White-headed Woodpecker occupancy in the Pacific Northwest Region (USFS R6) FINAL

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Report Highlights

- Six years (2011–2016) of regional occupancy monitoring was completed for White-headed Woodpeckers (WHWO) in the Pacific Northwest Region (Oregon and Washington) as planned.
- We summarize resulting data and provide estimates for yearly transect occupancy rates using occupancy models.
- We also provide descriptive statistics for key remotely sensed and field-measured environmental attributes at survey points (along transects) with and without WHWO detections.
- Finally, we provide guidance for potential future monitoring efforts needed to measure long-term population trends drawing upon an analysis of the timing of detections within surveys (presented here) and results from a simulation study (Latif et al. In Review).
- WHWO were detected consistently at transects in each of three sub-regions (East Cascades, Blue Mountains, and North Cascades). We did not find any indication of obvious population trends, but we could not draw meaningful conclusions regarding trends given data limitations and the short timeframe of sampling.
- Environmental conditions associated with point-level WHWO detections were consistent with habitat relationships documented in previous studies.
- For potential future regional monitoring aimed at quantifying long-term population trends, we recommend four main adjustments to the monitoring protocol implemented in 2011–2016: 1) implement a single-survey approach with auxiliary sampling to estimate within-survey detectability while (possibly) conducting repeat surveys during some years for documenting shifts in breeding phenology due to climate change, 2) monitor more transects with fewer [4] points each arranged in a square configuration, 3) monitor transects in clusters with member transects spaced sufficiently for statistical independence to reduce travel time between transects and thereby allow more transects to be monitored, 4) depending upon questions of interest, possibly implement a panel design whereby a rotating subset of transects would be surveyed each year to allow monitoring a larger overall sample.

INTRODUCTION

The White-headed Woodpecker is a regional endemic species of the Inland Northwest and California. This woodpecker may be particularly vulnerable to environmental change because it occupies a limited distribution and it has narrow habitat requirements. They are year-round residents of dry coniferous forests, typically found in open ponderosa pine forests with mature, cone-producing trees that provide seasonal foraging resources, and snags and stumps that provide nest cavity substrates. Mature, open, ponderosa pine habitat has declined more dramatically than any other forested habitat of the Interior Pacific Northwest (Wisdom et al. 2002). Dry forest habitat occupied by White-headed Woodpeckers is the target of most restoration and fuels reduction projects in the USFS Pacific Northwest Region, which have the potential for beneficial or negative effects on their habitat. Concerns for this species provided the incentive to establish regional monitoring for a better understanding of habitat needs and to inform restoration projects and fuels prescriptions.

Regional occupancy-based monitoring of White-headed Woodpeckers (*Picoides albolarvatus*; hereafter WHWO) across the interior Pacific Northwest Region was initiated in 2011. The survey protocol was based on results from 16 transects from a pilot study in 2010. Call-broadcast surveys were conducted each year at 300 survey points arranged along 30 transects distributed across potential habitat. Surveyors repeatedly visited transects twice per year to provide data for estimating detectability and modeling occupancy (MacKenzie et al. 2003, Royle and Kéry 2007). Additionally, habitat was measured at survey points twice over the study period (once in 2011–2013 and again in 2014–2016) to allow analysis of habitat relationships with WHWO occurrence. This report follows six years of data collection (2011–

2016), which completes the currently funded regional monitoring effort (Mellen-McLean et al. 2015).

In this report, we provide a final summary and analysis of regional monitoring data to inform future monitoring efforts. We present 1) yearly transect occupancy estimates and an overall estimate of detectability, 2) a summary of which transects were occupied during the study period, 3) a comparison of environmental conditions at survey points with and without WHWO detections, and 4) an analysis of the timing of detections. We synthesize ecological information and knowledge gained from these efforts, and provide a suggested sampling design for continued regional long-term monitoring to document population trends.

METHODS

We estimated yearly occupancy probabilities over the study period (2011–2016) and overall detectability using an occupancy model fitted to transect detection data. We modeled the probability of transect occupancy on a logit scale: $logit(\psi_t) = b_t$, where b_t varied as a fixed effect of year *t*. We modeled the occupancy state of transect *i* in year *t* as a function of the occupancy probability: $z_{it} \sim Bernoulli(\psi_t)$. For transect detection data, $y_{itk} = 1$ when ≥ 1 WHWO was detected at any survey point along transect *i* in year *t* during visit *k*. We modeled detection data as $y_{itk} \sim Bernoulli(p \times z_{it})$, where *p* is the probability of detecting WHWO when surveying an occupied transect. We formulated this model using Bayesian methods (Royle and Kéry 2007) fitted using JAGS (v. 4.2.0; Plummer 2003) programmed from R (v. 3.3.2; R Core Team 2017) via the R2jags package (Su and Yajima 2014). We used independent non-informative priors for all parameters and sampled posterior parameter distributions with 4 parallel MCMC chains. We verified sufficient sampling and chain convergence by checking $n_{effective} \geq 100$ and $\hat{R} \leq 1.1$, respectively (Gelman and Hill 2007).

We summarized and tabulated environmental data at survey points along regional monitoring transects. We summarized data for 5 remotely sensed and 7 field-collected variables describing topography, forest structure, and tree species composition (Table 1). Relevance of these environmental attributes, data sources (remotely sensed), measurement protocols (field-collected), and relationships with WHWO occurrence are described in detail elsewhere (Wightman et al. 2010, Hollenbeck et al. 2011, Latif et al. 2014, 2015). In this report, we provide basic summary statistics for survey points with and without WHWO detections over the study period (2011–2016) to describe the data generated from regional monitoring and inform future analyses. We conducted two-sample *t*-tests to identify variables with statistically significant differences in means ($\alpha = 0.05$) between points with versus without WHWO detections.

We analyzed the timing of detections to inform survey duration for future WHWO monitoring. Considerations of survey duration were motivated by simulation study showing greater effectiveness of single surveys (accompanied by auxiliary sampling, e.g., detection timings, to inform within-survey detectability) over repeat surveys for monitoring population trends (Latif et al. In Review). In 2012–2016, surveyors recorded the time remaining until point-survey completion (max = 4.5 min) when WHWO were first detected. We examined the distribution of detection timings classified into 1.5-min sub-periods (3 sub-periods per survey) to qualitatively assess the potential need for longer surveys. We reasoned that if detections were primarily recorded during sub-periods 1 or 2 (first 3 min), lengthening survey duration would be unnecessary. Conversely, a similar or larger proportion of detections recorded in sub-period 3 relative to sub-periods 1 or 2 would suggest longer surveys are needed to allow sufficient chances of detecting WHWO where present.

We supplemented qualitative assessment of detection timing data with model-based estimates of perceptibility, p_p – the probability of perceiving WHWO during a survey given their physical presence (e.g., Rota et al. 2009, *sensu* Latif et al. 2016; for modeling details, see Appendix A). We modeled p_p for 1.5 min survey sub-periods and derived estimates for entire surveys ($p*_{p, R} = 1 – [1 - p_p]^R$, where R = survey duration in minutes). We considered $p*_{p, R} \lesssim 0.9$ indicative of low perceptibility and a need for longer surveys (MacKenzie and Royle 2005). For model-based analysis, we used boot-strapping to fill in missing detection timing data, i.e., we resampled existing data to fill in missing data for 30 boot-strapped datasets, and then summarized posterior estimates of within-survey detectability across boot-strapped data. We used qualitative and quantitative assessments of detection timings, along with other considerations, to inform sampling design for potential future monitoring.

We evaluated timing data for both point- and transect-level detections. At the transect-level, we considered WHWO detected when detected at ≥ 1 point and the timing of a detection equal to the earliest point detection timing along a given transect. We evaluated transect detection timings for full-length transects (10 points each) and for reduced-length transects (4 points each; recommended for potential future monitoring by Latif et al. In Review). When analyzing detection timings for reduced-length transects, we treated the first and last four survey points along each 10-point transect as separate transects.

RESULTS

Surveyors detected WHWO during 248 surveys at 123 points along 22 transects over the 6-year study period. WHWO were detected in each of 3 sub-regions representing different mountain ranges in every year of the study period (Figure 1). Yearly occupancy probability estimates ranged 0.46–0.67 and suggested no obvious population trends (Figure 2).

Environmental values differed between survey points with and without WHWO detections for 3 remotely-sensed and 3 field-measured variables (Table 2). Points where WHWO were detected had lower canopy cover at 1-ha and 314-ha scales and more ponderosa pine-dominated forest than points where WHWO were never detected. Points with WHWO detections also had fewer medium-diameter trees and snags, but more large ponderosa pine trees than points without detections.

Detection timing data were associated with 171 point detections, 103 10-point (full length) transect detections, and 101 4-point (reduced length) transect detections. Detections were recorded at similar frequencies during earlier versus later 1.5-min survey sub-periods (Figure 3). Model-based estimates indicated low perceptibility for when surveying either full-length 10-point transects or reduced-length 4-point transects with the current 4.5-min survey duration, and suggested longer surveys may be needed for sufficient perceptibility (Table 3).

DISCUSSION

Regional occupancy-based monitoring has contributed to current knowledge of white-headed woodpecker population status. Early research in the Blue Mountains (late 1970s – early 1980s) found white-headed woodpecker to be relatively common, whereas subsequent research (early 2000s) in the same area found no WHWO (Altman 2000, Bull 1980, Nielsen-Pincus 2005).

Regional monitoring in 2011–2016 show persistent WHWO occurrence at several widely distributed locations in the Blue Mountains. More generally, monitoring data suggest broad persistence throughout the region. Long-term population trends, however, will remain uncertain without more extensive monitoring (Latif et al In Review).

Environmental conditions associated with WHWO detections during regional monitoring were largely consistent with relationships quantified in previous work (Wightman et al. 2010, Hollenbeck et al. 2011, Latif et al. 2014, 2015). White-headed woodpeckers favor large-diameter ponderosa pine for nesting and foraging, such that breeding habitat favors ponderosa pine-dominated forests. Nesting habitat is also associated with canopy mosaics whereby nests are located in canopy openings adjacent to more closed-canopy forests thought to provide foraging habitat (Hollenbeck et al. 2011, Latif et al. 2015). Lower canopy cover and fewer medium trees and snags at point detection locations reported here likely reflect nesting preferences for canopy openings. Our simplified univariate analyses were limited for discerning previously documented scale-specific relationships with canopy cover reflecting associations with canopy mosaics (Latif et al. 2015). More sophisticated model-based analyses of regional monitoring data hinted at these relationships but were still limited by the ambiguity regarding whether point detections signify habitat use for nesting versus foraging (Latif et al. 2014). Nevertheless, longer-term monitoring could complement published studies of nesting distributions by quantifying habitat relationships with occupancy dynamics (e.g., Kéry et al. 2013).

Given interest in extending monitoring to measure population trends, simulations indicate single surveys (i.e., 1 visit per year) accompanied with detection timings would provide more statistical power for observing trends and better trend estimates than the repeat-survey approach implemented in 2011–2016 (Latif et al. In Review). Our analysis of detection timing data indicate a need for a longer survey duration, however, to provide sufficient detectability with a single-survey approach. MacKenzie and Royle (2005) provide optimal numbers of replicate surveys given various levels of occupancy and detectability. Applying their recommendations to our estimates of perceptibility and probability of species presence (Table 3), one might infer optimal survey durations of ~9–13 min depending on transect length. Published recommendations are based on known occupancy and detectability (MacKenzie and Royle 2005), however, whereas our estimates are uncertain and likely biased due to insufficient detectability (MacKenzie et al. 2002, McKann et al. 2013).

Given these uncertainties, we recommend initially conducting 10-min surveys and subsequently adjusting survey duration depending upon the distribution of detection timings. As a rule of thumb, the frequency of new detections should ideally drop noticeably in the final sub-period immediately preceding the end of the survey. If the frequency of new detections drops earlier, surveys can be shortened, whereas if no drop is observed, surveys would need to be lengthened. Quantitative analyses based on published recommendations and tools (MacKenzie and Royle 2005, Bailey et al. 2007) should ideally supplement qualitative evaluation of detection timings to identify an optimal survey length. Whereas we estimated perceptibility for 1.5-min sub-periods, perceptibility estimated for shorter (e.g., 30-sec) sub-periods could inform finer resolution assessment of optimal survey length (for analysis details, see Appendix A).

FUTURE MONITORING

Based on results reported here and from a separate simulation study (Latif et al. In Review), we have several recommendations for adjusting the protocol applied in 2011–2016 (Mellen-McLean et al. 2015) for monitoring regional WHWO population trends.

1. We recommend switching to a single-survey approach to monitoring. A single-survey protocol would allow monitoring of more transects over a broader area, likely improving statistical power for observing trends and reducing error of estimated trends with respect to actual trends in population size (Latif et al. In Review). We provide two caveats to our recommendation for single surveys. First, auxiliary sampling of detection timing would be needed to estimate within-survey detectability (i.e., perceptibility, *sensu* Latif et al. 2016), and preliminary assessment of optimal survey duration would be strongly advised as described above. Second, the single survey approach relies on consistent responsiveness of WHWOs to call broadcasts across years, and because responsiveness varies over the nesting period (Mellen-McLean 2015), this approach also requires maintaining survey timing in relation to breeding phenology. Shifts in breeding phenology resulting from climate change and consequent changes in responsiveness to broadcast calls could cause spurious observations of apparent population trends with single surveys. Repeat surveys conducted during some years (e.g., once in 3–5 years), along with nesting data, could help uncover shifts in breeding phenology. Alternatively, analysis of single-survey data could test for relationships between occupancy estimates and seasonal timing.
2. We also recommend monitoring shorter transects of 4 points each arranged as a square. Such transects would offer several advantages over the 10-point straight-line transects monitored in 2011–2016. Shorter transects can improve statistical power for observing trends by allow monitoring of more transects (Latif et al. In Review). A 4-point square transect would also align more closely to the size and shape of a single home range, which would minimize variability in local abundance among occupied transects and

thereby provide occupancy estimates that better track abundance (Efford and Dawson 2012, Latif et al. In Review). Finally, the route taken to survey a square transect would form a loop, reducing the travel time back to the surveyor's field vehicle, potentially allowing surveys of multiple transects per day.

3. We recommend monitoring transects in clusters with member transects spaced sufficiently to ensure sampling of different individuals (e.g., 5–10 km apart). Such an arrangement would allow more transects to be monitored by reducing travel time between transects. Additionally, occupancy models that allow random variation among clusters (i.e., random effects of cluster) could reveal spatial variability in population size (indexed by occupancy rates) and trends.
4. Depending upon questions of interest, we suggest considering a panel design, whereby a rotating subset of transects would be surveyed each year. A panel design can improve statistical power for observing population trends by allowing monitoring of a larger overall sample of transects (Latif et al. In Review). By monitoring each transect less frequently, however, there would be less opportunity for quantifying occupancy dynamics (i.e., colonization, extinction, and turnover; MacKenzie et al. 2003, Bailey et al. 2007, Kéry et al. 2013). Thus, the value of a panel design would depend on which aspects of WHWO population dynamics are of greatest interest. For example, if we are interested in understanding variation in long-term trends among sub-regions (East Cascades, Blue Mountains, North Cascades), a panel design may be valuable to boost the number of transects surveyed within each sub-region. If instead we are interested in understanding how suspected environmental drivers affect occupancy dynamics at individual transects, we may be better off surveying a smaller set of transects every year.

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TABLES

Table 1. Environmental variables measured at survey points along regional monitoring transects. Remotely sensed variables (RS) were derived from Gradient Nearest Neighbor (GNN; forest structure and composition) and LANDFIRE (slope) data extracted at 30 m resolution. Field-collected variables (FC) were measured within plots centered on survey points (see Appendix 2 in Mellen-McLean 2015).

Variable	Type	Description
ccov_local	RS	percent canopy cover for 0.81ha (3×3-cell) neighborhood
ccov_landscape	RS	percent canopy cover for 314ha (1km radius) neighborhood
pipo_landscape	RS	percent coverage of ponderosa pine-dominated forest for 314-ha (1-km radius) neighborhood
slope	RS	topographic % rise over run for 30m pixel
edg_landscape	RS	length (km) of edge between alternate patch types defined by canopy cover (10–40%, 40–80%) for 314ha (1km radius) neighborhood
shrub_cover	FC	percent shrub cover within plot
trees_medium	FC	count of all live trees 25-50 cm dbh within plot
trees_large	FC	count of all live trees >50 cm dbh within plot
PIPO_medium	FC	count of live ponderosa pine trees 25-50 cm dbh within plot
PIPO_large	FC	count of live ponderosa pine trees >50 cm dbh within plot
snags_medium	FC	count of snags 25-50 cm dbh within plot
snags_large	FC	count of snags >50 cm dbh within plot

Table 2. Descriptive statistics for environmental variables measured at survey points with (Detected) and without (Not detected) WHWO detections during the regional monitoring study period (2011–2016).

Variable	Mean (SD, SE)	
	Detected (*n* = 123)	Not detected (*n* = 177)
ccov_local*	38.6 (12.85, 1.16)	42.56 (13.27, 1)
ccov_landscape*	38.59 (9.52, 0.86)	41.52 (8.48, 0.64)
pipo_landscape*	60.04 (18.38, 1.66)	51.13 (19.22, 1.44)
slope	15.32 (11.63, 1.05)	17.72 (13.83, 1.04)
edg_landscape	23.63 (11.42, 1.03)	23.84 (9.23, 0.69)
shrub_cover	32.36 (35.64, 3.21)	38.97 (36.35, 2.75)[a]
trees_medium*	10.03 (6.98, 0.63)	12.33 (6.68, 0.5)[a]
trees_large	9.3 (7.37, 0.66)	7.78 (6.71, 0.51)[a]
PIPO_medium	7.15 (7.41, 0.67)	6.61 (6.58, 0.5)[a]
PIPO_large*	7 (6.35, 0.57)	4.91 (4.88, 0.37)[a]
snags_medium*	2.74 (3.6, 0.33)	5.69 (8.77, 0.66)[a]
snags_large	1.05 (1.58, 0.14)	1.06 (1.9, 0.14)[a]

[a]*n* = 175 for field-collected variables due to missing data at 2 points
*means differed significantly, i.e., $p < 0.05$ from Student's t-test

Table 3. Posterior parameter estimates from analysis of detection timing data to inform survey duration for white-headed woodpecker regional monitoring (for model details, see Appendix A). $p_a \times \Psi_{2011–2016}$ = the unconditional probability of ≥ 1 white-headed woodpecker being physically present during a given transect survey. p_p = probability of perceiving white-headed woodpecker within a 1.5-min survey sub-period given their physical presence. $p^*_{p,\,t}$ = the overall perceptibility estimate over a survey period of *t* minutes.

Parameter	median estimates (95th %-iles)	
	10-point transects	4-point transects
p_p	0.32 (0.25, 0.42)	0.2 (0.13, 0.33)[a]
$p_a \times \Psi_{2011–2016}$	0.57 (0.36, 0.79)	0.4 (0.2, 0.74)
$p^*_{p,\,4..5}$	0.68 (0.57, 0.8)	0.5 (0.34, 0.7)
$p^*_{p,\,6}$	0.78 (0.68, 0.88)	0.6 (0.43, 0.8)
$p^*_{p,\,9}$	0.9 (0.82, 0.96)	0.75 (0.57, 0.91)
$p^*_{p,\,10.5}$	0.93 (0.86, 0.98)	0.8 (0.63, 0.94)
$p^*_{p,\,13.5}$	0.97 (0.92, 0.99)	0.87 (0.72, 0.97)

[a]Even though p_p is less for 4-point transects, they are recommended because they provide greater statistical power to observe population trend and align better with home range size (Latif et al. In Review). A surveyor is less likely to observe WHWO along a shorter transect, but more transects can be surveyed.

FIGURES

Figure 1. Locations of transects surveyed yearly to monitor White-headed Woodpeckers across the Pacific Northwest Region. Transects where WHWO were detected (red) and not detected (black) are depicted in each year and for the entire 6-year study period.

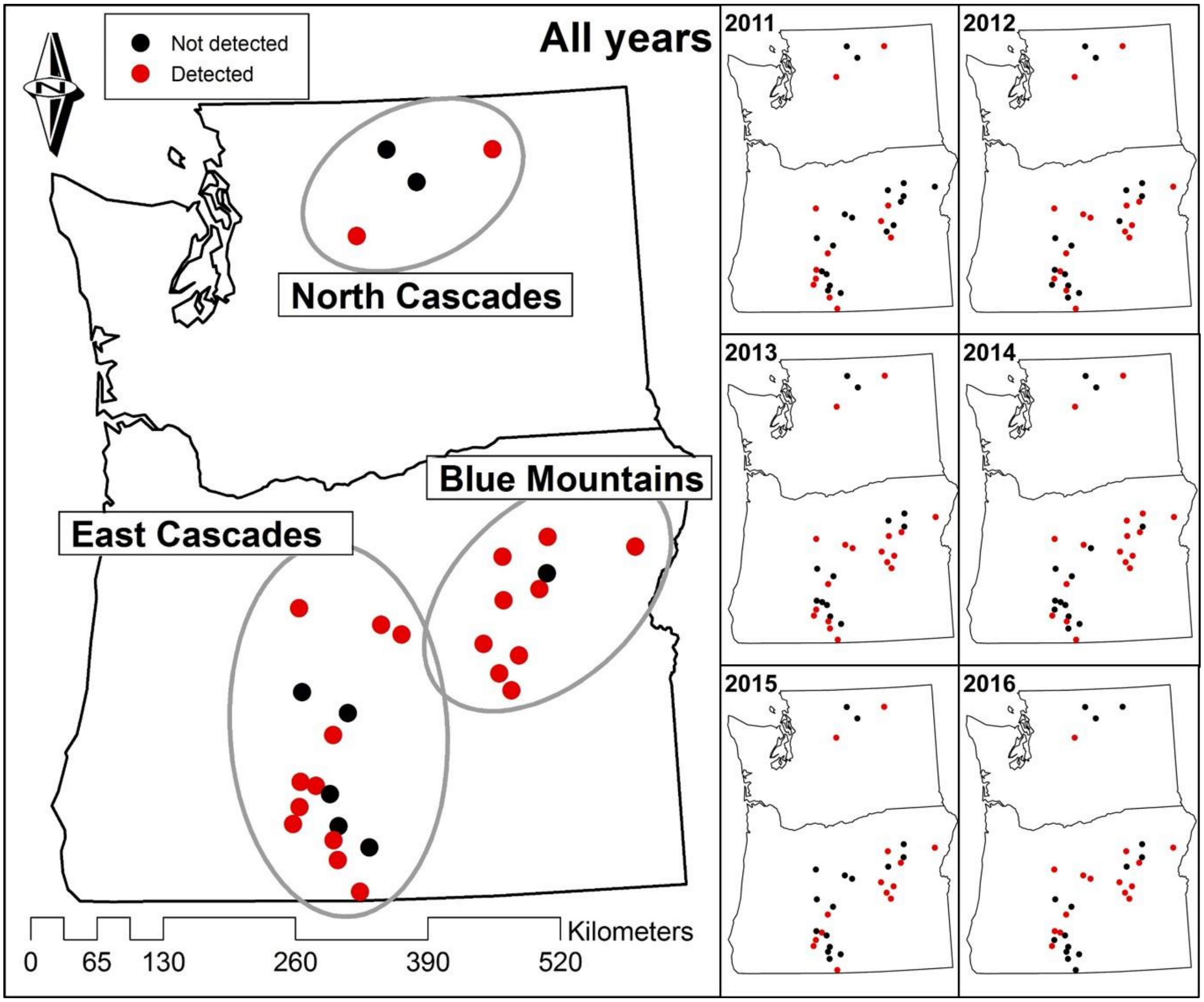


Figure 2. Mean transect-scale occupancy probabilities (ψ) by year. Occupancy probabilities were estimated with a model that assumed constant detectability fitted to 2011–2016 regional monitoring data for white-headed woodpeckers.

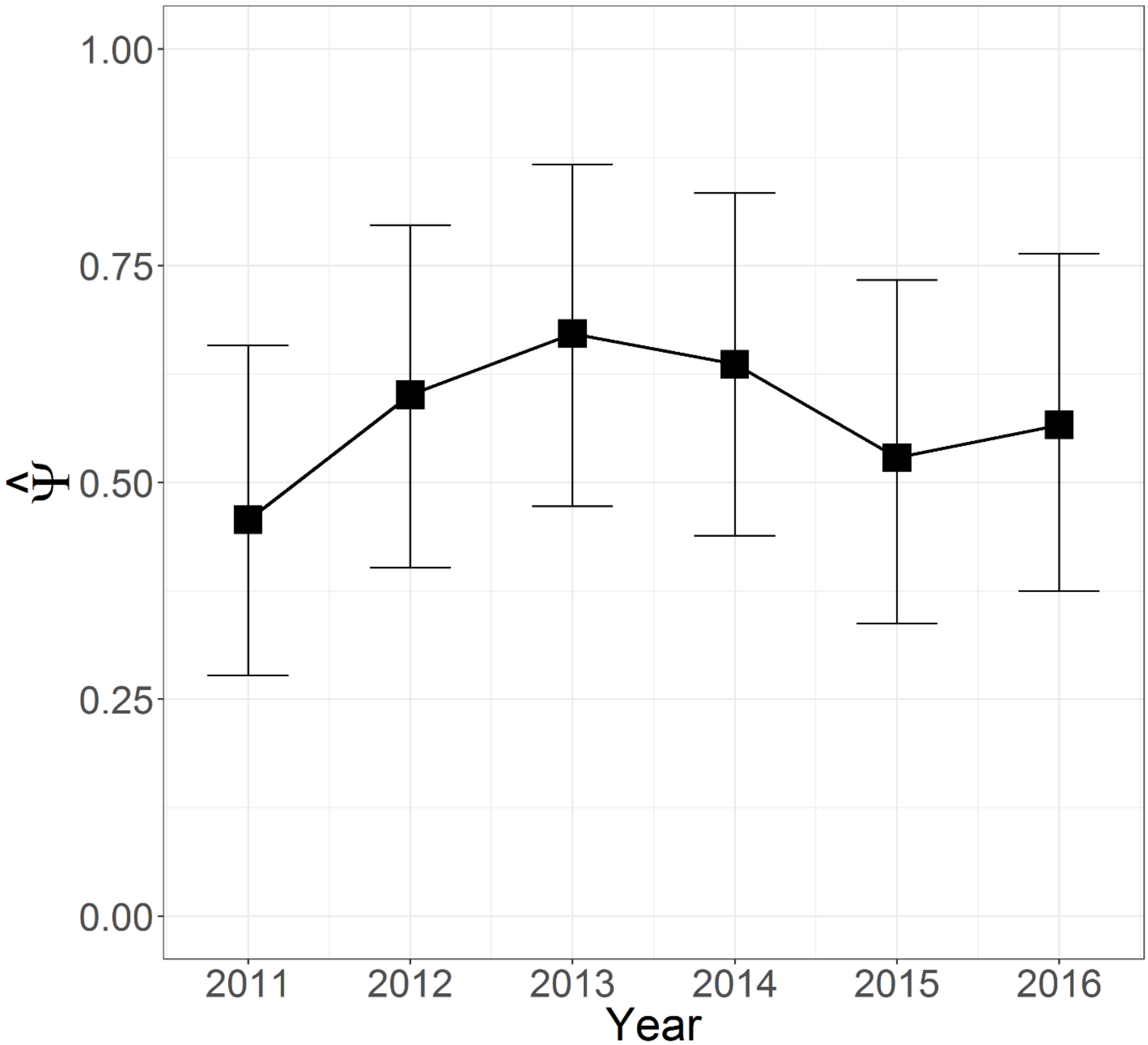
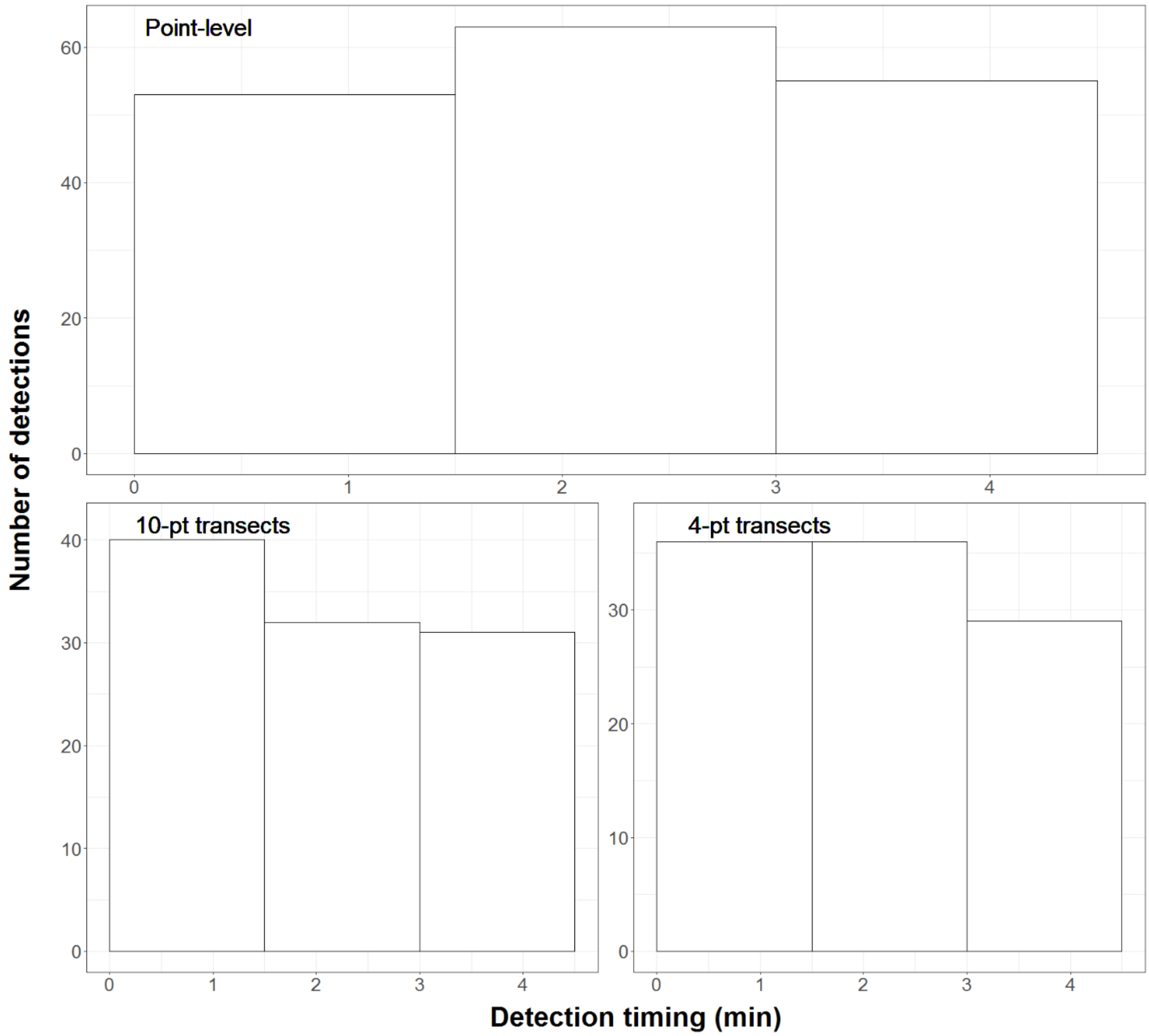


Figure 3. Timing of WHWO detections (min) recorded within 4.5 min surveys in 2012–2016. Detections were recorded at survey points (top panel; *n* = 171), 10-point (full length) transects (lower left; *n* = 103), and 4-point (reduced length) transects (lower right; *n* = 101).



Appendix A. Description and BUGS code for occupancy model used to analyze detection timing data to inform survey duration.

We estimated perceptibility to inform survey duration using an occupancy model with an additional level to account for the timing of detections. This model estimated three fundamental parameters: ψ is the probability of a given transect intersecting ≥ 1 WHWO home range (i.e., occupancy), p_a is the probability of physical presence of ≥ 1 WHWO within the sampled area when surveying an occupied transect (i.e., availability), and p_p is the probability of perceiving ≥ 1 WHWO during a transect survey assuming they are physically present (i.e., perceptibility). As with the basic model used to estimate yearly occupancy probabilities (see Methods), we modeled the probability of transect occupancy on a logit scale: $logit(\psi_t) = b_t$, where b_t varied independently by year *t*, and we modeled the occupancy state of transect *i* in year *t* as a Bernoulli process: $z_{it} \sim Bernoulli(\psi_t)$. We modeled availability as another Bernoulli process conditional on occupancy: $z_{a,itk} \sim Bernoulli(p_a \times z_{it})$, where $z_{a,itk} \in \{0, 1\}$ for transect *i* in year *t* during survey *k*. Finally, we modeled detection data as a third Bernoulli process conditional on availability: $y_{itkr} \sim Bernoulli(p_p \times z_{a,it})$, where $y_{itkr} \in \{0, 1\}$ for transect *i* in year *t* during survey *k* and survey sub-period *r*. We used a removal design to represent non-independence of detections during successive sub-periods, i.e., we represented data for sub-periods following first detection within a given survey as missing (possible detection histories for a survey were 0 0 0, 0 0 1, 0 1 NA, or 1 NA NA). We formulated and fitted this model using Bayesian methods using the same tools and criteria applied for the basic model with two fundamental parameters (see Methods). BUGS code defining this model for implementation in JAGS is as follows:

```
model {
  # prior distributions
  pp ~ dunif(0, 1)   # perceptibility
  pa ~ dunif(0, 1)   # availability

  for(t in 1:n.yrs) {
    psi[t] ~ dunif(0, 1)  # Occupancy probability in each year
    for(i in 1:n.trns) {
      z[i, t] ~ dbin(psi[t], 1) #  Occupancy state of each transect
      for(k in 1:n.vsts) {
        za[i, t, k] ~ dbin(z[i, t]*pa, 1) # Availability status at transect i in year t during survey k
        for(r in 1:n.reps) {
          Y[i, t, k, r] ~ dbin(za[i, t, k]*pp, 1) # Data model
          }
        }
      }
    }
  }
```

The parameter p_p was used to derive estimates for overall perceptibility for a survey of a given duration: $p^*_{p,R} = 1 – [1 - p_p]^R$, where R = survey duration in minutes.