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Research Article

Understanding *Picoides articus* (Black-backed Woodpecker) occupancy in fire-suppressed forests of the northern Blue Mountains, USA

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ABSTRACT

Fire is a significant disturbance agent, impacting forest structure and composition. In fire-adapted forests, fire can foster biodiversity by resetting successional processes and increasing habitat heterogeneity. However, fire suppression practices have altered historical fire regimes and left fire-adapted ecosystems largely unburned and the use of unburned forests by post-fire habitat specialists is understudied. *Picoides arcticus* (Black-backed Woodpecker) is a post-fire specialist that thrives in recently burned coniferous forests by exploiting heterogeneous patches of live and dead trees. Despite being a regional species of conservation concern, its occurrence and habitat use remains poorly understood in the managed forests of the northern Blue Mountains of Washington and Oregon, USA. Here, we combine passive acoustic monitoring and Bayesian occupancy modeling to understand *P. arcticus* occurrence across two National Forests during the breeding season. We examined how the prevalence of prominent tree species, attributes of forest structure, and fire history relate to occurrence. We found the odds of *P. arcticus* occupancy was 3.67 times larger for every 2.88 m^2 ha^{-1} increase in lodgepole pine (*Pinus contorta*) basal area and 2.16 times higher with every 5.04 m^2 ha^{-1} increase in ponderosa pine (*P. ponderosa*) basal area. The small number of survey stations classified as burned limited our ability to identify an effect of fire history. Our findings provide insight into how a fire-adapted species is using largely unburned forest. We also fill important knowledge gaps for a priority species of conservation concern by creating a species distribution map. Collectively, this information can inform active forest management and conservation decisions.

Keywords: cavity nester, fire suppression, habitat use, occupancy, unburned forest

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LAY SUMMARY

- Fire has long shaped forests and the biodiversity they support.
- Years of fire suppression have altered forests of the western USA, and it is not well understood how fire-adapted species use fire-suppressed forests.
- We passively measured soundscapes at nearly 300 locations in the northern Blue Mountains of Oregon and Washington, USA, to quantify the occurrence of breeding *Picoides arcticus* (Black-backed Woodpecker), a species commonly associated with burned forests.
- *Picoides arcticus* were more often found in areas that had more lodgepole and ponderosa pine trees.
- We did not find a clear link between woodpecker presence and fire history in this region, likely because few of our sampling sites burned in the last 10 yr.
- Our results provide the first regional species distribution map and offer insights for land managers on how different forest treatments and changing environmental conditions may impact *P. arcticus*.

Entendiendo la ocupación de *Picoides articus* en bosques con supresión de fuego en las Montañas Azules del norte, EUA

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RESUMEN

El fuego es un agente de perturbación significativo que afecta la estructura y la composición de los bosques. En bosques adaptados al fuego, el fuego puede favorecer la biodiversidad al reiniciar los procesos sucesionales y aumentar la heterogeneidad del hábitat. Sin embargo, las prácticas de supresión del fuego han alterado los regímenes históricos de incendios y han dejado a los ecosistemas adaptados al fuego en gran medida sin quemarse, y el uso de bosques no quemados por especialistas de hábitat post-incendio ha sido poco estudiado. *Picoides arcticus* es un especialista post-incendio que prospera en bosques de coníferas recientemente quemados al explotar parches heterogéneos de árboles vivos y muertos. A pesar de ser una especie de interés regional para la conservación, su ocurrencia y uso del hábitat siguen siendo poco comprendidos en los bosques manejados de las Montañas Azules del norte de Washington y Oregón, EUA. Aquí combinamos monitoreo acústico pasivo y modelado bayesiano de ocupación para comprender la ocurrencia de *P. arcticus* en dos Bosques Nacionales durante la temporada reproductiva. Examinamos cómo la prevalencia de especies arbóreas dominantes, los atributos de la estructura forestal y el historial de incendios se relacionan con la ocurrencia. Encontramos que la probabilidad de ocupación de *P. arcticus* fue 3,67 veces mayor por cada incremento de 2,88 m^2 ha^{-1} en el área basal de *Pinus contorta* y 2,16 veces mayor por cada incremento de 5,04 m^2 ha^{-1} en el área basal de *P. ponderosa*. El reducido número de estaciones de muestreo clasificadas como quemadas limitó nuestra capacidad para identificar un efecto del historial de incendios. Nuestros resultados aportan información sobre cómo una especie adaptada al fuego utiliza bosques en gran medida no quemados. Además, cubrimos vacíos de conocimiento importantes para una especie prioritaria de conservación mediante la creación de un mapa de distribución de la especie. En conjunto, esta información puede orientar decisiones de manejo forestal activo y de conservación.

Palabras clave: ave que anida en cavidades, bosque no quemado, ocupación, supresión del fuego, uso del hábitat

INTRODUCTION

Fire is a significant natural disturbance agent that impacts both forest structure and composition. Despite its destructive potential, fire plays a vital ecological role in fostering biodiversity in fire-adapted ecosystems by resetting successional processes and increasing habitat heterogeneity (Martin and Sapsis 1992, He et al. 2019, Jones and Tingley 2022). For example, in the southeastern United States of America (hereinafter, USA), frequent low-intensity fires help maintain the open canopy and grassy understory in longleaf pine savannah ecosystems that, in turn, provide important habitat to a multitude of avian species (Allen et al. 2006). In many forests of the western USA, however, prolonged fire suppression, stemming from historical forest management, has disrupted modern fire regimes (Reilly et al. 2017, Parks et al. 2025). As a result, fire-adapted forests experience fewer natural fires than historically necessary to maintain their structure, composition, biodiversity, and ecological health. In turn, fuel loads are increasing, leading to more destructive and severe wildfires (Millar and Stephenson 2015). This shift in fire regime and forest structure has created a significant knowledge gap regarding how fire-adapted species use habitats in modern forest ecosystems. Addressing this knowledge gap is essential for forest management that aims to conserve fire-dependent biodiversity, even during periods of active fire suppression.

Picoides arcticus (Black-backed Woodpecker) is a post-fire specialist that thrives in recently burned coniferous forests across western North America (Tingley et al. 2018). Natural wildfire regimes create mosaic landscapes with patches of live and dead trees that *P. arcticus* exploits (Stillman et al. 2019, 2023). Specifically, this species benefits from heterogeneously dispersed patches of live and dead trees by primarily foraging on abundant woodboring beetle larvae (Cerambycidae and Buprestidae; Tremblay et al. 2020, Stillman et al. 2022). Although they are strongly associated with snag-rich post-fire habitats, *P. arcticus* also utilize green forest patches by nesting in live trees, particularly favoring lodgepole pine (*Pinus contorta*) with heart rot (Goggans et al. 1987, Fogg et al. 2014, Kerstens and Rivers 2023). These patch effects create a dynamic and ephemeral niche that supports *P. arcticus* (Tarbill et al. 2015, Stillman et al. 2019). Once established, *P. arcticus* serves as an ecosystem engineer, shaping succession dynamics and modifying post-fire habitats through cavity excavation, with occupancy typically peaking 2–3 yr after fires (Saab et al. 2007, Saracco et al. 2011, Tarbill et al. 2015, Tingley et al. 2020). *P. arcticus* is designated as a candidate species for listing by the Washington Department Fish and Wildlife (Washington Department of Fish and Wildlife 2025) and a sensitive species of management concern by the Oregon Department of Fish and Wildlife (Oregon Department of Fish and Wildlife 2025). However, the species has predominantly been studied in the Sierra Nevada (Saracco et al. 2011, Fogg et al. 2014, Tarbill et al. 2015, Tingley et al. 2020, Stillman et al. 2023) and southern Cascades ecoregions (Bull et al. 1986, Goggans et al. 1987, Verschuyl et al. 2021, Kerstens and Rivers 2023), which encompass a relatively small proportion of *P. arcticus*' range.

Given the relatively limited information on the habitat preferences of *P. arcticus* outside of the Sierra Nevada and southern Cascades ecoregions, along with their importance in shaping forest ecosystems, we set out to understand how *P. arcticus* use the fire-suppressed forest habitats in the northern Blue Mountains. In particular, we employed passive acoustic monitoring (PAM) to collect detection/non-detection data on *P. arcticus* and we then fit Bayesian occupancy models to identify ecologically and management relevant habitat characteristics that best predict *P. arcticus* occurrence. For example, previous evidence has linked lodgepole pine (*Pinus contorta*) and snag availability to *P. arcticus* foraging ecology and nest site selection (Tremblay et al. 2020) and we predicted these two variables would be positively related to *P. arcticus* occurrence. We also predicted *P. arcticus* occupancy would be positively related to areas that were burned in the last 1–5 yr and then subsequently decline (Saab et al. 2007). We used the resulting occupancy model to predict *P. arcticus* occurrence across the entire study region to help inform forest management in an otherwise data deficient landscape. By examining the occurrence of this fire-adapted species in the largely fire-suppressed northern Blue Mountains, our study provides valuable insights into how such species persist under altered fire regimes.

METHODS

Study Area

We conducted this study on the Wallowa-Whitman and Umatilla National Forests, located in the Northern Blue Mountains of Northeastern Oregon and Southeastern Washington, USA, in 2022 and 2023 (Figure 1). Prominent vegetation types of the northern Blue Mountains include Columbia Plateau Western Juniper Woodland and Savannah, Inter-mountain Basins Big Sagebrush Steppe, Northern Rocky Mountain Dry-Mesic

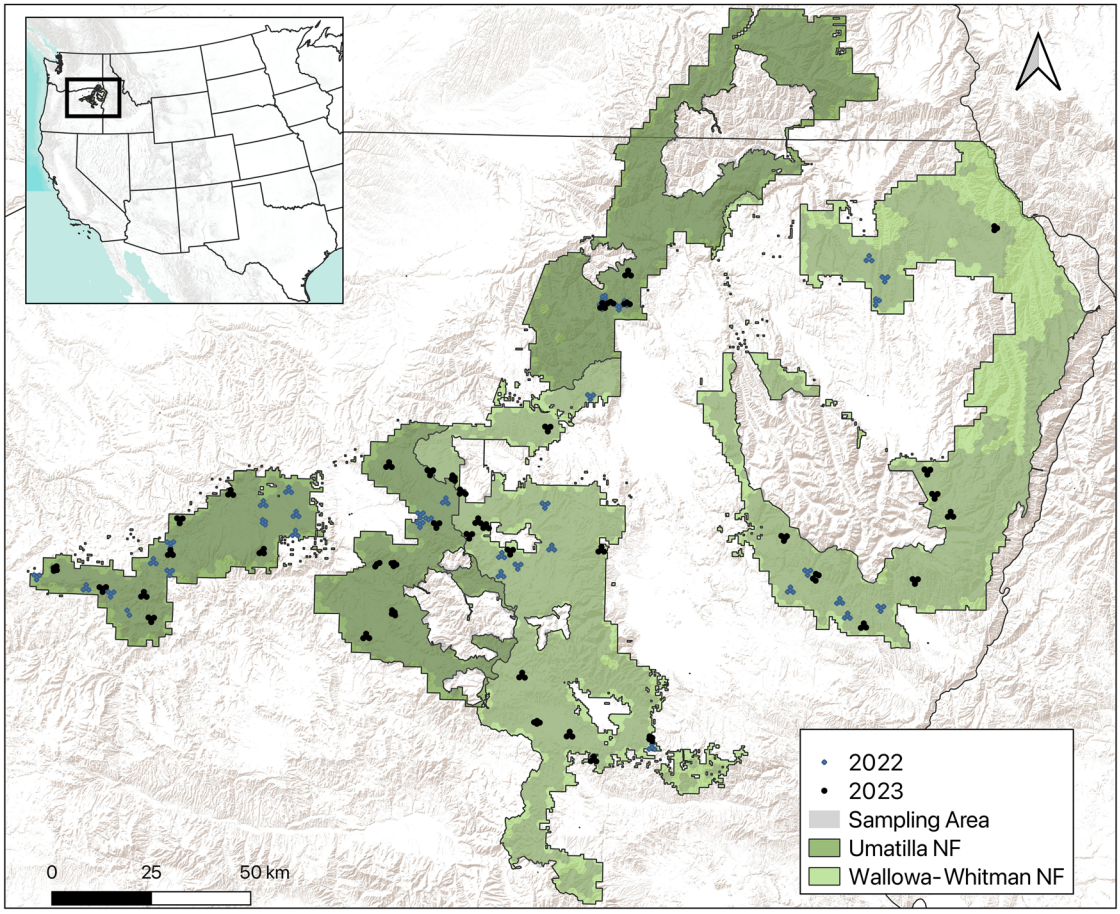

FIGURE 1. Map of survey stations on the Umatilla and Wallowa-Whitman National Forests. Blue diamonds and black circles indicate locations where autonomous recording units were deployed between May 1st and June 31st in 2022 and 2023. Inset map shows the study area (black box) relative to the Western USA Dark and light green areas depict the Umatilla and Wallowa-Whitman National Forests (NF), respectively. Shaded area denotes the extent of the sampling area defined by extent of forested habitat and land ownership.

Montane Mixed Conifer Forests, Rocky Mountain Subalpine Dry Mesic Spruce Fir Forest, and Northern Rocky Mountain Ponderosa Pine Woodland and Savannah (Thompson 2001). Dominant tree species include ponderosa pine (*Pinus ponderosa*), western larch (*Larix occidentalis*), Engelmann spruce (*Picea engelmannii*), Douglas fir (*Pseudotsuga menziesii*), lodgepole pine, and grand fir (*Abies grandis*). Elevation in the Northern Blue Mountains ranges from 762 to 2,700 m above sea level and lower elevation habitats receive <250 mm of precipitation while higher elevation, mountainous habitats can receive >2,030 mm of precipitation (Altman and Bresson 2017). The Umatilla and Wallowa-Whitman National Forests have a complex land management history, where fire-adapted forests have been shaped by both natural disturbances and human interventions (Mutch et al. 1993, Agee and Maruoka 1994, Reilly et al. 2017). The preferential harvesting of old-growth ponderosa pine along with fire-suppression practices have led to the encroachment of dense stands of mid-successional fir-dominated forests (Altman and Bresson 2017). Estimates show that the proportion of late successional ponderosa pine-dominated forest in the Blue Mountains declined from 80% to 25% in between 1936 and 1992 (Hessburg et al. 1994).

Sampling Design

We developed a 500-ha hexagon tessellation sampling frame that spanned both national forests, where each hexagon contained up to four survey stations. Two hexagons had 2 stations, 6 hexagons had 3 stations, and 68 hexagons had 4 stations. In 2022, we selected hexagons using a stratified random sampling design by first categorizing hexagons based on their intersection with proposed forest treatment types (i.e., commercial thinning, non-commercial thinning, prescribed burns, and no treatment). In 2023, we used the same hexagonal sample frame as 2022, but we selected hexagons using simple random sampling across both national forests. The simple random sampling differed from the stratified random sampling in that we did not consider proposed treatment types before selecting hexagons. In both years, we omitted hexagons that contained relatively few forest-capable lands (Davis et al. 2015) on federal property (<25% and <50% in 2022 and 2023, respectively). Hexagons were also omitted if they were deemed unsafe for fieldwork (typically based on steepness) or predominantly comprised wilderness or experimental forest lands. We surveyed 44 hexagons (172 survey stations) in 2022 and 43 hexagons (170 survey stations) in 2023. A more detailed description of our sampling design is provided in Duarte et al. (2024).

Passive Acoustic Monitoring

We collected audio recordings using autonomous recording units (ARUs). In 2022, we used Song Meter 4 and Song Meter 4 Mini Bat units equipped with acoustic microphone stub attachments and, for the 2023 field season, we primarily used Song Meter Mini and Song Meter 4 Mini Bat units equipped

with acoustic microphone stub attachments (Wildlife Acoustics, Inc., Maynard, MA, USA). A sampling rate of 32,000 Hz was used both in years. We mounted ARUs on trees with a diameter at breast height (DBH) of <30 cm and placed them ~1.5 m above ground level. To minimize noise interference and tampering with equipment, we cleared branches within a 30-cm radius of the ARUs prior to deployment and placed ARUs at minimum 50 m from roads, trails, and loud streams.

We designed the recording and deployment schedule to capture soundscapes during times associated with avian activity patterns (Singer et al. 2025). Specifically, ARUs recorded continuously for 2 hr before and 2 hr after sunrise, 1 hr before and 3 hr after sunset, and for 10 min at the top of every hour. We deployed ARUs starting May 10, 2022 and April 24, 2023. The varying start dates of deployments reflect differences in snowpack and personnel availability. We retrieved ARUs from the field after being deployed for a minimum of three weeks, although ARUs often remained deployed in the field for longer. This led us to monitor survey stations before (2023) and after (2022 and 2023) the nesting season. However, we subsequently filtered all of the monitoring data to only contain data collected during periods when *P. arcticus* nest in our region and occupancy is considered to be static (i.e., May 1st to June 31st).

Audio Processing and Detection Validation Protocol

We processed recordings with BirdNET v2.4 (Kahl et al. 2021) using the default settings. We grouped species detections by station and sampling week, wherein the first day of deployment was designated as Day 1 and the first 7 days of recordings at each station were classified as sampling week 1. We considered every subsequent 7-day period a new sampling week. We excluded sampling weeks that included May 1st or any preceding dates and sampling weeks containing or occurring after July 1st. We applied this filtering scheme to avoid sampling migratory movements and the post-fledging period, when adult home range size fluctuates (Tremblay et al. 2020). By restricting our sampling period, we minimized any potential violations of the closure assumption of occupancy models (MacKenzie et al. 2002) and we also better standardized the sampling window for both years.

We manually reviewed BirdNET detections using the Simple Passive Acoustic Monitoring protocol described in Vernasco et al. (2025). We used BirdNET confidence scores to prioritize manual review of BirdNET detections. Specifically, we filtered *P. arcticus* detections at each station during each sampling week to those with a BirdNET confidence score >0.5 and ranked in descending order by BirdNET confidence score, a unitless measure ranging from 0 to 1 that quantifies BirdNET's certainty in its species prediction (Wood and Kahl 2024). We then selected the top 50 detections from each sampling week at each station for manual validation. We reviewed all available detections for weeks with fewer than 50 detections.

We considered 3 true positive detections in a given survey period as evidence that a station is occupied by *P. arcticus*. We chose the threshold of 3 to balance reducing the likelihood of an unoccupied station being considered occupied with the amount of effort associated with the manual review of detection data. This threshold minimizes the odds that a survey station is considered occupied due to transient birds (i.e., *P. arcticus* that are simply passing through an area without establishing a territory). During review, we classified *P. arcticus* detections as either true or false positive detections. A true positive detection was determined by the presence of a *P. arcticus* specific call type that we could confidently identify. Call types included a short, sharp, shrill "kip" and/or a "kip" accompanied by a harsher, rasping sound (Tremblay et al. 2020).

Fire and Habitat Covariates

We quantified habitat and fire histories within a 200-m radius, circular buffer centered on each survey station to capture relevant habitat characteristics while preventing overlap between buffers at adjacent stations. To assess the effects of time since fire on *P. arcticus*, we created a 4-level categorical variable relating to 4 time intervals: fire within the last year, fire within the last 2–5 yr, fire within the last 6–10 yr, and no fire in the last 10 yr. We classified stations within a given fire-history category if at least one 30-m^2 pixel within them had burned during the relevant time interval. This temporal stratification accounts for the successional changes in vegetation and habitat suitability for *P. arcticus*, which are known to respond to fire-disturbed habitats differently depending on time since fire disturbance (Saab et al. 2007). We gathered fire history from the Fuel Disturbance Atlas from LANDFIRE (2016), a comprehensive dataset covering the conterminous USA.

To select habitat covariates, we identified ecologically and management relevant forest structure and composition variables. These included the biomass (kg ha^{-1}) of snags and downed woody debris, which provide nesting habitat and relate to the abundance of wood boring beetles, the primary food source of *P. arcticus* (Tremblay et al. 2020), as well as the basal area (m^2 ha^{-1}) of different tree species (Table 1). We selected tree species due to their relevance to *P. arcticus* ecology and prominent distribution in the Blue Mountains region (Altman and Bresson 2017, Tremblay et al. 2020). We quantified habitat covariates using the 2021 gradient nearest neighbor (GNN) data from the Landscape Ecology, Modeling, Mapping & Analysis (LEMMA) research group (Bell et al. 2024). This dataset incorporates regional forest inventory plots and satellite imagery to depict vegetation across the west coast of the USA.

Detection Covariates

We included multiple covariates that may be related to our ability to detect *P. arcticus* vocalizations (Table 1). Specifically, we considered elevation, calculated as the average elevation within the 200-m radius buffer using LANDFIRE data, since elevation has previously been shown to affect detection probabilities through elevational changes in vegetation structure, species abundance or composition, or environmental factors that influence the distance noise can travel (e.g., temperature or humidity; Furnas and Callas 2015). We also included the day of year for the first day of each survey period as a detection covariate to account for seasonal changes in detection probability (Tremblay et al. 2020). We included monitoring hours (i.e., the total number of hours recorded each survey period) to account for differences in survey effort and a categorical variable denoting sampling year. Last, we included mean canopy cover, calculated using the same 200-m radius buffer and canopy cover data from LEMMA, because it can influence how sound travels in a forest and has previously been shown to impact detection probabilities (Furnas and Callas 2015).

Occupancy Modeling

We fit single-season occupancy models within a Bayesian framework to evaluate how *P. arcticus* occupancy was associated

TABLE 1. Covariate list representing variables that were predicted to correlate with either *P. arcticus* occupancy or detection probabilities in the northern Blue Mountains, USA Basal area (BA, m^2 ha^{-1}) of relevant tree species and size classes as well as biomass (kg ha^{-1}) of snags and downed wood at various diameter at breast height (DBH) classifications are indicated.

Occupancy covariates
Western larch BA
Englelmann spruce BA
Douglas fir BA
Ponderosa pine BA
Lodgepole pine BA
Grand fir BA
Medium snag biomass (25–50 cm DBH)
Large snag biomass (50–75 cm DBH)
Medium downed wood biomass (50–75 cm DBH)
Large downed wood biomass (≥100 cm DBH)
Fire history (unburned in last 10 years; burned within 1 yr; burned in last 2–5 yr; burned within 6–10 yr)
Detection covariates
Day of year
Monitoring hours
Elevation (m)
Mean % canopy cover
Sampling year

See Methods for additional details. Mean, SD, and range of each covariate is provided in Supplementary Material Table S1 (see Online Supplementary Material) and their distributions by sampling year are displayed in Supplementary Material Figure S1 (see Online Supplementary Material for a color version of this figure). Day of year represents the Julian day of the first survey period and monitoring hours is the hours of recordings collected in the survey period. All covariates were continuous except for the categorical effects of fire history and sampling year. DBH = diameter at breast height.

TABLE 2. Top 10 supported models as identified using indicator variables with spike-and-slab priors.

Posterior probability	Detection covariates	Occupancy covariates
0.033	Monitoring hours + Elevation + Year	Lodgepole pine BA + Ponderosa pine BA
0.020	Monitoring hours + Elevation	Lodgepole pine BA + Ponderosa pine BA
0.018	Monitoring hours + Elevation + Year	Lodgepole pine BA + Ponderosa pine BA + Medium Downed Wood Biomass
0.016	Monitoring hours + Elevation + Year	Lodgepole pine BA + Ponderosa pine BA + Large Downed Wood Biomass
0.015	Monitoring hours + Elevation + Year + Canopy Cover	Lodgepole pine BA + Ponderosa pine BA + Medium Downed Wood Biomass
0.012	Monitoring hours + Elevation + Year + Canopy Cover	Lodgepole pine BA + Ponderosa pine BA
0.012	Monitoring hours + Elevation + Year	Lodgepole pine BA + Ponderosa pine BA + Larch BA
0.011	Monitoring hours + Elevation	Lodgepole pine BA + Ponderosa pine BA + Medium Downed Wood Biomass
0.011	Monitoring hours + Canopy Cover + Elevation	Lodgepole pine BA + Ponderosa pine BA + Medium Downed Wood Biomass
0.011	Monitoring hours + Canopy Cover + Elevation	Lodgepole pine BA + Ponderosa pine BA + Large Downed Wood Biomass

Posterior Prob. indicates the proportion of iterations the model structure was observed. Occupancy Covariates describe the covariates included in the occupancy probability model and the Detection Covariates describe the covariates in the detection probability model. All occupancy models also included a 4-level, categorical covariate describing the fire history of a given station. See Methods section for additional details.

with habitat characteristics, while accounting for imperfect detection (MacKenzie et al. 2002, Royle and Kéry 2007). Occupancy models allow for the estimation of two main parameters: occupancy probability and detection probability. Occupancy probability is the probability that at least one individual occupies the area around a survey station. Detection probability is the probability that we detected *P. arcticus* given the species occupied the area around a survey station. We modeled the two parameters as a function of the covariates described above and in Table 1. Global models for detection and occupancy probability included all covariates listed in the respective section of Table 1. A random effect denoting hexagon ID was included in the occupancy probability model to account for the spatial proximity of stations within each hexagon.

We identified covariates important to detection and occupancy 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) represented a candidate model (Royle et al. 2013). 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 (SDs) 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 did not include the fire covariate in the indicator analysis due to the known effect of fire on *P. arcticus* occupancy and the limited number of burned areas in the study area (i.e., only 14% of sampling area shown in Figure 1 has burned). However, we did include the categorical fire variable in all models fit. After identifying the top-supported model structure, the final model was refit using the uninformative prior specifications described below.

We fit occupancy models using JAGS (Plummer and others 2003) which was called from program R v4.2.0 (R Core Team 2022) using the *jagsUI* package (Kellner 2024). Before model fitting, we rescaled all continuous variables to have a mean of 0 and SD of 1. Correlation coefficients between all covariates included in the same model were >–0.7 and <0.7. For all model intercepts and coefficients aside from the slab and spike priors, we used uninformative priors with a mean of 0 and a precision of 0.368. We also specified an uninformative prior for the variance of the random effect by using a uniform distribution that ranged from 0 to 20. We fit models using three independent chains, each consisting of 20,000 iterations following a burn-in and adaption phase of 10,000 each. All parameters converged

($\hat{R}$ <1.01; Brooks and Gelman 1998). We described model parameters by their mean and 95% credible interval (CI) and reported results using the odds ratios (i.e., the odds of detection or occupancy for every 1 SD change in the covariate; Hosmer et al. 2013) of model coefficients found to be important to *P. arcticus* occurrence.

We constructed a species distribution map by predicting *P. arcticus* occurrence for each pixel within the entire study region using the parameter estimates from the top-supported occupancy model. To begin, we used a moving window analysis within the *terra* package (Hijmans 2023) to calculate habitat covariate values that match the scale of the values used in the occupancy model for each 30 m^2 pixel within the study area. The moving window analysis calculates covariate values for each pixel by averaging all pixel values within a 200 m circular buffer centered on each pixel within the sampled area. We then used the means and SD from the distributions of habitat covariates at survey stations to rescale the region-wide habitat covariate values to the scale of the values used to estimate the model coefficients. For the fire covariates, we used the 2022 regionl fire history data to categorically assigned each pixel to one of the four fire history categories. If one pixel had burned within a 200-m radius circular buffer of the pixel, it was assigned to the corresponding time-based category. After rescaling the covariate values and assigning fire histories, we used parameter estimates from the top supported model and pixel-specific covariate values to calculate the probability of occupancy for each pixel. We set the random effect term in the model to 0 such that predictions represent those of an average hexagon. We also assigned pixels within the national forest boundaries that were not forest capable (Davis et al. 2015) an occupancy value of 0.

RESULTS

Survey Effort and BirdNET Results

From 342 acoustic monitoring stations across 87 hexagons, we analyzed 99,044 hr of audio data from the 2022 and 2023 sampling seasons combined. On average, each station was surveyed for 68.51 hr per week (SD = 22.27), with a total mean survey effort per station of 255.64 hr (SD = 110.17) across the sampling period. BirdNET yielded a total of 171,211 *P. arcticus* detections with 81,201 detections from 2022 and 90,010 detections from 2023. Filtering detections with a confidence score ≥ 0.5 and selecting the top 50 detections per sampling station yielded 11,028 detections, including 4,962 and 6,066 detections from 2022 and 2023, respectively.

After omitting data collected outside the nesting season (i.e., before May 1st and after July 1st), we included data collected across 294 stations representing 76 hexagons in our analyses. The distribution of survey stations across fire history categories included stations 1-yr post-fire (n = 8), 2–5 yr post-fire (n = 16), and 6–10 yr post-fire (n = 15), and no recent fire (n = 200). The average number of weeks of sampling per survey station (±1 SD) was 3.46 (±1.24). The naïve occupancy estimate, calculated as the proportion of stations where we detected *P. arcticus*, was 0.51.

Occupancy Probability Model

We estimated an overall average occupancy probability of 0.616 (95% CI: 0.578, 0.667). Of the covariates considered in the initial global model (Table 1), two covariates—lodgepole pine basal area and ponderosa pine basal area—were identified as important to *P. arcticus* occurrence during the breeding season (Table 2). *Picoides arcticus* occupancy was positively related to lodgepole pine and ponderosa pine basal area (Figure 2, Table 3). The odds of occupancy were 3.67 times higher for every 2.88 m^2 ha^{-1} increase in lodgepole pine basal area. The odds of *P. arcticus* occupancy were 2.16 times higher with every 5.04 m^2 ha^{-1} increase in ponderosa pine basal area (Figure 2, Table 3). No strong relationships were found between *P. arcticus* occupancy and time since fire as all CIs for the estimated model coefficients overlapped zero (Table 3, Figure 3).

The estimated probability of *P. arcticus* occupancy across both national forests as determined by the top-supported occupancy model is illustrated in Figure 4. Occupancy was relatively lower in the northern Umatilla National Forest, with the exception of the far northern area that burned in the last 2–5 yr. Occupancy was also found to be relatively higher in the southwestern Wallowa-Whitman National Forest in areas that burned and wherein both *Pinus* species are particularly abundant. The canyonlands of the northeastern Wallowa-Whitman National Forest had low occupancy due to the lack of forested habitat.

Detection Probability Model

Mean detection probability for a single week of sampling effort was moderate, 0.476 (95% CI: 0.427, 0.475), but cumulative detection probability (i.e., the probability of detecting the species across a survey season when present) increased to 0.93 after 4 weeks of sampling effort. Of the covariates considered in the initial global detection model (Table 1), 3 covariates—number of monitoring hours, elevation, and sampling year—were identified as important to *P. arcticus* detection during the breeding season (Table 2). Detection probability was positively correlated to the number of monitoring hours per survey period (Table 3). An increase in monitoring hours by 22.7 hr per 7-day survey period increased the odds of detection by a factor of approximately 1.70. Detection probability was negatively correlated with elevation (Table 3), with the odds of detection being 1.49 times lower with every 175-m increase in elevation. Detection probability was also lower in 2023, with the odds of detection being 1.59 times lower in 2023.

DISCUSSION

We examined how forest structure and composition as well as fire history relate to the occurrence, habitat use, and distribution of a species of conservation concern in an otherwise data deficient area. We found that *P. arcticus* occurrence was positively correlated with lodgepole pine basal area and ponderosa pine basal area. Using these results, we developed the first species distribution map for *P. arcticus* in this region, which managers can use to inform land management decisions related to forest management and promote the conservation of this species. *Picoides arcticus* plays a key role in forest succession, especially in the context of ongoing challenges posed by fire suppression and drought. Thus, maintaining suitable habitat conditions for this species of conservation concern has a direct link to maintaining forest integrity.

The relationship between *P. arcticus* occurrence and lodgepole pine and ponderosa pine is consistent with previously

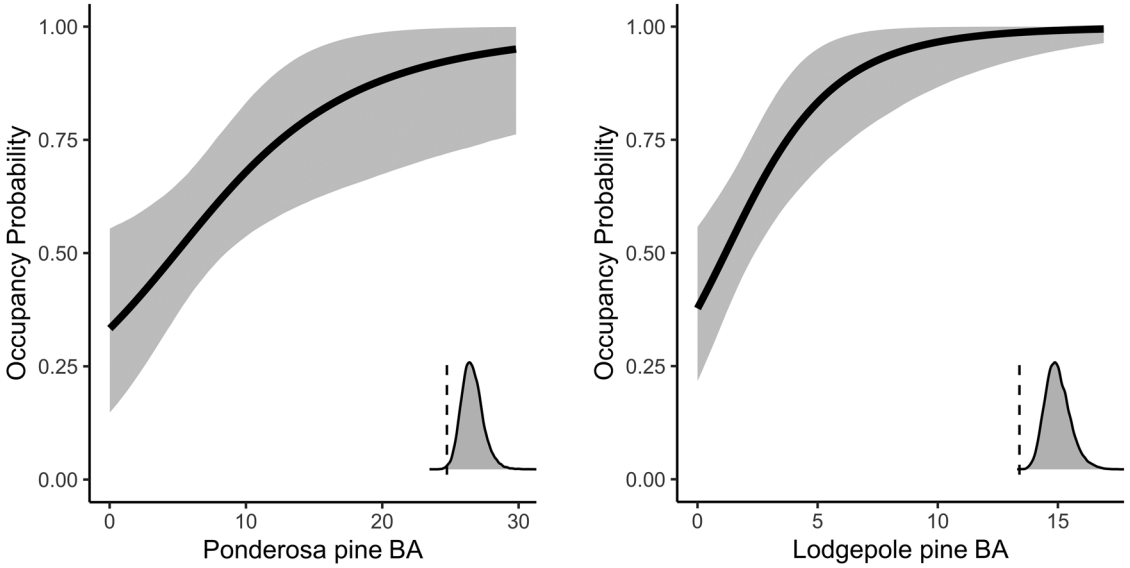

FIGURE 2. *Picoides arcticus* (Black-backed Woodpecker) occupancy probability increased with ponderosa pine and lodgepole pine basal area. The shaded region represents 95% credible intervals. Inset graphs show the posterior probability distribution of the slope estimates relative to 0 (i.e., dashed line).

TABLE 3. Model summaries (means, SD, and upper/lower 95% credible intervals) showing model intercepts and coefficients of the top-supported detection and occupancy models.

Variable	Mean	SD	Lower 95%	Upper 95%
Detection probability				
Intercept	0.105	0.140	–0.168	0.376
Monitoring hours	0.535	0.104	0.336	0.743
Elevation	–0.388	0.128	–0.636	–0.139
Year—2023	–0.457	0.195	–0.842	–0.067
Occupancy probability				
Intercept	0.684	0.322	0.121	1.390
Ponderosa pine BA	0.769	0.323	0.202	1.472
Lodgepole pine BA	1.300	0.424	0.576	2.239
Fire within 1 yr	0.608	1.082	–1.451	2.817
Fire within 2–5 yr	0.657	0.868	–0.968	2.466
Fire within 6–10 yr	1.505	1.117	–0.492	3.884

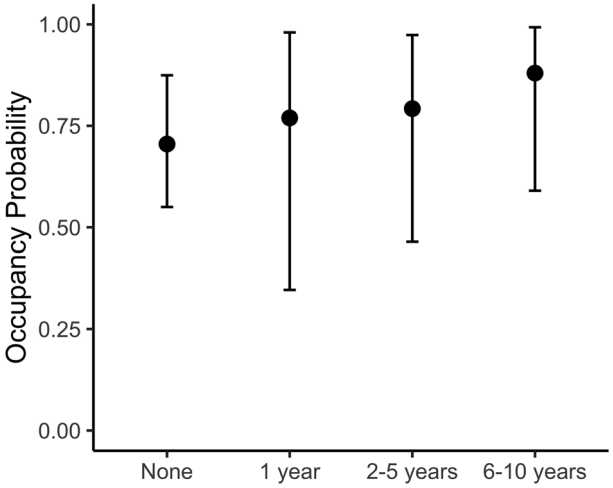

FIGURE 3. No relationship was observed between *P. arcticus* occupancy probability and time since fire. Error bars represent 95% credible intervals. Sample sizes of survey stations in each fire category are unburned in the last 10 yr (i.e., none, $n = 200$), 1 yr ($n = 8$), 2–5 yr ($n = 12$), and 6–10 yr ($n = 7$).

reported habitat associations identified in the eastern Cascades of Oregon (Goggans et al. 1987, Kerstens and Rivers 2023), the Sierra Nevada Mountains (Fogg et al. 2014), and northeastern (Bull et al. 1986) and south-central Oregon (Forristal 2009). One possible reason for this preference is that the thicker, softer sapwood of *Pinus* species relative to many other conifers makes them easier to excavate for nesting (Bull et al. 1986, Goggans et al. 1987). Another potential explanation involves the interaction between *Pinus* species and *Dendroctonus ponderosae* (mountain pine beetle), which has a history of infesting forests in the northern Blue Mountains (Wickman 1992). lodgepole pine forests typically exhibit high tree density and thin bark and are relatively more susceptible to *D. ponderosae* and other insect pests compared to many other conifer species (Altman and Bresson 2017). Indeed, *D. ponderosae* thrives in dense, mature lodgepole pine and mid-sized ponderosa pine forests across western North America (Kaufmann et al. 2008) and in the Black Hills of South Dakota (Bonnot et al. 2008). Because *P. arcticus* preys on a variety of wood-boring beetles and their larvae, including *D. ponderosae* (Tremblay et al. 2020), stands of lodgepole pine and ponderosa pine may provide important foraging opportunities. Although lodgepole pine is often used by *P. arcticus* in the early years following fire, especially for nesting, Forristal (2009) documented a shift toward greater use of ponderosa pine as the time since fire increased. This pattern is likely due to the faster decay rate of lodgepole pine snags. A closer examination of *P. arcticus* behavior and demography will be important to revealing the extent to which *P. arcticus* differentially use and rely on each tree species.

We found no clear relationship between occupancy and time since fire, despite previous research demonstrating a higher occurrence of *P. arcticus* in burned areas (Tremblay et al. 2020). The lack of a strong relationship is likely due to the limitations associated with the small number of burned survey stations in

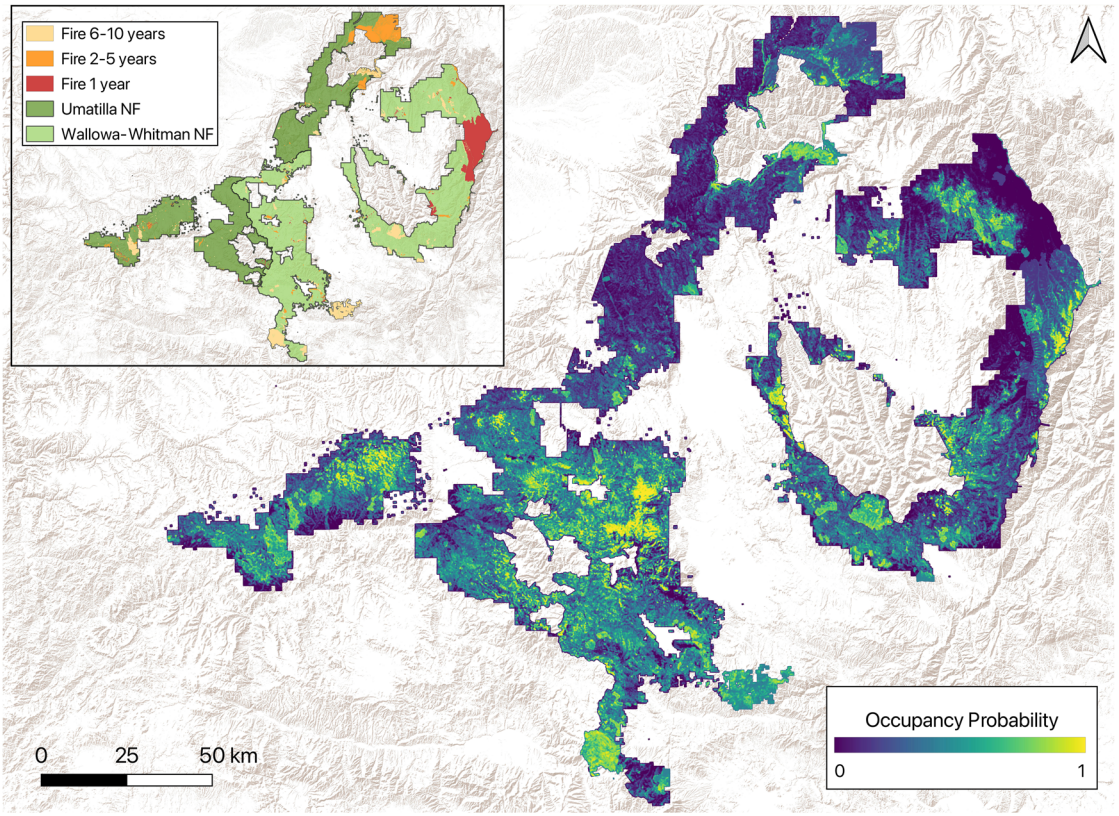

FIGURE 4. Predicted *P. arcticus* occupancy probability across the Umatilla and Wallowa-Whitman National Forests. Darker shades indicate a lower occupancy probability and lighter shades indicate a higher occupancy probability. The predicted area is limited to managed forests on the Umatilla and Wallowa-Whitman National Forests. Wilderness and experimental forests are excluded. The inset map shows the area of both national forests (NF) and the fire history relative to 2022.

our sample. The low number of survey stations classified as burned in our dataset is certainly related to our sampling design, which lacked a specific focus on monitoring burned areas, and the low percentage of the study area that has burned in the last 10 yr. Employing a stratified sampling approach, wherein survey stations are grouped by burn history and then randomly selected from within each group, can further reveal habitat use in recently burned areas. Additionally, landscape-scale monitoring efforts, wherein unburned areas burn during the monitoring period, can also clarify use of recently burned landscapes by wildlife in the fire-suppressed landscapes like the northern Blue Mountains. Nonetheless, while our results do not demonstrate a clear relationship between *P. arcticus* occupancy and fire history, it does reveal how a fire specialist is using largely unburned forests, adding to a modest yet expanding field of study (Fogg et al. 2014, Tremblay et al. 2015a, Verschuyl et al. 2021, Kerstens and Rivers 2023). As a whole, the current results reveal patterns of habitat use in unburned habitat and demonstrate the persistence of *P. arcticus* in landscapes where natural fire regimes have been disrupted.

We found no relationship between snag or dead wood biomass and *P. arcticus* occurrence, contrasting with previous studies on *P. arcticus* occupancy (Saracco et al. 2011, Tremblay et al. 2015b, Tingley et al. 2020). Indeed, *P. arcticus* is classified as a U.S.D.A. Forest Service Management Indicator Species for snags in Sierra Nevada (USDA Forest Service Pacific Southwest Region 2007). Not all studies have found snags to be an important predictor of *P. arcticus* occurrence. Verschuyl et al. (2021), for instance, analyzed *P. arcticus* occurrence in green forests of the southern Cascades Mountains in Oregon and found that neither large snag density nor basal area were related to occurrence. Fogg et al. (2014), on the other hand, found that *P. arcticus* occupancy was related to the maximum number of snags in green forests of the Sierra Nevada. The lack of the relationship between occupancy and snags found here is therefore not necessarily attributed to the fact that we studied *P. arcticus* in forests with a limited fire history. One consideration is that our snag and dead wood covariates were derived from remotely sensed data (see "Fire and Habitat Covariate" section for more details) and remotely sensed measurements of snags are known to have reduced accuracy in our study region (Bell et al. 2021). Field-measured habitat variables could therefore reveal additional relationships between *P. arcticus* occurrence, snags, and downed wood that are not captured here. Alternatively, *P. arcticus* may rely less on snags and downed wood in the unburned forests of the northern Blue Mountains, particularly since they are known to excavate cavities in live trees (Tremblay et al. 2020).

Monitoring and Management Implications

The U.S.D.A. Forest Service and its partners are implementing a management strategy to restore forests of the northern Blue Mountains to their historical structure and composition. This management strategy prioritizes multiple objectives, including improving ecosystem health, reducing wildfire risk, and providing a sustainable supply of timber. We initiated the

landscape-scale PAM program described herein to help understand the prescribed management strategies and improve their effectiveness for meeting some of the wildlife objectives. The combination of PAM, acoustic classifiers, and remote sensing we used to predict the regional *P. arcticus* distribution represents an emerging and scalable approach for understanding and informing land management within an adaptive management framework (Borker et al. 2015, Wood et al. 2024, Brunk et al. 2025). Further, the cost-effectiveness of our approach is demonstrated by our ability to (1) collect occurrence data for all reliably identifiable vocal species with just two site visits for ARU deployment and retrieval and to (2) harness the potential of publicly available, regional habitat data currently used in land management decision making.

Our current results can readily be used by land managers of the Umatilla and Wallowa-Whitman National Forests in at least three ways. First, when planning forest management activities these results can be used to assess if proposed treatment areas have a high probability of *P. arcticus* occurrence. Second, the models we developed can be used to help identify potential land management impacts on this species of conservation concern by predicting how *P. arcticus* occurrence may change locally (e.g., in treatment areas). Finally, our models can be used to make regional predictions of *P. arcticus* occurrence under contrasting fire regimes or environmental changes (e.g., an elevational shift in tree species distribution). As we accumulate additional years of monitoring data, we will also collect the data needed to evaluate and refine our model predictions with additional occurrence data. Continued acoustic monitoring will also facilitate examining patterns of occurrence dynamics across time and evaluating and informing the effects of forest treatments using an adaptive management framework (e.g., Peterson and Freeman 2016). As the U.S.D.A. Forest Service aims to increase the pace and scale of active forest management to meet multiple objectives, we believe the integration of monitoring, modeling, and management using the adaptive management framework described above will be useful for evaluating tradeoffs in management actions in the face of ecological uncertainty.

Supplementary material

Supplementary material is available at *Ornithological Applications* online.

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Ethics statement

All procedures were approved by the U.S.D.A. Forest Service Institutional Animal Care and Use Committee (Proposal #2022-004).

Conflict of interest statement

The authors declare no conflicts of interest.

Author contributions

B.J.V. and A.D. conceptualized the research question. A.D. and J.R. designed the sampling scheme and collected audio recordings. B.J.V. processed audio recordings and M.B. reviewed species detection data. B.J.V. and A.D. analyzed the data. M.B. and B.J.V. wrote the first draft of the manuscript and all authors edited subsequent drafts.

Data availability

All materials necessary to reproduce the results including the data and R code are available at Burgess et al. (2026).

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