Occupancy of White-headed Woodpecker in the Pacific Northwest Region (USFS R6)

2012 Progress Report
May 2013

Quresh S. Latif[1], Vicki Saab[1], Kim Mellen-McLean[3], Jon Dudley[2]
USFS Rocky Mountain Research Station, Bozeman, MT[1] and Boise, Idaho[2]; USFS Pacific Northwest Region[3]

Report Highlights

- Two years (2011 and 2012) of monitoring trends in the distribution of White-headed Woodpeckers (WHWO) throughout the Pacific Northwest Region (Oregon and Washington) have been completed.
- We analyzed overall occupancy trends for 30 transects sampling the entire region and spatial variation in occupancy dynamics, including differences among sub-regions (East Cascades, Blue Mountains, and North Cascades) and trends related with environmental variation, using multi-season occupancy models.
- We also analyzed seasonal trends in detectability and compared those between years. This allowed an evaluation of whether 2012 adjustments to the survey protocol aimed at improving detectability (i.e., narrowing the range of dates when surveys were conducted) were successful.
- We found no major differences in overall transect occupancy rates between years, but occupancy rates doubled in the Blue Mountains during 2012. Potential reasons for this increase include a long-term trend, annual variation in occupancy rates, or observer effects. We also found notable associations between occupancy and environmental covariates, the strongest of which were consistent with previous work on habitat relationships with nesting WHWO: a negative relationship with slope and a positive relationship with density of large trees.
- Detection probabilities were slightly higher in 2012 and more importantly the hump-shaped trend related to seasonal timing observed in 2011 was not apparent in 2012. This difference between years suggests changes in survey timing carried out in 2012 were successful, although variation in the timing of the nesting cycle could also be contributing to differences between the two years.

INTRODUCTION

Monitoring of White-headed Woodpeckers (*Picoides albolarvatus*; hereafter WHWO) to examine their distribution and population trends across the interior Pacific Northwest Region was initiated in 2011. The core component of regional monitoring consists of call-broadcast surveys conducted along 30 transects distributed across three sub-regions (East Cascades [n = 14], Blue Mountains [n = 12], North Cascades [n = 4]; Figure 1). Surveys are conducted twice per year to facilitate analysis of distributional dynamics while accounting for imperfect detection of using occupancy multi-season models (MacKenzie *et al.*, 2003). This report follows two years of data collection (2011–2012) and has two objectives: 1) to analyze distributional trends and spatial variation in these trends apparent in 2011–2012 data, and 2) to compare detectability of WHWO in 2011 versus 2012 to evaluate the success of survey protocol adjustments implemented in 2012.

METHODS

To meet both objectives, we used multi-season occupancy models to estimate occupancy rates for transects during 2011 and changes in occupancy from 2011 to 2012 while correcting for imperfect detection (MacKenzie *et al.*, 2003). These models estimated four fundamental parameters: 1) the probability of initial occupancy in 2011 (ψ), 2) the probability of occupied transects becoming unoccupied from 2011 to 2012 (i.e., *extinction*; ε), 3) the probability of unoccupied transects becoming occupied from 2011 to 2012 (i.e., *colonization*; γ), and 4) the probability of detecting WHWO during a survey given their occurrence along the surveyed transect (p). Covariates of any fundamental parameter can be incorporated via a logit link

function: $\log\left(\frac{\psi,\gamma,\varepsilon,\ \ or\ p}{1-(\psi,\gamma,\varepsilon,\ \ or\ p)}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n$, where β_n is the slope of the relationship between the logit of a fundamental parameter and x_n, the nth covariate.

We examined variation in occupancy rates and trends using models with sub-region as a categorical covariate of initial occupancy (ψ) and changes in occupancy between years (γ, ε). We also examined environmental trends in occupancy rates and dynamics by relating these parameters with remotely sensed environmental covariates (Table 1). Environmental covariates considered here were identified in previous work examining important habitat relationships for nesting WHWO (Wightman *et al.*, 2010; Hollenbeck *et al.*, 2011; Latif *et al.*, In Review). We also examined seasonal variation in detection probabilities using a quadratic relationship with date ($\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 Date + \beta_2 Date^2$, *Date* being represented as day-of-season during analysis). Latif *et al.* (2011) found a hump-shaped seasonal trend whereby detectability was relatively low at the beginning (late April) and end (early July) of the 2011 field season. In response to this finding, the range of dates during which surveys were conducted was reduced by ~1 week at either end of the field season. By eliminating the earliest and latest surveys associated with minimal detectability, we expected detection probabilities to increase and the hump-shaped relationship with date to diminish in 2012. We used an interaction between the quadratic date and *Year* effects on detectability ($\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 Date + \beta_2 Date^2 + \beta_3 Year + \beta_4(Date \times Year) + \beta_5(Date^2 \times Year)$) to compare seasonal detection trends between the two years.

We examined the statistical evidence for covariate effects by comparing models with versus without covariates of interest using an information theoretic approach (Burnham & Anderson, 2002). We used AIC (Akaike's information criterion) to compare models according to

how well they fit the data penalized for complexity (i.e., the number of parameters, *k*; lower AICs indicate better performing models). When examining environmental-occupancy relationships, we used a series of model selection steps to identify a top model with an optimal combination of covariates. Focusing on one fundamental parameter at a time (i.e., initial occupancy [ψ], colonization [γ], or extinction [ε]), we began with a "null model" without any covariates for the focal parameter. The remaining fundamental parameters were assigned either the maximum number of covariates (LandCC + $LandCC^2$ + PIPO + TPH + ED + SLP; for variable abbreviations, see Table 1) or the optimal combination identified previously for that parameter. We then monitored AIC while adding one covariate at a time, retaining covariates that reduced AIC. Highly correlated variables ($r > 0.7$) were never included in the same model (i.e., LandCC and LocCC: $r = 0.93$). Thus, we first identified the optimal covariate combination for ψ using a null model with all possible covariates for γ and ε. We then identified the optimal combination for γ using a null model with the optimal combination identified for ψ and all possible covariates for ε. Finally, we identified the optimal combination for ε using a null model previously identified combinations for ψ and γ. To examine occupancy and detection relationships described by selected models, we report β parameter estimates and standard errors. We also graphed estimates for occupancy (ψ_{2011}, ψ_{2012}) and detection (p_{2011}, p_{2012}) probabilities and 95% confidence bands against covariates included in selected models. Occupancy probabilities for 2012 were extrapolated from extinction and colonization probabilities ($\psi_{2012} = \psi_{2011} \times (1 - \varepsilon) + (1 - \psi_{2011}) \times \gamma$). We calculated variances and resulting confidence bands using the delta method (Powell, 2007). For this document, we report unconditional occupancy probability estimates, which only reflect covariate relationships with occupancy without accounting for detection histories recorded at sampled transects.

RESULTS

In 2011, WHWO were detected during 18 surveys conducted along 12 transects, and in 2012, WHWO were detected during 27 surveys conducted along 16 transects. Overall transect occupancy probabilities did not change substantially from 2011 to 2012 (Table 2). A model describing a difference in the probability of unoccupied sites in 2011 becoming occupied in 2012 was supported over other models (Table 3). Assuming regional differences, we estimated a substantially higher occupancy rate in 2012 versus 2011 in the Blue Mountains (Table 2). In this sub-region, 4 detections along 3 transects were recorded in 2011 whereas 14 detections along 8 transects were recorded in 2012. A model with distinct occupancy and detection parameters for the Blue Mountains (ψ(BLMT), γ(BLMT), ε(BLMT), p(BLMT + *Year* + *Year*×BLMT)) also estimated a difference in occupancy between years for the Blue Mountains (2012: ψ = 0.27 [95% CLs = 0.08–0.60]; 2011: ψ = 0.68 [0.38–0.88]) along with less of a difference in detection (2012: p = 0.73 [0.16–0.98]; 2011: ψ = 0.86 [0.55–0.97]). Thus, the data supported a difference in occupancy more than a difference in detection probability between years at Blue Mountains sites.

The best supported model examining environmental relationships with WHWO occupancy described relationships with slope, density of large trees, amount of ponderosa pine, landscape heterogeneity (edge density), and local-scale canopy cover. This model fitted the data much better (AIC = 111.1) than a model without these covariates (i.e., detection covariates only; AIC = 141.8). Due to substantial correlations between environmental covariates (Table 4) and a limited sample size, however, standard errors for parameter estimates describing these relationships were extremely large (Table 5). These estimates indicated a highly over-fitted model, making estimation of occupancy probabilities from this model unreliable. Therefore, to

examine relationships with variables appearing in this model, we used univariate models that contained one covariate at a time (Figure 2). This approach provided more reliable depictions of occupancy relationships with individual environmental covariates, although these depictions should be interpreted with caution since they do not account for inter-correlations among covariates. The AIC-supported model (Table 5) and occupancy relationship graphs (Figure 2) described negative occupancy relationships with slope and positive relationships with large tree density in both years, although the strength of these relationships appeared to diminish somewhat in 2012 (Figure 2). The AIC-supported model also suggested increases in 2012 occupancy probabilities associated with ponderosa pine (i.e., a positive relationship with colonization) and decreases associated with landscape heterogeneity (edge density) and local-scale canopy cover (i.e., positive relationships with extinction; Table 5). In both years, however, occupancy associations with the latter three covariates were relatively weak.

The data described different seasonal detectability trends in 2011 versus 2012. The data supported a model with detection covariates describing an interaction between *Year* and quadratic *Date* effects over alternative models (Table 6). Detectability in 2012 tended to be higher than in 2011 and the tendency for lower detectability early and late in the 2011 season was not apparent in 2012 (Figure 3). Instead, model estimates tended to be slightly higher early and late in the 2012 season compared to the middle of the season, although the relatively wide confidence bands suggested a weak seasonal trend in 2012 detectability.

DISCUSSION

In general, transect-occupancy rates remained relatively constant across the Pacific Northwest region from 2011 to 2012. We did find evidence for an increase in occupancy rates within the

Blue Mountains sub-region from 2011–2012. The reason for this increase is unclear, and we cannot be sure whether it reflects a long-term trend, inter-annual variability, or observer effects. Blue Mountains transects differed environmentally somewhat from transects in other sub-regions (Table 7). These differences, however, did not clearly suggest why occupancy rates might be increasing or varying between years more than in other sub-regions. Changes in Blue Mountains surveyors between years could have played a role. The data did not support a difference in detection probability between the two years, but we estimated detectability with low precision for Blue Mountains surveys, so observer effects could not be ruled out.

The data collected thus far provided preliminary evidence for occupancy relationships with environmental variation. Results indicated a clear negative relationship with slope and a positive relationship with density of large trees. The data also suggested a positive relationship with forests dominated by ponderosa pine. All of these relationships are consistent with those found in previous work (Hollenbeck *et al.*, 2011; Latif *et al.*, In Review). Additionally, results suggested possible declines in 2012 occupancy associated with higher edge density and local-scale canopy cover (i.e., positive relationships with extinction probability). Such relationships would be less consistent with previous research (Wightman *et al.*, 2010; Hollenbeck *et al.*, 2011; Latif *et al.*, In Review), but the strength of these relationships was relatively weak, so more data are needed to determine their validity.

Detection probabilities were consistent with our expectations given adjustments made to the timing of surveys. By narrowing the range of dates when surveys were conducted, we expected to increase overall detection probabilities by replacing early- and late-season surveys with higher-detection mid-season surveys. The data suggested a somewhat higher detection probability in 2012 mainly attributable to a disappearance of the hump-shaped season-related

detection trend observed in 2011. Although the seasonal trend appeared to reverse somewhat in 2012 (i.e., detectability was slightly higher early and late in the season), confidence bands indicated 2012 detectability was relatively constant. Thus, our objective was achieved by adjusting the timing of surveys. Inter-annual variation in detectability could also arise from variation in nesting phenology. Data from future years will help confirm whether differences in detectability between 2011 and 2012 were a product of changes to the survey protocol versus ecological factors.

FUTURE RESEARCH

As regional monitoring progresses and new data become available, various additional lines of research will be carried out to investigate WHWO distributional dynamics. For this report, we focused on occupancy dynamics at a transect scale. Occupancy dynamics at different spatial scales likely reflect different aspects of population ecology (Pavlacky *et al.*, 2012; Latif *et al.*, In Review), so multi-scale models could suggest population drivers not apparent from analysis of transect-scale data alone. Previous work examined spatial patterns in occupancy rates within a single season for both transects (a coarser scale) and for points along transects (a finer scale) using multi-scale occupancy models (Latif *et al.*, 2011, In Review). Future efforts will include development of multi-scale, multi-season models for simultaneous analysis of occupancy dynamics at both coarse and fine spatial scales. In addition, following the third year of monitoring, field measurements of habitat at survey points will be completed, providing additional covariates for modeling occupancy dynamics. Field-collected habitat metrics are often more precise than remotely sensed metrics, so the introduction of field-measured variables into occupancy models should improve statistical power for detecting environmental relationships.

Finally, simulation studies have revealed systematic biases in model parameters when sample sizes and detection probabilities are low (MacKenzie *et al.*, 2002; McKann *et al.*, 2013). With respect to regional monitoring data, sample sizes at transect scales and detection probabilities at point scales are low enough to incur biased estimation. Moreno and Lele (2010) developed penalized likelihood estimation for improving numerical stability and reducing biased estimation for single-season models fitted to limited datasets. In collaboration with S. Lele and M. Moreno, we will implement simulation work to examine and correct for biases associated with multi-season and multi-scale occupancy models fitted to WHWO monitoring data.

LITERATURE CITED

Burnham, K.P. & Anderson, D.R. (2002) *Model selection and multimodel inference: a practical information-theoretic approach*, 2nd edn. Springer-Verlag, New York.

Garrett, K.L., Raphael, M.G. & Dixon, R.D. (1996) White-headed woodpecker (*Picoides albolarvatus*). Birds of North America. Cornell Lab of Ornithology. Issue 252.

Hollenbeck, J.P., Saab, V.A. & Frenzel, R.W. (2011) Habitat suitability and nest survival of White-headed Woodpeckers in unburned forests of Oregon. *Journal of Wildlife Management*, **75**, 1061-1071.

Landscape Ecology Modeling, Mapping, and Analysis (LEMMA). (2012) http://www.fsl.orst.edu/lemma/splash.php. last accessed March 2012.

Latif, Q.S., Saab, V.A., Mellen-McLean, K., Dudley, J.G. (2011) Occupancy of White-headed Woodpecker in the Pacific Northwest Region. 2011 Progress Report, USFS Region 6.

Latif, Q.S., Saab, V.A., Mellen-McLean, K., Dudley, J.G. (In Review) Validation of habitat suitability models for nesting White-headed Woodpeckers using occupancy analysis. *Diversity and Distributions*.

MacKenzie, D.I., Nichols, J.D., Hines, J.E., Knutson, M.G. & Franklin, A.B. (2003) Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly. *Ecology*, **84**, 2200-2207.

MacKenzie, D.I., Nichols, J.D., Lachman, G.B., Droege, S., Royle, J.A. & Langtimm, C.A. (2002) Estimating site occupancy rates when detection probabilities are less than one. *Ecology*, **83**, 2248-2255.

McKann, P.C., Gray, B.R. & Thogmartin, W.E. (2013) Small sample bias in dynamic occupancy models. *The Journal of Wildlife Management*, **77**, 172-180.

Moreno, M. & Lele, S.R. (2010) Improved estimation of site occupancy using penalized likelihood. *Ecology*, **91**, 341-346.

Pavlacky, D.C., Blakesley, J.A., White, G.C., Hanni, D.J. & Lukacs, P.M. (2012) Hierarchical multi-scale occupancy estimation for monitoring wildlife populations. *The Journal of Wildlife Management*, **76**, 154-162.

Powell, L.A. (2007) Approximating variance of demographic parameters using the delta method: A reference for avian biologists. *Condor*, **109**, 949-954.

Wightman, C.S., Saab, V.A., Forristal, C., Mellen-McLean, K. & Markus, A. (2010) White-headed Woodpecker nesting ecology after wildfire. *Journal of Wildlife Management*, **74**, 1098-1106.

TABLES

Table 1. Environmental variables considered as covariates of WHWO occupancy. Habitat variables were derived from Gradient Nearest Neighbor (GNN) data. All variables were extracted at 30×30-m pixel resolution. Values for pixels containing survey points along each transect were averaged (mean) to generate one value per transect. Topographic variables were derived from digital elevation model layers (DEM; USGS Seamless Server) and forest structure variables from gradient-nearest-neighbor data (GNN; Landscape Ecology, Modeling, Mapping, and Analysis [LEMMA 2012]). Pixels classified as "non-forest" by GNN were excluded.

Variable name (abbreviation)	Description
Slope (SLP)	pixel slope as % rise over run
Local-scale canopy cover (LocCC)	percent canopy cover for 1-ha (3×3-cell) neighborhood
Landscape-scale canopy cover (LandCC) [H]	percent canopy cover for 314 ha (1-km-radius) neighborhood
Ponderosa pine (PIPO)[H]	Percent ponderosa-pine-dominated forest for 314 ha (1-km-radius) neighborhood
Density large trees (TPH)	Number of large trees (> 50 cm dbh) within 1 ha neighborhood.
Edge density (ED)[H]	Length of edge between alternate patch types characterized according to canopy cover class (0-10%, 10-40%, and 40-80%) within 314 ha (1-km-radius) neighborhood.

[H] 314 ha (1-km radius) neighborhoods approximated the home range size reported by Garret et al. (1996).

Table 2. Estimates of White-headed Woodpecker occupancy probabilities from multi-season models fitted to regional monitoring data. Estimates for the overall region were derived from a model without any covariates (2nd model, Table 3). Estimates for sub-regions were derived from a model with categorical covariates identifying the three sub-regions (6th model, Table 3).

Region (no. transects)	Transect occupancy rates (95% CLs)	
	2011	2012
All (30)	0.50 (0.27, 0.72)	0.55 (0.36, 0.72)
East Cascades (14)	0.56 (0.27, 0.81)	0.44 (0.21, 0.70)
Blue Mountains (12)	0.33 (0.10, 0.69)	0.68 (0.38, 0.88)
North Cascades (4)	0.50 (0.12, 0.88)	0.50 (0.12, 0.88)

Table 3. Model selection results from analysis occupancy dynamics. Lower AICs identify better-performing models. ΔAIC = the difference in AIC between a given model and the top model. K = the number of estimated parameters associated with a model. "Region" represents covariates that identify transects belonging to different sub-regions (East Cascades, Blue Mountains, North Cascades). All models accounted for seasonal trends in detection probabilities that varied among years: p(Year + Date + Date^2 + Year×Date + Year×Date^2).

Model	AIC	ΔAIC	K
ψ(.)ε(.)γ(Region)	141.5	0.0	11
ψ(.)ε(.)γ(.)	141.8	0.3	9
ψ(.)ε(Region)γ(Region)	143.8	2.3	13
ψ(.)ε(Region)γ(.)	143.9	2.4	11
ψ(Region)ε(.)γ(Region)	144.6	3.1	13
ψ(Region)ε(.)γ(.)	145.1	3.6	11
ψ(Region)ε(Region)γ(Region)	146.8	5.3	15
ψ(Region)ε(Region)γ(.)	147.3	5.8	13

Table 4. Correlations (Pearson's *r*) among environmental variables considered as covariates of occupancy. For full variable names and descriptions, see Table 1.

	LocCC	LandCC	PIPO	SLP	TPH	ED
LandCC	0.939	1.000				
PIPO	-0.544	-0.603	1.000			
SLP	0.245	0.344	-0.421	1.000		
TPH	0.507	0.456	-0.284	0.217	1.000	
ED	-0.388	-0.393	0.494	0.201	-0.206	1.000

Table 5. Parameter estimates and standard errors for the model with environmental and detection covariates that minimized AIC. Other than "Intercept" parameters, all parameters describe the relationship between a given variable and the logit of a fundamental parameter (initial occupancy [ψ], colonization [γ], extinction [ε], and detection [p]). For full variable names and descriptions, see Table 1.

Parameter	Est.	S.E.
ψ(Intercept)	49.1	214.0
ψ(TPH)	114.8	454.0
ψ(SLP)	-78.3	318.0
γ(Intercept)	-48.5	70.5
γ(PIPO)	142.5	207.2
γ(SLP)	57.9	84.2
ε(Intercept)	-2.1	204.0
ε(ED)	72.2	322.0
ε(LocCC)	73.0	345.0
ε(TPH)	-81.7	368.0
p(Intercept)	0.51	0.48
p(Year$_{2012}$)	0.60	0.83
p(Date)	-0.58	0.45
p(Date^2)	-0.73	0.46
p(Date×Year$_{2012}$)	0.97	0.74
p(Date^2×Year$_{2012}$)	1.28	0.84

Table 6. Comparison of models with alternative parameterizations for describing detection probabilities. Lower AICs identify better-performing models. ΔAIC = the difference in AIC between a given model and the top model. K = the number of estimated parameters associated with a model. All models contained covariates for occupancy parameters (ψ, γ, and ε) listed in Table 5.

Model	AIC	ΔAIC	K
p(Yr + Dt + Dt^2 + Yr×Dt + Yr×Dt^2)	111.1	0.0	16
p(Year)	116.5	5.4	12
p(Year + Date + Date^2)	119.6	8.5	14
p(.)	120.8	9.7	10
p(Date + Date^2)	124.4	13.3	13

Table 7. Descriptive statistics (medians and 95th median-unbiased percentiles) for environmental variable values within sub-regions. For complete variable names and descriptions, see Table 1.

Variable	East Cascades	Blue Mountains	North Cascades
LocCC	38.4 (18.9, 57.2)	38.8 (34.7, 46.5)	51.5 (40.5, 53.3)
LandCC	38.1 (17.8, 60.7)	41.4 (32.4, 43.1)	49.9 (36.3,55.5)
PIPO	0.64 (0.39, 0.82)	0.56 (0.35, 0.78)	0.15 (0.10, 0.49)
SLP	9.8 (2.6, 19.2)	21.6 (9.1, 47.8)	18.8 (16.4, 23.8)
TPH	16.8 (7.4, 24.1)	16.1 (8.7, 24.1)	14.1 (5.8, 29.8)
ED	89.9 (50.1, 106.4)	111.5 (99.5, 120.1)	46.7 (23.6, 119.2)

FIGURES

Figure 1. Locations of transects surveyed yearly to monitor White-headed Woodpeckers across the Pacific Northwest Region.

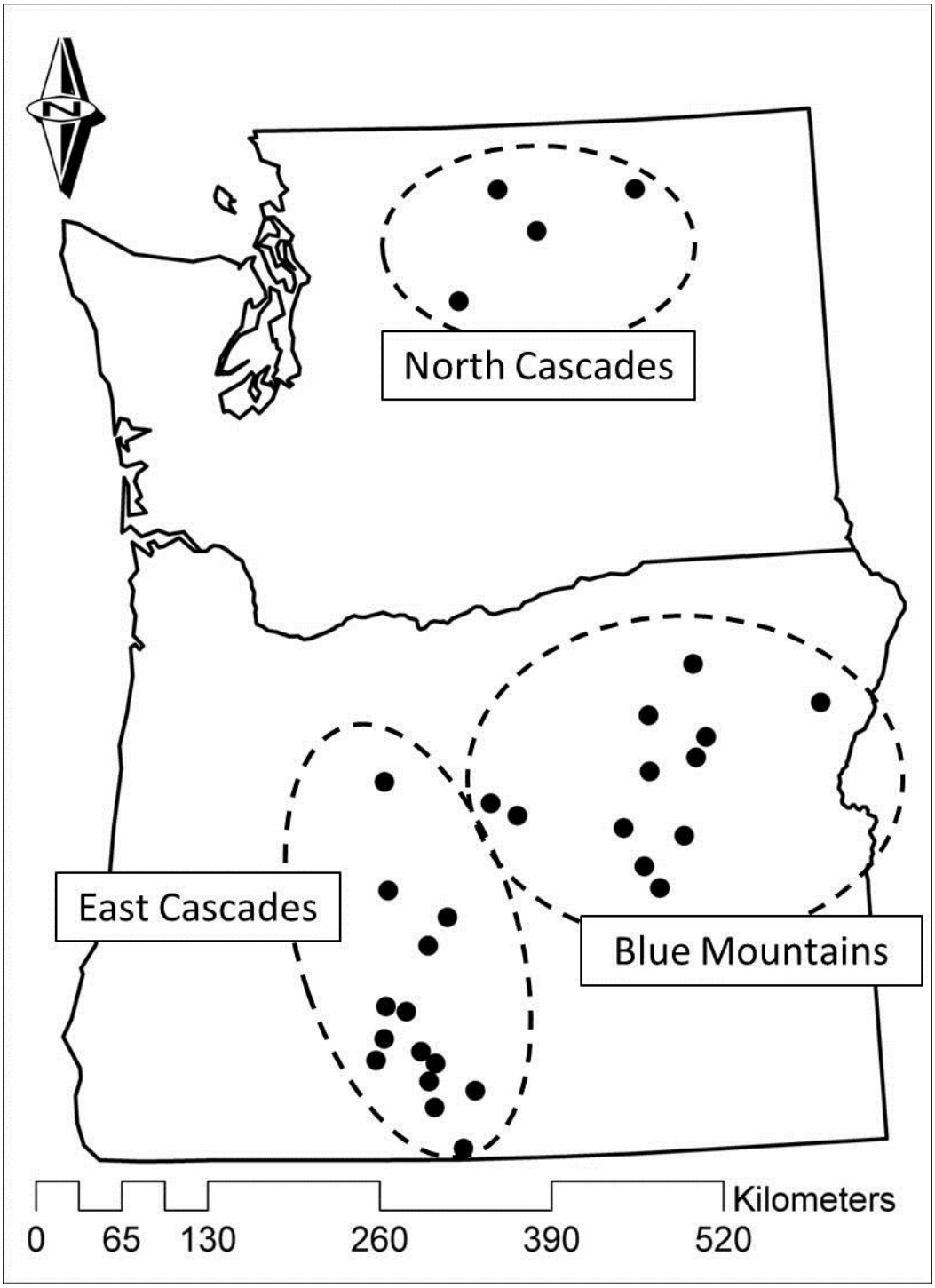

Figure 2. Occupancy relationships with environmental covariates described by univariate models. The models used to produce each plot contained only the specified variable as a covariate of all three fundamental parameters describing occupancy (ψ, γ, and ε). Solid lines depict maximum likelihood estimates and dotted lines depict 95% confidence bands. All models contained detection covariates listed in Table 5.

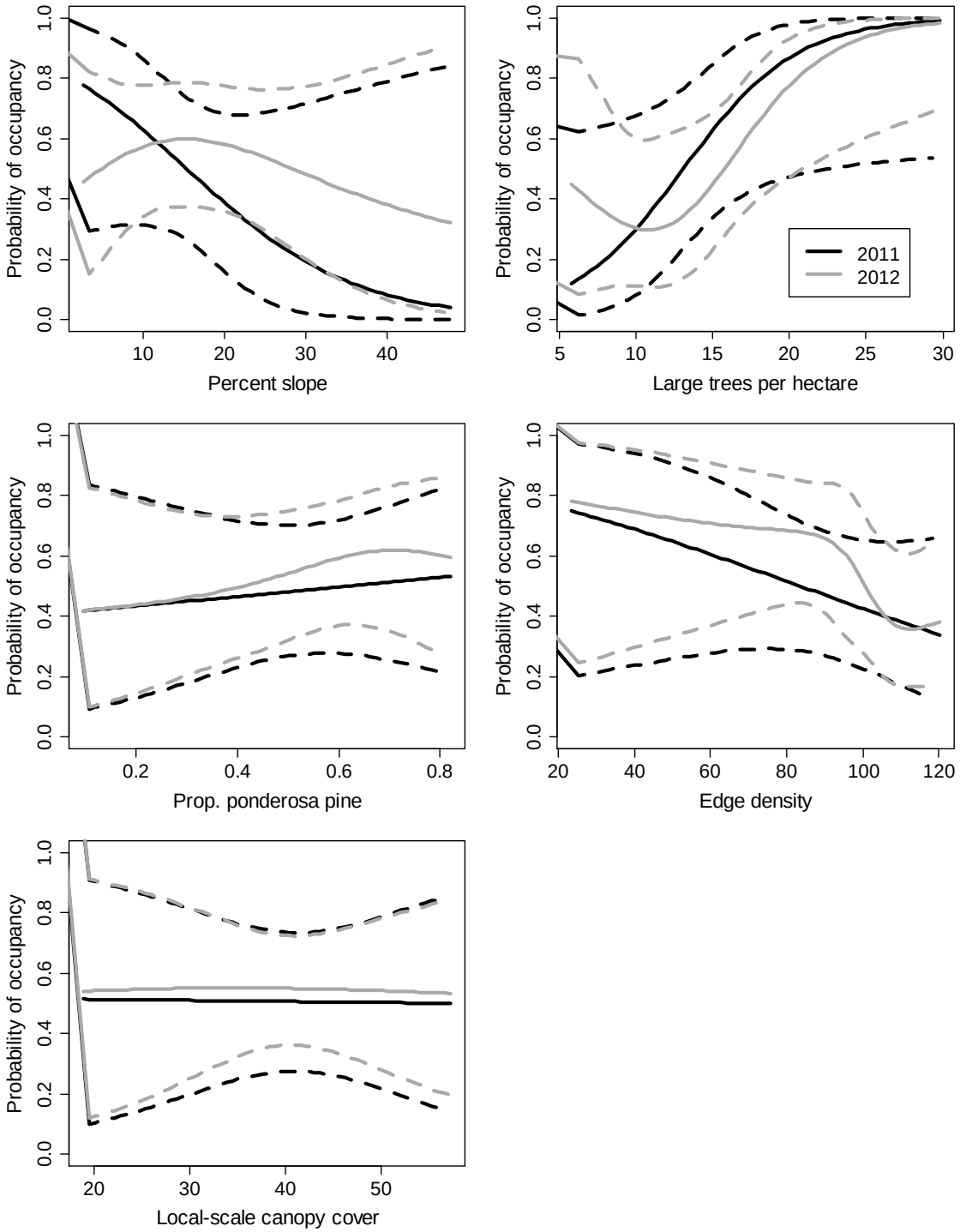
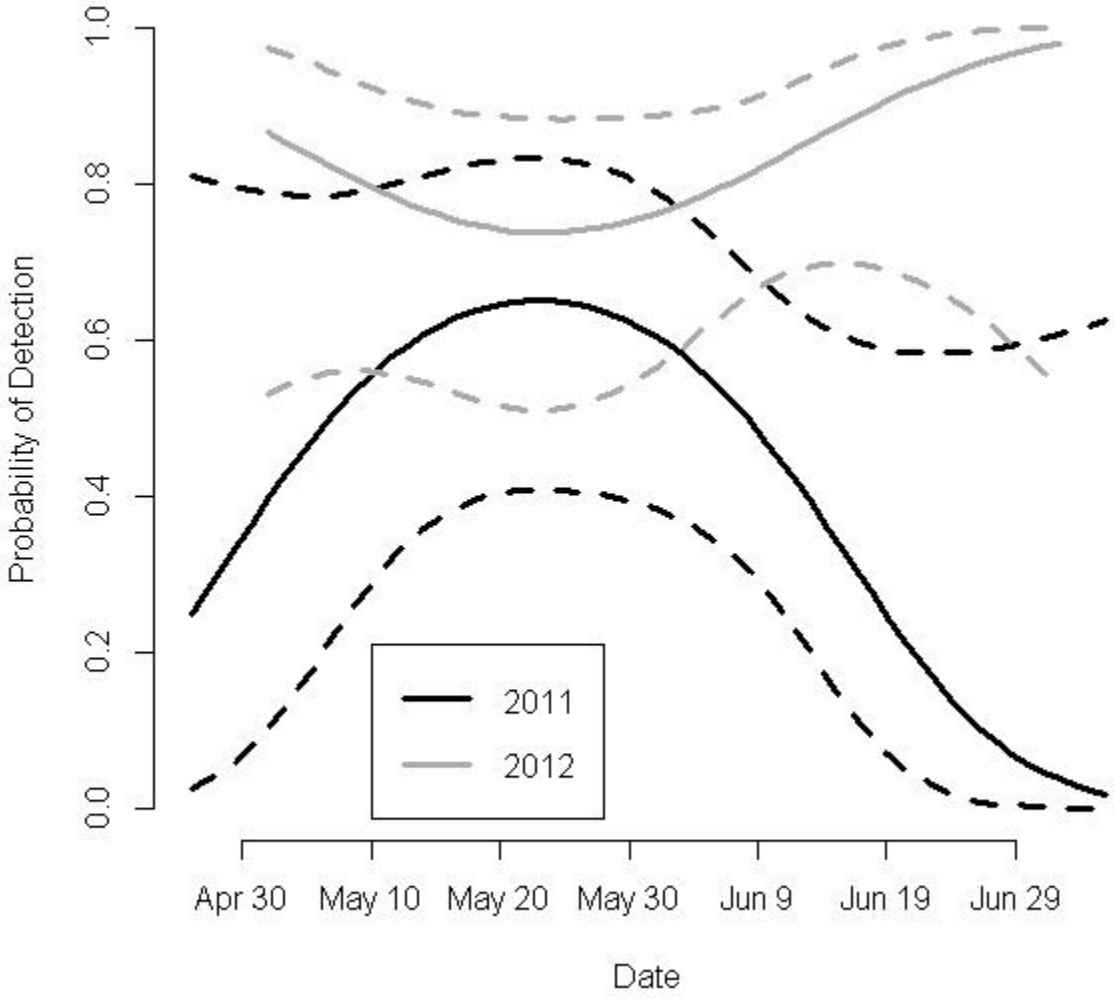
Figure 3. Seasonal trends in WHWO detectability estimated with the model described in Table 5. Solid lines depict maximum likelihood estimates and dotted lines depict 95% confidence bands.