Wildlife Society Bulletin 36(1):155–160; 2012; DOI: 10.1002/wsb.97

*Tools and Technology*

# Modeling Seasonal Detection Patterns for Burrowing Owl Surveys

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**ABSTRACT** To guide monitoring of burrowing owls (*Athene cunicularia*) in the Coachella Valley, California, USA, we analyzed survey-method-specific seasonal variation in detectability. Point-based call-broadcast surveys yielded high early season detectability that then declined through time, whereas detectability on driving surveys increased through the season. Point surveys without call-broadcasts yielded the lowest detectability rates overall. To maximize detectability, we recommend coupling early season point-based call-broadcast surveys with late-season driving surveys. Occupancy models proved useful for integrating data from multiple methods to analyze distributional patterns while accounting for variation in detectability. © 2012 The Wildlife Society.

**KEY WORDS** *Athene cunicularia*, burrowing owl, California, call-broadcast surveys, detectability, occupancy models, population monitoring.

Recent declines in burrowing owl (*Athene cunicularia*) populations (Skeel et al. 2001, Conway and Pardieck 2006) have drawn the attention of conservationists (Holroyd et al. 2001, Warnock and Skeel 2004). Population monitoring provides data necessary to understand demographic and distributional trends and, thus, inform conservation (Barrows et al. 2005), and researchers have employed various survey techniques to study burrowing owl demography and distributions (DeSante et al. 2004, Conway et al. 2006, Tipton et al. 2008, Crowe and Longshore 2010).

Surveyors need to estimate *detectability* (the probability of recording owls at occupied sites) to elucidate the accuracy of survey data and to inform design of survey protocols (Conway and Simon 2003, Conway et al. 2008, Tipton et al. 2008, Crowe and Longshore 2010). Detectability can vary with survey methodology (Conway and Simon 2003), making method selection a critical step in planning population monitoring protocols. Researchers can survey for owls while moving (e.g., walking or driving surveys; Conway and Simon 2003, Tipton et al. 2008) or from stationary locations (e.g., point counts; Haug and Didiuk 1993, Conway and Simon 2003). Surveys may be passive (Conway and Simon 2003, Tipton et al. 2008) or employ call-broadcasts to elicit behavioral responses by owls and, thus, improve detectability (Haug and Didiuk 1993, Conway and Simon 2003, Rocha Braga and Motta-Junior 2009). Detectability can also correlate with the progression of the nesting cycle or weather parameters such as temperature and precipitation (Conway et al. 2008). These latter factors are inherently seasonal, so seasonal timing of surveys may also co-vary with detectability and is, therefore, important to consider.

To inform population monitoring under the recently established Coachella Valley Multiple Species Habitat Conservation Plan (CVMSHCP; Coachella Valley Association of Governments 2007), we quantified method-specific seasonal detection patterns for surveys of burrowing owls within the CVMSHCP boundary. We repeatedly surveyed sites throughout the Coachella Valley, including sites occupied by burrowing owls, using 3 standardized survey methods also used elsewhere (i.e., driving routes, passive point counts, and point counts incorporating call-broadcasts; Conway and Simon 2003, Conway et al. 2008). Using occupancy models fitted to survey data, we analyzed method-specific detection probabilities and variation in seasonal detectability patterns among methods. In light of our results, we suggest how to survey Coachella Valley burrowing owls to maximize detectability and how the models developed here could be used for future studies of burrowing owl distributions.

## STUDY AREA

We surveyed burrowing owls within the 170,295-ha (420,629-acre) area of the Coachella Valley of Riverside

Received: 23 January 2011; Accepted: 26 October 2011;
Published: 19 January 2012

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County, California, USA (33°47′N, 116°20′W). Historically the valley bottom consisted of several aeolian sand communities (e.g., active and stabilized dunes and sand fields; Barrows and Allen 2007), whereas the surrounding alluvial fans and bajadas were covered with creosote-dominated (*Larrea tridentata*) Sonoran creosote scrub and Sonoran mixed woody and succulent scrub communities. Today, the central-west portion of the valley is largely urbanized, and much of the southern valley nearing the Salton Sea has been developed for agriculture. Average yearly rainfall ranged from 80 mm to >300 mm across an east–west precipitation gradient within the valley; rainfall could also vary widely among years (3.6–70 mm in 2002 vs. 200–500 mm in 2005). Temperatures ranged widely from a low approaching 0° C in the winter to highs exceeding 45° C commonly recorded during July and August.

# METHODS

In 2009, we used 3 standardized methods to survey the Coachella Valley for burrowing owls throughout that year: linear surveys, point surveys, and audio point surveys. Here, we focus on data collected from the April–August breeding season. We conducted all surveys from 0700 hours to 1600 hours. During this period, ambient temperatures were approximately 24–49° C and no precipitation fell. We did not conduct surveys when winds exceeded 20 km/hour. We distributed routes and points (spaced approx. 800 m apart along routes) for surveys throughout the Coachella Valley floor, avoiding heavily urbanized areas clearly unsuitable for owls (Fig. 1). Most routes were accessible by automobile, but some routes in irrigation–flood-control areas (total length = 61.5 km) were accessible only by foot.

## Linear Surveys

We traveled linear routes (mainly along secondary roads) at a speed below 20 km/hour while continuously scanning roadside landscape, stopping only when an owl was detected. We surveyed automobile-accessible routes (384 km) from an automobile and the remaining routes (61.5 km) on foot. In some systems, foot surveys are of minimal value because owls behave so as to avoid detection at the approach of people (Conway and Simon 2003), but the landscape in our study area was relatively open, allowing detection of owls from a substantial distance. We used binoculars (8 × 42 Nikon Trailblazer ATB; Nikon, Tokyo, Japan) during linear surveys only to count the number of individuals after detecting owls at a location.

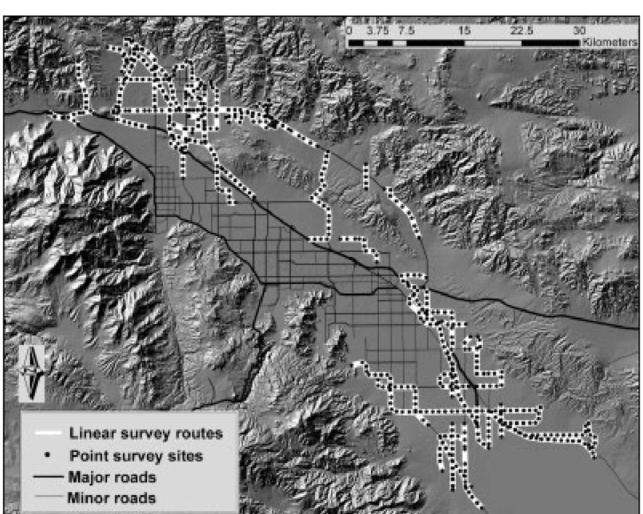


**Figure 1.** Distribution of roadside survey routes and points at which surveys for burrowing owls were conducted in the Coachella Valley, California, USA in 2009.

## Point and Audio Point Surveys

We conducted point surveys and audio point surveys at a priori established points along the linear survey routes. During each point survey, surveyors visually searched for owls for 4 minutes with binoculars. Audio point surveys were similar, except during the survey period we broadcast looped burrowing owl calls with an SME–AFS (Saul Mineroff Electronics, Elmont, NY) amplified field speaker and iPod® (Apple, Inc., Cupertino, CA). The broadcasted calls originated from the Salton Sea and were played at 97 decibels when measured 1 m from the speaker. A loop consisted of 12 "coo–coo" calls (common M call) lasting 30 seconds followed by 30 seconds of silence repeated for 3 minutes, then 1 minute of the defensive ("chuck and chatter") call, and finally 1 minute of silence (5 min total).

## Survey Effort

We aimed to conduct each method along each route ≥3 times within the study period, although due to weather and timing constraints, we did not fully realize this goal. In addition to weather and timing constraints, unanticipated impacts on owls (call-broadcasts induced some within-pair aggression particularly after 15 Jul; K. D. Fleming, personal observation) led us to conduct fewer audio point surveys. Nevertheless, the survey effort expended using each method was substantial throughout most of the study period (Table 1). As much as possible, we conducted surveys using different methods along a given route on separate days to avoid temporal pseudo-replication. To minimize logistic demands on surveyors, however, we surveyed walking routes with linear and audio-point survey methods concurrently (i.e., we applied the audio-point survey protocol at points and the linear-survey protocol while traveling between points). Along walking routes, owls detected during linear surveys were never detectable during a concurrent audio point survey and we only detected owls during on-foot audio point surveys by sound. Thus, concurrent surveys along walking routes did not result in pseudo-replication. Our principal surveyor (K. D. Fleming) was present during all roadside surveys (additional surveyors accompanied her during some surveys), minimizing the potential for observer-related heterogeneity in detectability.

## Occupancy Modeling

We fitted single-season, single-species occupancy models (MacKenzie et al. 2002, 2006) to the survey data using maximum-likelihood methods. Each occupancy model estimated site-occupancy probabilities ($\psi$) and the probability of

**Table 1.** Total monthly survey effort expended during 2009 surveys for burrowing owls in the Coachella Valley, California, USA. Survey effort is indicated as the total length (km) of road traveled during linear surveys, the number of times a point was visited for a point survey or audio point survey. The lower section provides the number of times owl-occupied cells were surveyed, with the number of times owls were detected in parentheses.

| Surveys | Month | Linear surveys (km) | Point surveys | Audio point surveys |
|---|---|---|---|---|
| Total survey effort | Apr | 208.5 | 116 | 36 |
| | May | 212.0 | 247 | 32 |
| | Jun | 138.6 | 262 | 171 |
| | Jul | 174.8 | 144 | 72 |
| | Aug | 6.4 | | |
| Surveys of owl-occupied cells (no. of surveys when owls were detected) | Apr | 8 (0) | 3 (2) | 7 (3) |
| | May | 15 (5) | 14 (0) | 2 (1) |
| | Jun | 11 (5) | 6 (1) | 29 (5) |
| | Jul | 29 (13) | 18 (5) | 3 (2) |
| | Aug | 11 (10) | | |

detection during a survey given owl presence ($p$) and a specified set of detection and occupancy covariates (described further below). We used 4,698 540-m × 540-m cells distributed across our study area as sites for occupancy models. To minimize spatial pseudoreplication, cell size approximated the likely home range of an owl (0.4–0.6 km in radius; Rosenberg and Haley 2004). The data to which we fitted occupancy models were nondetections (0) and detections (1) for each occasion a cell was surveyed. A cell was considered surveyed if it intersected the detection range of a roadside route or point. The detection range for linear surveys was the maximum distance from an owl sighted during a linear survey to the nearest survey route (130 m; excludes one outlier of 280 m). Similarly, the detection ranges for point counts and audio point counts were the maximum owl-to-survey-point distances (400 m for both). On 2 occasions when owls were heard but never seen, the surveyor estimated distances to the owls from which their locations were derived. Eye level for a surveyor in our field vehicle was approximately 8–18 cm lower than when standing on the ground, potentially decreasing detection ranges during driving surveys. Owls were detected during walking surveys, on average, further away (owl-to-survey-site = 40 ± 38 m [SD] from routes, $n = 20$ owl sightings; 173 ± 156 m from points, $n = 11$) than during driving surveys (29 ± 58 m from routes, $n = 15$; 105 ± 103 m from points, $n = 8$), but linear-survey distances differed from point-survey distances more than did walking- versus driving-survey distances. Separate estimation of detectability for walking versus driving surveys would have been ideal. Nevertheless, our sample sizes were limited, so we pooled data from these relatively similar survey categories to maintain adequate statistical power. This decision was supported by the results of our goodness-of-fit test (see Results). Detection ranges here were similar to those described elsewhere (150 m for driving surveys and 500 m for point surveys; Conway and Simon 2003).

We fitted occupancy models to survey data in Program R (CRAN v. 2.11.1) using code adapted from Royle and Dorazio (2008). We constructed multiple models with various sources of heterogeneity in detectability and occupancy (covariates). We then examined the evidence for specific models and covariate effects using model weights ($w_i$) and evidence ratios calculated from Akaike's Information Criteria (Burnham and Anderson 2002). Detection covariates potentially included in our models were survey method (a class variable), survey date (day of season), a quadratic transformation of date, and date × method interactions. We considered date interactions with individual methods separately (i.e., date × point-survey and/or date × audio point survey, each referencing linear surveys). Models also included the area of the cell surveyed (Area; the area of the cell within the surveyor's detection range, described above) and method × Area interactions as detection covariates. Area provided an index of cell proximity to the surveyor; Area parameters, therefore, accounted for the influence of survey intensity on detectability. We first fitted 2 "full-rank" models containing all possible detection covariates and several occupancy covariates (identified below). We then fitted a series of "reduced-rank" models that excluded individual detection covariates from the full-rank models. Our intention was to continue excluding covariates from any reduced-rank models that fit better than the full-rank models, although this never occurred (see Results). We averaged across the best-fit models ($\sum w_i \geq 95$) when calculating detectability estimates and their standard errors (Burnham and Anderson 2002) across the time period during which data were collected.

All occupancy models included 7 environmental variables (scored for each cell) as covariates of occupancy: average annual Sonoran water-year precipitation (Oct–Sep 1971–2000), road density, % agriculture, % development, % aeolian sand, and quadratic transformations of the latter three. We initially considered a larger set of occupancy covariates describing climate, vegetation, and land cover (topography was not considered because surveys only sampled the valley floor). Following initial univariate model comparisons and a subsequent backward-stepwise removal process (as described above for detection-model selection), the above 7 parameters appeared in the top model and, thus, emerged as the strongest correlates of occupancy variation among sampled cells.

Within a given cell, survey events usually occurred on separate days, but cells were sometimes surveyed more than once in a given day, potentially inducing nonindependence among them, which could cause unmodeled heterogeneity in the data. To test for unmodeled heterogeneity, we tested the goodness-of-fit of a maximally parameterized model containing all possible detection and all occupancy covariates retained following initial variable screening (in

**Table 2.** Occupancy models fitted to 2009 burrowing owl survey data from the Coachella Valley, California, USA. Candidate models included various combinations of detection covariates: within-season timing ($D$; day-of-season), the survey method ($M$; a class variable with linear survey, point survey [PS], and audio point survey [APS]), the cell area within surveyor detection range ($A$), $M \times A$ and $M \times D$ interactions, and a quadratic transformation of date ($D + D^2$). All models contained 9 occupancy parameters: road density, average yearly precipitation, % agriculture, % development, % aeolian, and quadratic transformations of the latter three. $-$LL = negative log-likelihood. $K$ = number of model parameters. $\Delta_i$ = Akaike Information Criterion (AIC) difference between the $i$th model and the best-fit (lowest AIC) model. $w_i$ = the weight of evidence for the $i$th model. $D$ = date. $M$ = method. $D^2$ = a quadratic transformation of date. $w_i = e^{-0.5\times\Delta_i} / \sum_{0-j} e^{-0.5\times\Delta_i}$

| Detection parameters | $-$LL | $K$ | $\Delta_i$ | $w_i$ |
|---|---|---|---|---|
| Intercept + $D + D^2 + M + A + (M \times A) + (M_{PS} \times D) + (M_{PS} \times D^2) + (M_{APS} \times D) + (M_{APS} \times D^2)$ | 194.1 | 21 | 0.0 | 0.75 |
| Intercept + $D + D^2 + M + A + (M \times A) + (M_{APS} \times D) + (M_{APS} \times D^2)$ | 197.6 | 19 | 3.1 | 0.16 |
| Intercept + $D + D^2 + M + A + (M \times A) + (M_{PS} \times D) + (M_{PS} \times D^2)$ | 198.7 | 19 | 5.2 | 0.06 |
| Intercept + $D + D^2 + M + A + (M \times A)$ | 201.1 | 17 | 6.1 | 0.04 |
| Intercept + $D + M + A + (M \times A) + (M_{PS} \times D) + (M_{APS} \times D)$ | 204.2 | 18 | 14.2 | 0.00 |
| Intercept + $D + D^2 + M + (M_{PS} \times D) + (M_{PS} \times D^2) + (M_{APS} \times D) + (M_{APS} \times D^2)$ | 205.0 | 18 | 15.9 | 0.00 |
| Intercept + $D + M + A + (M \times A)$ | 208.6 | 16 | 19.0 | 0.00 |
| Intercept + $D + D^2$ | 218.6 | 12 | 31.1 | 0.00 |
| Intercept + $M + A + (M \times A)$ | 221.8 | 15 | 43.5 | 0.00 |
| Intercept | 239.5 | 10 | 68.8 | 0.00 |

addition to parameters listed above, the fully parameterized model contained % mesquite, % sand, soil water content, min. Jan temp [1971–2000], % dunes, and quadratic transformations of the latter two) using a parametric boot-strap ($\hat{c} = \chi^2_{data}/\chi^2_{boot-strapped}$; $\hat{c} > 1$ indicates significant unmodeled heterogeneity; MacKenzie and Bailey 2004).

## RESULTS

In total, we conducted 740.3 km of linear surveys, 769 point surveys, and 311 audio point surveys (Table 1). These surveys effectively sampled 1,625 cells 6,276 times. Each cell was surveyed on average 4 times and at most 14 times. Owls were confirmed to occupy 36 cells, which were surveyed on 156 occasions, during which 52 detections were recorded (Table 1). During 85% of these detections, we observed only a single breeding pair (i.e., 1 or 2 individuals; max. = 3 breeding pairs or 6 individuals); reducing observations to presence–absence data resulted in little loss of information.

During linear surveys and point surveys, all owls were detected visually, whereas 9 of 11 audio point count detections were aural. Owls responding to call-broadcasts mainly did so at the end of the broadcast following the defensive chuck-and-chatter call (K. D. Fleming, personal observation). We potentially pseudo-replicated 365 surveys in total and 20 surveys of owl-occupied cells (i.e., repeat surveys of a cell within a day); nevertheless, we found no evidence for unmodeled heterogeneity in detection histories ($\hat{c} = 1.0$), suggesting independence among observations.

Of 10 candidate detection covariate combinations, 3 were associated with 97% of the weight-of-evidence (Table 2). Although confidence intervals around detectability estimates (averaged across models) were wide (Fig. 2), our analysis revealed significant patterns. A difference between seasonal detection patterns for audio point surveys relative to linear surveys was strongly supported (evidence ratio = 12.5). A difference between point-survey and linear-survey detectability was also supported but less so (evidence ratio = 4.7). The data strongly supported an effect of survey intensity (i.e., cell area surveyed) on detectability (evidence ratio > 100); not surprisingly, detectability increased with increasing Area (parameter estimates were all positive; Table 3). Assuming mean values for Area, audio-point survey detectability was highest at the beginning of the breeding season, whereas linear survey detectability was highest late-seasonally (Fig. 2). The data suggested U-shaped detectability trends for audio point surveys and point surveys (Fig. 2). Given our sample size limitations (Table 1), however, early season estimates for point surveys and late-season estimates for audio point surveys may be influenced by sampling error. More data supported late-seasonal increases in detectability for all methods except audio point surveys. Throughout the breeding season, detectability tended to be relatively low for point surveys (Fig. 2).

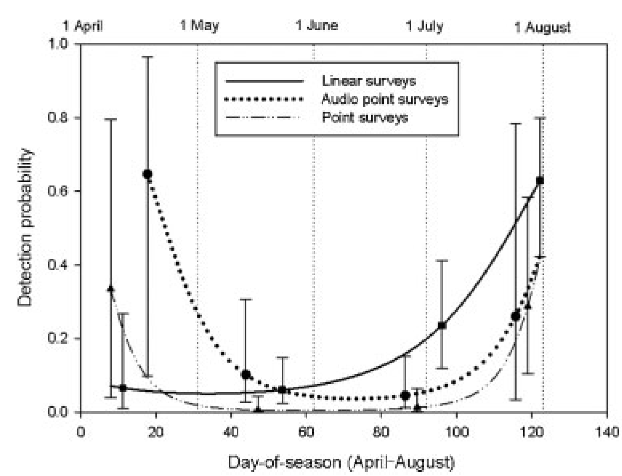


**Figure 2.** Seasonal estimates of detection probabilities when surveying owl-occupied cells using each of 4 methods (linear surveys, point surveys, audio point surveys, and track surveys at wild-land plots) during 2009 surveys for burrowing owls in the Coachella Valley, California, USA. Estimates and 95% confidence intervals are for surveys of 540-m × 540-m cells and were averaged across best-fit occupancy models. Detectability was estimated only for the time periods during which data were collected (linear surveys: Apr–early Aug, point counts: Apr–Jul, audio point counts: mid-Apr–Jul). Vertical dotted lines indicate the first of each month (May–Aug).

**Table 3.** Parameter estimates and their standard errors describing variation in detectability for occupancy models fitted to burrowing owl survey data from the Coachella Valley, California, USA. Estimates were averaged across the 3 best-fit models selected from 10 models with various combinations of detection covariates. The mean effective area of owl-occupied cells ($n = 36$ total) surveyed are also provided. Prior to model-fitting, we standardized Area scores (i.e., subtracted the mean across survey events [11.1 ha] and divided by the SD [8.4 ha]). Date$^2$ values are the model-averaged parameter estimates associated with Date squared for each method.

| Method | Parameter estimates ± SE | | | | Mean area (ha) |
|---|---|---|---|---|---|
| | Intercept | Area | Date | Date$^2$ | |
| Linear surveys | −2.6 ± 0.5 | 0.1 ± 0.4 | 0.9 ± 0.3 | 0.4 ± 0.3 | 9.8 |
| Point surveys | −6.4 ± 1.8 | 0.9 ± 1.0 | 0.0 ± 0.7 | 1.6 ± 0.8 | 19.4 |
| Audio point surveys | −4.6 ± 1.7 | 1.7 ± 1.1 | −0.8 ± 0.9 | 1.3 ± 0.9 | 18.2 |

# DISCUSSION

Differences in seasonal detection patterns among methods observed here are consistent with results from other studies and likely arise from underlying differences in how and when owls were surveyed. Conway et al. (2008) reported an increase in visual detection of burrowing owls with the progression of the nesting cycle, purportedly because adult females are more likely to perch outside the burrow late in nesting, and older chicks perch outside the burrow even when adults are not present. Thus, the progression of the nesting cycle likely contributed to late-seasonal increases in visual detection rates, especially during point surveys and linear surveys. A positive effect of temperature on visual detection (reported by Conway et al. 2008), and late-season increases in temperature, may have also contributed to the late-seasonal increases in detectability (mean Apr–May max. temp in 2009 was 32.9° C, whereas the Jul–Aug mean was 41.5° C; unpublished University of California weather station data from the University of California, Riverside, Palm Desert campus). By contrast, aural detection (Conway et al. 2008) and burrowing owl responses to call-broadcasts (Haug and Didiuk 1993) reportedly decline with the breeding season, either because owls become habituated to call-broadcasts or because of a seasonal decline in territoriality (Haug and Didiuk 1993). Such processes likely caused the initial seasonal decline (Apr–Jun) in detectability during audio point surveys in this study (see also Crowe and Longshore 2010).

Overall detectability estimates for roadside survey methods reported here are lower than some others reported, but our study differs from others. Elsewhere, researchers either surveyed all a priori identified cells with an equally high intensity (Rosenberg and Haley 2004, Tipton et al. 2008), or they fixed the proximity of surveyors to known occupied burrows (Conway and Simon 2003, Conway et al. 2008). By contrast, we sampled cells with variable intensity. Survey intensity was often low (indexed by the cell-area-surveyed), resulting in reduced detectability when averaged across all surveys.

Our models assume a monotonic relationship between survey intensity (Area) and detectability. An alternative to this approach could be to describe detectability as a function of the distance between the surveyor and individual owls (i.e., distance sampling; described in Royle and Dorazio [2008]). We chose a cell-based approach because this approach readily accommodates the translation of model predictions into habitat suitability maps (Fig. 3). Alternative modeling strategies may be worth considering depending upon the specific research questions of interest.

# MANAGEMENT IMPLICATIONS

Our results indicate that a protocol consisting of early season audio point surveys coupled with late-season linear surveys would minimize the effort needed to effectively monitor Coachella Valley burrowing owl populations. Within the sampling period of this study, audio point surveys were most effective in April. Territory and pair establishment may begin even earlier, particularly in the hotter, southeastern end of the valley. We also conducted surveys throughout March. During this period we only detected owls on 3 occasions, 2 of which were recorded during audio point surveys (9 Mar and 30 Mar). Initiation of audio point surveys in March starting with eastern routes and working westward could be helpful for maximizing detectability, although extremely early season data could violate the assumptions of occupancy models if surveyed sites become occupied after

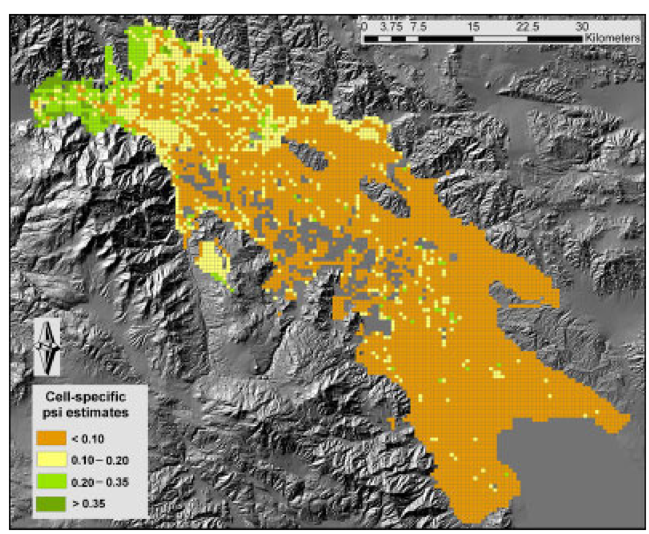


**Figure 3.** Estimates of cell-occupancy probabilities (ψ; unconditional upon detection histories) averaged across the 26 occupancy models that best fit 2009 data from breeding season surveys (Apr–Aug) of burrowing owls in the Coachella Valley, California, USA. These estimates principally reflect a positive habitat relationship with precipitation, a negative relationship with road density, and nonlinear relationships with agricultural development, urban development, and % aeolian sand. This map should be interpreted with caution because our surveys only sampled the valley floor, avoiding mountains and heavily urbanized areas where we had no expectation of finding owls. Nevertheless, the figure depicts the type of output provided by the fitted models.

initially surveyed. Our data suggest July and August to be the best months for conducting linear surveys, although (just as for audio surveys) linear surveys of eastern routes should probably occur first. Mid-seasonal surveys (May and Jun) can probably be avoided given the generally low detection rates during this period. Although our data were limited for examining late-season detectability for audio point surveys, declining detectability trends reported elsewhere for call-broadcast surveys and potential impacts on owl behavior strongly suggest visual surveys are more effective late in the breeding season. Owl phenology mediates the detectability relationship with date and phenology and might vary among years. Therefore, phenological data could improve the precision of detectability estimates and further inform survey planning. Given the parallels between our results and detection patterns reported elsewhere, a survey protocol similar to the one suggested here may also be useful in other systems.

Funding limitations may restrict survey effort below the necessary levels for achieving optimal detectability. We estimated the highest detection rates and the most owls during linear surveys, but our estimates were not very precise. Additional data from early April audio point surveys and August linear surveys could improve the precision of detectability estimates and allow a more definitive assessment of which of these survey types would locate the most owls. Early season detections, however, would be critical for nest-monitoring and measurements of reproductive success (Green and Anthony 1989, Lantz and Conway 2009), so early season surveys may be especially valuable in a broader monitoring context.

Our analytic approach allowed us to integrate data from multiple survey methods into a cohesive analysis of the distribution of owls. Building upon the models presented here, extensions of single-season occupancy models (e.g., multiseason models [MacKenzie et al. 2006], or abundance models [Royle and Dorazio 2008, Wenger and Freeman 2008]) could be useful for studying distributional dynamics or other aspects of burrowing owl demography.

## ACKNOWLEDGMENTS

We thank M. Murphy, M. Felix, and N. Prendergast for help with owl surveys. Funding was provided by the California Department of Fish and Game through a Local Assistance Grant to the Coachella Valley Association of Governments. We thank A. Lopéz-Sepulcre, J. Hines, and S. Wenger for guidance during data analysis. We thank M. Davis and R. Johnson for assistance with ArcGIS when designing the study and compiling data.

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*Associate Editor: DeStefano.*