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RESEARCH ARTICLE

High-resolution remote sensing for quantifying vegetation structure as avian habitat

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Abstract

Monitoring trends in the structure and composition of vegetation structure is a critical part of land and wildlife management. Advanced tools and technologies can help reduce the cost and improve the implementation of such monitoring. Most applications of remote-sensing technologies, however, focus on either vegetation structure reflecting habitat requirements of a single avian species or on general measures of ecosystem productivity or biodiversity. While important, these applications ignore the needs of many applied land and wildlife managers who are often legally or administratively tasked with managing landscapes for multiple avian species with divergent habitat requirements. We used current state-of-the-art technologies to assess vegetation structure in a dryland riparian ecosystem and compared this structure to avian nesting habitat metrics. We demonstrated how 3-dimensional canopy structure, including multi-layer canopy cover, voxelized leaf area density, and habitat-based patch-level leaf area density, can be quantified and tied to each species' *a priori* known nesting habitat. We evaluated these results in light of monitoring vegetation potentially serving as nesting habitat for 3 species of management concern. We also provided directions on future monitoring to ensure that managed parcels provide suitable vegetation structure for at least some, and possibly all, of the species given their divergent habitat requirements.

KEYWORDS

aerial lidar, lidar, remote sensing, vegetation structure

Land and wildlife managers use monitoring to identify undesired changes in ecological systems and monitor progress towards restoration of naturally or human-degraded systems. Most ecosystems are monitored to some extent, and each extent can present its own practical challenges. In many ecosystems, riparian zones present additional challenges because the higher average presence and availability of water stimulates additional plant growth, making manually-collected field observations and data difficult to obtain (Macfarlane et al. 2016). A separate challenge is the issue of extent, such that the size of the areas we usually wish to monitor vastly exceeds the resources available to conduct large-scale monitoring of riparian habitats (Pace et al. 2022). Both types of challenges have spurred rapid development and adoption of new conservation tools for riparian monitoring, especially focused on the use of remotely-sensed data sources such as light detection and ranging (lidar) and multispectral imagery (Macfarlane et al. 2016, Acebes et al. 2021, Lahoz-Monfort and Magrath 2021, Rusnák et al. 2022). These tools have dramatically improved our ability to understand, among many other things, riparian vegetation communities and ecosystem function (Pace et al. 2022, Rommel et al. 2022), vegetation structure (Bergen et al. 2009, Moudrý et al. 2023) avian abundance, distribution, and species richness (Mcfarland et al. 2012, Bakx et al. 2019), and general biodiversity (Acebes et al. 2021). While managers' main goals are often to identify and monitor habitat for focal species, that can be very difficult due to the complexity of habitat as a whole, so we tend to use components of habitat such as the list above as proxies for direct measures of habitat.

While powerful, useful, and important, the current applications of these tools tend to focus on either end of a spatio-ecological spectrum, i.e., general indices of ecological function and biodiversity over large spatial scales, or a highly detailed small-scale focus on habitat requirements of an individual species (Bakx et al. 2019). Both foci are necessary in their own right. Ecosystems and landscapes are large, concomitant with negative human impacts, and such general views require ignoring fine-scale patterns in order to monitor the bigger picture. This broad focus can better assist regional or global efforts aimed at monitoring and ameliorating decline in ecological structure and function (Vihervaara et al. 2017, Acebes et al. 2021, Rusnák et al. 2022). On the other hand, species-specific monitoring using remote sensing tools at small scales is also important, as individual species are often of specific management importance. Collecting better and lower cost data can improve management outcomes for those species (Hopkins et al. 2022, Hu and Tong 2022, Dickie et al. 2023). We argue that what is currently missing in this spatio-ecological spectrum is the middle ground, whereby remote sensing technologies are applied over moderate scales or levels (e.g., entirety or portions of management areas) and for vegetation structure related to multiple targeted wildlife species simultaneously (White et al. 2013, Van Lanen et al. 2023).

In contrast to focusing on broad, multi-jurisdictional questions, most land and wildlife managers work at local to regional levels, for example, in individual parks, districts, or geopolitical regions. These managers have responsibilities over some of the activities that, in aggregate, result in positive or negative impacts on local habitat and populations. For example, a manager's sphere of influence may include permitting individual energy development projects, reducing subsistence poaching in protected areas, or restoring degraded vegetation along streambanks. As part of these responsibilities, local and regional managers are also often required to implement monitoring programs for species and habitats of concern, such as at-risk species (e.g., those listed under legal frameworks such as the U.S. Endangered Species Act) or at-risk habitats (e.g., Murray-Darling Basin wetlands in Australia). Methods that increase the accuracy and decrease the cost of monitoring could be invaluable to these managers in achieving their missions.

Current applications of remote sensing of the environment focus on the ability of remotely-sensed data to address large-scale questions, often at the level of entire rivers or the distribution of a species (Rodríguez-González et al. 2017, Hopkins et al. 2022, Rusnák et al. 2022). This has allowed data to be collected at scales not previously possible, which is a huge step forward for global conservation (Vihervaara et al. 2017). However, much, or even most, of land and wildlife management activities occur at small scales such as wildlife management areas or individual river reaches. We suggest that remote sensing can also play a role in quantifying and monitoring vegetation structure that is reflective of avian nesting habitat at these smaller scales to provide a quicker, less expensive, and more comprehensive quantification of habitat structure than field sampling has traditionally provided. Some examples of remote sensing at this scale exist, such as forest stand structure for pileated woodpecker

(*Drycopus pileatus*) habitat (Hu and Tong 2022). Yet, even in that case, the focus is usually on a single species of management priority. While legal status can certainly prioritize the management of some species over others, land and wildlife managers are often interested in identifying and managing habitat for multiple species simultaneously (White et al. 2013, Van Lanen et al. 2023).

Monitoring of habitat has the added challenge of habitat reflecting interactions between individual organisms and the environment (Johnson 2007). A working definition of habitat was provided by Hall et al. (1997:175), where they defined habitat as "the resources and conditions present in an area that produce occupancy—including survival and reproduction—by a given organism." But managers must balance the depth of information desired (e.g., detailed information on reproductive habitat for a given species) with the breadth of information required (e.g., multiple habitats for multiple species). A common balance is monitoring vegetation communities that, in general, are associated with known habitat for species of interest. For example, reproductive habitat of California northern spotted owls (*Strix occidentalis occidentalis*) has been demonstrated to be positively linked to higher canopy coverage of tall trees, therefore managers often monitor the vegetation structure of forest stands only (North et al. 2017). In the current study we also monitored vegetation structure, not habitat *per se*. Point count survey data were available but were at a coarse resolution and only reflected bird presence, not necessarily habitat quality in general nor nesting habitat presence specifically (Van Horne 1983). Therefore, we compared distributional overlaps of species-specific nesting habitat variables and measured vegetation structure.

In this study, we applied high-resolution remote-sensing technologies to a small management area, but have used techniques that are scalable to a more intermediate-size management area. Clark County, Nevada, USA, is home to several state- and federally listed species of concern, including multiple threatened or endangered species. As part of a permit from the U.S. federal government to allow development of private land within Clark County, including incidental take of protected species, the Clark County Desert Conservation Program implements a habitat conservation plan that requires them to conserve and manage 76 avian, mammal, amphibian, reptile, invertebrate, and plant species. Managing multiple species, often with diverging habitat requirements, requires effective and efficient monitoring to identify declines in species abundance or habitat quality so that conservation projects can be implemented where needed (Clark County 2000). Our objective was to use multispectral imagery and aerial lidar to quantify vegetation structure for 3 bird species known to occur in our study area: Bell's vireo (*Vireo bellii*), blue grosbeak (*Passerina caerulea*), and phainopepla (*Phainopepla nitens*). Our ultimate goal was to demonstrate the use of remote-sensing tools that quantify vegetation structure for use by land and wildlife managers globally.

STUDY AREA

The 43.1-ha study area was located in the northeast Mojave Desert, in northeastern Clark County, USA, a 20,880 km^2 geopolitical division at the southern end of the state of Nevada (Figure 1). Clark County is home to the city of Las Vegas, with a metropolitan population of >1.8 million (U.S. Census Bureau 2022). The northeast Mojave Desert is characterized by winter rain and snow and summer monsoon rains (Pietrasiak et al. 2014). Precipitation is low, averaging 11 cm per year (Abella et al. 2009). The study area included the active floodplain of the Virgin River, with the river cutting through the site from east to west. The area included large portions that have been anthropogenically disturbed such as a large historic levee and areas that have been completely cleared of vegetation.

Riparian and upland vegetation were present throughout the study area. The vegetation on site was a mosaic of varying types and sizes, including arrowweed (*Pluchea sericea*), tamarisk (*Tamarix* spp.), seep willow (*Baccharis salicifolia*), big saltbush (*Atriplex lentiformis*), screwbean mesquite (*Prosopis pubescens*), and a few mature Gooding's

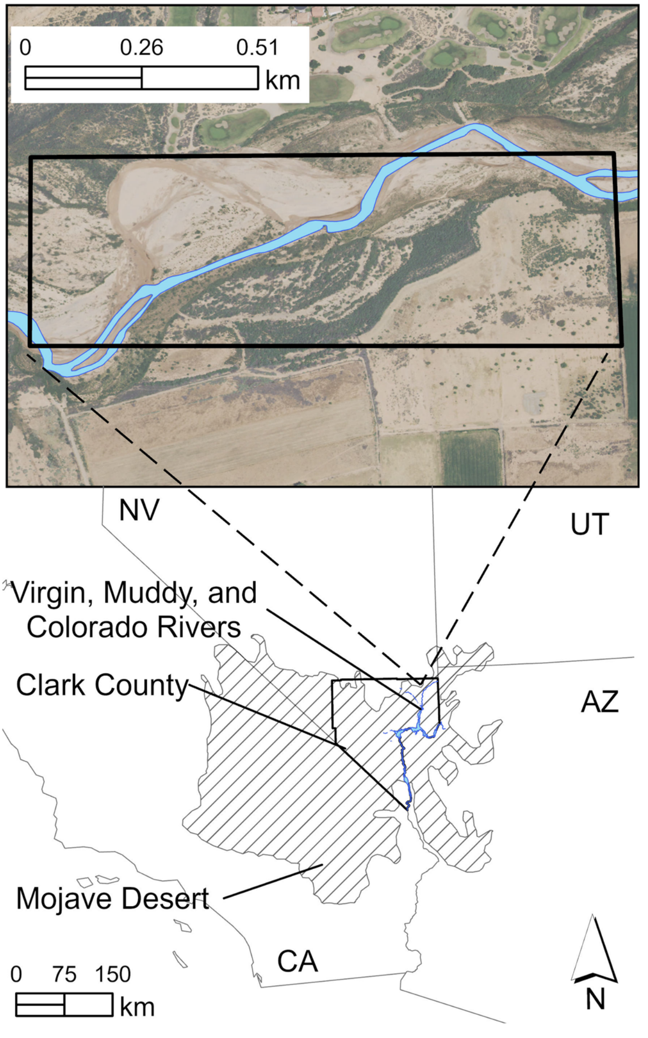

FIGURE 1 Study area for quantifying structural composition of riparian avian habitat along the Virgin River, Nevada, USA, April 2021.

willows (*Salix gooddingii*) within the floodplain itself. The tops of many of the tamarisks appeared dead, most likely as a result of repeated defoliation by the tamarisk leaf beetle (*Diorhabda carinulata*).

METHODS

To develop a suite of tools to support quantitative avian vegetation monitoring, we used imagery and aerial lidar data to conduct 3 primary analyses. These analyses were structural and included canopy height-specific percent canopy cover estimation, voxelized leaf area density (LAD), and patch-based LAD.

We focused on 3 of the avian species that Clark County is required to monitor and conserve on managed properties (blue grosbeak, phainopepla, and Bell's vireo) because these species have been observed in the study area on previous point count surveys (S. Cambrin, Clark County Department of Environment and Sustainability, unpublished data). These species are similar in that they all require trees or shrubs as nest substrates, but the types of trees and stands they nest in varies. For example, Bell's vireo nest low (~1 m) in small trees with dense understory vegetation, whereas phainopepla nest a bit higher (~3.5 m) and blue grosbeak nest high (~7–8 m) with low understory vegetation density (Powell and Steidl 2000). Phainopepla prefer lower canopy cover (~45%), whereas Bell's vireo and blue grosbeak prefer moderately high canopy cover (~60%; Powell and Steidl 2000, Allison et al. 2003).

Field data collection

We collected field data on 7–8 April, 2021, which was during the transition from winter leafless conditions (for deciduous plants) and summer leafout conditions. We chose this period to balance capturing leafed-out vegetation stands along with other management goals that required that the aerial lidar points were able to reach ground level. Thus, some of our leaf-based calculations may have been underestimates of conditions later in the avian breeding season, but we expected that they were comparable given partial leafout and permanent vegetation features (e.g., stems, perennial plants).

We collected aerial lidar using a single return Velodyne HDL-32E LiDAR sensor (Velodyne Lidar, San Jose, CA, USA) with 32 individual lasers flown on a Matrice 600 Pro hexacopter (DJI, Shenzhen, China) at a 60-m altitude. We established 5 ground control points to improve the absolute accuracy in location and measurements (distance, area, height) of all collected data. Ground control points were dispersed primarily through the southeastern two-thirds of the study area because the Virgin River restricted access to the northwestern portion of the study area. We located the ground control points using a Trimble R8 Base Station (Trimble, Westminster, CO, USA) with 1-cm root square mean error accuracy and a Trimble R10 real-time kinematic rover. We also set a CHC Global Navigation Satellite System Base Station (CHCNAV, Shanghai, China) on a surveyed point to collect position data for use in lidar trajectory processing.

Data processing and analysis

We used Waypoint Inertial Explorer (v 8.9; NovAtel, Calgary, AB, Canada) and the CHC Base Station data to process the aerial lidar flight trajectory and Global Mapper (v 22; Blue Marble Geographics, Hallowell, ME, USA) for lidar ground classification using the ground control points. Observed point density averaged 208.8 points per square meter.

Leaf area density is the total 1-sided leaf area per unit volume (i.e., m^2/m^3) and represents the density of vegetation, an important metric for breeding riparian birds (Powell and Steidl 2000). For the LAD-based structural analyses, we made calculations at the voxel level. Voxels are the regular subunits of a 3-dimensional grid the same as pixels are the regular subunits of a 2-dimensional grid, and thus, the dimensions of a voxel are defined by x, y, and z. We set the x, y dimensions as 10 × 10 m to match the field measurements of nesting desert riparian bird habitat in Powell and Steidl (2000). We set the vertical z dimension at 0.6069 m to match the California Department of Fish and Wildlife guidelines (California Department of Fish and Wildlife [CDFW] 2021) for height categories (e.g., 2-ft increments). Based on CDFW (2021), we further delineated vertical structural categories into non-breeding vegetation below 0.6069 m (i.e., 2 ft, as delineated by CDFW), small trees/shrubs between 0.6069 and 3.048 m (2–10 ft), medium trees/shrubs between 3.048 and 6.069 m (10–20 ft), and large trees/shrubs over 6.069 m (>20 ft; CDFW 2021). For simplicity from here throughout we simply refer to the height class breaks as 0.6 m, 3 m, and 6 m.

For all structural analyses, we cleaned the raw aerial lidar points file by classifying noise points using the statistical outlier analysis in the lidR package (Roussel et al. 2021) in Program R (v 4.3, R Core Team 2023). We created a digital terrain model in a geographic information system and then used this model to height-normalize the point file. We used the k-nearest neighbor approach with the inverse-distance weighting algorithm in lidR to remove the effect of variable ground heights (i.e., topography, rocks, etc.) on the absolute elevation of each aerial lidar return point. All analyses were conducted in Program R (v 4.3) and ArcMap (v 10.4).

TABLE 1 Vegetation structure of nest site locations for 3 avian species in the Mojave Desert, USA. Adapted from Powell and Steidl (2000).

Vegetation structure		Bell's Vireo	Blue grosbeak	Phainopepla
Canopy cover		64.0% (SD 25.2)	61.1% (SD 22.1)	44.9% (SD 13.9)
Vegetation volume	Understory (<2 m)	58.2% (SD 9.3)	20.8% (SD 7.6)	35.7% (SD 5.0)
	Midstory (2–5 m)	47.8% (SD 11.3)	24.4% (SD 8.1)	32.7% (SD 6.2)
	Overstory (>5 m)	21.5% (SD 11.3)	38.9% (SD 8.5)	7.3% (SD 4.6)
Nest height		0.9 m (SD 0.7)	7.1 m (SD 3.8)	3.5 m (SD 2.3)
Nest plant height		2.8 m (SD 1.3)	13.0 m (SD 5.1)	5.1 m (SD 2.7)

Canopy cover

We estimated canopy cover for each of our height classes by subsetting the height-normalized points layer into each height class, counting all aerial lidar return points within each height class and dividing the number of points within a class by the number of points in the height class of interest plus all lower height classes, including below 0.6 m and ground returns. Essentially, we calculated the proportion of points that entered each height class but did not pass through the height class. Thus a given pixel could have estimates of canopy cover for multiple height classes simultaneously (e.g. a shrub canopy under a tall tree canopy, with low vegetation cover in between those height classes). Although this can technically be described as canopy closure from a very high number of single point vantages, we refer to it as canopy cover (Jennings et al. 1999). We calculated canopy cover at a 10-m resolution raster for each of the 3 height classes of interest to align with vegetation resolution of previous nesting habitat research on our focal species (Powell and Steidl 2000; Table 1). Finally, we generated a truncated normal distribution of canopy cover associated with nesting habitat for each of the 3 avian species, where the distributions were parameterized with the means and standard deviations reported in Powell and Steidl (2000). We compared the distributions of nesting habitat canopy cover with canopy cover distributions within discrete vegetation patches within our study area.

Voxelized LAD

We calculated the LAD within each voxel cell in the analysis area, from 0.6 m aboveground to the highest observed vegetation height using the canopyLazR package (Kamoske et al. 2019) in Program R. Prior to voxelization, canopyLazR mimics a canopy height model to height-normalize the array of voxels. We then used the height-normalized array to calculate the LAD within each voxel using the method of MacArthur and Horn (1969). Finally, we created a raster stack to view and manipulate the array LAD results.

Patch-based LAD

We also separated the study area into habitat patches, using the structural categories of canopy height for nesting riparian bird species defined by CDFW (2021), specifically height classes of 0 (<0.6 m), 1 (small trees/shrubs, 0.6–3.0 m), 2 (medium trees/shrubs, 3.0–6.0 m), or 3 (large trees/shrubs, >6.0 m). First, we created a simple canopy height model with a pixel size of 10 m using the lidR package. We replaced any pixels with a value of NA with a value of 0, then smoothed the canopy height model by replacing each pixel with the mean value of its immediate neighborhood (i.e., 3 × 3 cells) using the terra package. We did this to generalize the canopy height model into a more ecologically realistic depiction, assuming that a single pixel with unusually low (i.e., a pit) or high (i.e., a single tall plant) height would still be part of the surrounding patch as defined by canopy height.

To delineate patches, we reclassified the smoothed canopy height raster, then we converted the reclassified raster into a simplified vector layer, which delineated patches of equal height classes. Next, we selected a subset of patches for visualization, retaining patches of height class 1 and 2 that were >0.8 ha (~2 ac) and all class 3 patches (all <0.8 ha). Then we calculated LAD within each discrete patch using the Bouvier et al. (2015) method implemented in lidR. Finally, we selected 3 patches and compared their vertical LAD distributions with literature-derived estimates of vegetation volume selected at 3 categories of height above ground for 2 avian species, blue grosbeak and phainopepla. Prior to plotting observed patch LAD vertical profiles, we converted height-specific vegetation volume (Table 1) into LAD values to reflect relative vegetation volume of known nesting habitat from Powell and Steidl (2000).

RESULTS

Canopy cover

Mean canopy cover of small trees/shrubs was 8.4% (SD = 12.8), 1.1% (SD = 4.4) for medium trees/shrubs, and 0.1% (SD = 3.6) for tall trees/shrubs. For all trees and shrubs over 0.6 m, mean canopy cover was 9.2% (SD = 16.0). All height classes had some grid cells with zero canopy cover or 100% cover. Most grid cells had some cover >0.6 m, although this also included tall herbaceous plants and was not necessarily trees or shrubs (Figure 2). For small trees/shrubs, 1.8% (0.76 ha) of the analysis area had small tree/shrub canopy cover >50%. For medium trees/shrub, only 0.03 ha had canopy cover >50%. No grid cells had tall tree/shrub canopy cover >70%. Mean canopy cover of all trees and shrubs, regardless of height class, was 0.09 (SD = 0.16, min–max = 0–1).

Voxelized leaf area density

The voxelized LAD provided similar information as the canopy cover, but better reflected vegetation density than simply cover. Because cover was highest at the lowest height class (i.e., 0.6–3.0 m), LAD was also highest at this height class (Figure 3). Leaf area density decreased at the 2 higher height classes but showed general homogeneity within each height class above ground at the resolution of 10-m pixels.

Patch-based leaf area density

The majority of the analysis area was comprised of 2 large patches of low trees/shrubs and one large patch of medium trees/shrubs. Leaf area density within the tall patches was more variable among patches than for small and medium height classes due to their comparably small size. For most patches, LAD profiles showed higher leaf area closer to the ground, with decreasing leaf area up to canopy tops. LAD profiles for large trees showed different vertical profiles reflecting tree physiognomy.

Avian nesting habitat

Based on canopy cover and voxelized leaf area density, we identified several patches with vegetation structure suitable for nesting habitat by our species of interest. Canopy cover was highly variable among patches, but 3 patches (Patches 5–7)

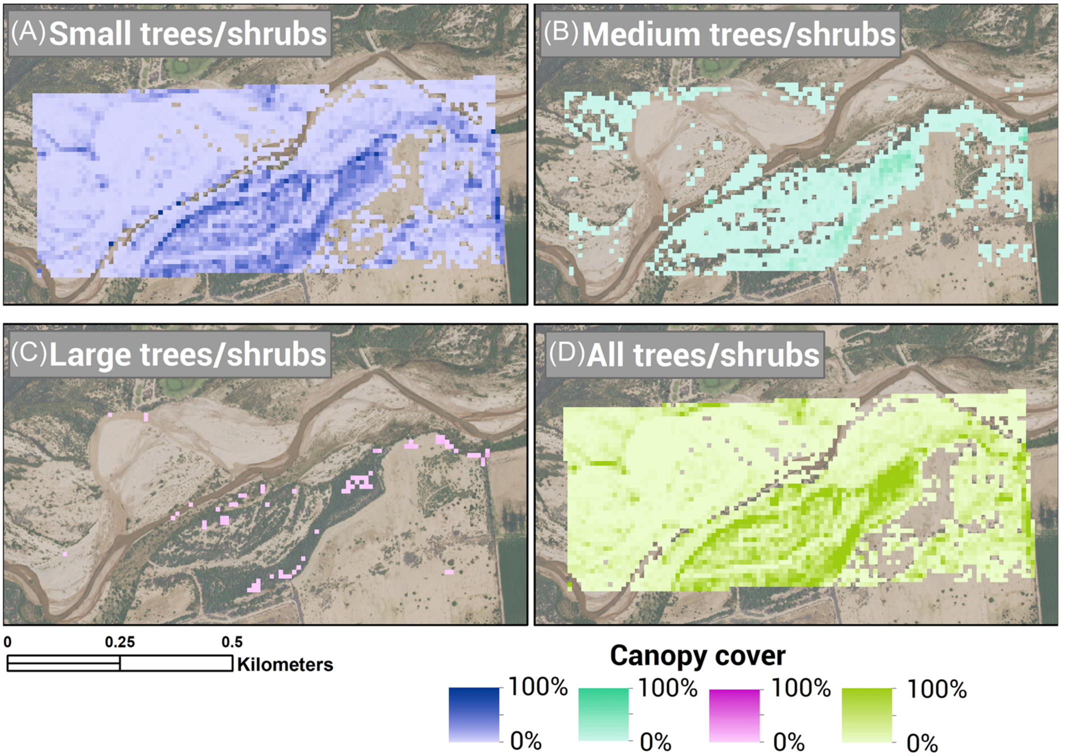

FIGURE 2 Canopy cover estimates derived from high-resolution remote sensing data for A) small (0.6–3.0 m), B) medium (3.0–6.0 m), C) large (>6.0 m), and D) all (>0.6 m) trees and shrubs along the Virgin River, Nevada, USA, April, 2021. Grid cells are 10-m resolution.

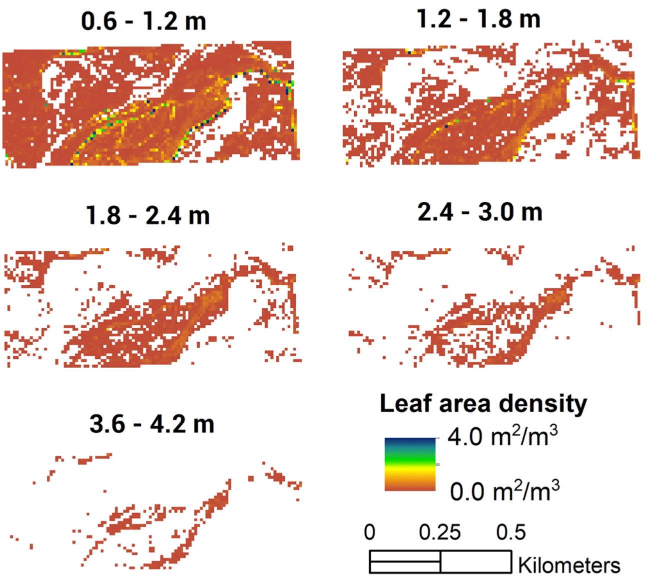

FIGURE 3 Voxelized leaf area density (m^2/m^3) at a sample of 0.6-m height classes along the Virgin River, Nevada, USA, April, 2021. Grid cells are 10-m resolution.

had distributions of canopy cover well within the observed distribution of canopy cover at nest sites (Figure 4). Patch 4 had high variability yet indicated some grid cells with suitable canopy cover, and Patches 1–3 had too low of canopy cover (Figure 4). Vertical profiles of leaf area density compared to vertical profiles of percent vegetation coverage served as a qualitative metric of suitability of patches for nesting habitat. For example, Patch 1 showed an equivalent vertical profile as that selected by phainopepla, but at lower total vegetation density (Figure 5). Patches 5 and 7, however, had vertical profiles similar to nesting stands selected by blue grosbeak and phainopepla, respectively.

Tall canopy patches were lacking within the study area, suggesting little to no nesting habitat for species that require tall, closed canopies and/or cottonwood stands. The largest single vegetation patch (Patch 1 in Figure 5), was shorter and more sparsely vegetated than nesting stands for either blue grosbeak or phainopepla. However, some small patches were of suitable canopy height, had suitable distributions of canopy cover, and had vertical vegetation density profiles similar to known nesting habitat. For example, Patch 5 roughly matched the vertical profile of vegetation volume

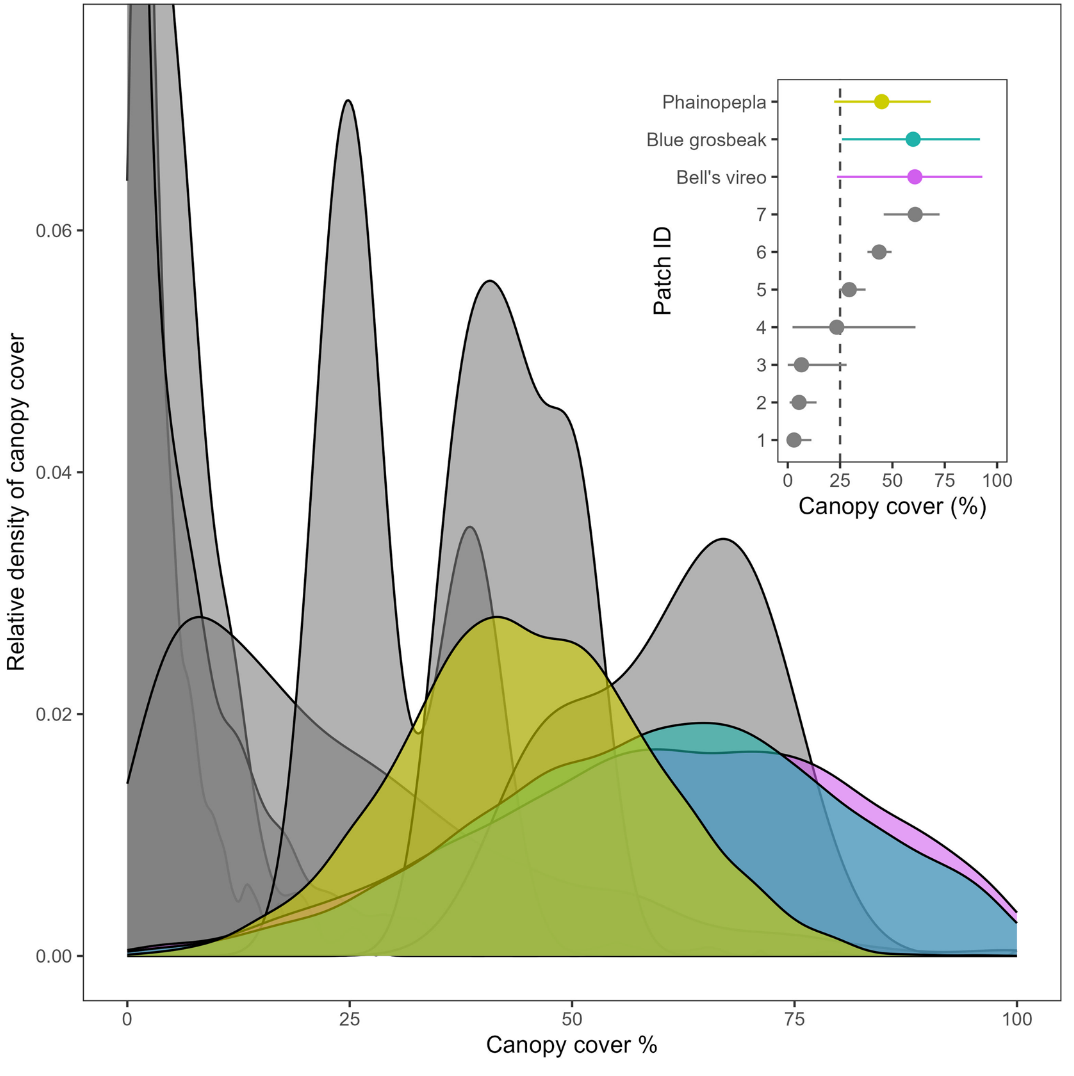

FIGURE 4 Density distributions of avian species of interest (color fill) and observed canopy cover at patches in the study area (gray fill). Inset plot is the mean (dot) and 90% interval (horizontal lines) for canopy cover. Vertical dashed line is approximate 90% minimum canopy cover for all 3 avian species.

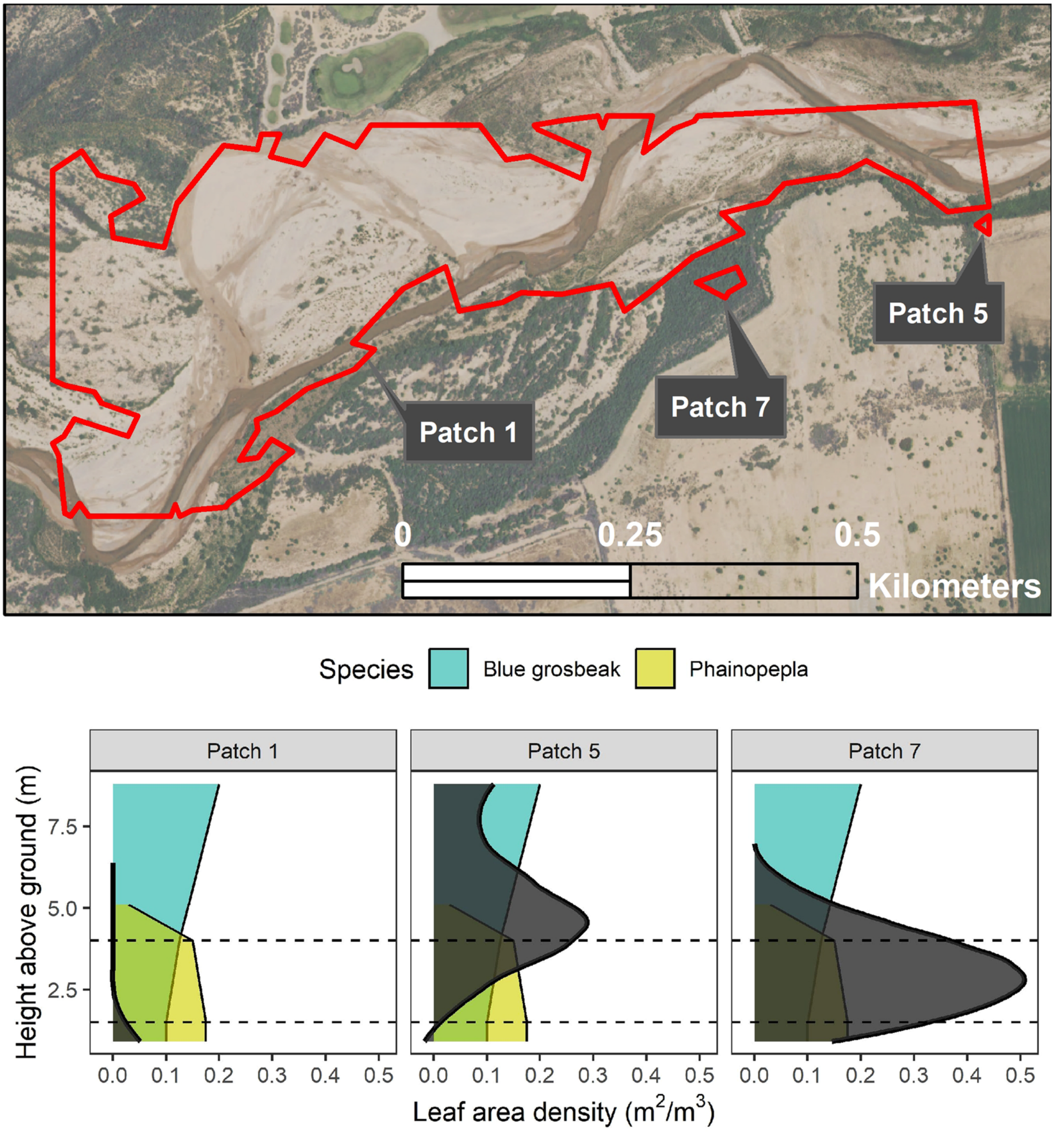

FIGURE 5 Vertical profile of leaf area density at 3 example patches (gray fill) compared to profile of relative vegetation density preferred by nesting blue grosbeak and phainopepla (adapted from Powell and Steidl 2000). Study area was in the northeastern Mojave Desert, Nevada, USA, 2021.

selected by blue grosbeaks, with low understory and high overstory density. In contrast, Patch 7 had high understory and midstory vegetation density, matching the vertical profile preferred by phainopepla.

DISCUSSION

We found that the vegetation structure in our study area likely provides nesting habitat for some but not for all of our avian species of interest. This is not necessarily a failure on the part of managers, as divergent habitat requirements of multiple species likely precludes any location from supporting all possible species. Instead, we found that the study area was likely supportive of Bell's vireo and phainopepla populations because of the generally low canopy heights and moderate canopy cover, even if much of these patches were comprised of invasive tamarisk (Haigh 1996). This is supported by independent observations of these species at this site (S. Cambrin, Desert Conservation Program, unpublished data). Patch 5 did meet the vertical profile for blue grosbeak, but the patch is small and there are no independent observations of that species in the area. We suggest that collecting similar remotely-sensed data and calculating the same metrics, but at other sites along the Virgin River, could be used to provide a more complete picture of the river's vegetative structure which would allow better inference into available habitat for all of the avian species of interest.

One important issue is that of scalability. Our field work at a 43.1-ha (106.5 ac) field site took 2 days, although it included the collection of additional data not presented in these analyses and the lidar data could have been collected in a single day. Thus, with multiple field days, data sampling could be scaled up to larger areas, especially when only a portion of the management area would benefit from such sampling. For example, desert riparian habitats are relatively narrowly confined to riparian corridors or surround ponds, lakes, and seasonally flooded marshes and thus contain substantial non-habitat that need not be surveyed if the focus is on tree-nesting riparian birds.

There are caveats to the approach we propose here. First, avian breeding habitat niches likely have fuzzy ecological boundaries. For example, waterfowl place nests nonrandomly, but do so across a gradient of vegetation structure (Clark and Shutler 1999). Thus, our application of remote sensing, while able to capture vegetation structure gradients, does not provide clear distinctions between used and unusable habitats. For example, blue grosbeak generally nest high in canopies (e.g., 7.1 ± 0.9 m, Powell and Steidl 2000), a height characteristic of individual trees in our study area but not of entire vegetation stands. Nonetheless, blue grosbeak have been observed within the study area on separate surveys, indicating occupancy (either breeding, feeding, or transitory) irrespective of our definition of blue grosbeak vegetative structure based on Powell and Steidl (2000). A second caveat to this approach is that, although it may allow for quantifying vegetation structure quickly, at high detail, and in areas inaccessible to field crews (Macfarlane et al. 2016), it requires data collection via specialized technology. Free multispectral and lidar data are often available but are at dramatically lower resolution than data collected in the field. For example, for our study area, freely available lidar data from the U.S. Geological Survey are at a resolution of 13.2 points/m^2 (U.S. Geological Survey 2021), whereas our aerial lidar data were 208.8 points/m^2. Widely available lidar data are likely not of sufficient resolution to quantify vegetation structure. A third caveat is that the methods described herein quantify vegetation structure, but not necessarily occurrence or use by the species of interest, which in some cases may be of more direct relevance to land and wildlife managers than monitoring habitat structure (MacKenzie and Nichols 2004).

Future work would strongly benefit from field studies that directly link avian occurrence, nest placement, and nest fate with similar remotely-sensed metrics of avian habitat as we have presented here. The comparison of our metrics to the field-based metrics described in reference citations hampered us, and thus comparisons were inherently imprecise (e.g., Powell and Steidl 2000). A more direct analysis would better elucidate potential thresholds in the remotely-sensed metrics to delineate habitat from non-habitat using remote-sensed data. For example, 3-dimensional coordinates of nests, compared to 3-dimensional vegetation structure metrics like those described here, would allow for definitive quantification of nesting habitat. Point counts hold some promise, but also have inherent challenges. Specifically, the precise 3-dimensional coordinates of the calling birds are usually unknown and territorial calling locations may represent location selection based on perceived visibility instead of habitat. If possible, comparison of remote-sensed vegetation structure metrics with reproductive performance would better differentiate source/sink habitats (Clark and Shutler 1999). In particular, developing 3-dimensional metrics for linking the matrix of voxels to avian nesting occurrence and success has great potential to better quantify, understand, and predict how high-resolution vegetation structure functions as habitat. Estimating nest success may be cost prohibitive for multiple species, thus focusing on nest placement may make a more cost-effective solution to obtain the necessary data. We propose that many land and wildlife managers would benefit from using very high-resolution, remotely-sensed imagery to quantify habitat both in determining vegetation structure as we did here and other uses like those mentioned in the introduction, and thus, its utility would increase with additional applied research.

MANAGEMENT IMPLICATIONS

Quantifying vegetation composition and 3-dimensional structure can help land and wildlife managers better monitor vegetation structure and its potential to serve as nesting habitat. Such quantification allows for repeatable monitoring over time at a fraction of the cost of field quantification of vegetation structure. When multiple species are of management focus, objective quantification of vegetation composition and structure can elucidate which of the suite of species are likely to be supported. For species not likely to be supported, quantification can also highlight missing structural components that can guide habitat management and restoration. Future research would benefit from linking metrics like we calculated here directly with field observations of nest locations to facilitate the transition to remote-sensed vegetation monitoring. We also note that while project-specific, remote-sensed data are necessary to quantify vegetation structure at the level of detail we did here, future developments in satellite technology will increase the resolution and availability of remote-sensed data and should be assessed as such technology is developed. The choice between using free and widely-available data versus highly detailed 3-dimensional data will require an assessment of resources available and the information needed.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

This study did not involve data collection on wild animals or humans.

DATA AVAILABILITY STATEMENT

We do not have data to submit, as all data used in these analysis are lidar and multispectral imagery files.

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REFERENCES

Abella, S. R., J. E. Spencer, J. Hoines, and C. Nazarchyk. 2009. Assessing an exotic plant surveying program in the Mojave Desert, Clark County, Nevada, USA. Environmental Monitoring and Assessment 151:221–230.

Acebes, P., P. Lillo, and C. Jaime-González. 2021. Disentangling LiDAR contribution in modelling species-habitat structure relationships in terrestrial ecosystems worldwide: a systematic review and future directions. Remote Sensing 13:3447.

Allison, L. J., C. E. Paradzick, J. W. Rourke, and T. D. McCarthey. 2003. A characterization of vegetation in nesting and non-nesting plots for southwestern willow flycatchers in central Arizona. Studies in Avian Biology 26:81–90.

Bakx, T. R. M., Z. Koma, A. C. Seijmonsbergen, and W. D. Kissling. 2019. Use and categorization of Light Detection and Ranging vegetation metrics in avian diversity and species distribution research. Diversity and Distributions 25:1045–1059.

Bergen, K. M., S. J. Goetz, R. O. Dubayah, G. M. Henebry, C. T. Hunsaker, M. L. Imhoff, R. F. Nelson, G. G. Parker, and V. C. Radeloff. 2009. Remote sensing of vegetation 3-D structure for biodiversity and habitat: review and implications for lidar and radar spaceborne missions. Journal of Geophysical Research 114:G00E06.

Bouvier, M., S. Durrieu, R. A. Fournier, and J. Renaud. 2015. Generalizing predictive models of forest inventory attributes using an area-based approach with airborne LiDAR data. Remote Sensing of Environment 156:322–334.

California Department of Fish and Wildlife [CDFW]. 2021. California Wildlife Habitat Relationship System, Version 10.1.29. Sacramento, CA. <https://apps.wildlife.ca.gov/cwhr/index.shtml> Accessed 01/15/24.

Clark County. 2000. Final Clark County Multiple Species Habitat Conservation Plan And Environmental Impact Statement for issuance of a permit to allow incidental take of 79 species in Clark County, Nevada. <https://www.clarkcountynv.gov/government/departments/environment_and_sustainability/desert_conservation_program/current_mshcp.php>. Accessed 09/25/24.

Clark, R. G., and D. Shutler. 1999. Avian habitat selection: Pattern from process in nest-site use by ducks? Ecology 80: 272–287.

Dickie, M., B. Hricko, C. Hopkinson, V. Tran, M. Kohler, S. Toni, R. Serrouya, and J. Kariyeva. 2023. Applying remote sensing for large-landscape problems: inventorying and tracking habitat recovery for a broadly distributed Species At Risk. Ecological Solutions and Evidence 4:e12254.

Haigh, S. L. 1996. Saltcedar (*Tamarix ramosissima*), an uncommon host for desert mistletoe (*Phoradendron californicum*). Great Basin Naturalist 56:186–187.

Hall, L. S., P. R. Krausman, and M. L. Morrison. 1997. The habitat concept and a plea for standard terminology. Wildlife Society Bulletin 25:171–182.

Hopkins, L. M., T. A. Hallman, J. Killbride, W. D. Robinson, and R. A. Hutchinson. 2022. A comparison of remotely sensed environmental predictors for avian distributions. Landscape Ecology 37:997–1016.

Hu, R., and S. T. Y. Tong. 2022. The use of remotely sensed data to model habitat selections of pileated woodpeckers (*Dryocopus pileatus*) in fragmented landscapes. Forest Ecology and Management 521:120433.

Jennings, S. B., N. D. Brown, and D. Sheil. 1999. Assessing forest canopies and understory illumination: canopy closure, canopy cover and other measures. Forestry 72:59–73.

Johnson, M. D. 2007. Measuring habitat quality: a review. Condor 109:489–504.

Kamoske, A. G., K. M. Dahlin, S. C. Stark, and S. P. Serbin. 2019. Leaf area density from airborne LiDAR: comparing sensors and resolutions in a forest ecosystem. Forest Ecology and Management 433:364–375.

Lahoz-Monfort, J. J., and M. J. L. Magrath. 2021. A comprehensive overview of technologies for species and habitat monitoring and conservation. BioScience 71:1038–1062.

MacArthur, R. H., and H. S. Horn. 1969. Foliage profile by vertical measurements. Ecology 50:802–804.

Macfarlane, W. W., C. M. McGinty, B. G. Laub, and S. J. Gifford. 2016. High-resolution riparian vegetation mapping to prioritize conservation and restoration in an impaired desert river. Restoration Ecology 25:333–341.

MacKenzie, D. I., and J. D. Nichols. 2004. Occupancy as a surrogate for abundance estimation. Animal Biodiversity and Conservation 27:461–467.

Mcfarland, T. M., C. Van Riper III, and G. E. Johnson. 2012. Evaluation of NDVI to assess avian abundance and richness along the upper San Pedro River. Journal of Arid Environments 77:45–53.

Moudrý, V., A. F. Cord, L. Gábor, G. V. Laurin, V. Barták, K. Gdulová, M. Malavasi, D. Rocchini, K. Stereńczak, J. Prošek, et al. 2023. Vegetation structure derived from airborne laser scanning to assess species distribution and habitat suitability: the way forward. Diversity and Distributions 29:39–50.

North, M. P., J. T. Kane, V. R. Kane, G. P. Asner, W. Berigan, D. J. Churchill, S. Conway, R. J. Gutiérrez, S. Jeronimo, J. Keane, et al. 2017. Cover of tall trees best predicts California spotted owl habitat. Forest Ecology and Management 405:166–178.

Pace, B., C. Gutiérrez-Cánovas, R. Henriques, C. Carvalho-Santos, F. Cássio, and C. Pascoal. 2022. Remote sensing indicators to assess riparian vegetation and river ecosystem health. Ecological Indicators 144:109519.

Pietrasiak, N., R. E. Drenovsky, L. S. Santiago, and R. C. Graham. 2014. Biogeomorphology of a Mojave Desert landscape – configurations and feedbacks of abiotic and biotic land surfaces during landform evolution. Geomorphology 206:23–36.

Powell, B. F., and R. J. Steidl. 2000. Nesting habitat and reproductive success of southwestern riparian birds. Condor 102: 823–831.

R Core Team. 2023. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rodríguez-González, M. P., A. Albuquerque, M. Martínez-Almarza, and R. Díaz-Delgado. 2017. Long-term monitoring for conservation management: lessons from a case study integrating remote sensing and field approaches in floodplain forests. Journal of Environmental Management 202:392–402.

Rommel, E., L. Giese, K. Fricke, F. Kathöfer, M. Heuner, T. Mölter, P. Deffert, M. Asgari, P. Näthe, F. Dzunic, et al. 2022. Very high-resolution imagery and machine learning for detailed mapping of riparian vegetation and substrate types. Remote Sensing 14:954.

Roussel, J. R., D. Auty, N. C. Coops, P. Tompalski, T. R. H. Goodbody, A. Sánchez Meador, J. F. Bourdon, F. De Boissieu, and A. Achim. 2021. lidR: an R package for analysis of Airborne Laser Scanning (ALS) data. Remote Sensing of Environment 251:112061.

Rusnák, M., T. Goga, L. Michaleje, M. S. Michalková, Z. Máčka, L. Bertalan, and A. Kidová. 2022. Remote sensing of riparian ecosystems. Remote Sensing 14:2645.

U.S. Census Bureau. 2022. 2020 census of population and housing, population and housing unit counts. U.S. Government Printing Office, Washington, DC, USA.

U.S. Geological Survey. 2021. USGS Lidar Point Cloud AZ_LowerColoradoRiver_2018_B18 w1593n1679: U.S. Geological Survey. <apps.nationalmap.gov/downloader>. Accessed 01/15/24.

Van Horne, B. 1983. Density as a misleading indicator of habitat quality. The Journal of Wildlife Management 47:893–901.

Van Lanen, N. J., J. E. Shyvers, C. J. Duchardt, and C. L. Aldridge. 2023. A multi-ecosystem prioritization framework to balance competing habitat conservation needs of multiple species in decline. Landscape Ecology 38:2795–2813.

Vihervaara, P., A. P. Auvinen, L. Mononen, M. Törmä, P. Ahlroth, S. Anttila, K. Böttcher, M. Forsius, J. Heino, J. Heliölä, et al. 2017. How essential biodiversity variables and remote sensing can help national biodiversity monitoring. Global Ecology and Conservation 10:43–59.

White, A. M., E. F. Zipkin, P. N. Manley, and M. D. Schlesinger. 2013. Conservation of avian diversity in the Sierra Nevada: moving beyond a single-species management focus. PLoS ONE 8:e63088.

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