Notes

Incorporating Shrub and Snag Specific LiDAR Data into GAP Wildlife Models

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Abstract

The U.S. Geological Survey's Gap Analysis Program (hereafter, GAP) is a nationally based program that uses land cover, vertebrate distributions, and land ownership to identify locations where gaps in conservation coverage exist, and GAP products are commonly used by government agencies, nongovernmental organizations, and private citizens. The GAP land-cover designations are based on satellite-derived data, and although these data are widely available, these data do not capture the 3-dimensional vegetation architecture that may be important in describing vertebrate distributions. To date, no studies have examined how the inclusion of snag- or shrub-specific Light Detection and Ranging (LiDAR) data might influence GAP model performance. The objectives of this paper were 1) to assess the performance of the National GAP models and Northwest GAP models with independently collected field data, and 2) to assess whether the inclusion of 3-dimensional vegetation data from LiDAR improved the performance of National GAP and Northwest GAP models. We included only two parameters from the LiDAR data: presence or absence of shrubs and presence or absence of snags $\geq$25 cm diameter at breast height. We surveyed for birds at$>$150 points in a 20,000-ha coniferous forest in northern Idaho and used data for eight shrub- and cavity-nesting species for validation purposes. On a guild level, National GAP models performed only marginally better than Northwest GAP models in correct classification rate, and LiDAR data did not improve vertebrate distribution models. At the scale used in this study, GAP models had poor predictive power and this is important for managers interested in using GAP models for species distributions at scales similar to ours, such as a small park or preserve $<$200 km^2 in size. Additionally, because the inclusion of LiDAR data did not consistently affect the performance of GAP models, future studies might consider whether LiDAR data affect GAP model performance by examining 1) different spatial scales, 2) different LiDAR metrics, and/or 3) species-specific habitat relationships not currently available in GAP models.

Keywords: birds; GAP; Idaho; LiDAR; shrub; snag; species modeling

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Introduction

The U.S. Geological Survey's Gap Analysis Program (hereafter, GAP) is a nationally based program that uses land cover, vertebrate distributions, and land ownership to identify locations where gaps in conservation coverage exist (e.g., Scott et al. 1993; http://gapanalysis.usgs.gov/). Primarily, GAP has modeled these conservation gaps for vertebrates using deductive modeling approaches, whereby literature and expert opinion are both incorporated into the modeling process (e.g., Aycrigg et al. 2010). Underlying assumptions of GAP are that vertebrate associations with land cover are known, land cover is accurately mapped, and land cover is mapped at a scale ecologically relevant to the species in question (Edwards et al. 1996; Boykin et al. 2010).

Data are available from GAP at a national scale (continental United States; hereafter, USGAP), regional scale (e.g., northwestern United States states, including Oregon, Washington, Montana, Idaho, and Wyoming; hereafter, NWGAP), and for some individual U.S. states (e.g., Idaho); and each scale uses different numbers and types of variables in their distribution models (Aycrigg et al. 2010, 2013). Modeling the distributions of multiple species at a regional or national scale has several challenges because these modeling efforts must balance ecologically relevant variables with the grain and extent of available spatial data (e.g., Elith and Leathwick 2009). Additionally, the amount of spatial data (>90 gigabytes) required to model species at regional and national extents challenges current computational power. Consequently, most models use fewer than 10 different metrics for each vertebrate species, regardless of their scale. For example, national models use a maximum of seven variables (land cover, hydrology [e.g., stream velocity, salinity, etc.], human avoidance, elevation, forest edge, woodland–shrubland, and minimum patch size [http://gapanalysis.usgs.gov/]), similar to regional programs such as Southwest GAP (slope, aspect, distance to water, land cover, soil type, percent rock outcrop, and landform; Boykin et al. 2010). Some regional programs use even fewer metrics; for example, NWGAP only used a single variable (land cover) in its species models (Aycrigg et al. 2013).

Validation of GAP distribution models is important because they are used by many different stakeholders and for multiple purposes (Scott et al. 1993; Edwards et al. 1996; Peterson et al. 2001; Collinge et al. 2005; North American Bird Conservation Initiative, U.S. Committee 2011; Boykin et al. 2013). However, research studies on GAP model accuracy have had differing findings, mostly dependent on scale. Edwards et al. (1996) found that the accuracy rate (percent correctly classified) of GAP distribution models for vertebrates was >69% for eight national parks in Utah. In Idaho, Peterson et al. (2001) noted accuracy rates of up to 85%, but also concluded that accuracy depended largely on scale, with fine-scale (approx. 2-ha) accuracy as low as 39%. In Southwest GAP, Boykin et al. (2010) noted concordance of approximately 60% between GAP models and field-collected data. These studies used independently derived data to examine the accuracy of GAP models, which is important to determine where improvements can be made in the GAP modeling process (Scott et al. 1996, 2002).

Land cover is a common denominator in all GAP vertebrate models and is typically derived solely upon satellite-based data. Although land cover is undoubtedly an important variable for vertebrates, the two-dimensional nature of satellite data may be insufficient to capture important habitat variables for some species (Vierling et al. 2008). Because LiDAR is a remote-sensing tool that describes 3-dimensional vertical structure, the incorporation of LiDAR data may improve our understanding of species distributions at both fine and broad spatial scales (Lefsky et al. 2002; Vierling et al. 2008; Bergen et al. 2009). Applications for wildlife habitat modeling using LiDAR data have increased in recent years, largely because LiDAR data can reflect ecologically relevant vegetation structure that may otherwise be difficult to gather through traditional field-based efforts (e.g., Bradbury et al. 2005; Müller et al. 2009).

The value of LiDAR is apparent from the growing number of research studies that have incorporated LiDAR-derived data in wildlife-habitat models (e.g., Goetz et al. 2007; Clawges et al. 2008; Vogeler et al. 2013). There are multiple metrics that might be used to model distribution of a specific species, but as mentioned above, two metrics that are broadly applicable in a GAP framework are LiDAR-derived shrub and snag data. These two metrics are likely to improve GAP vertebrate models because they represent real structural components of the landscape used by wildlife (Martinuzzi et al. 2009). Our objectives were to assess 1) the performance of USGAP and NWGAP models with independently collected field data, and 2) whether the inclusion of LiDAR-derived shrub and snag data improved the performance of USGAP and NWGAP models. We used data from field surveys of four shrub-nesting and four cavity-nesting bird species to assess the accuracy of distribution models created by 1) the national USGAP data set only, 2) the regional NWGAP data set only, 3) LiDAR-derived data only, and 4) combinations of LiDAR, USGAP, and NWGAP data.

Study Area

We conducted this study on Moscow Mountain in northern Idaho (approx. 46°44′N, 116°58′W). Moscow Mountain encompasses about 20,000 ha of mixed coniferous forest. Vegetation in our study varied by aspect, elevation, and management history. Dominant tree species included ponderosa pine *Pinus ponderosa,* Douglas-fir *Pseudotsuga menziesii,* grand fir *Abies grandis,* western red cedar *Thuja plicata,* and western larch *Larix occidentalis* (Martinuzzi et al. 2009; Vogeler et al. 2013; Washington State University 2014). Common shrub species included ocean-spray *Holodiscus discolor,* ninebark *Physocarpus malvaceus,* common snowberry *Symphoricarpos albus,* white spirea *Spiraea betulifolia,* huckleberry *Vaccinium membranaceum,* and Rocky mountain maple *Acer glabrum* (Martinuzzi et al. 2009; Washington State University 2014). Most of Moscow Mountain is managed

for timber production by private industrial forest companies, but a portion is used for research by the University of Idaho. Both logged and unlogged areas occur on Moscow Mountain (Falkowski et al. 2005) and past forest management practices include prescribed burning, such as annual burns on approximately 1–2% of the University of Idaho's Experimental Forest (Falkowski et al. 2005). For snags ≥25 cm diameter at breast height (DBH), the snag density is approximately 30–35% of the area (Martinuzzi et al. 2009).

Methods

Selection of focal species

We selected four shrub-nesting and four cavity-nesting birds as focal species for our analyses. Shrub-nesting species included dusky flycatcher *Empidonax oberholseri,* MacGillivray's warbler *Geothlypis tolmiei,* orange-crowned warbler *Oreothlypis celata,* and Swainson's thrush *Catharus ustulatus*. Cavity-nesting species included hairy woodpecker *Picoides villosus,* northern flicker *Colaptes auratus,* mountain chickadee *Poecile gambeli,* and red-breasted nuthatch *Sitta canadensis.* The cavity-nesting guild selected for this study included two species that function mostly as primary-cavity excavators (northern flicker and hairy woodpecker) and two species that are usually classified as secondary-cavity users or weak excavators (mountain chickadee and red-breasted nuthatch). Secondary-cavity users are species that utilize cavities for nesting, but that do not necessarily excavate their own cavity and are often dependent upon primary-cavity excavators for cavities (Martin et al. 2004; Gentry and Vierling 2008). Both primary-cavity excavators and secondary-cavity users will use cavities for roosting (Martin et al. 2004). Although the number of species we selected is small, we chose species that we anticipated would be sensitive to either shrub or snag presence and for which we had sufficient sample sizes to examine our objectives.

Survey data

To assess the performance of USGAP and NWGAP models, we conducted point counts to detect all focal species within our study area. We randomly stratified point-count stations by locating stations within eight strata that represented a range of successional stages from early successional to mature forest stages (Vogeler et al. 2013). We placed stations a minimum of 250 m apart to minimize the chance of sampling the same bird at multiple stations and used 8-min variable-radius point-count methods. We identified bird species by sight or sound and estimated distance to each individual (Reynolds et al. 1980; Vogeler et al. 2013, 2014).

We conducted standard point counts in 2009 at 151 sites on Moscow Mountain for all focal species. As part of a concurrent study on cavity-nesting birds, we also conducted playback point counts for woodpeckers at all of these sites, plus an additional five sites. Thus, we surveyed for all eight birds at 151 sites, and then used playbacks to survey for woodpeckers alone at an additional 5 sites, for 156 total woodpecker sites. For woodpecker detections, if a point detected a woodpecker during either the standard point count or the playback point count, we considered that site occupied.

To increase our chances of detecting the majority of breeding bird species in our study area, we visited each site twice between 15 May and 5 July 2009 (Petit et al. 1995; Smith et al. 1995). Standard point-count surveys lasted 8 min (Vogeler et al. 2013, 2014), and we followed the methods of Vierling et al. (2013) for woodpecker playback surveys. For each detection, we recorded the distance to the bird and omitted from analysis all birds detected >100 m from stations. We began surveys at sunrise and continued until 5 h after sunrise to capture the period of active vocalization (Manuwal and Carey 1991). We did not survey during periods of strong wind or heavy rain, when the observers' abilities to detect birds were compromised (Vogeler et al. 2013).

Determining predicted species presence

To assess whether the inclusion of 3-dimensional vegetation data improved the performance of USGAP and NWGAP models, we obtained GAP species-distribution data from USGS GAP (http://gapanalysis.usgs.gov/) and NWGAP (http://www.gap.uidaho.edu/). Predictors of the GAP models for our focal species include between 55 and 344 land-cover classes in addition to hydrology, human avoidance, elevation, forest edge, and minimum patch size. We then obtained LiDAR data sets from multiple-return LiDAR that had been flown by Horizons, Inc., in summer 2003. Data were acquired using a Leica ALS40 system at an elevation of 2,500 m and using a wavelength of 1,064 nm. The mean LiDAR point density was 0.4 points/m^2. We separated data into ground and nonground returns following Evans and Hudak (2007) and constructed the classification of snag and shrub presence and absence using the Random Forest algorithm (Breiman 2001) following Martinuzzi et al. (2009). Shrub cover was defined as vegetation returns between 1 m and 2.5 m in height (Martinuzzi et al. 2009) and we classified understory shrubs as "present" if they covered >25% of a 20 m × 20 m pixel (Data S1, *Supplemental Material*). We estimated the accuracy of our shrub prediction as 83% and our snag prediction as 86–88% (Martinuzzi et al. 2009). The LiDAR data could not distinguish between hardwood and nonhardwood shrubs, such as saplings of Douglas-fir, ponderosa pine, and grand fir. Additional details on the mapping of snags and shrubs are available in Martinuzzi et al. (2009).

Presence and absence of snags based on LiDAR-derived data were available for three size categories: snags ≥15 cm DBH (Data S2, *Supplemental Material*), snags ≥25 cm DBH (Data S3, *Supplemental Material*), and snags ≥30 cm DBH (Data S4, *Supplemental Material*). We completed a review of the literature on the sizes of snags used for each of our focal cavity-nesting species to determine which size classes were important for nesting (see Table S1, *Supplemental Material,* for list of scientific literature included in review). For all species, 90% of all snags used in the reviewed studies (n = 36) were ≥25 cm DBH. We therefore considered that the LiDAR layer for snags ≥25 cm DBH should accurately represent

Table 1. Estimated proportion of suitable habitat on Moscow Mountain, Idaho, from 15 May to 5 July 2009 for each of eight focal bird species based on distribution models for 1) the regional Northwest Gap Analysis Project data set only (NWGAP), 2) the national U.S. Geological Survey Gap Analysis Program data set only (USGAP), 3) Light Detection and Ranging (LiDAR) –derived data only, and 4) combinations of LiDAR-derived data with national and regional GAP maps. Number in parentheses following each species' name represents the proportion of sites where the species was detected using survey data.

Species	NWGAP only	NWGAP + LiDAR	USGAP only	USGAP + LiDAR	LiDAR only
Shrub-nesters					
Swainson's thrush *Catharus ustulatus* (0.73)	0.78	0.46	0.71	0.44	0.48
MacGillivray's warbler *Geothlypis tolmiei* (0.46)	0.13	0.04	0.05	0.02	0.48
Orange-crowned warbler *Oreothlypis celata* (0.27)	0.81	0.47	0.00	0.00	0.48
Dusky flycatcher *Empidonax oberholseri* (0.33)	0.65	0.46	0.74	0.45	0.48
Cavity-nesters					
Hairy woodpecker *Picoides villosus* (0.29)	0.73	0.34	0.71	0.33	0.35
Northern flicker *Colaptes auratus* (0.47)	0.78	0.34	0.60	0.26	0.35
Red-breasted nuthatch *Sitta canadensis* (0.82)	0.69	0.32	0.69	0.33	0.35
Mountain chickadee *Poecile gambeli* (0.51)	0.69	0.32	0.72	0.33	0.35

the size of snags needed for nesting by all cavity-nesters (Data S3, *Supplemental Material*).

We created 100-m buffers around each point-count location and calculated the proportion of each circular buffer area that was classified as suitable for each species for each of the distribution models (USGAP only, NWGAP only, LiDAR only, USGAP + LiDAR combined, NWGAP + LiDAR combined). If ≥50% of the buffer around a point-count station was predicted as suitable habitat, we classified that point as having a "predicted presence" for that species. If <50% of the buffer was predicted to be suitable, we classified the point as "predicted absence." For combination GAP and LiDAR models, we used ArcMap 10 (ESRI, Redlands, CA) to overlay LiDAR data with GAP distribution models for each species, and the resulting model represented the intersection of these two layers. For predicting species presence of our LiDAR + GAP models, we determined that a pixel had to contain predicted presence for both individual models, and absence was predicted in all other cases.

Similar to other studies (e.g., Edwards et al. 1996; Peterson et al. 2001; Boykin et al. 2010), we calculated the percentage of correct positive predictions (positive predictive power), the percentage of correct negative predictions (negative predictive power), and the correct classification rate (the percentage of correct present and absent predictions together; Table S2, *Supplemental Material*). For each model, we then computed 95% confidence intervals for proportions as,

$$\beta \pm 1.96\sqrt{\frac{\beta(1-\beta)}{n}}$$

where β represents the parameter estimate (in this case, proportions), and n the sample size. When confidence intervals for different models did not overlap, we considered that there was a difference between models.

Results

We detected all eight focal species on Moscow Mountain, and both shrub- and cavity-nesting birds were detected on at least one-quarter of all points (Table 1). Red-breasted nuthatch and Swainson's thrush were the most common species, occurring on 82% and 73% of surveys, respectively (Table 1). Orange-crowned warbler was the least commonly detected species, but still occurred on 27% of point-count surveys.

On a species-specific level, there was great variability in the amount of suitable habitat predicted by the GAP models (Table 1). For example, USGAP predicted that 0% of Moscow Mountain was suitable for orange-crowned warbler, whereas NWGAP predicted 81%. The only species for which USGAP and NWGAP predicted the same amount of suitable habitat was red-breasted nuthatch (Table 1).

On a guild level, USGAP models performed marginally, though consistently better than NWGAP models in correct classification rate (Table 2). However, on a species level, these differences were only significant for a single species—orange-crowned warbler (Figure 1). Negative predictive power (percent of correct negative predictions) values were higher for USGAP models compared with NWGAP models across all species, shrub-nesters only, and cavity-nesters only (Table 2). Five of the eight species had significantly greater negative predictive power values for USGAP-only models compared with NWGAP-only models (Figure 1). For most species, both GAP models poorly predicted species presence on Moscow Mountain. We estimated that for all species together, NWGAP and USGAP correctly classified only 44% and 51% of our point-count surveys (Table 2).

The addition of LiDAR data to the GAP maps decreased the amount of predicted suitable habitat for all species except orange-crowned warbler, for which USGAP predicted no suitable habitat (Table 1). On a guild level, the addition of LiDAR data improved the correct classification rate of both USGAP and NWGAP by up to 12 percentage points (Table 2). The only guild–model combination that did not see an improvement with the addition of LiDAR data was the USGAP model for shrub-nesters, which performed poorly overall because USGAP underestimated the presence of two common

Table 2. Mean diagnostic values to assess the performance of Northwest Gap Analysis Project (NWGAP), U.S. Geological Survey Gap Analysis Program (USGAP), Light Detection and Ranging (LiDAR), and LiDAR + GAP models for predicting species occurrence for eight focal species in 2009 on Moscow Mountain, Idaho. The NWGAP models are applicable in the Northwest, and USGAP refers to national GAP models. The correct classification rate is the percentage of total correct presence and absence predictions, positive predictive power is the percentage of correct positive predictions, and the percentage of correct negative predictions is the negative predictive power.

Model	Correct classification rate	Positive predictive power	Negative predictive power
All species			
NWGAP only	0.44	0.44	0.38
NWGAP + LiDAR	0.52	0.46	0.60
USGAP only	0.51	0.42	0.64
USGAP + LiDAR	0.52	0.44	0.53
LiDAR only	0.50	0.43	0.60
Shrub-nesters only			
NWGAP only	0.43	0.44	0.42
NWGAP + LiDAR	0.56	0.50	0.67
USGAP only	0.55	0.39	0.71
USGAP + LiDAR	0.55	0.46	0.53
LiDAR only	0.52	0.61	0.53
Cavity-nesters only			
NWGAP only	0.44	0.45	0.35
NWGAP + LiDAR	0.48	0.42	0.53
USGAP only	0.47	0.45	0.57
USGAP + LiDAR	0.49	0.42	0.53
LiDAR only	0.48	0.43	0.53

species—MacGillivray's and orange-crowned warbler (Table 1). The largest improvements from LiDAR data occurred with the negative predictive power (the ability to accurately describe "absent" sites correctly). With the addition of LiDAR data, there was a 22% increase in negative predictive power for all species compared with a 2% increase for positive predictive power (Table 2).

On a species-specific level, the effect of LiDAR data on GAP model performance varied widely, even within the same guild. The LiDAR data improved both USGAP and NWGAP models for some species (such as dusky flycatcher), had no effect on others (MacGillivray's warbler), and actually decreased model performance for the Swainson's thrush USGAP model (Figure 1). The performance of LiDAR data alone for predicting species distribution was likewise variable (Table 2). For example, the LiDAR-only model performed better than the NWGAP model for northern flicker, showed no difference for mountain chickadee, and performed worse than the USGAP model for orange-crowned warbler (Figure 1).

Discussion

Our assessment of USGAP and NWGAP models with independently collected field data showed that the ability of USGAP and NWGAP models to predict species distributions is highly species-specific. Even within the same guild, GAP models were highly variable. For example, within the shrub- and cavity-nesting guild, respectively, some GAP models correctly classified >70% of points for orange-crowned warbler and red-breasted nuthatch, but classified <40% of Swainson's thrush and hairy woodpecker points. It is possible that we missed presence of some species by surveying in only 1 y and on two occasions. But it is also possible that these differences arise because GAP models predict suitable habitat for a species, rather than the actual occurrence of a species in a specific area, and not all habitat may be occupied (Jennings 2000; Boykin et al. 2010; Franklin 2010). Additionally, some species rely on fairly specific components of a habitat types. These finer scale habitat components may be missing from GAP models that only consider coarse depictions of habitat when modeling species distributions, and thus some areas considered suitable by coarse habitat classifications may in actuality be unsuitable.

After combining all species in this study, both GAP models on average correctly classified presence and absence of our focal bird species in half the cases, or about equal to what would be expected from random chance alone. These conclusions support those of McClure et al. (2012) that GAP models perform poorly at small spatial scales such as 100-m-radius point-count circles used in this study. McClure et al. (2012) examined the accuracy of GAP maps for vertebrate distributions in the southeastern United States and noted that the accuracy of GAP maps decreased with spatial scale. In addition, it is possible these models performed poorly because we surveyed for birds only two to four times in 1 y and thus missed detecting some species at our point-count stations. Points classified as unoccupied may have been occupied (MacKenzie et al. 2006), and if this is the case, then GAP may have higher positive predictive

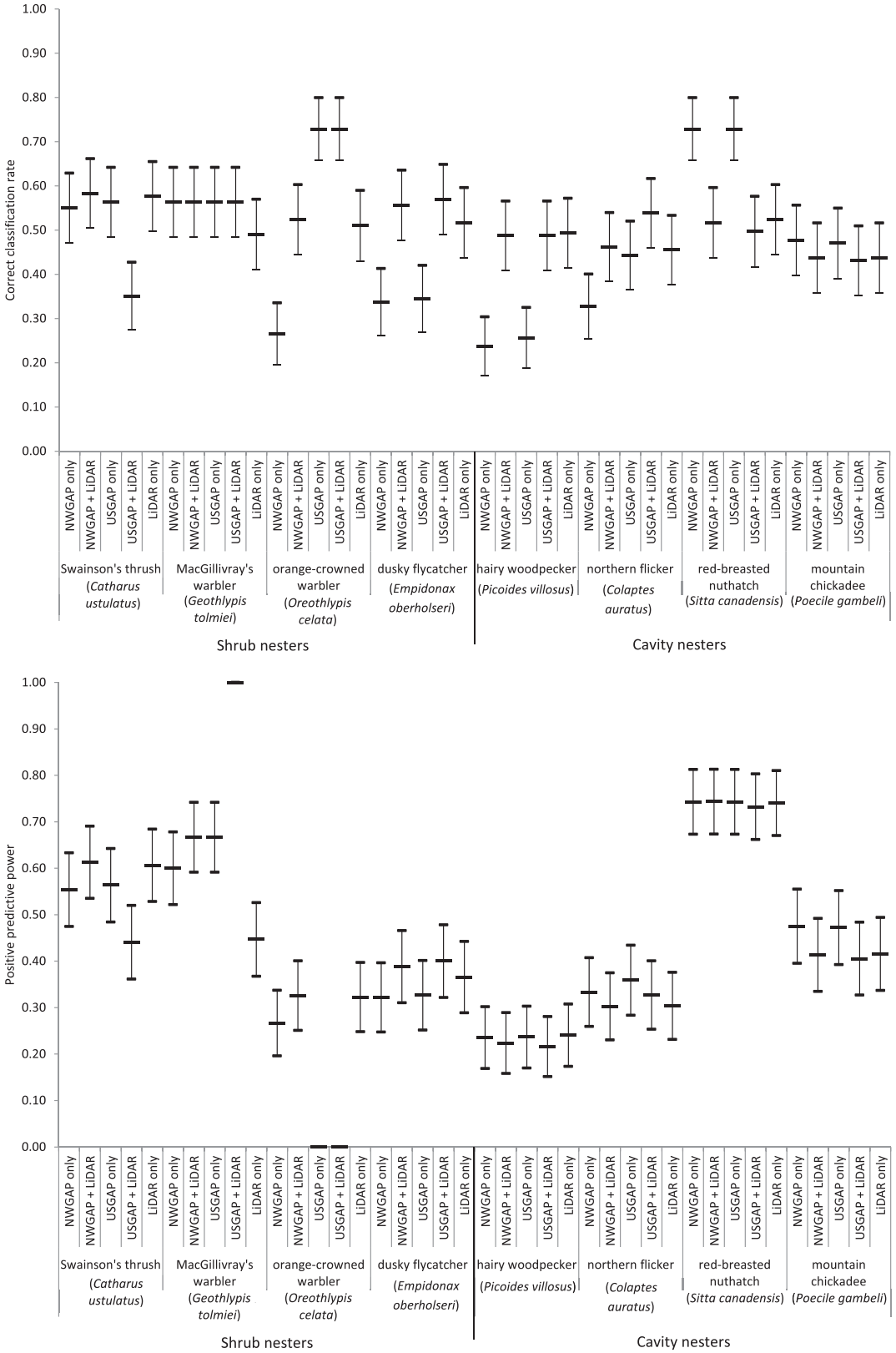

Figure 1. Correct classification rate, positive predictive power, and negative predictive power values with associated 95% confidence intervals by species and by model. Models predict species occurrence for eight focal bird species in 2009 on Moscow Mountain, Idaho, and include Northwest Gap Analysis Project (NWGAP), U.S. Geological Survey Gap Analysis Program (USGAP), Light Detection and Ranging (LiDAR), and LiDAR + GAP models. The NWGAP models are applicable in the Northwest and USGAP refers to national GAP models. The correct classification rate is the percentage of total correct presence and absence predictions, positive predictive power is the percentage of correct positive predictions, and negative predictive power is the percentage of correct negative predictions.

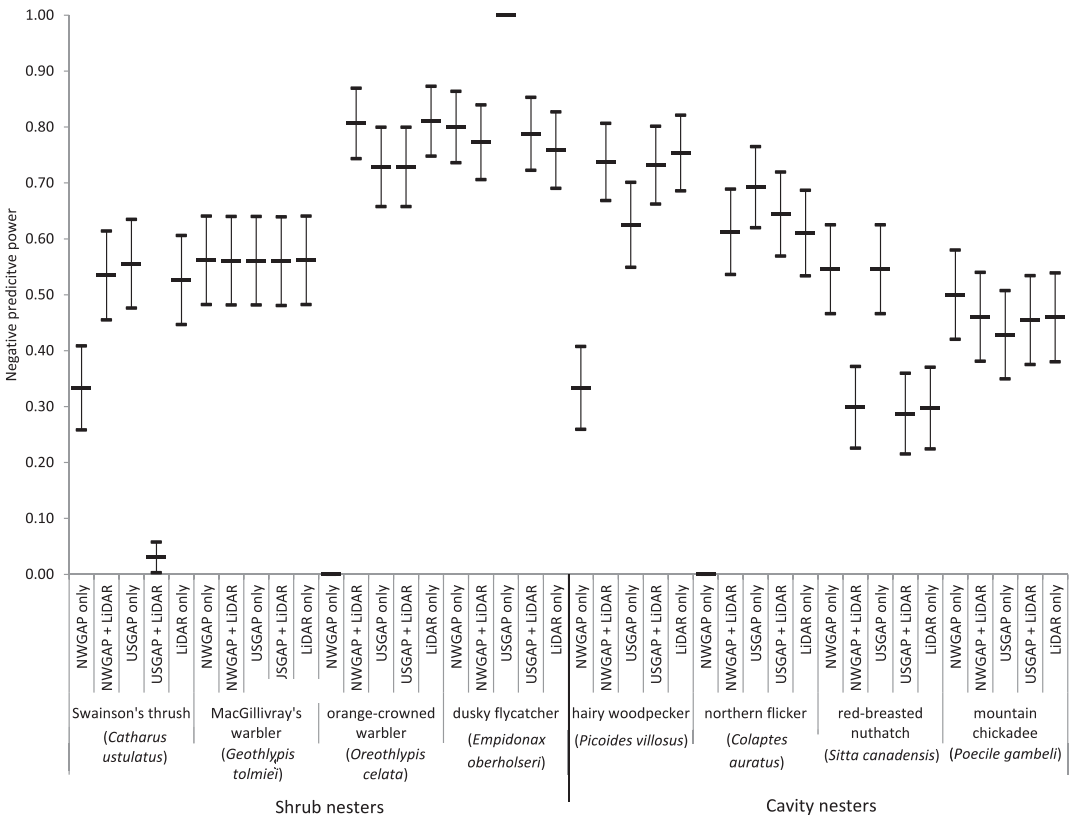

Figure 1. Continued.

power than reflected in our results. We suggest that future studies account for this possibility and consider more rigorous surveys.

Comparing USGAP and NWGAP models on a species level, the USGAP models performed slightly better than NWGAP models, and this difference was significant for dusky flycatcher and orange-crowned warbler. Our results for orange-crowned warbler should be treated with caution, however, because of the low level of predicted habitat for this species in the USGAP models. For dusky flycatcher, the USGAP models may have outperformed NWGAP models because NWGAP models were based on a single variable (e.g., land cover), whereas USGAP models included multiple variables (e.g., land cover, elevation, and minimum patch size). The ability to accurately map the distribution of species is partly dependent on the selection of the correct variables and spatial scale used in the modeling framework (e.g., Austin 2007; Elith and Leathwick 2009; Franklin 2010), and it is likely the species that we examined were sensitive to the model variables included in USGAP models compared with land cover alone. This finding supports GAP's iterative approach to their species-modeling effort in which species models are updated as new data or information regarding species occurrences and habitat relationships become available (Aycrigg et al. 2010).

LiDAR data are derived at a smaller scale for bird point-count surveys; therefore, we were surprised that the addition of LiDAR data did not consistently improve models. Previously, researchers have examined the ability of either GAP or LiDAR data separately to predict species distributions (e.g., Howell et al. 2008; Bellamy et al. 2009; Goetz et al. 2010; McClure et al. 2012), but none have combined shrub- and snag-specific LiDAR data with NWGAP or USGAP models to assess model performance. In our study, the addition of LiDAR data to GAP models improved model performance only for some species. Within the same guild, some species, such as dusky flycatcher, showed higher correct classification rate with LiDAR data; but others, such as MacGillivray's warbler, showed no overall improvement. Still others, such as Swainson's thrush, actually had poorer predictive power with LiDAR data than without. For such species, LiDAR data resulted in poorer predictive power because GAP models tended to overpredict suitable habitat and therefore had inflated positive predictive power. All three of these species should have responded positively to shrub cover. However, it is possible that LiDAR data did not improve these species models because these birds were responding to other unmeasured stand features, such as the presence of nonhardwood shrub cover (Morrison 1981; Ellis et al. 2012). The LiDAR data alone cannot distinguish between hardwood and nonhardwood shrub layers, and for LiDAR data to improve species-distribution maps, additional information about species-specific habitat requirements and the appropriate spatial scale of those habitat variables would have to be included.

It is noteworthy, however, that in some cases, LiDAR data could not improve models because the underlying models themselves were highly inaccurate. For example, USGAP models predicted virtually no suitable habitat on Moscow Mountain for MacGillivray's warbler, even though the species is common in the region. This species is most likely to be detected in streamside riparian cover and has been classified as a riparian-dependent species (Pitocchelli 2013). Linear riparian habitats are challenging to accurately map using 30 m × 30 m resolution satellite imagery. Therefore GAP models based on land cover and other broadly occurring model variables will have lower accuracy, and this demonstrates that LiDAR data cannot improve GAP models if the GAP models themselves vastly under-predict species presence.

Overall, we found that the ability of GAP models to predict species distributions within the spatial extent of our study was highly species-specific and LiDAR data did not consistently improve GAP models. This may be encouraging for land managers who lack LiDAR data. At the present time, airborne LiDAR data are limited in spatial extent to temperate areas (Müller and Vierling 2013), and even though LiDAR data are increasingly available in multiple states within the United States, there are still operational challenges to the incorporation of airborne LiDAR data into conservation and management plans. Our study results suggest that managers should consider the limitations of LiDAR data; LiDAR data may only be appropriate for cases where the specific habitat requirements of the animal are considered, and it may only improve species-distribution models if the underlying models themselves are accurate. Given our findings, we caution land managers from using GAP models at small spatial scales without field-collected data, at least until GAP models are improved and validated by field studies (Fielding and Bell 1997). In our study, GAP models were not accurate in predicting species presence in our 200-km^2 study area, which is similar in size to a small park or preserve. The GAP models are more appropriate at national, regional, or statewide scales or for providing context for finer level maps, such as prioritizing areas for further research (Jennings 2000; Aycrigg et al. 2013; USGS-GAP 2013). Future studies should consider using LiDAR data to improve GAP models at larger spatial scales and more appropriate to the scale at which GAP models were designed. Given the differences in model performance by species, we also encourage researchers to first consider GAP and LiDAR models on a species-specific level and to be careful about making generalizations across guilds.

Supplemental Material

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Data S1. The LiDAR-derived shrub presence and absence data for Moscow Mountain, Idaho. Requires ArcGIS software (ESRI, Redlands, CA) to convert text file to raster map.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S1 (2502 KB TXT).

Data S2. The LiDAR-derived snag presence and absence data for snags ≥15 cm on Moscow Mountain, Idaho. Requires ArcGIS software (ESRI, Redlands, CA) to convert text file to raster map.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S2 (2483 KB TXT).

Data S3. The LiDAR-derived snag presence and absence data for snags ≥25 cm on Moscow Mountain, Idaho. Requires ArcGIS software (ESRI, Redlands, CA) to convert text file to raster map.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S3 (2483 KB TXT).

Data S4. The LiDAR-derived snag presence and absence data for snags ≥30 cm on Moscow Mountain, Idaho. Requires ArcGIS software (ESRI, Redlands, CA) to convert text file to raster map.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S4 (2483 KB TXT).

Table S1. List of scientific literature reviewed to determine the appropriate snag size requirements for the hairy woodpecker *Picoides villosus,* northern flicker *Colaptes auratus,* mountain chickadee *Poecile gambeli,* and red-breasted nuthatch *Sitta canadensis.* (Includes References S8, S9, S10, and S11).

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S5 (41 KB DOC).

Table S2. Comparisons of actual and predicted occurrence data for eight bird species across Moscow Mountain, Idaho, during 15 May to 5 July 2009. Predicted occurrence models were based on 1) the regional Northwest Gap Analysis Project data set only (NWGAP), 2) the national U.S. Geological Survey Gap Analysis Program data set only (USGAP), 3) Light Detection and Ranging (LiDAR) –derived data only, and 4) combinations of LiDAR-derived data with national and regional GAP maps. The LiDAR-derived data reflected either presence of absence of snags of ≥25-cm DBH for cavity-nesting species, or shrub presence or absence for shrub-nesting species.

Found at DOI: http://dx.doi.org/10.3996/092013-JFWM-064.S6 (69 KB DOC).

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Reference S2. Aycrigg JL, Andersen M, Beauvais G, Croft M, Davidson A, Duarte L, Kagan J, Keinath D, Lennartz S, Lonneker J, Miewald T, Ohmann J, editors. 2013. Ecoregional Gap analysis of the northwestern United States. Moscow, Idaho: U.S. Geological Survey Gap Analysis Program.

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