, are then determined by selecting the most common decision rule at each node within the

group of multiple trees (Breiman 2001, Prasad *et al.* 2006, Lawrence *et al.* 2006). As the algorithm runs, bootstrap error estimates are calculated with the training data not used in the random selection process. The algorithm produces precise, unbiased decision rules, and does not overfit the training data (Breiman 2001). Because the BCC's bootstrapped error estimates are very accurate, researchers have recommended that it is unnecessary to estimate error from an independent dataset (i.e., all ground reference data can be used to develop classification rules (Breiman 2001, Lawrence *et al.* 2006)).

Accuracy Assessment and Classification

We used 2 separate methods of applying the BCC algorithm to assess accuracy of the level III crop classification: 1) with all of the ground reference data and 2) with 25% of the ground reference data held back for an independent accuracy assessment. We performed these 2 methods of assessing accuracy/error because we originally proposed the latter approach, but later decided that the former approach may be more reliable (Breiman, 2001, Lawrence *et al.* 2006).

Preliminary results from the 2 methods of assessing error (BBC and 25% of the ground reference data held back for an independent reference assessment) were similar (Level III species-level classification error was 68.6 % and 69.05 % for reduced and full datasets, respectively). Based on these comparable results and the conclusions of Breiman (2001) and Lawrence *et al.* (2006), we used the full set of ground reference data and their associated classification rules developed by the BCC algorithm to classify all of the time series data in lieu of using the originally proposed method.

We also used kappa statistics (KHAT; Cohen, 1960) to determine if our classifications were significantly better than that expected by chance (i.e. a random result) (Congalton and Green 1999). Kappa statistics are the most commonly used method of assessing the classification of subjects into categorical groupings. The kappa coefficient is an index that compares the agreement against that which might be expected by chance. It is considered as the chance-corrected proportional agreement, and possible values range from +1 (perfect agreement) via 0 (no agreement above that expected by chance) to -1 (complete disagreement). In other words, it corrects for chance agreement and tells us how much of the possible agreement over and above chance each classification achieved. Generally, kappa values >0.75 are considered to have a high degree of agreement beyond chance, values <0.40 have a low degree of agreement, and values between 0.40 and 0.75 represent a fair to good level of agreement beyond chance alone.

Once accuracy was assessed, the results from the image classification were used to generate 5 separate GIS polygon layers of predicted crop types in agricultural fields present in the HCP from late March to early April in 2003, 2004, 2005, 2006, and 2007 (Appendix A).

Classification Assumptions

Retrospectively classifying agricultural crops prior to 2007 assumes that the types of crops cultivated in the Imperial Valley from 2003-2006 were not drastically different than the crops present in 2007. In addition any future classifications will only be valid if the types of crops in cultivation reaming consistent.

RESULTS

The level II crop classification had an overall accuracy of 84%, with the accuracy of bare ground = 66.76 %, grass crop = 81.41 %, and broad leaf/other crop = 88 % (Table 6.2). The level III classification, classified 31 individual crops, and had an overall accuracy of 69.05%, with individual class accuracies ranging from 0 % to 100 % (Table 6.2). There was a good degree of agreement beyond chance alone (kappa statistics = 0.71 and 0.67) for level II and level III classifications, respectively,

In the level III classification, five crops (artichoke, asparagus, cauliflower, cilantro, and parsley) were classified with 100% accuracy, four (alfalfa, sugar beets, watermelon, and triticale) were classified with 80-99% accuracy, and six others (corn, potato, radish, Bermuda grass, Sudan grass, and wheat) with 70-80%. Bell pepper, broccoli, carrot, kline grass, lettuce, mixed flowers all had class accuracies >50 %, while the cabbage, citrus, sugar cane, and wild oat classes each had accuracies of 0 %. Errors of omission and commission for the level II and level III classification are listed in Tables 6.3 and 6.4, respectively.

According to the level III classification, the total land area each crop occupied in the study area varied annually (Table 6.5). Alfalfa was the most common crop in cultivation, occupying about 45,000 – 70,000 ha of the HCP between March and April from 2003 to 2007. Sudan grass, Bermuda grass, and wheat also occupied large tracts of land between 2003 and 2007. Some of the least common crops in cultivation included potato, radish, bell pepper, and watermelon, among others.

DISCUSSION

The overall goal of this project was to use remotely sensed data to classify crop assemblages and individual crop types in order to assess their importance to burrowing owls across the HCP. We employed an object-based BCC classification algorithm to classify 31 different crop types with a 3-date time series of Landsat data (March – April), and achieved reasonably high accuracy, given the large number of crop categories classified.

Many of our level III individual crop categories had accuracies $\geq$75 %; and overall, our approach achieved accuracies equal to or higher than similar studies. For example, Akbari *et al.* (2006) classified Landsat imagery into 20 different crop categories and attained an accuracy of 62 %, while Belward and Hoyos (1986) classified Landsat imagery into 8 different crop categories and attained an overall accuracy of 64.8 %.

Lower numbers of crop categories can yield higher accuracies, as seen in our classification level II, but such groupings may not yield enough detail for relating crops to burrowing owl abundance in localized areas within the HCP. In fact, other studies have reported slightly higher accuracies (e.g., Janssen 1992 and Turker and Arikan 2004 attained 81 % accuracy), but this is likely due to classifying only 7 to 11 crop types, respectively. Given the relatively high number of crops classified in this study, which is important in order to assess their relative importance to burrowing owls, the accuracy is reasonably high.

The approximate 20% decline in overall accuracy between level II and III classifications was expected given the increased number of classes between the 2 categories. The GIS polygon layers produced by the level III classification predicted individual crop types with reasonable accuracy, given the 69.05% overall accuracy, and should be suitable for relating individual crops to burrowing owl abundance.

Of particular interest are the accuracies of bare ground (level II = 66.67%, level III = 41.17%) and grass crops (level II = 81.41%, level III: alfalfa=88.46%, Bermuda grass=70%, Sudan grass=76.09%, triticale=80%, and wheat=77.78%) because the results from one study suggest that owls may use bare ground more than other cover types near nests and hay crops more than other types at distances away from nests (Rosenberg and Haley 2004). The high levels of accuracy for those crops from these analyses should produce a dataset suitable for assessing their importance as correlates of owl abundance.

Table 6.1. Acquisition dates and sensor of Landsat data used.

Year	Acquisition Date	Sensor
2007	28-Mar	Landsat 5
	13-Apr	Landsat 5
	29-Apr	Landsat 5
2006	1-Mar	Landsat 7
	10-Apr	Landsat 5
	26-Apr	Landsat 5
2005	30-Mar	Landsat 7
	7-Apr	Landsat 5
	15-Apr	Landsat 7
2004	27-Mar	Landsat 7
	12-Apr	Landsat 7
	20-Apr	Landsat 5
2003	25-Mar	Landsat 7
	10-Apr	Landsat 7
	26-Apr	Landsat 7

Table 6.2. Crop classes and associated class accuracies. Overall accuracies for the level II and Level III classifications are 84 %and 69.05 %, respectively.

Level I	Level II	% Accuracy	Level III	Sample Size	% Accuracy
Agriculture	Broad Leaf Crops / Other	88.00	Alfalfa	52	88.46
			Artichoke	4	100.00
			Asparagus	4	100.00
			Bamboo	4	50.00
			Bell Pepper	5	40.00
			Broccoli	9	44.44
			Cabbage	4	0.00
			Cantaloupe	13	61.54
			Carrot	7	42.85
			Cauliflower	4	100.00
			Cilantro	4	100.00
			Citrius	3	0.00
			Corn	27	74.07
			Cotton	6	66.67
			Lettuce	7	42.85
			Mixed Flowers	4	25.00
			Onion	23	69.56
			Parsley	4	100.00
			Potato	4	75.00
			Radish	4	75.00
			Sugar Beets	33	93.94
			Sugar Cane	4	0.00
			Watermelon	5	80.00
	Grass Crops	81.41	Bermuda Grass	50	70.00
			Fox Tail Grass	3	0.00
			Kline Grass	11	36.36
			Sudan Grass	46	76.09
			Triticale	4	80.00
			Wheat	36	77.78
			Wild Oat	6	0.00
	Bare Ground / Fallow	66.67	Bare Soil	17	41.17
			Fallow Field	13	53.85

Table 6.3. Level II **c**rop classes and associated errors of omission and commission

Level II	% Omission Error	% Commission Error
Broad Leaf Crops / Other	11.96	13.81
Grass Crops	18.59	15.33
Bare Ground / Fallow	33.33	35.48

Table 6.4. Level III **c**rop classes and associated errors of omission and commission.

Level III	% Omission Error	% Commission Error
Alfalfa	11.54	25.81
Artichoke	0.00	20.00
Asparagus	0.00	0.00
Bamboo	50.00	0.00
Bell Pepper	60.00	0.00
Broccoli	55.56	55.56
Cabbage	100.00	100.00
Cantaloupe	38.46	38.46
Carrot	57.14	0.00
Cauliflower	0.00	20.00
Cilantro	0.00	0.00
Citrius	100.00	100.00
Corn	25.93	53.49
Cotton	33.33	33.33
Lettuce	57.14	25.00
Mixed Flowers	75.00	50.00
Onion	30.43	5.88
Parsley	0.00	20.00
Potato	25.00	0.00
Radish	25.00	0.00
Sugar Beets	6.06	24.39
Sugar Cane	100.00	100.00
Watermelon	20.00	0.00
Bermuda Grass	30.00	30.00
Fox Tail Grass	100.00	100.00
Kline Grass	63.64	20.00
Sudan Grass	23.91	36.36
Triticale	25.00	0.00
Wheat	22.22	20.00
Wild Oat	100.00	100.00
Bare Soil	58.82	58.82
Fallow Field	46.15	50.00

Table 6.5. Total area (hectares) in Level III crops on a yearly basis.

Level III	2007	2006	2005	2004	2003
Alfalfa	54019.28	45084.26	58967.96	61656.46	70045.57
Artichoke	836.39	3860.93	410.76	955.77	1445.97
Asparagus	80.79	3.52	19.42	32.30	18.79
Bamboo	174.04	59.95	172.40	100.87	19.50
Bell Pepper	32.73	0.00	0.00	1.58	2.77
Broccoli	588.93	1039.94	576.68	667.59	504.58
Cabbage	112.66	105.76	63.13	8.04	112.34
Cantaloupe	3131.67	1422.76	4333.37	1677.43	2753.94
Carrot	1305.15	2397.77	1394.95	2147.18	1745.02
Cauliflower	104.68	5.97	14.57	7.71	14.55
Cilantro	53.12	18.92	170.37	167.58	258.25
Citrius	242.05	107.96	107.65	0.00	160.61
Corn	7793.99	12033.17	10736.31	7733.00	7830.95
Cotton	602.29	23.52	766.88	30.99	76.15
Lettuce	1092.11	1634.90	402.66	559.38	295.38
Mixed Flowers	24.78	0.00	23.07	3.82	17.66
Onion	4642.11	4548.52	4997.87	5777.00	6228.10
Parsley	133.09	88.25	99.96	177.46	4.67
Potato	23.09	14.32	0.00	0.00	0.00
Radish	43.27	0.00	1.21	2.62	0.00
Sugar Beets	9449.51	9061.19	10272.95	16770.93	13345.18
Sugar Cane	116.91	200.53	238.36	226.13	69.67
Watermelon	80.33	0.00	0.00	108.93	109.25
Bermuda Grass	30153.54	22318.60	29766.65	24178.47	17775.63
Sudan Grass	20608.22	41135.88	11646.85	18126.97	13928.84
Kline Grass	2940.99	848.37	269.93	1662.74	1188.23
Triticale	226.40	30.58	0.00	9.34	0.00
Wheat	18508.90	12096.07	16877.82	18142.11	25131.63
Wild Oat	1600.12	647.29	167.54	51.73	572.46
Bare Soil	9281.53	6470.37	19233.90	8089.26	5743.65
Fallow Field	11505.73	14305.72	7853.73	10491.60	10165.68

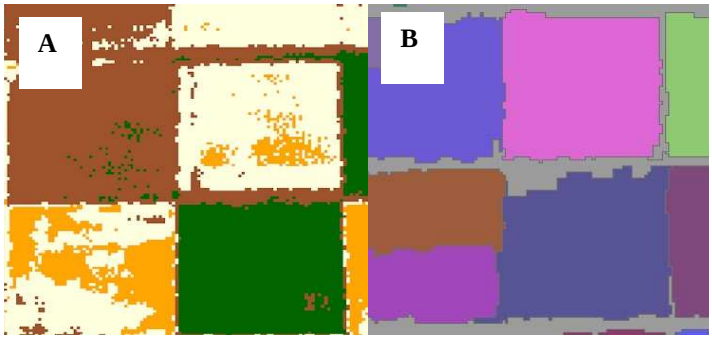


Figure 1. Pixel-based (A) and object-based (B) classifications

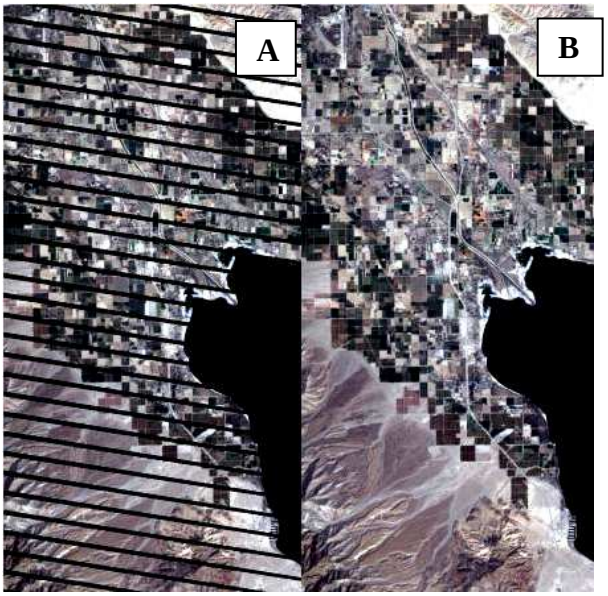


Figure 2. Landsat 7 Image with SLC error uncorrected (A) and corrected via interpolation (B). Image courtesy of the U.S. Geological Survey.

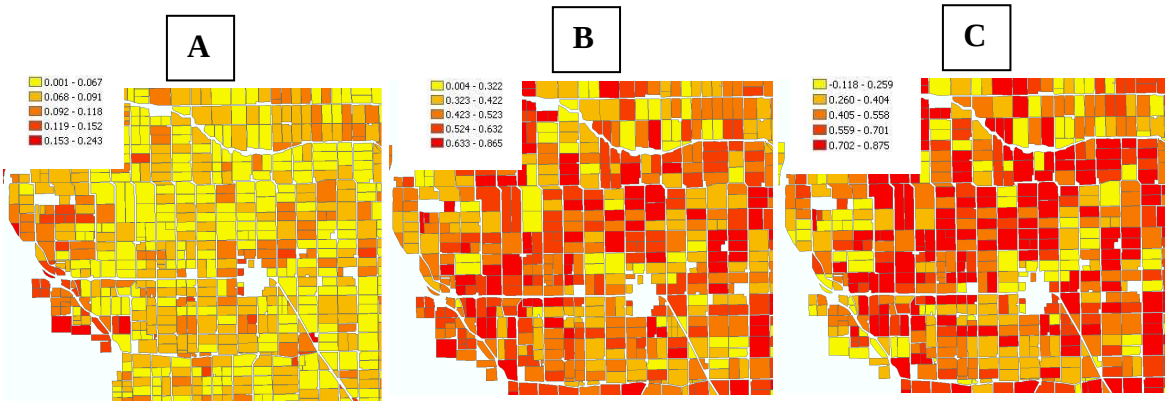


Figure 3. Distributional statistic GIS layer color coded by the mean (A), maximum (B) and standard deviation (C) of a single Landsat band.

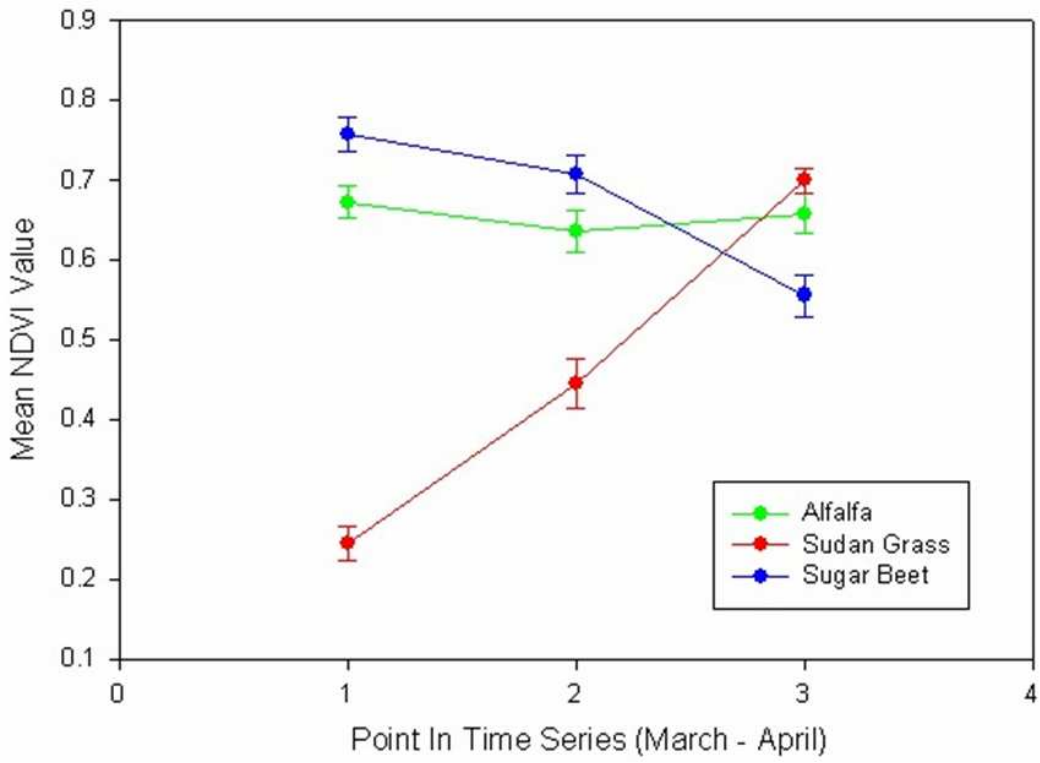
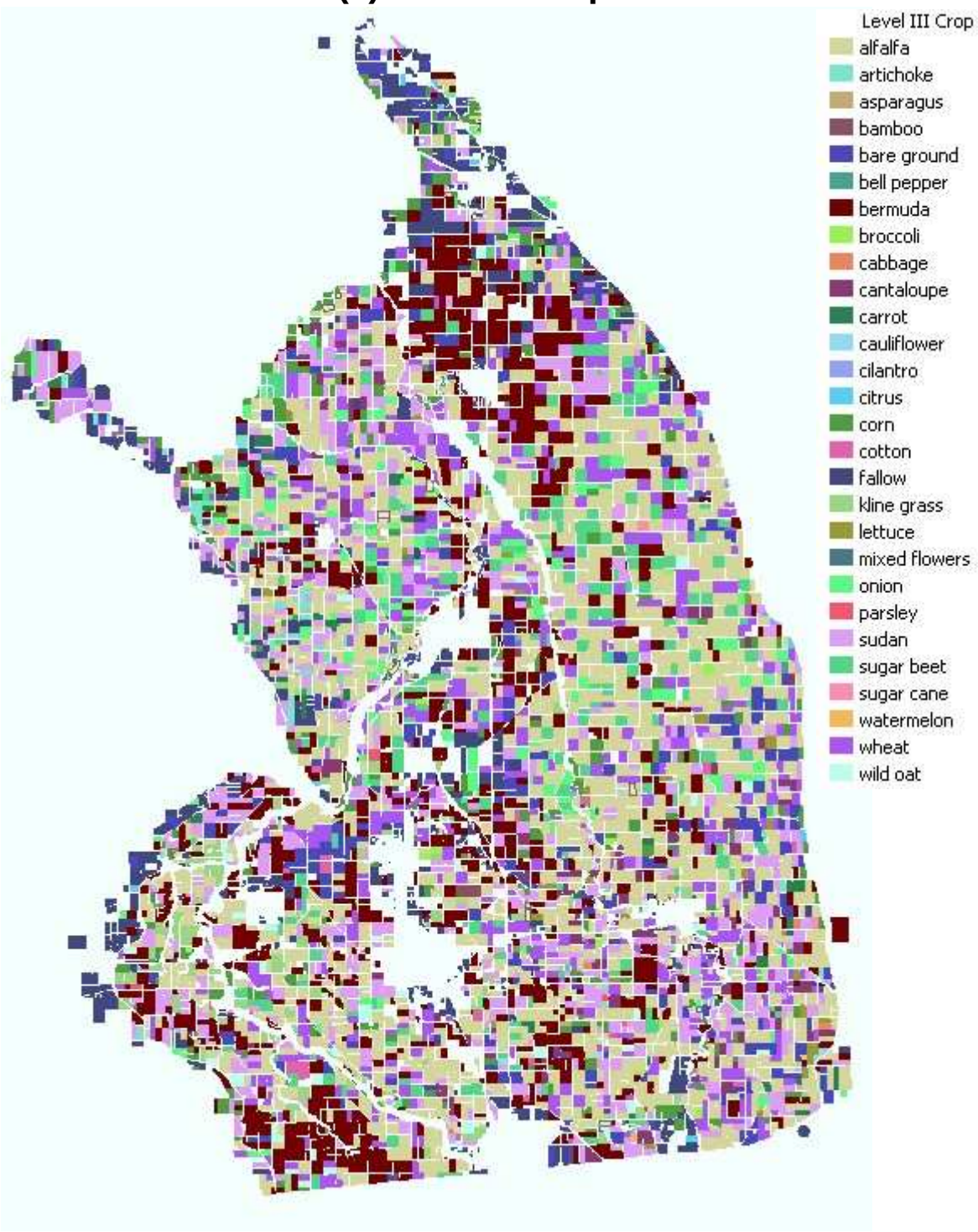


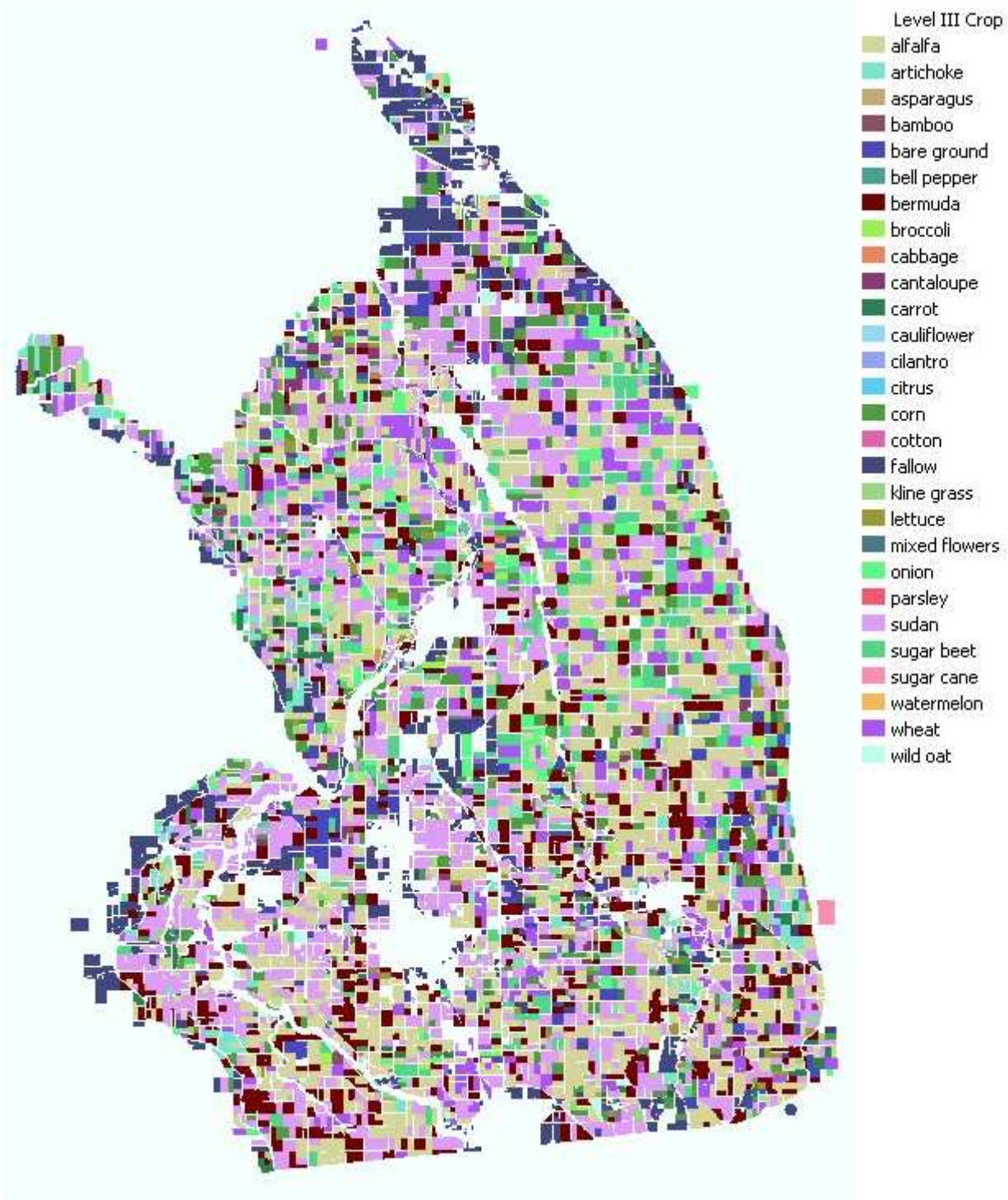
Figure 4. Phenologic trajectories for three selected crops.

APPENDIX A

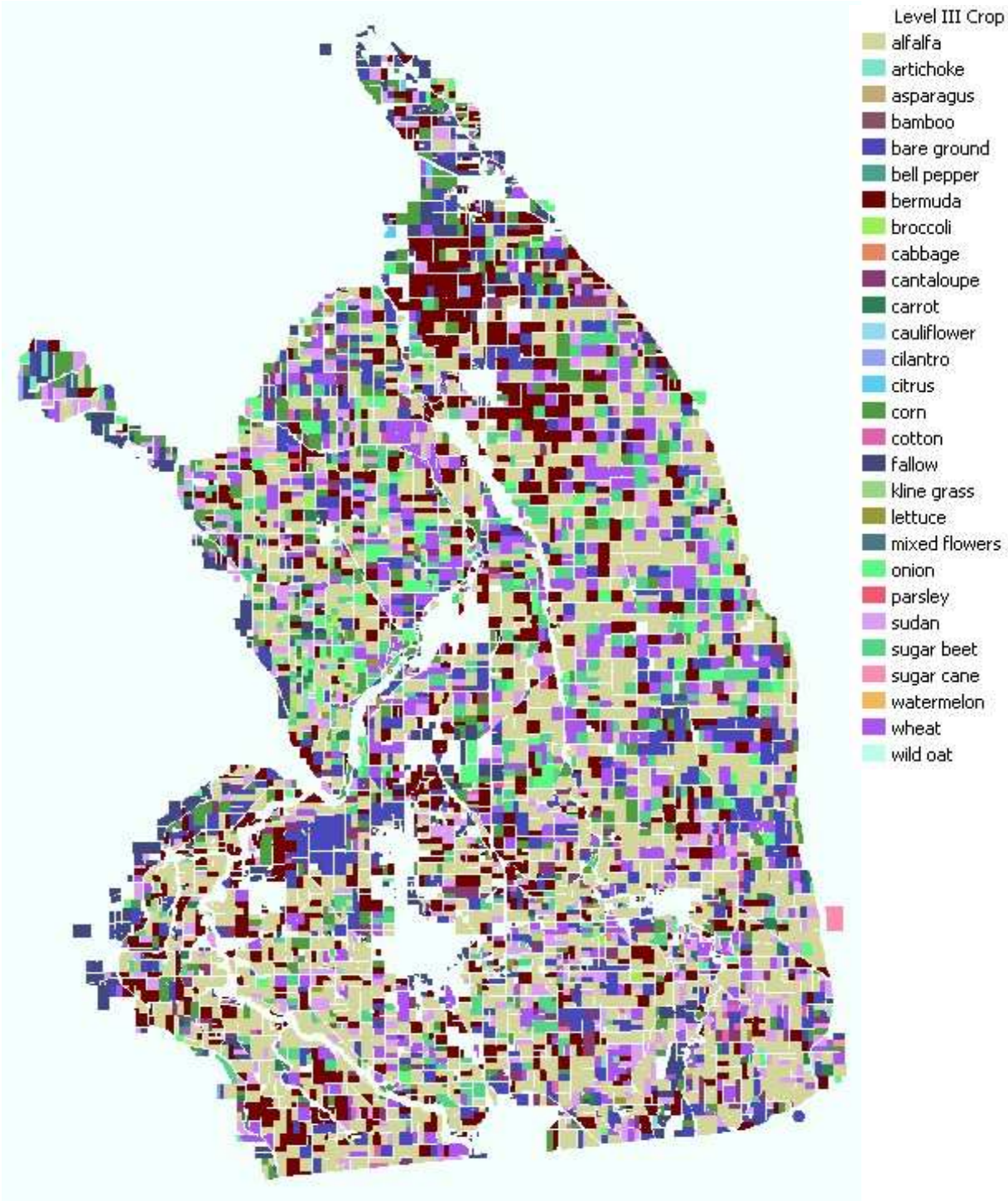
(a) Level III Crops - 2007



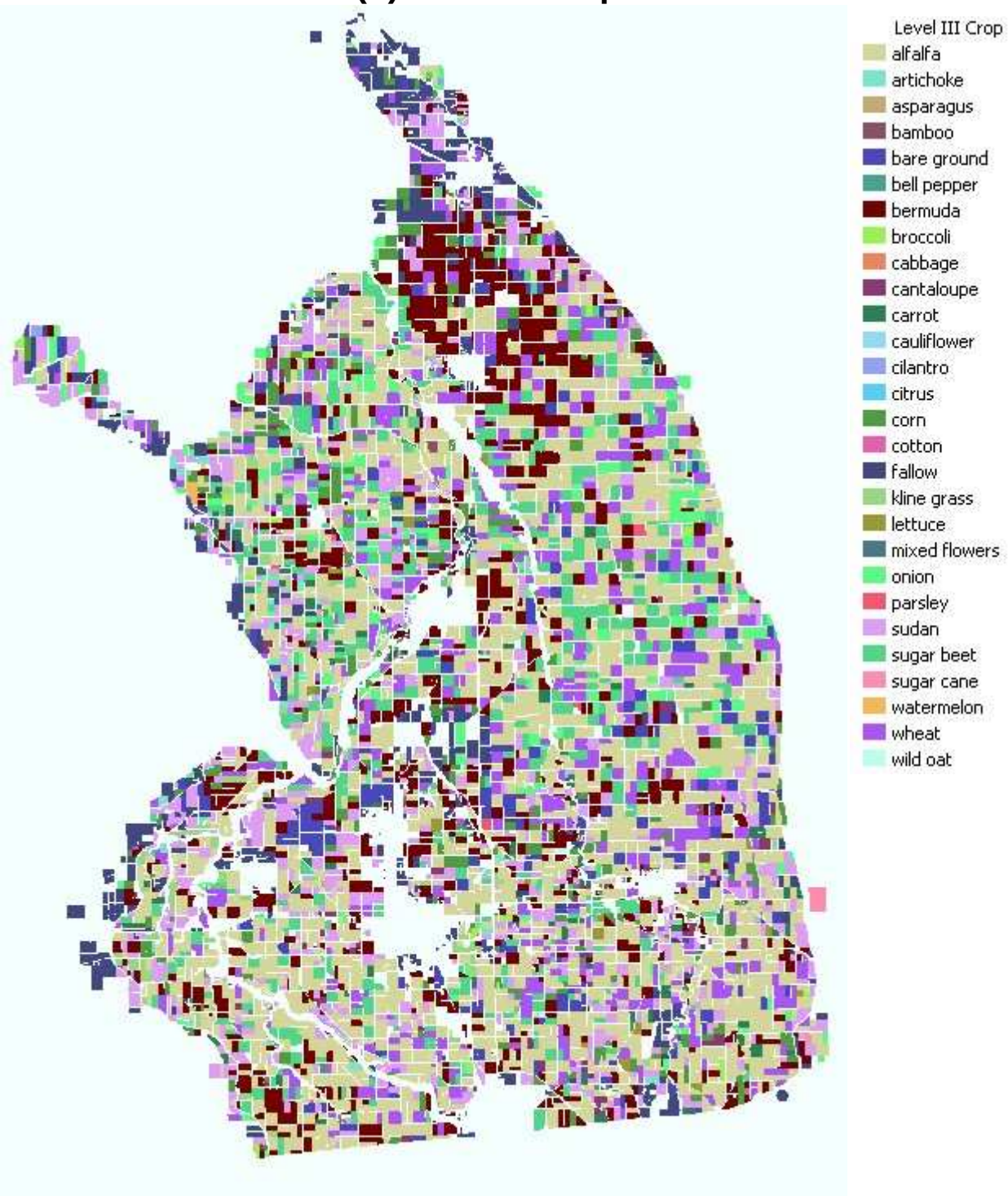
(b) Level III Crops - 2006



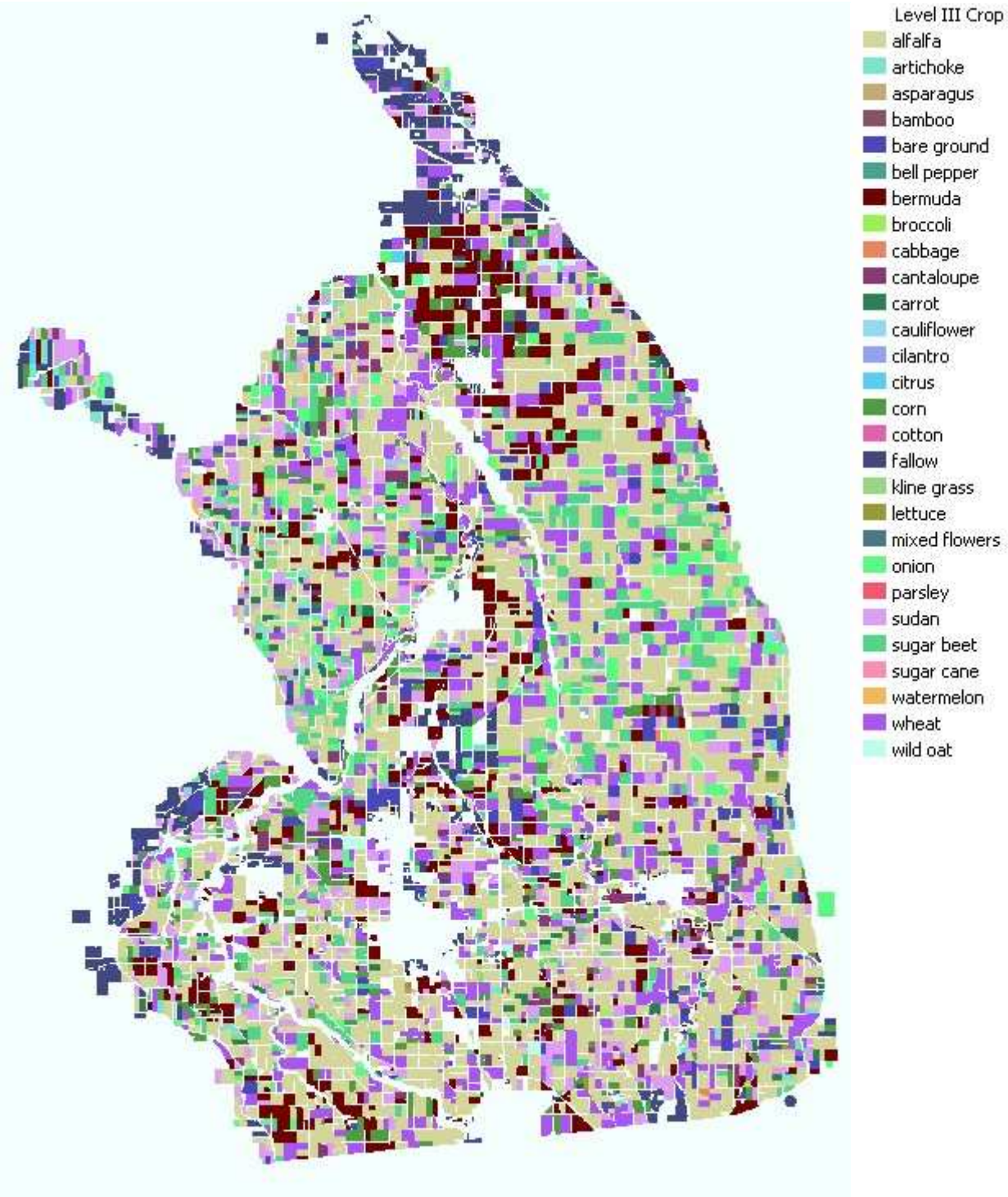
(c) Level III Crops - 2005



(d) Level III Crops - 2004



(e) Level III Crops - 2003



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Appendix IV

INCIDENTAL OBSERVATIONS OF DEAD BURROWING OWLS IN 2006, 2007, AND 2008

JEFFREY A. MANNING

INTRODUCTION

Incidental observations recorded during a population census can prove to be valuable for elucidating general patterns that can facilitate wildlife management, conservation, and research objectives. The locations of incidentally observed dead animals may be valuable in helping direct future studies of cause-specific mortality to particular areas where mortality is known to occur and be readily recordable. The standardized survey effort used to conduct the extensive Burrowing Owl population censuses in the HCP Study Area provides a unique opportunity to present known locations of dead Burrowing Owls.

METHODS

The locations of dead Burrowing Owls were recorded incidental to conducting capture-recapture population surveys during the prehatch stage of the breeding cycle (April) in 2007 and 2008. During the pilot study in 2006, we also conducted similar surveys along 412 Km of the IID's rights-of-way in April. During each year, a capture-recapture survey included 4 repeated occasions along asphalt and dirt roads paralleling water conveyance structures within the IID's rights-of-way. The specific survey methods were described in chapter 7. We also recorded information on dead Burrowing Owls observed along primary roads and highways we used to access the IID's rights-of-way. We traveled primary roads repeatedly throughout a field season, but we traveled along some more than others to gain quick access to the IID's rights-of-way. Thus, while our level of survey effort on the rights-of-way was constant within and between the 2007 and 2008 censuses, they were not equal among primary roads. The location coordinates of each dead Burrowing Owl were recorded with a hand-held GPS unit.

RESULTS

A total of 33 incidental observations of dead Burrowing Owls were recorded over the 3 years (Table IV.1). Their locations were spatially distributed across much of the HCP Study Area (Figure IV.1).

CONCLUSIONS AND RECOMMENDATIONS

The HCP Study Area is over 2,000 Km^2, dominated by agricultural activities, and encompasses a variety of urban, suburban, and rural human developments. Burrowing Owls in this system nest along irrigation drains and canals that border highways and

maintenance roads where vehicular activities can be high and maintenance activities frequent. Vehicle collisions have been cited as a potentially significant source of mortality (Haug et al. 1993, Clayton and Schmutz 1997), and the risk of vehicle collisions is likely greater in developed areas with dense human populations or along areas where owls nest predominately near roads. For example, higher post-fledging mortality from vehicle collisions occurred in an agricultural landscape with >90% of land area under cultivation compared to an unfragmented rangeland with <20% cultivation (Clayton and Schmutz 1997).

Inadvertent nest destruction from road maintenance activities in the HCP Study Area have been shown to effect survivorship of breeding Burrowing Owls in natural burrows along above-ground water conveyance structures (Catlin and Rosenberg 2006). However, the causes of mortality in this diverse area are likely to be numerous. The incidental observations presented here do not represent a complete set of locations where mortality occurs because the data collected here did not include the locations of dead owls outside of the IID rights-of-ways or those that were unavailable for detection during visual surveys from vehicles (e.g., inside burrows, concealed in vegetation like agricultural crops, or removed by predators, scavengers, or people).

Table IV.1. Count of dead Burrowing Owls by year in the Imperial Valley, California, 2006-2008. Data from 2006 are from a partial survey.

Year	Count of dead Burrowing Owls
2006	10
2007	15
2008	8

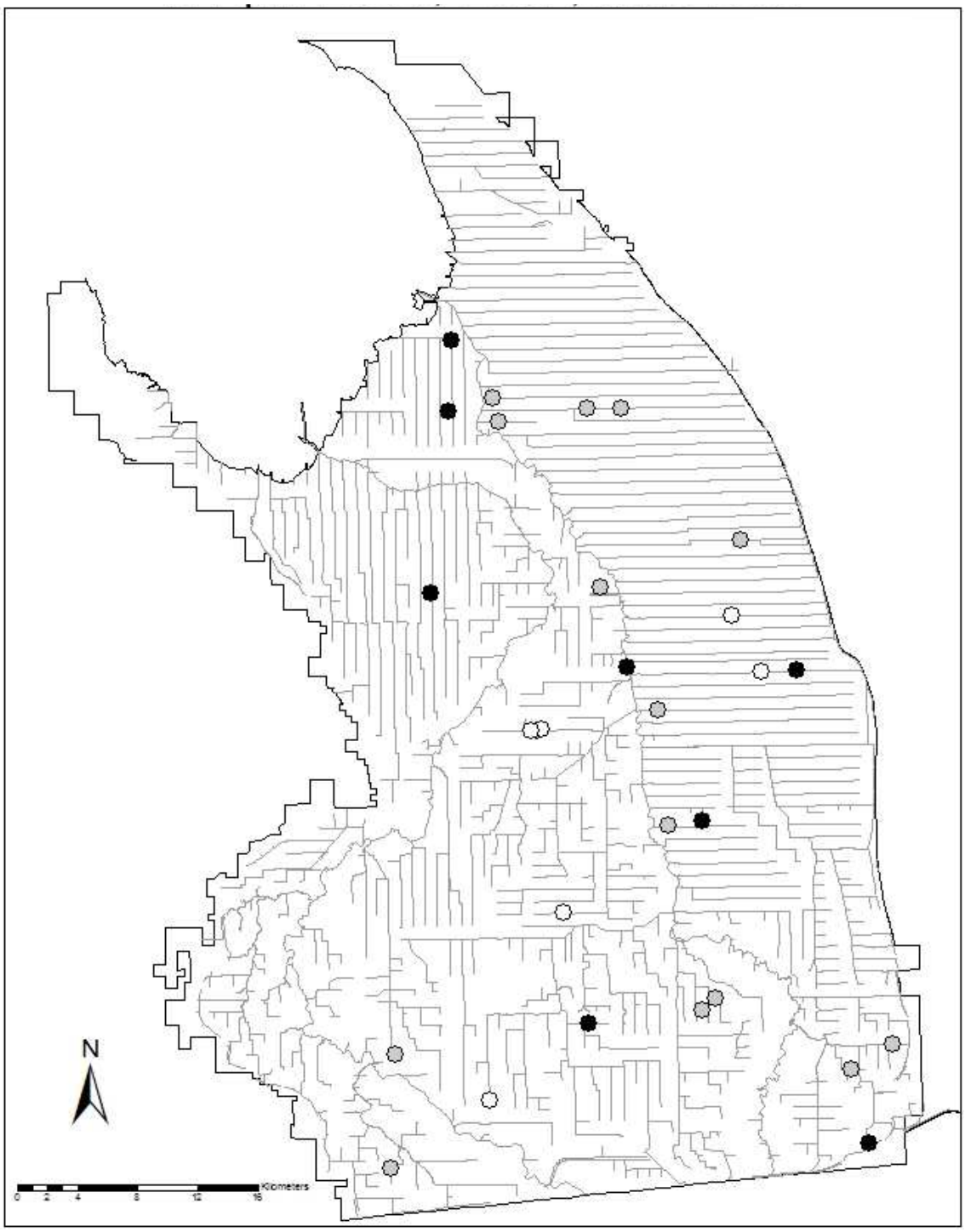

Figure IV.1. Locations of dead Burrowing Owls in the Imperial Valley, California, 2006-2008. Data from 2006 are from a partial survey. Solid black circles are locations of dead owls observed in 2006, solid grey circles are from 2007, and hollow circles are from 2008. Thin lines represent irrigation drains.

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Appendix V

LOCATIONS OF BANDED OWLS IN 2006, 2007, AND 2008

JEFFREY A. MANNING

INTRODUCTION

There were 2 sources for reporting banded owls. The first was recording the locations of owls we banded during our various studies at the time we banded them. The second was locations of all banded owls (those we and others banded) incidentally detected while conducting standardized population surveys in 2007 and 2008. We detected no banded Burrowing Owls and did not band owls during the 2006 pilot study.

METHODS

See Chapters 2, 7,and 16 for details on banding and surveying methodologies.

RESULTS

We banded 94 Burrowing Owls in 2007 (Figure V.1, Table V.1).

In 2007, we incidentally detected 39 banded Burrowing Owls during the 4 survey occasions, and with equal survey effort during that same period in 2008, we detected 26 (Figure V.2, Tables V.2 and V.3).

CONCLUSIONS AND RECOMMENDATIONS

None.

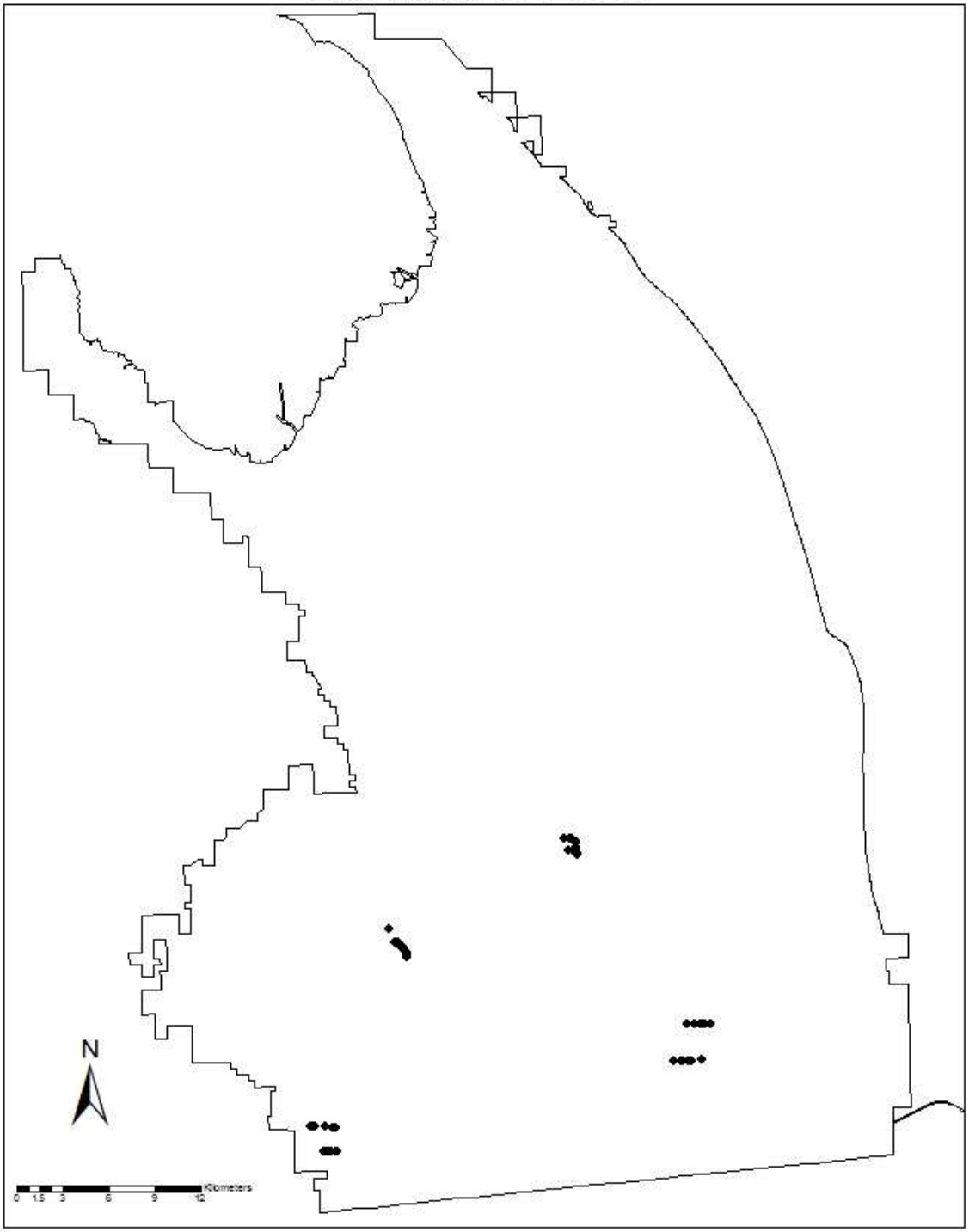

Figure V.1. Locations of Burrowing Owls banded in the HCP Study Area, Imperial County, California, 2007. Coordinates provided in Table V.1.

Table V.1. Coordinates of Burrowing Owls banded in the HCP Study Area, Imperial County, California, 2007.

Date	Bander Name	Color Band	Band No.	X	Y
2/16/2007	Jeff Kidd	Red	1	623713	3619031
2/16/2007	Jeff Kidd	Red	2	623811.7	3619034
2/16/2007	Jeff Kidd	Red	3	623959.4	3619036
2/17/2007	Jeff Kidd	Red	4	625182	3619001
2/17/2007	Jeff Kidd	Red	5	625182.4	3619000
2/17/2007	Jeff Kidd	Red	6	624828.3	3617379
2/17/2007	Jeff Kidd	Red	7	624972.6	3617380
2/17/2007	Jeff Kidd	Red	8	624829.3	3617379
2/17/2007	Jeff Kidd	Red	9	625105.9	3617383
2/17/2007	Jeff Kidd	Red	10	624663	3617402
2/17/2007	Jeff Kidd	Red	11	624867.9	3617402
3/3/2007	Jeff Kidd	Red	15	647949.6	3623291
3/3/2007	Jeff Kidd	Red	18	647948.7	3623287
3/3/2007	Jeff Kidd	Red	16	648302.2	3623288
3/3/2007	Jeff Kidd	Red	13	648357	3623289
3/3/2007	Jeff Kidd	Red	14	648356.7	3623289
3/3/2007	Jeff Kidd	Red	17	648542.9	3623293
3/3/2007	Jeff Kidd	Red	20	648542.8	3623293
3/3/2007	Jeff Kidd	Red	19	648428.9	3623295
3/3/2007	Jeff Kidd	Red	12	649153.1	3623363
3/3/2007	Jeff Kidd	Red	41	647324.3	3623279
3/3/2007	Jeff Kidd	Red	42	647814.7	3623282
3/3/2007	Jeff Kidd	Red	43	647814.6	3623282
3/3/2007	Jeff Kidd	Red	44	647397.2	3623281
3/3/2007	Jeff Kidd	Red	45	647394.5	3623280
3/9/2007	Jeff Kidd	Red	46	641029.8	3637478
3/9/2007	Jeff Kidd	Red	47	641029.7	3637557
3/9/2007	Jeff Kidd	Red	48	641035.6	3636840
3/9/2007	Jeff Kidd	Red	50	641032.7	3637176
3/9/2007	Jeff Kidd	Red	51	641035.3	3637036
3/9/2007	Jeff Kidd	Red	52	641038	3636838
3/9/2007	Jeff Kidd	Red	49	641028.9	3637559
3/9/2007	Jeff Kidd	Red	53	641035.8	3637037
3/9/2007	Jeff Kidd	Red	54	640507.9	3636976
3/9/2007	Jeff Kidd	Red	55	641032.8	3637175
3/9/2007	Jeff Kidd	Red	56	641039.3	3636759
3/9/2007	Jeff Kidd	Red	57	641039.4	3636759
3/10/2007	Jeff Kidd	Red	58	640660.3	3637789
3/10/2007	Jeff Kidd	Red	59	640660	3637788
3/10/2007	Jeff Kidd	Red	59	640564.6	3637787
3/10/2007	Jeff Kidd	Red	91	640203.3	3637784
3/16/2007	Jeff Kidd	Red	92	625054.5	3617377
3/16/2007	Jeff Kidd	Red	93	624971.3	3617378
3/16/2007	Jeff Kidd	Red	94	625426.9	3617402
3/17/2007	Jeff Kidd	Red	95	625426.3	3617403

3/17/2007	Jeff Kidd	Red	96	625311.7	3617400
3/17/2007	Jeff Kidd	Red	97	625313.5	3617400
3/17/2007	Jeff Kidd	Red	98	624574.3	3617394
3/17/2007	Jeff Kidd	Red	99	624575.2	3617394
2/17/2007	Scott Thomas	Red	40	624668.4	3619012
2/17/2007	Scott Thomas	Red	21	625285.2	3619000
2/18/2007	Scott Thomas	Red	30	625335.1	3618983
2/18/2007	Scott Thomas	Red	28	629692.3	3630666
2/18/2007	Scott Thomas	Red	31	629692.3	3630666
2/18/2007	Scott Thomas	Red	25	629566.2	3630789
2/18/2007	Scott Thomas	Red	22	629837.9	3630523
2/18/2007	Scott Thomas	Red	29	629526.5	3630827
3/4/2007	Scott Thomas	Red	23	629573.1	3630790
3/4/2007	Scott Thomas	Red	72	629612	3630749
3/4/2007	Scott Thomas	Red	27	629508.7	3630845
3/4/2007	Scott Thomas	Red	35	629527.2	3630828
3/4/2007	Scott Thomas	Red	38	629839.5	3630521
3/4/2007	Scott Thomas	Red	36	629936.1	3630449
3/4/2007	Scott Thomas	Red	32	629936.5	3630447
3/4/2007	Scott Thomas	Red	73	629352.6	3630951
3/4/2007	Scott Thomas	Red	70	629302.8	3631043
3/4/2007	Scott Thomas	Red	61	629241.2	3631047
3/5/2007	Scott Thomas	Red	65	629509.3	3630845
3/5/2007	Scott Thomas	Red	75	629516.9	3630842
3/5/2007	Scott Thomas	Red	80	629432.1	3630917
3/5/2007	Scott Thomas	Red	62	629375.1	3630972
3/11/2007	Scott Thomas	Red	77	629615.5	3630748
3/11/2007	Scott Thomas	Red	79	629378.5	3630970
3/11/2007	Scott Thomas	Red	74	629906.1	3630413
3/11/2007	Scott Thomas	Red	73	629353.2	3630949
3/11/2007	Scott Thomas	Red	71	629626.3	3630691
3/15/2007	Scott Thomas	Red	64	629943	3630315
3/15/2007	Scott Thomas	Red	76	628795.8	3631898
3/19/2007	Scott Thomas	Red	78	629760.6	3630598
3/19/2007	Scott Thomas	Red	69	629947.6	3630063
3/19/2007	Scott Thomas	Red	66	629947.8	3630128
3/19/2007	Scott Thomas	Red	69	629948.1	3630126
4/6/2007	Scott Thomas	Red	89	649807	3625701
4/5/2007	Pete Bloom	Red	81	649359.2	3625726
4/5/2007	Scott Thomas	Red	84	648733.1	3625721
4/5/2007	Scott Thomas	Red	83	648183.3	3625702
4/5/2007	Scott Thomas	Red	87	649223	3625720
4/5/2007	Scott Thomas	Red	90	649067.2	3625714
4/5/2007	Scott Thomas	Red	82	649067.3	3625716
4/5/2007	Scott Thomas	Red	88	649185.6	3625722
4/11/2007	Scott Thomas	Red	85	649807	3625701

Proj Coord Sys: NAD_83_UTM_Zone_11N; Proj: Transverse_Mercator; False_Easting: 500000.00000000; False_N.: 0.0000; Central_Meridian: -117.00000000; Scale_Factor: 0.9996; Lat_Of_Orig: 0.0000; Linear Unit: Meter; Geog Coord Sys: GCS_N._Am_83; Datum: D_N._Am._1983; Prime Merid: Greenwich; Ang. Unit: Degree.

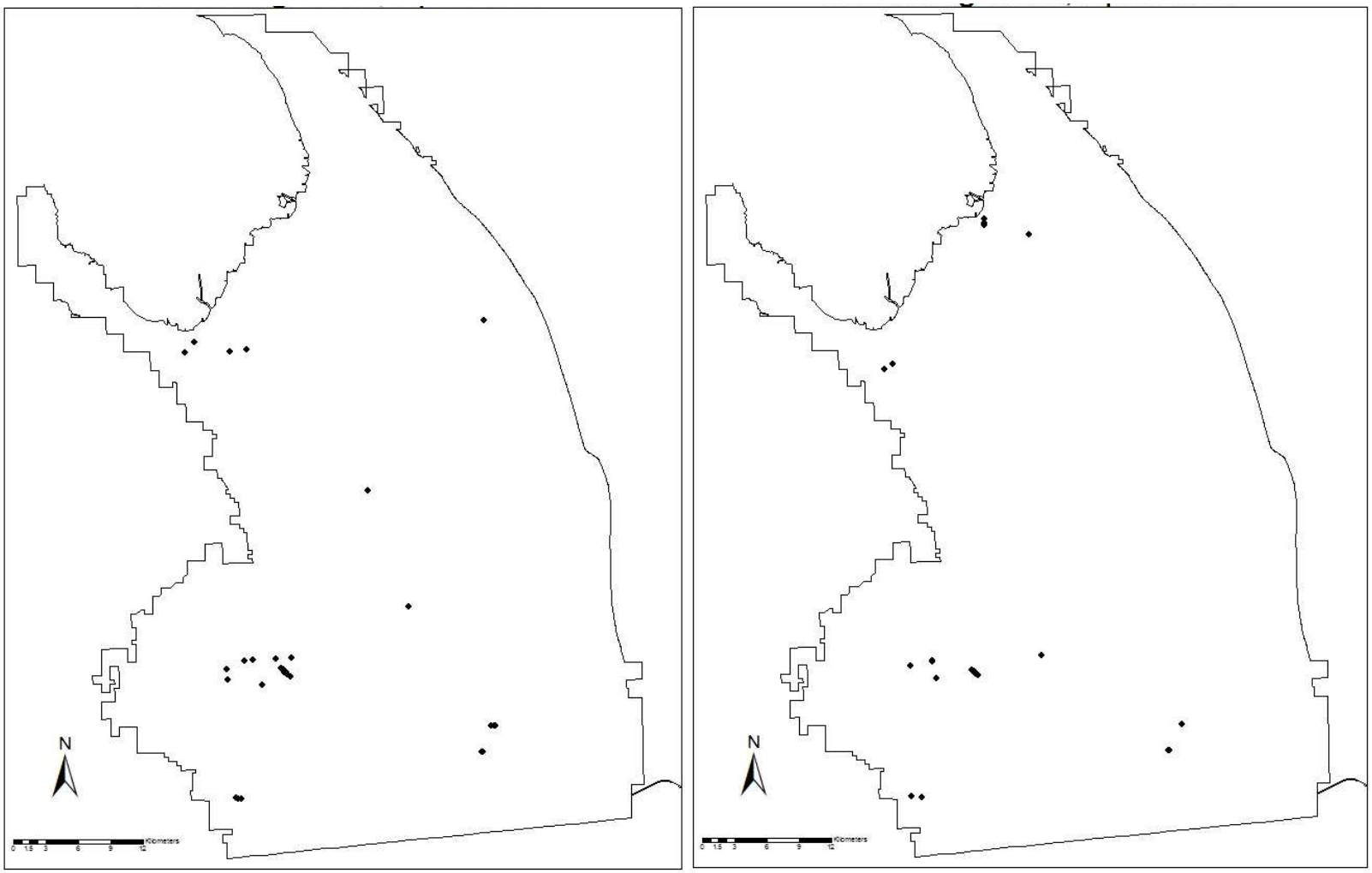

Figure V.2. Locations of banded Burrowing Owls incidentally detected during 4 survey occasions in the HCP Study Area, Imperial County, California, April 2007 and 2008. Coordinates provided in Table V.2 and V.3.

Table V.2. Coordinates of banded Burrowing Owls incidentally detected during 4 survey occasions in the HCP Study Area, Imperial County, California, April 2007.

Date	X	Y
4/13/2007	626143.9	3660471
4/17/2007	624625.1	3660246
4/11/2007	621292.5	3661131
4/10/2007	621286.5	3661137
4/10/2007	620439	3660210
4/3/2007	648014.3	3663108
4/16/2007	624371.7	3629942
4/2/2007	626709.7	3631777
3/30/2007	625936.9	3631667
4/16/2007	624332.3	3630938
4/2/2007	625936.8	3631666
4/3/2007	625400.5	3619003
4/3/2007	625185.5	3619018
4/5/2007	625936.8	3631667
4/5/2007	627541.8	3629430
4/9/2007	629761	3630600
4/9/2007	629841.6	3630522
4/9/2007	629907.7	3630411
4/9/2007	629637.3	3630660
4/10/2007	629762	3630598
4/10/2007	629840.9	3630522
4/10/2007	629907.5	3630413
4/10/2007	629639.9	3630658
4/10/2007	629537.3	3630930
4/11/2007	629303.8	3631044
4/11/2007	629378.6	3630971
4/11/2007	630157.4	3630208
4/11/2007	629639.3	3630658
4/4/2007	625936	3631666
4/10/2007	630302.6	3632004
4/18/2007	641037.6	3636758
4/3/2007	625611.8	3618963
4/5/2007	637334	3647406
4/10/2007	628798.7	3631897
4/16/2007	649066.7	3625714
4/16/2007	648732.2	3625710
4/16/2007	647815.8	3623283
4/16/2007	647946.8	3623287
4/16/2007	649043	3625693

Proj Coord Sys: NAD_83_UTM_Zone_11N; Proj: Transverse_Mercator; False_Easting: 500000.00000000; False_N.: 0.0000; Central_Meridian: -117.00000000; Scale_Factor: 0.9996; Lat_Of_Orig: 0.0000; Linear Unit: Meter; Geog Coord Sys: GCS_N._Am_83; Datum: D_N._Am._1983; Prime Merid: Greenwich; Ang. Unit: Degree.

Table V.3. Coordinates of banded Burrowing Owls incidentally detected during 4 survey occasions in the HCP Study Area, Imperial County, California, April 2008.

Date	Recorded by	C_COL_MARK	C_COL_CODE	C_CODE	C_LEG	M_CODE	M_LEG	X	Y
4/3/2008	Scott Thomas	none	none	none	none	not read	L	622283.89	3658990.45
4/3/2008	Elias Elias	red	white	F0	R	0934-28519	L	630751.55	3672046.22
4/3/2008	Elias Elias	red	white	A5	R	0934-28518	L	630770.85	3671792.06
4/9/2008	Scott Thomas	red	white	64	R	0804-42929	L	629943.84	3630314.54
4/9/2008	Scott Thomas	red	white	74	R	0804-42925	L	630157.64	3630203.55
4/3/2008	Jim Luttrell	none	none	none	none	not read	R	626359.23	3629912.22
4/3/2008	Jim Luttrell	red	white	1A	L	0844-80354	R	625937.19	3631537.48
4/4/2008	Scott Thomas	none	none	none	none	0934-26583	L	630764.48	3672384.55
4/4/2008	Scott Thomas	red	white	A6	R	0934-28516	L	630770.46	3671867.23
4/10/2008	Scott Thomas	red	white	32	R	0804-42913	L	629957.59	3630446.81
4/10/2008	Scott Thomas	red	white	25	R	0804-42907	L	629580.75	3630776.25
4/10/2008	Scott Thomas	red	white	78	R	0804-42932	L	629760.46	3630597.18
4/4/2008	Jim Luttrell	red	white	E9	L	not read	R	625937.53	3631605.71
3/31/2008	Jim Luttrell	red	white	2K	L	not read	R	623898.86	3631131.45
4/11/2008	Scott Thomas	red	white	36	R	0804-42911	L	629935.88	3630450.91
4/8/2008	Scott Thomas	none	none	none	none	not read	L	621453.64	3658495.59
4/14/2008	Scott Thomas	none	none	none	none	0804-06603	L	634942.72	3670977.96
4/7/2008	Mary Coolidge	Red	White	1	Left	not read	Right	623960.93	3619037.43
4/7/2008	Mary Coolidge	Red	White	5	Left	not read	Right	624939.11	3618985.12
4/8/2008	Mary Coolidge	Red	White	F4	Right	not read	Left	636113.57	3632078.82
4/11/2008	Mary Coolidge	Red	White	18	Left	not read	Right	647951.20	3623269.17
4/11/2008	Mary Coolidge	Red	White	43	Left	not read	Right	647818.17	3623267.20
4/11/2008	Mary Coolidge	Red	White	42	Left	not read	Right	647817.59	3623266.34
4/18/2008	Mary Coolidge	Red	White	82	Left	not read	Right	649122.42	3625714.18
4/23/2008	Mary Coolidge	Red	White	1A	Left	not read	Right	625938.45	3631530.67
4/24/2008	Mary Coolidge	Red	White	E9	Left	not read	Right	625935.92	3631626.01

Proj Coord Sys: NAD_83_UTM_Zone_11N; Proj: Transverse_Mercator; False_Easting: 500000.00000000; False_N.: 0.0000; Central_Meridian: -117.00000000; Scale_Factor: 0.9996; Lat_Of_Orig: 0.0000; Linear Unit: Meter; Geog Coord Sys: GCS_N._Am_83; Datum: D_N._Am._1983; Prime Merid: Greenwich; Ang. Unit: Degree.

Appendix VI

SELECTED COMMENTS AND REVIEWS

PETER BLOOM (Bloom Biological, Inc., Santa Ana, California)

Received report on December 10, 2008

From: phbloom1@aol.com <phbloom1@aol.com>
Subject: IID BUOW report
To: manningbiological@yahoo.com
Date: Thursday, December 11, 2008, 8:17 AM

Jeff, ... A most impressive document and something we can all feel proud of, thanks to you and the team you managed. ...

JEFF TUPEN (CH2M Hill, Sacramento, California)

Received report on December 10, 2008

From: "Jeff.Tupen@CH2M.com" <Jeff.Tupen@CH2M.com>
Subject: Draft IT notes from 12/11 meeting
To: andrew_thompson@fws.gov, BTippets@sdcwa.org, bwilcox@iid.com, carol_a_roberts@fws.gov, guy_wagner@fws.gov, jmgarber@iid.com, Jeff.Tupen@CH2M.com, jsheridan@dfg.ca.gov, KNICOL@dfg.ca.gov, skeeney@dfg.ca.gov, sgibson@dfg.ca.gov, tshields@iid.com
Cc: manningbiological@yahoo.com, PHBloom1@aol.com, LMacNair@dfg.ca.gov
Date: Tuesday, December 23, 2008 1:37 PM
2008 12-11 IT Meeting Notes draft.doc (55KB)

With respect to the Draft Report submitted by the Bloom team:

Overall, I think the document is very well done, and incredibly scholarly. It undoubtedly forms a solid basis for future BUOW survey efforts. This written, I'd suggest the following changes for Bloom team consideration (please feel free to add to, or rebut, my suggestions):

1. Define the Study Area early in the document, and use this term instead of the HCP area, or HCP. HCP Plan Area, Imperial Valley, and IID Service Area all come to mind as related terms, but I think Study Area, once defined, is the better term for this effort and deliverable.

2. Re-write/re-format the Executive Summary to more clearly communicate the important outcomes/results of the effort. Currently, its pretty method-heavy. I'm thinking something similar to the way that I've crafted the IT notes from the meeting. The current ES is 6.5 pgs...I suggest it can/should be pared to something less than 2.

3. I suggest reformatting to a more-traditional report format, and away from the thesis structure currently used. Pool all refs in single References section. Separating chapters is ok, but no need for

individual chapter authorship. If chapter authorship is important to others, this can be communicated in an Acknowledgements section of Forward section. I think this reorganization will improve the flow and readability of the document.

4. Cover sheet should reflect the contracted team effort. I suggest "Prepared by Bloom Biological, Inc., in association with Manning Biological Research and Wildlife Research Institute". I suspect Jeff Manning did the lions share of writing on this deliverable, but re-tooling the cover page ties this deliverable to IID contracting requirements more precisely.

5. Delete word "guise" globally from this document. The same is true for any other technically correct, but distracting terms. I'll defer to others for ferreting other terms out during review.

ANDREW THOMPSON (U.S. Fish and Wildlife Service, Carlsbad, California)

Received report on December 10, 2008

From: Andrew_Thompson@fws.gov [mailto:Andrew_Thompson@fws.gov]
Subject: RE: Draft IT notes from 12/11 meeting
To: Tupen, Jeff/SAC
Cc: Carol_A_Roberts@fws.gov
Date: Friday, February 06, 2009 5:00 PM
Comments on the Imperial Valley Burrowing Owl Population Study 2006 v2.doc (27KB)

Attachment: Comments on the Imperial Valley Burrowing Owl Population Study 2006 v2.doc (27KB)

Comments on the Imperial Valley Burrowing Owl Population Study 2006-2008

Jeff Manning and the Bloom Team have conducted extensive surveys in the Imperial Valley with the overriding goal of developing a protocol that accurately and cost-effectively samples burrowing owls in the future.

The report, overall, was excellent. They used the most up to date statistical methods to account for effects of sampling and methodological variability on estimates of owl population size. Their results provide clear guidance for an optimal strategy to generate acceptable levels of confidence around abundance estimates for a future sampling protocol.

One issue that was not completely resolved in my mind was the use of the spatial coordinates to generate capture histories. This method assumes that even if an owl is misidentified results will not be biases because detection probability will come out the same for the entire population. A potential problem with this assumption occurs if there is individual heterogeneity in the detection probability of owls. For example, if there is a proportion of the population that naturally has a lower detection probability, then assuming misclassification could bias the results. If there individual heterogeneity does not occur and misclassification is random, then the results would be unbiased.

It may be possible to resolve this issue by conducting a limited mark-recapture survey where owls are actually banded. Then, you could use model selection to determine whether a model that includes individual heterogeneity is selected over those that lack individual heterogeneity. If there is no evidence of individual heterogeneity, then we would achieve greater confidence in the use of spatial data in lieu of actual mark-recapture data. Given that they did band some owls to examine movement and site fidelity, maybe this data set could be used for such an evaluation.

As mentioned above, I agree with the recommendations given by the Bloom Team for measuring owl abundance in the future. One aspect we need to think about, however, is how to better establish the types of management activities that could alleviate population declines. The report showed that there was an appreciable decline in owl abundance between 2007 and 2008 and tells us what we need to do to be able to detect changes in the future. It is unknown what caused this decline, however, and thus the results do not provide guidance for management actions. Given that even the most highly selected models described only a small (yet significant) proportion of the variation in owl abundance, there is a need to more precisely explain potential causes of population fluctuation. It is possible that the covariates collected by the Bloom Team were too coarse and thus operated at a different spatial scale than what affects the owls. It is also possible that the decline was caused by something that went on outside of the Imperial Valley. Our task is now to determine whether factors within our control are impacting owls and provide guidance for how management can minimize detrimental factors.

A first step might be to evaluate the relationship of covariates to owls in 2008. The strongest models from 2007 identified the current number of burrows (Burrows in 2007) and alfalfa 3 and 4 years prior as correlating with owl abundance. Based on this finding, an expectation would be that alfalfa in 2005 would more strongly correlate with 2008 owls than 2007 owls. Is this the case? To further the goal of understanding how to adaptively manage this species it will be necessary to evaluate further the effect of covariates on burrowing owl distribution and abundance.