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Passive acoustic monitoring reveals the limited distribution of an indicator species, the White-headed Woodpecker (*Leuconotopicus albolarvatus*), in the northern Blue Mountains, USA

El monitoreo acústico pasivo revela la distribución limitada de una especie indicadora, el Carpintero de Cabeza Blanca (*Leuconotopicus albolarvatus*), en las Montañas Azules del norte, EE. UU.

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ABSTRACT. Indicator species can facilitate the assessment, management, and conservation of biodiversity. The White-headed Woodpecker (*Leuconotopicus albolarvatus*) is a species of conservation concern that is considered an indicator species for mature ponderosa pine ecosystems, a priority restoration habitat that has declined by 90% in the northern Blue Mountains, USA. Here, we employed passive acoustic monitoring at 227 randomly selected locations across two National Forests in the northern Blue Mountains. Autonomous recording units were deployed for an average of 4.41 weeks per station (SD = 1.21) and audio recordings were processed with BirdNETv2.4. White-headed Woodpecker predictions were manually reviewed to create detection/non-detection data. We estimated occupancy and detection probabilities using a Bayesian occupancy model and compared the habitat suitability between occupied and unoccupied sites. Naïve occupancy was 7.5%, and the estimated proportion of sites occupied was 0.08 (95% Credible Interval: 0.075, 0.092). The average weekly detection probability was 0.71 (0.60, 0.80), indicating we detected the species with little error when present. Following model selection, we found the odds of occupancy were 5.26 times lower for every 2.87 m^2/ha increase in lodgepole pine basal area. Sites considered occupied were also found to have higher values of a habitat suitability metric currently used to inform land management decisions. Low occupancy of White-headed Woodpeckers potentially indicates the northern Blue Mountains cannot currently support a broad distribution of an indicator species for mature ponderosa pine forests. More broadly, this study provides insight into the condition of a regional, priority restoration habitat and provides important information for forest management.

RESUMEN. Las especies indicadoras pueden facilitar la evaluación, el manejo y la conservación de la biodiversidad. El Carpintero de Cabeza Blanca (*Leuconotopicus albolarvatus*) es una especie de interés para la conservación considerada como especie indicadora de los ecosistemas maduros de pino ponderosa, un hábitat prioritario para la restauración que ha disminuido en un 90% en las Montañas Azules del norte, EE. UU. En este estudio, empleamos monitoreo acústico pasivo en 227 sitios seleccionados aleatoriamente en dos Bosques Nacionales de las Montañas Azules del norte. Se instalaron unidades de grabación autónomas durante un promedio de 4,41 semanas por estación (DE = 1,21) y las grabaciones de audio se procesaron con BirdNET v2.4. Las predicciones del Carpintero de Cabeza Blanca fueron revisadas manualmente para generar datos de detección/no detección. Estimamos las probabilidades de ocupación y detección mediante un modelo bayesiano de ocupación y comparamos la idoneidad del hábitat entre sitios ocupados y no ocupados. La ocupación ingenua fue del 7,5%, y la proporción estimada de sitios ocupados fue 0,08 (intervalo creíble del 95%: 0,075–0,092). La probabilidad media semanal de detección fue 0,71 (0,60–0,80), lo que indica que detectamos la especie con poco error cuando estuvo presente. Tras la selección de modelos, encontramos que las probabilidades de ocupación fueron 5,26 veces menores por cada aumento de 2,87 m^2/ha en el área basal de pino contorta. Los sitios considerados ocupados también presentaron valores más altos de una métrica de idoneidad del hábitat utilizada actualmente para informar decisiones de manejo del territorio. La baja ocupación del Carpintero de Cabeza Blanca indica potencialmente que las Montañas Azules del norte no pueden sostener actualmente una distribución amplia de una especie indicadora de los bosques maduros de pino ponderosa. De manera más general, este estudio aporta información sobre el estado de un hábitat regional prioritario para la restauración y proporciona información importante para el manejo forestal.

Key Words: *cavity nester; habitat suitability; ponderosa pine; Umatilla; Wallowa-Whitman*

INTRODUCTION

A species' breeding distribution is determined by the extent of ecosystems that contain resources associated with their survival, reproduction, and population viability (Patton 1992). The presence of certain species of wildlife (e.g., habitat specialists) can therefore act as indicators of the resources and attributes present in an area, which reflect more broadly, ecosystem function and integrity (Lambeck 1997, Canterbury et al. 2000, Betts et al. 2024, Brunk et al. 2025). For example, the Black-backed Woodpecker (*Picoides arcticus*) is used as an indicator of ecosystem responses to management actions in burned forests (U.S. Forest Service Pacific Southwest Region 2007). Similarly, the Three-toed Woodpecker (*Picoides tridactylus*) is used as an indicator of structural diversity and bird species richness in boreal forests (Roberge et al. 2008, Pakkala et al. 2018). The relationships between indicator species and ecosystem health, species diversity, and management outcomes highlights the utility of monitoring their populations to inform forest management.

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The Blue Mountains of northeastern Oregon and southeastern Washington, USA is a highly complex and heavily managed landscape that has historically lacked a robust wildlife monitoring program. The region was once covered by a mosaic of ponderosa dry forest, mesic mixed conifer forest, riparian woodland, and various shrublands and grasslands (Altman and Bresson 2017, Hanberry et al. 2020). However, late successional ponderosa pine-dominated forests have substantially declined in the region. The decline is attributed to a combination of insect pathogens, the preferential harvest of old-growth ponderosa pine trees for human goods and services, and a long-standing effort to suppress fire in this historically fire-adapted landscape (Hessburg et al. 1994, Johnston et al. 2025). Many forested areas in the region have therefore transitioned to dense stands of mid-successional fir-dominated forests (Altman and Bresson 2017, Hanberry et al. 2020). More recently, there has been a concerted effort to restore these forests to their historical structure and composition for various objectives including improving ecosystem health, reducing wildfire risk, and providing a sustainable supply of timber.

White-headed Woodpeckers (*Leuconotopicus albolarvatus*) are a species of conservation concern (Kozma et al. 2025) that are considered an effective indicator species for mature ponderosa pine ecosystems with open understories, varying canopy cover, and snags (Latif et al. 2015, Altman and Bresson 2017). White-headed Woodpeckers commonly nest in 25–50 cm diameter-at-breast height sized snags in areas of varying fire severity with high amounts of edge habitat (i.e., > 75 m/ha; Latif et al. 2015, Lorenz et al. 2015). White-headed Woodpeckers mainly eat seeds from large-coned pines like the ponderosa pine, but will supplement their diet with insects, including wood boring beetles (*Buprestidae*) found in dead wood and recently burned stands (Kozma et al. 2025, Stillman et al. 2022). Despite our ecological understanding of White-headed Woodpeckers, there is a large knowledge gap related to the distribution of this indicator species in the northern Blue Mountains because of a lack of a targeted monitoring effort in the region. Quantifying the distribution of White-headed Woodpeckers in the Blue Mountains can aid our understanding of the forest ecosystems and help with the restoration of ponderosa pine ecosystems in the region.

In 2021, we evaluated the efficacy of passive acoustic monitoring (PAM) to detect White-headed Woodpecker in mixed ponderosa pine forests within two watersheds on the Wallowa-Whitman National Forest that were known to be occupied by the species. We found PAM was more effective and efficient than traditional survey techniques (i.e., playback surveys) at detecting White-headed Woodpeckers when making inferences across multiple sampling stations in remote forest environments (Gaylord et al. 2023). In this study, our objectives were to (1) describe the distribution of White-headed Woodpeckers on the Umatilla and Wallowa-Whitman National Forests, (2) identify ecologically and management relevant habitat variables associated with forest structure and composition related to White-headed Woodpecker occurrence, and (3) examine the relationship between White-headed Woodpecker occurrence and an independently created White-headed Woodpecker Habitat Suitability Index (i.e., Latif et al. 2015) currently used in land management decision making. Habitat suitability models can have limited accuracy when applied outside the region used to develop them (Latif et al. 2020). Our analysis therefore provides essential information on if the habitat suitability model is accurately identifying habitat that currently supports breeding White-headed Woodpeckers. Last, we use previously reported White-headed Woodpecker juvenile dispersal distances (Lorenz et al. 2024) to understand the extent to which juvenile dispersal may be limiting the colonization of suitable White-headed woodpecker habitat. To accomplish our objectives, we expanded the PAM effort to gather detection/non-detection data for the White-headed Woodpeckers across the Umatilla and Wallowa-Whitman National Forests. We then used Bayesian occupancy modeling to quantify occurrence probability while correcting for imperfect detection (Royle and Kéry 2007, MacKenzie et al. 2017). As a whole, our study promotes the conservation and understanding of a priority indicator species in a relatively data deficient area.

METHODS

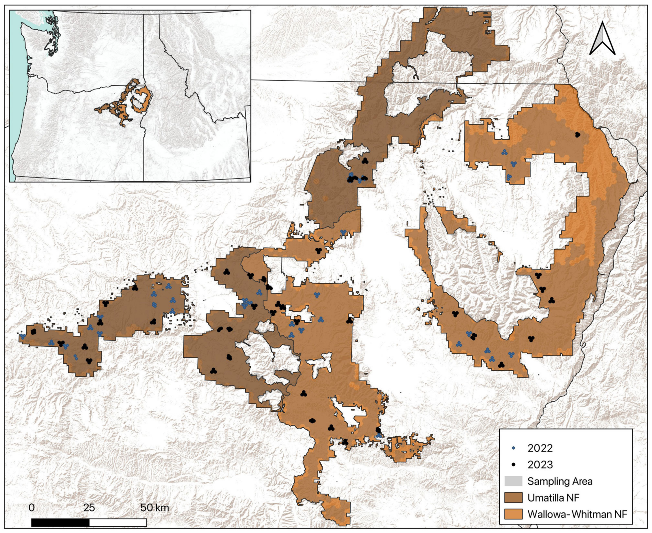
Study location

We conducted PAM surveys on the Umatilla and the Wallowa-Whitman National Forest in the northern Blue Mountains, USA. The northern Blue Mountains are made up of multiple different mountain ranges that include many canyons and valleys that range between 762 and 2700 meters above sea level in elevation. Low elevation habitats receive less than 25 cm of precipitation while higher elevation, mountainous areas can receive > 203 cm of precipitation (Altman and Bresson 2017). As part of the Collaborative Forest Landscape Restoration Program, the U.S. Forest Service is implementing forest treatments (i.e., commercial logging, non-commercial thinning, prescribed fire) to promote the restoration of the historical forest structure and composition in the northern Blue Mountains. Specific restoration goals include creating open forest structures with fire-resistant tree species, reducing the prevalence of true firs, and enhancing the overall heterogeneity of the forests to promote forest health.

Data collection

We used a 500-hectare hexagon tessellation sampling frame that spanned both National Forests to select the sampling locations in 2022 and 2023 (Fig. 1). In 2022, we used a stratified random sampling design to select 44 hexagons to sample by first grouping hexagons based on their proposed forest treatment types (i.e., commercial thinning, non-commercial thinning, prescribed burns, and no treatment). In 2023, we used the same sampling frame but selected hexagons using simple random sampling (i.e., we did not group by proposed treatments before selecting). Before selecting locations to sample, we omitted hexagons that contained relatively little forest-capable lands (< 25% in 2022 and < 50% in 2023; Davis et al. 2015), were deemed unsafe for fieldwork, and/or largely comprised wilderness areas or experimental forests. We established up to four stations per hexagon, resulting in 172 survey stations in 2022 and 170 survey stations in 2023. We placed stations at least 500 m from other stations, 200 m from the edge of the hexagon, and, to reduce noise interference and theft, 50 m from a path, road, or loud running water. To maximize consistency in the quality of recordings across stations, we mounted all autonomous recording units (ARUs) on trees with a diameter-at-breast height of < 30 cm at approximately 1.5 m above ground level, and we cleared branches within 30 cm of the ARU microphones. We used a combination of Wildlife Acoustics Song Meter 4 units, Song Meter 4 Mini units, and Song Meter 4 Mini

Fig. 1. Map of the Umatilla (dark brown) and Wallowa-Whitman (light brown) National Forests. Black circles and blue diamonds indicate locations where recording units were deployed between 1 May and 31 June in 2022 and 2023. Shaded area within each national forest denotes the extent of the sampling area defined by amount of forested habitat and land ownership. Inset map shows the study area in relation to Oregon, Washington, and Idaho.



Bat units equipped with acoustic microphone stub attachments to collect soundscape recordings. These ARUs all have external microphones and have very similar sensitivity and signal to noise ratios. The differences in recording units are unlikely to influence our ability to detect White-headed Woodpecker vocalizations in a meaningful way, particularly given our study objectives (Wildlife Acoustics [date unknown]). We collected soundscape recordings during the breeding season of the White-headed Woodpecker, from mid-May to early July in 2022 and early May through early September in 2023. We programmed ARUs to record continuously for two hours before and after sunrise, one hour before and three hours after sunset, and the first 10 minutes of every hour not included in the continuous recording period. For more details related to the sampling design see Duarte et al. (2024).

Audio processing and validation

Before processing audio recordings, we first narrowed the monitoring period to only include recordings collected between 1 May to 31 June. This filtering scheme focused our processing efforts on recordings collected during the White-headed Woodpecker nesting period, as the home range of the species changes outside of this time window (Lorenz et al. 2015). We then processed audio recordings with BirdNET v.2.4 (Kahl et al. 2021). We filtered White-headed Woodpecker predictions to those with confidence scores 0.5 to prioritize reviewing high confidence predictions (Pérez-Granados 2023) and reduce the effort associated with the manual review process. We grouped BirdNET predictions by station and sampling week and treated each seven-day period as a unique sampling occasion or survey period. We then randomly selected up to 50 predictions per station per survey period (i.e., 1 week of monitoring) for manual review. We randomly selected the 50 predictions to prioritize selecting temporally independent predictions. This resulted in 1889 predictions for manual review. We used the Simple Passive Acoustic Monitoring protocol, as described in Vernasco et al. (2025), to conduct manual review. This protocol facilitates efficient review by allowing reviewers to simultaneously listen to audio and inspect spectrograms of BirdNET predictions. We marked each reviewed prediction as a true- or false-positive prediction. We classified a BirdNET prediction as a true-positive prediction based on the presence of a White-headed Woodpecker specific call type that we could confidently identify (i.e., the three- or four-note "pee-kik-kik" call). We required three true-positive predictions for White-headed Woodpecker to be considered detected at a station within a survey period (i.e., week). We chose a threshold of three to minimize the likelihood of false positives (i.e., classifying an unoccupied site as occupied because of a transient or dispersing individual, for example) and managed the amount of effort associated with manual review process. Additionally, as shown in Table 1 of Gaylord et al. (2023), sites with greater than three White-headed Woodpecker detections were also found to have an average of 17 days with detections, indicating three detections reflects birds consistently using an area.

Estimating BirdNET precision and recall

We used two sources of data to estimate BirdNET's precision and recall, metrics that are essential to understanding the reliability of an acoustic classifier. Precision is the number of true positive predictions divided by the total number of true positive and false positive BirdNET predictions. Recall is the number of true positive predictions divided by the total number of true positive and false negative predictions.

To estimate precision, we selected the first three reviewed predictions from each week of each station ($n = 870$ predictions). These first three predictions represent three randomly selected predictions above a confidence score 0.5. We selected up to the first three predictions reviewed because the manual validation approach used to review predictions herein (i.e., stopping upon the third positive prediction) causes the dataset as a whole to contain a greater number of false positive predictions. We calculated precision by dividing the number of true positive predictions by the total number of predictions selected for estimating precision. To estimate recall, we used a selection of White-headed Woodpecker vocalizations gleaned from audio recordings collected as part of a separate PAM study from the same region (i.e., Gaylord et al. 2023). White-headed Woodpecker vocalizations were identified by manually scanning the recordings. Audio segments containing the vocalization were extracted by selecting the time the vocalization began to the time preceding when there was two seconds of audio with no White-headed Woodpecker vocalization. This two second buffer ensures that there is a White-headed Woodpecker call within every three second segment of audio, the duration of BirdNET's detection window. After identifying the length of the audio clip, a half second buffer was added to the beginning and end of the audio segment. The duration of each audio segment was then trimmed to the nearest multiple of three to ensure only complete 3 second windows were considered. We determined the potential number of White-headed Woodpecker predictions based on the length of

Table 1. Environmental covariates considered in the initial occupancy and detection models. We selected these variables as they represent prominent tree species in the region and habitat variables that capture aspects of forest structure that are ecologically relevant to White-headed Woodpeckers (*Leuconotopicus albolarvatus*) and relevant to forest management. Basal area was measured in m^2/ha. We indicate in the source column which dataset was used to generate the covariate data. We indicate if the covariate was used in the occupancy or detection model in the Model column. The mean, standard deviation, min, and max value of each variable is presented in Table A1.1.

Covariate name	Description	Source	Model
Grand Fir Basal Area	Basal area of Grand Fir (*Abies grandis*)	LEMMA	Occupancy
Western Larch Basal Area	Basal area of western larch (*Larix occidentalis*)	LEMMA	Occupancy
Douglas Fir Basal Area	Basal area of Douglas fir (*Pseudotsuga menziesii*)	LEMMA	Occupancy
Ponderosa Pine Basal Area	Basal area of ponderosa pine (*Pinus ponderosa*)	LEMMA	Occupancy
Lodgepole Pine Basal Area	Basal area of lodgepole pine (*Pinus contorta*)	LEMMA	Occupancy
Vegetation Height	Average height of all vegetation, measured in meters	LANDFIRE	Occupancy
Canopy Cover SD	Average standard deviation in percent canopy cover of all live trees	LEMMA	Occupancy
Canopy Cover	Average percent canopy cover of all tree species	LEMMA	Detection
Elevation	Average elevation of survey station, measured in meters above sea level	LANDFIRE	Detection
Day of Year	Day of year of the first day of each survey period		Detection
Monitoring Hours	Number of hours of audio recordings collecting per survey period		Detection
Monitoring Year	Categorical variable denoting if the station was sampled in 2022 or 2023		Detection

the audio segment (e.g., three seconds = 1 potential prediction, 6 seconds = 2 potential predictions, etc.). All audio segments were then processed with BirdNET using the default settings, as described above. We filtered the BirdNET predictions to those with a confidence score 0.5 to match the threshold we used in the review of prediction data used for our study. We then calculated recall by dividing the total number of White-headed Woodpecker predictions by the total number of 3 second audio segments containing White-headed Woodpecker vocalizations.

Data analysis

We fit a single species, single season Bayesian occupancy model (Royle and Kéry 2007, MacKenzie et al. 2017) to the detection/non-detection data to quantify the probability of White-headed Woodpecker occupancy at a station, while accounting for the possibility that the species may sometimes go undetected even when present at a station. We considered ecologically and management relevant covariates describing forest structure and composition in the occupancy model and sampling-related covariates in the detection model.

Our habitat variables include the amount of prominent tree species, measured in basal area (m^2/ha), and characteristics of forest structure previously found to be ecologically relevant to White-headed Woodpecker occurrence (Table 1). We quantified habitat variables within a 200 m radius, circular buffer centered on each survey station to capture the habitat characteristics while also minimizing overlap between spatially adjacent stations (Table 1). We gathered data for each tree species from the latest data provided by the Landscape Ecology, Modeling, Mapping & Analysis (LEMMA) research group (Bell et al. 2024). We also gathered data on forest structure from the LANDFIRE database (LANDFIRE 2016). All variables were measured on a 30-m pixel resolution and average or sum values were calculated using a moving window analysis in the terra package (Hijmans 2023). Although ecologically relevant, we did not consider the fire history of the area because only 27 of our stations have burned at any severity in the last 10 years. Examining the effects of fire requires consideration of the time since fire because of the successional changes that occur and even fewer of our sites have burned within ecologically relevant time intervals (i.e., 1 year since n = 8, 2–5 years since n = 12, and 6–10 years since fire n = 7).

We considered detection covariates that are likely to influence our ability to detect White-headed Woodpeckers. We included the hours of audio recordings collected each survey period to control for differences in sampling amounts. We also considered the Julian day of the first day of the sampling week to capture potential seasonal changes in White-headed Woodpecker vocalizations. Because forest structure can influence how sound travels, we included the average canopy cover for each station calculated using a 200m radius, circular buffer centered on each survey station. Last, forest structure and species abundance can change with elevation and we therefore also included an effect of elevation on our detection covariate.

We conducted model selection using indicator variables (Kuo and Mallick 1998). Specifically, we multiplied each model coefficient by a latent binary variable, where a covariate is included in the model when the indicator variable equals one. Each indicator variable was assigned a Bernoulli prior, assigning equal prior probability (0.5) of including or excluding each covariate. In this process, each unique sequence of indicator variables (i.e., combinations of ones and zeroes across detection and occupancy covariates) represents a candidate model (Royle et al. 2014). We used the model structure with the highest posterior probability for inference (Table 2). To help with model fitting and to ensure covariates did not artificially drop out, we implemented this model selection approach using slab-and-spike priors (Mitchell and Beauchamp 1988). To do so, we first fit the global model without indicator variables using uninformative priors. We then used the resulting coefficient estimates and their standard deviations for the values of the spike priors. This process ensures the informed prior distributions are near the posterior distribution for each coefficient, as recommended by Dellaportas et al. (2002).

We fit models using JAGS (Plummer 2003), in program R v4.2.0 (R Core Team 2022) using the jagsUI package (Kellner 2024). Before models were fit, we rescaled all continuous variables to have a mean of zero and a standard deviation of one. We inspected correlations between variables to ensure that all correlation coefficients were > -0.7 and < 0.7. We included a random effect of hexagon ID on occupancy probability to account for any potential spatial autocorrelation associated with the spatially

Table 2. Top 10 supported models identified by model selection. The posterior probability indicates the proportion of iterations a given model was observed. Detection covariates describe the covariates included in the detection model, while occupancy covariates describe those included in the occupancy model.

Posterior probability	Detection covariates	Occupancy covariates
0.026		Lodgepole Pine BA
0.017		Larch BA, Lodgepole Pine BA
0.016		Lodgepole Pine BA, Canopy Cover SD
0.014		Larch BA, Lodgepole Pine BA, Canopy Cover SD
0.011		Grand Fir BA, Lodgepole Pine BA
0.01	Year	Lodgepole Pine BA
0.01	Canopy Cover	Lodgepole Pine BA
0.009		Grand Fir BA, Lodgepole Pine BA, Canopy Cover SD
0.008		Lodgepole Pine BA, Ponderosa Pine BA
0.008		Larch BA

clustered stations within our hexagonal sampling design. We used uninformative priors with a mean of zero and precision of 0.368 for all model intercepts and coefficients. We also used an uninformative prior for the variance of the random effect by specifying a uniform distribution that ranged from 0 to 20. We fit models using three independent chains, each consisting of 20,000 iterations with a burn-in and adaption phase of 10,000 each. All parameters converged (< 1.01; Brooks and Gelman 1998). We used the top-supported model identified using the model selection process described above (i.e., indicator variables) to estimate occupancy and detection probability. We describe model parameters using their mean values and 95% credible intervals (CIs) and report results using the odds ratios (i.e., the odds of detection or occupancy for every 1 standard deviation change in the covariate; Hosmer et al. 2013) of model coefficients found to be important to occurrence. Last, we assessed the fit of the global model using a posterior predictive check by calculating the Bayesian p-value (Gelman et al. 1996). Specifically, we simulated data using the estimated model, calculated the sum of the absolute value of residuals of our simulated data and our empirical data, and estimated the Bayesian p-value as the proportion of times the simulated data were more extreme (i.e., had a larger sum of the absolute value of residuals) than our empirical data (Kéry 2010).

Evaluating the habitat suitability index

To evaluate the habitat suitability index produced by Latif et al. (2015), we compared the habitat suitability index at sites where White-headed Woodpeckers were and were not detected. The habitat suitability index was created using habitat data at White-headed Woodpecker nest locations collected within the eastside of the Cascade Mountains of Oregon. The specific habitat variables included in the index are topographical characteristics (i.e., slope, aspect), local- and landscape-scale canopy cover, proportional area of ponderosa pine forest, and the density of habitat edges (for additional details see Latif et al. 2015). The habitat suitability metric represents an estimated relative probability of habitat use quantified using Maxent (Phillips et al. 2006). We compared the relationship between White-headed Woodpecker occurrence and the habitat suitability at two spatial scales using linear regression. The first spatial scale we evaluated was at the station level. We calculated the average habitat suitability index for each station using a 200m radius, circular buffer centered on the station location. We included a random effect of hexagon ID to account for spatially clustered stations and fit the model using the lme4 package (Bates et al. 2015). The second spatial scale was at the hexagon level. We calculated the average habitat suitability index for each 500 ha hexagon and fit the model in Program R (R Core Team 2022).

RESULTS

During the White-headed Woodpecker nesting period, we monitored 294 stations for an average of 244.8 hours (SD = 105.6 hours) and 3.46 weeks (SD = 1.24 weeks), with 56% of ARUs recording for 4 weeks (Fig. 1, Fig. A.1). Our manual review of audio recordings from Gaylord et al. (2023) generated 1039 three second audio segments containing White-headed Woodpecker vocalizations. Of those, 856 were three seconds long, 92 were six seconds long, 48 were nine seconds long, 18 were 12 seconds long, and 25 were 15 seconds long. There were therefore 1381 3-second audio segments containing White-headed Woodpecker vocalizations. We estimated recall using a BirdNET confidence score threshold of 0.5 to be 0.469. Using the first three detections per survey period for each station (n = 870 predictions), we estimated precision to be 0.35.

White-headed Woodpeckers were detected at 22 stations, resulting in a naïve occupancy of 7.5% of stations occupied. The total number of sites estimated as occupied after correcting for imperfect detection was 23 (95% credible intervals: 22, 27). The proportion of variance in the occupancy probability attributed to the random effect of hexagon ID was 0.55 [95% CIs: 0.29, 0.78]. The estimated detection probability was, on average, 0.71 (0.60, 0.80) per week of monitoring. The cumulative detection probability reached 0.99 after 4 weeks of monitoring, meaning we were able to detect White-headed Woodpecker, when present, without error using our PAM protocol after 4 weeks of monitoring. Of the habitat covariates considered in the global model (Table 1), the top-supported occupancy model was found to include lodgepole pine basal area and the top-supported detection model was the intercept only model (Table 2, Table 3). The odds of occupancy were 5.26 times lower for every 2.87 m^2/ha increase in lodgepole pine basal area (Fig. 2). We estimated the Bayesian p-value of the global model to be 0.24, indicating adequate model fit. We provide a summary of the global model in Table A.2.

We found stations wherein White-headed Woodpecker were detected to have significantly higher habitat suitability indices (Fig. 3A, Table 4A). The adjusted intra-class correlation coefficient of the random effect of hexagon ID was 0.75 [95% confidence intervals: 0.61, 0.80), indicating most of the variation in habitat suitability values were among hexagons. Hexagons with White-headed Woodpecker also had higher suitability indices (Fig. 3B, Table 4B).

DISCUSSION

We provide the first landscape-scale assessment of White-headed Woodpecker occupancy in the Umatilla and Wallowa-Whitman National Forests of the northern Blue Mountains, USA. Our study found that White-headed Woodpecker occupancy probability in the northern Blue Mountains region was low, while the probability of detecting the White-headed Woodpecker with PAM, given it is present, was relatively high. We also found that

Table 3. Summary of the top-supported detection and occupancy models showing the mean, standard deviation (SD), and lower and upper 95% credible intervals of model coefficients.

	Mean	SD	Lower 95%	Upper 95%
Detection model				
Variable				
Intercept	0.899	0.256	0.403	1.410
Occupancy model				
Variable				
Intercept	-4.379	0.647	-5.786	-3.247
Lodgepole Pine BA	-1.645	0.685	-3.052	-0.391
Random Effect of Hexagon	2.169	0.590	1.187	3.518

Fig. 2. Model selection revealed White-headed Woodpecker (*Leuconotopicus albolarvatus*) occurrence declined with increasing Lodgepole Pine Basal Area. The shaded region represents the 95% credible intervals, and the inset graph shows the posterior distribution of the associated slope estimate relative to zero, as indicated by the dashed line. Model selection results are displayed in Table 2 and a summary of the top-supported model is provided in Table 3.

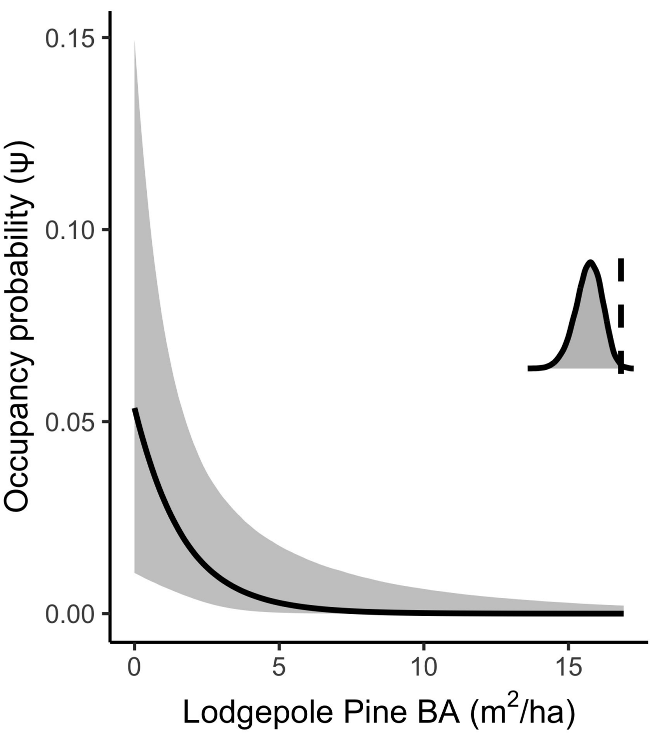
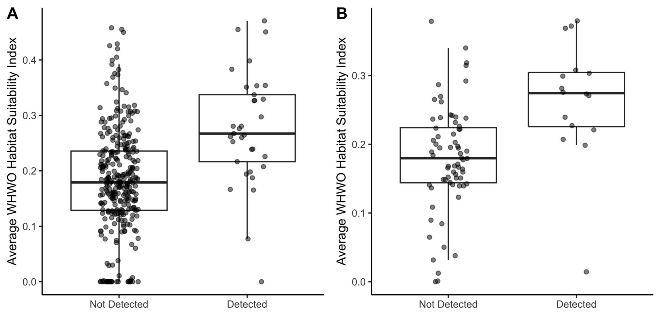


Fig. 3. Relationships between the White-headed Woodpecker presence and the White-headed Woodpecker (*Leuconotopicus albolarvatus*) Habitat Suitability Index by Latif et al. (2015) at the station (A) and hexagon (B) scale. Stations and hexagons wherein White-headed Woodpeckers were detected had significantly higher values of the habitat suitability index. Points indicate individual stations (A) or hexagons (B). The associated model summaries can be found in Table 3.



White-headed Woodpecker occupancy declined with lodgepole pine basal area. Further, stations and hexagons wherein White-headed Woodpeckers were detected had significantly higher habitat suitability indices. Our results suggest areas with relatively high habitat suitability (e.g., > 0.3 HSI at the station scale and > 0.2 HSI at the hexagon scale), but unknown White-headed Woodpecker occupancy likely offers more suitable breeding locations compared to areas below these HSI thresholds. More broadly, our results provide further evidence that the distribution of late-successional ponderosa pine forests capable of supporting wildlife dependent on such forests is limited in this region. Because wildlife is considered a useful indicator of ecosystem function and integrity (Chase et al. 2020, Matricardi et al. 2020, Betts et al. 2024), this study provides important insight into the health of the dry forests in the northern Blue Mountains.

Our results indicate a low occupancy probability for White-headed Woodpeckers in the northern Blue Mountains. Notably, the random effect of hexagon ID explained a large proportion of the variance in occupancy (i.e., 0.55), highlighting there are extensive differences among hexagons in occupancy (i.e., some hexagons have higher occupancy probability than others). In other words, overall occupancy is low across the landscape, but in a few spatially adjacent locations, occupancy probability is comparatively high. White-headed Woodpeckers therefore exhibit a sparse, but spatially clumped distribution in the northern Blue Mountains. The negative relationship between occupancy and lodgepole pine we observed could be related to contrasts between the preferred habitats of White-headed Woodpeckers and forests containing lodgepole pine. Specifically, White-headed Woodpeckers rely on dry forests composed of mature ponderosa pine and an open understory that is maintained by low severity fires (Kozma et al. 2025). Lodgepole pine, on the other hand, is more often associated with moist mixed conifer forests that tend to have more closed understories and burn less frequently with mixed fire severity. In the northern Blue Mountains, dry ponderosa-dominated forests occur at relatively lower elevations and the moist mixed conifer forests tend to be found at relatively higher elevations (Stine et al. 2014). Given the differences between the types of forest ponderosa pine and lodgepole pine are most commonly associated with, further study will be needed to understand the extent to which lodgepole pine directly affects White-headed Woodpecker occupancy or rather indicates broader habitat characteristics associated with unsuitable White-headed Woodpecker habitat. Importantly, the large proportion of the variance in occupancy explained by the random effect represents variation in occupancy not attributed to lodgepole pine

Table 4. Summaries of linear models comparing sites White-headed Woodpeckers (WHWO; *Leuconotopicus albolarvatus*) were and were not detected on the Umatilla and Wallowa-Whitman National Forests, 2022 and 2023 breeding seasons. Table 4A summarizes the analysis of habitat suitability indices between stations. Table 4B summarizes the comparison of habitat suitability values between hexagons. For both models, the reference category is undetected. Plots of associated data can be found in Figure 2. For the model summarized in Table 4A, the random-intercept variance component for hexagon was 0.007 (SD = 0.084).

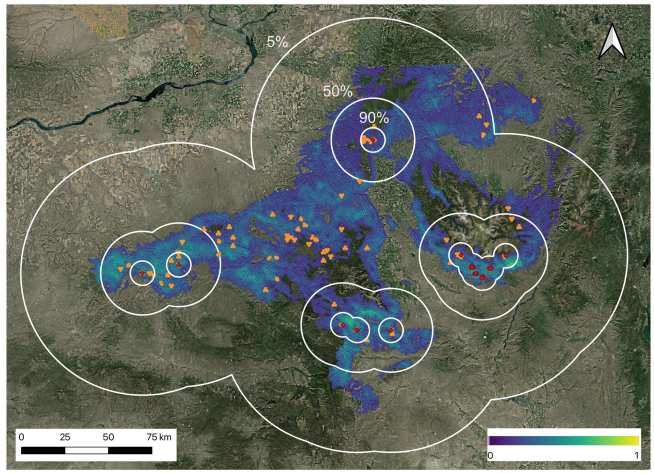
	Mean	Std. error	df	t value	p value
Table 4A					
Coefficient					
Intercept	0.19	0.01	87.13	19.87	< 0.0001
WHWO State - detected	0.03	0.01	302.11	2.02	0.04
Table 4B					
Coefficient					
Intercept	0.18	0.01	82	18.81	< 0.0001
WHWO State - detected	0.09	0.02	82	3.9	0.0002

basal area. Additional, unidentified site-level differences are therefore contributing to the observed patterns of White-headed Woodpecker occurrence.

PAM was previously shown to provide a similar cumulative detection probability estimate following 7 days of monitoring and after validating all detections produced by a custom classifier trained on recordings from the same study region (Gaylord et al. 2023). We used a classifier trained on publicly available White-headed Woodpecker recordings (i.e., BirdNET v2.4; Kahl et al. 2021) and validated only 50 detections per survey period, yet still obtained a cumulative detection probability > 0.9 after 2 weeks of monitoring. Both our results and the previous results therefore suggest PAM is a highly effective means for monitoring White-headed Woodpeckers. Based on these detection probability estimates, it seems PAM survey data collected and processed using our protocol, the same ARUs models, and BirdNET v2.4 can be used to directly inform forest management decisions without using statistical models that account for imperfect detection when > 4 weeks of audio recordings are collected at a site.

Mature ponderosa pine forests of the northern Blue Mountains are a priority restoration ecosystem because of their ability to support multiple species of conservation concern and for the regional decline of the ecosystem (Altman and Bresson 2017). The relatively low occupancy estimate identified in our current study may indicate that the amount or health of mature ponderosa pine forest in the northern Blue Mountains is insufficient or incapable of sustaining a broad distribution of White-headed Woodpeckers. This could be especially indicative of a lack of specific forest resources, such as snags, in areas that contain otherwise suitable habitat. Indeed, suitable habitat is seemingly unoccupied because there are areas without detections that have habitat suitability indices similar to stations with detections. It is also possible the Habitat Suitability Index does not completely identify suitable habitat because it was created using topographic variables, measurements of canopy cover, ponderosa pine prevalence, and forest edge density (Latif et al. 2015). White-headed Woodpeckers rely on snags and open understories for nesting and also select areas with variable canopy cover (Lorenz et al. 2015, 2024). Importantly, these forest characteristics are not represented by the Habitat Suitability Index developed by Latif et al. (2015). As additional occurrence data accumulates, updating the habitat suitability model can further improve the utility of the White-headed Woodpecker Habitat Suitability Index in our region (Duarte et al. 2025).

Fig. 4. Potential juvenile White-headed Woodpecker (*Leuconotopicus albolarvatus*) dispersal distances from areas found to be occupied by White-headed Woodpeckers. Red diamonds indicate stations occupied by White-headed Woodpeckers and orange circles indicate unoccupied stations. Blue to yellow gradient show the Habitat Suitability Index generated by Latif et al. (2015) on National Forest lands. The smallest white buffers indicate the minimum distance 90% of woodpeckers dispersed (i.e., 7 km radius), the middle white buffers indicate the minimum distance 50% of woodpeckers dispersed (i.e., 24km radius), and the largest white buffers show minimum distance 5% of juvenile woodpeckers dispersed (i.e., 70 km radius), as reported by Lorenz et al. (2024).



The absence of White-headed Woodpecker does not necessarily indicate that it is habitat that is limiting its distribution. Other factors, such as juvenile dispersal, could limit the distribution of these birds across the National Forests. Lorenz et al. (2024) quantified biased-corrected estimates of White-headed Woodpecker juvenile dispersal and found 90% of woodpeckers disperse at least 7 km while 5% dispersed 70 km. Figure 4 shows the minimum dispersal distances of 90%, 50%, and 5% of juvenile woodpeckers, based on juvenile dispersal distances reported by Lorenz et al. (2024), centered on the sites classified as occupied. This figure suggests that White-headed Woodpeckers are not dispersal limited if individuals are capable of dispersing the maximum distance previously observed. Within our study area, however, the dispersal buffers contained many non-forested areas and the extent to which such habitats limit dispersal is not known. If non-forested habitats are impervious to juvenile dispersal and many individuals do not disperse further than the minimum distance 50% of juveniles were observed to disperse (i.e., 24 km), then the ability of dispersing juveniles to colonize existing suitable habitat may be limited. Further resolving the habitat differences between occupied and unoccupied stations, particularly those containing suitable habitat, and understanding patterns of juvenile dispersal and survival represent promising future directions for understanding White-headed Woodpecker distributions in the northern Blue Mountains.

Here, we reveal that the White-headed Woodpecker distribution across the National Forests of the northern Blue Mountains is limited and spatially clumped. We found that sites where White-headed Woodpeckers were detected had significantly higher habitat suitability. With increased knowledge on the species' distribution and the validation of a management tool currently used to identify suitable habitat, land managers can now more confidently identify areas that currently support this species of conservation concern during the breeding season and restore and monitor unoccupied areas that contain suitable habitat, as indicated by the habitat suitability model. The negative relationship between lodgepole pine and White-headed Woodpecker occupancy suggests restorations efforts may benefit from considering lodgepole pine management in suitable habitat. Forests, and the dry forests of the Pacific Northwest in particular, are facing a myriad of threats including increased frequency of drought, non-native insects and pathogens, and shifting wildfire regimes (Millar and Stephenson 2015, Johnston et al. 2025). Using PAM to identify and monitor the distribution of indicator species across managed landscapes, particularly those that are otherwise data deficient, represents a promising approach for understanding and quantifying changes in forest health and prioritizing areas for habitat restoration.

Author Contributions:

AD, BJV, and JR conceptualized the idea for the research questions, designed the sampling scheme, and collected audio recordings. BJV processed the data with BirdNET and AJF reviewed detection data. BJV and AD analyzed the data. AJF and BJV wrote the first draft of the manuscript, and all authors edited subsequent drafts.

Acknowledgments:

This work could not have been carried out without the hard work and dedication of our field crew, which included Emily Church, Matthew Conrad, Emily Crouch, Holy Daly, Natalie Franklin, Kristin Fratella, Casey Kroening, Meredith Matthews, Mary Nicholes, Megan Porter, and Jesse Rodriguez. We'd like to thank Julia Boland for sharing the White-headed Woodpecker Habitat Suitability Index map. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official U.S. Government determination or policy. The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Government of any product or service.

Data Availability:

All materials necessary to reproduce the results, including data and R code, can be accessed using this link: https://doi.org/10.5281/zenodo.17886791.

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Supplementary Figures and Tables

Title Passive acoustic monitoring reveals the limited distribution of an indicator species, the White-headed woodpecker (*Picoides albolarvatus*), in the northern Blue Mountains

Table of Contents

Figure A.1. Weeks of monitoring for White-Headed Woodpeckers per station in the Umatilla and Wallowa-Whitman National Forests. The majority of station were monitored for 4 weeks (42.9%), followed by 3 weeks (21.8%), 2 weeks (14.6%), 1 week (7.5%), 5 weeks (6.8%), and 6 weeks (6.5%).

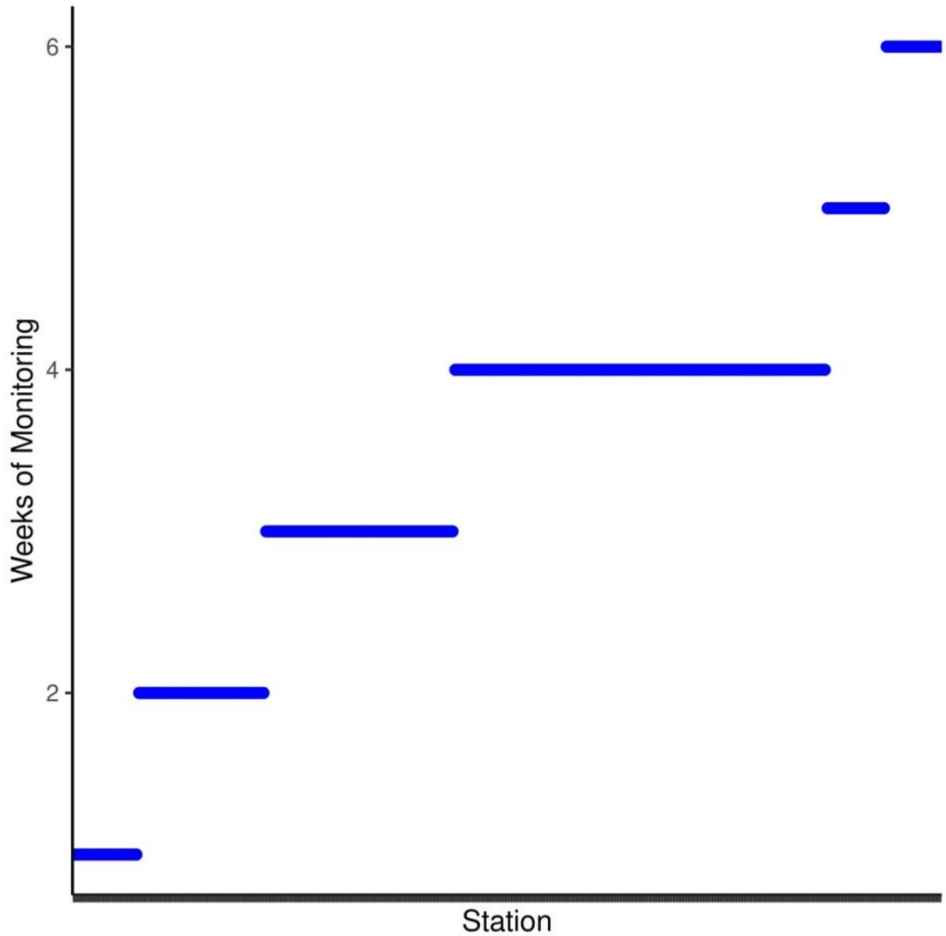

Figure A.2. White-headed Woodpecker occurrence and the observed relationships with covariates considered in the global model. Within each graph, the top row of points are those stations considered occupied by White-headed Woodpeckers while the bottom row are unoccupied stations. Histograms show the posterior distribution of the slope estimates relative to zero, indicated by the dotted line. See Supplementary Table 2 for a summary of the associated model. Additional details related to covariates can be found in Table 1 and the Methods section of the main text.

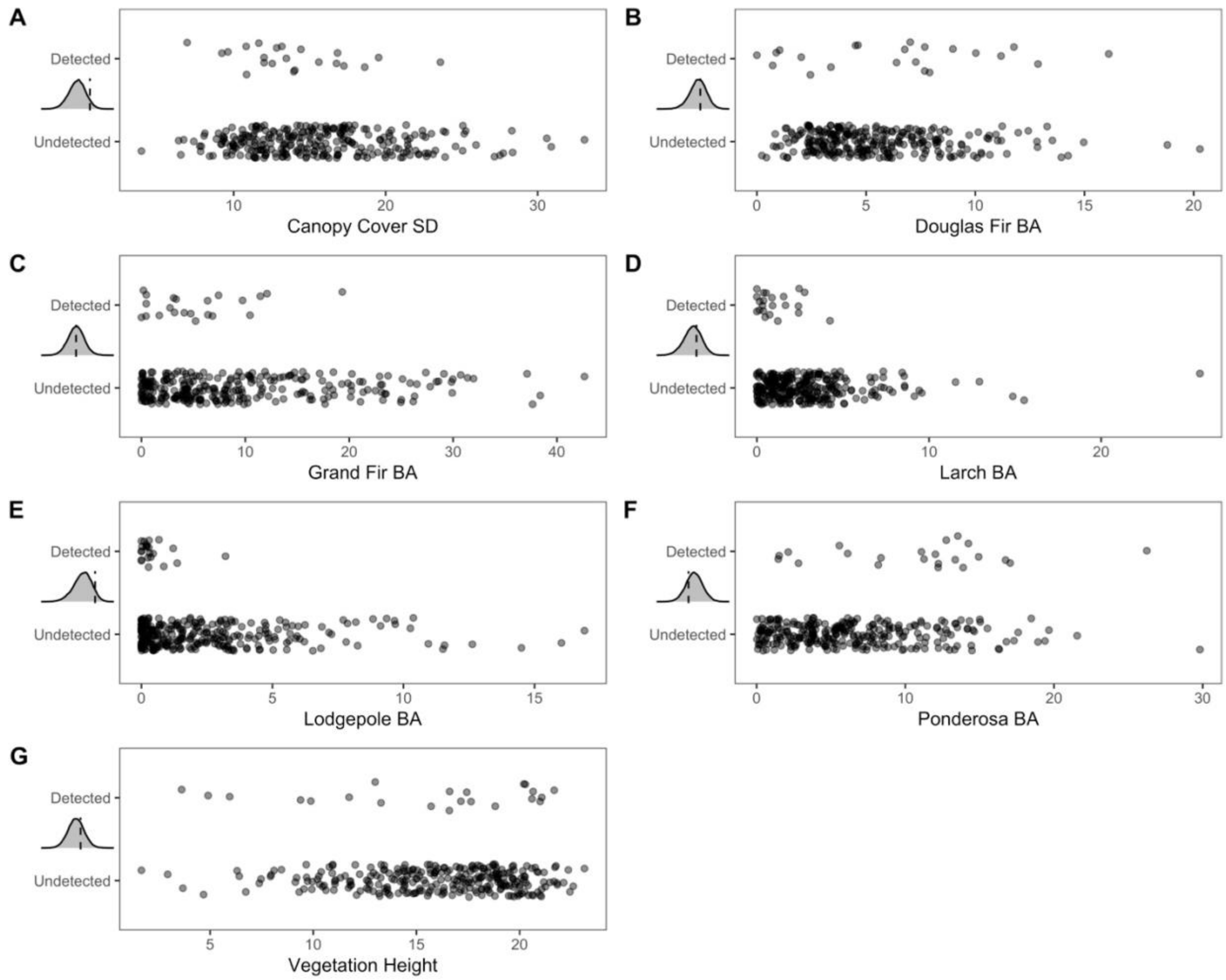

Table A.1. Environmental covariate values and descriptions. All variables were measured on a 30-m pixel resolution within 200 m radius, circular buffers centered on each station. Basal area was measured in m^2/ha. Covariate data were generated from the 2021 gradient nearest neighbor (GNN) data created by the Landscape Ecology, Modeling, Mapping & Analysis (LEMMA) research group (Bell et al. 2024) and the LANDFIRE database (LANDFIRE 2016).

Covariate Name	Mean	SD	Min	Max	Description
Western Larch Basal Area	2.76	2.78	0	25.73	Basal area of Western Larch (*Larix occidentalis*) within each buffer
Douglas Fir Basal Area	5.53	3.22	0	20.28	Basal area of Douglas Fir (*Pseudotsuga menziesii*) within each buffer
Ponderosa Pine Basal Area	6.68	5.04	1.74	29.81	Basal area of Ponderosa Pine (*Pinus ponderosa*) within each buffer
Lodgepole Pine Basal Area	2.39	2.88	0	16.91	Basal area of Lodgepole Pine (*Pinus contorta*) within each buffer
Vegetation Height	15.91	4.07	1.67	23.14	Average height of all vegetation, measured in meters
Canopy Cover	45.89	14.62	3.72	77.66	Average percent canopy cover of all live trees
Canopy Cover SD	15.40	4.87	3.93	33.08	Average standard deviation in percent canopy cover of all live trees
Elevation	1416.65	175.26	990.28	1866.09	Average elevation of survey station, measured in meters above sea level

Table A.2. Global model summaries (means, standard deviations (SD), and upper/lower credible intervals) showing detection and occupancy probability estimates for White-Headed Woodpeckers on the Umatilla and Wallowa-Whitman National Forests, 2022 and 2023 breeding seasons. Estimates are presented on a logit scale. Relationships between each covariate and the occurrence data are displayed in Supplementary Figure 2.

Detection Model

Variable	Mean	SD	2.50%	97.50%
Intercept	0.195	0.758	-1.222	1.756
Monitoring Hours	-0.427	0.228	-0.882	0.007
Day of Year	-0.476	0.311	-1.072	0.139
Canopy Cover	-0.977	0.482	-1.970	-0.075
Elevation	0.167	0.405	-0.636	0.951
Year - 2023	0.713	0.814	-0.946	2.243

Occupancy Model

Variable	Mean	SD	2.50%	97.50%
Intercept	-4.843	0.750	-6.415	-3.469
Grand Fir BA	0.005	0.653	-1.292	1.293
Larch BA	-0.343	0.777	-1.942	1.116
Lodgepole Pine BA	-1.142	0.826	-2.900	0.335
Ponderosa Pine BA	0.350	0.507	-0.649	1.352
Douglas Fir BA	-0.130	0.485	-1.141	0.793
Canopy Cover SD	-0.720	0.477	-1.687	0.181
Average Vegetation Height	-0.312	0.557	-1.396	0.775
Random Effect of Hexagon	2.719	0.752	1.460	4.385