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How much does the time lag between wildlife field-data collection and LiDAR-data acquisition matter for studies of animal distributions? A case study using bird communities

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Vegetation structure quantified by light detection and ranging (LiDAR) can improve understanding of wildlife occupancy and species-richness patterns. However, there is often a time lag between the collection of LiDAR data and wildlife data. We investigated whether a time lag between the LiDAR acquisition and field-data acquisition affected mapped wildlife distributions ranging from an individual species distribution to total avian species richness in a conifer forest. We collected bird and LiDAR data in 2009 across a 20,000 ha forest in northern Idaho. Using the 2009 LiDAR data, we modelled the probability of occurrence for the brown creeper (*Certhia americana*). Using the same 2009 LiDAR data, we additionally modelled total avian species richness and richness of three different bird nesting guilds (ground/understory, mid/upper canopy and cavity). We mapped brown creeper occupancy probability and species richness using the 2009 models, and then compared these maps with maps based on the same models applied to a 2003-LiDAR dataset. A prior study identified areas harvested between 2003 and 2009. There was on average a 5% absolute decrease in mapped probabilities of brown creeper occurrence in non-harvest areas between 2003 and 2009. Species richness changed by less than one species in all cases within non-harvest areas between the 2003 and 2009 maps. Although these comparisons were statistically significant at the $p < 0.0001$ level, it is likely that the high number of map cells (~480,000) influenced this result. Similar patterns between our 2003 and 2009 maps in non-harvest areas for this suite of avian responses suggests that a 6-year difference between field-data collection and LiDAR-data collection has a minimal effect on mapped avian patterns in an undisturbed coniferous forest. However, because this is one case study in one ecosystem, additional work examining the effect of temporal lags between LiDAR and field-data collection on mapping wildlife distributions is warranted in additional ecosystems.

1.   Introduction

The ability of scientists to map fine scale 3-D vegetation structure over broad spatial scales using light detection and ranging (LiDAR) is likely to influence the conservation and management of a broad spectrum of animal taxa. LiDAR-based mapping of 3-D habitat features creates the potential to use these data to explore animal–habitat relationships ranging from fine spatial scales (e.g. arthropods; Müller and Brandl 2009; Vierling

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et al. 2011) to coarser spatial scales, such as in the case of birds (Goetz et al. 2007; Clawges et al. 2008; Flaspohler et al. 2010; Müller, Stadler, and Brandl 2010; Lesak et al. 2011) and bats (Jung et al. 2012).

The use of LiDAR for wildlife applications has included assessments of distribution, habitat quality, and diversity. For instance, LiDAR products have been utilized to map the distribution of avian species of special concern (Smart et al. 2012; Wilsey, Lawler, and Cimprich 2012). LiDAR products have also been used to describe forest structure that influences avian-habitat quality (Hinsley et al. 2002, 2006; Goetz et al. 2010), and current studies that incorporate LiDAR-derived metrics note that species-diversity patterns of birds (e.g. Lesak et al. 2011), and arthropods (e.g. Vierling et al. 2011) can be described. Generally, foliage height diversity has a positive influence on species diversity, but other structural factors can also have strong influences on species diversity (e.g. Flaspohler et al. 2010).

These studies indicate that LiDAR-derived metrics can advance our understanding of how vegetation structure influences multiple animal–habitat relationships, but it is important to acknowledge that LiDAR acquisitions do not always coincide in time with the collection of animal-related field data. Vegetation structure characterized by a LiDAR acquisition at one point in time will change due to plant growth and/or disturbance. Our objective was to compare maps based on concurrent bird and LiDAR-data collection with maps where LiDAR data were collected 6 years previous to bird data collection. We generated maps utilizing previously developed models describing occurrence for (1) the brown creeper, (2) total avian species richness and (3) the species richness of the ground/ understory nesting guild, the mid/upper canopy nesting guild and the cavity nesting guild (Vogeler 2011; Vogeler et al. 2013). Because managers rely on maps in planning and assessment activities, it is important to determine whether maps depicting animal–habitat relationships are sensitive to the age of the LiDAR acquisition relative to the collection of the animal data.

2. Methods

2.1. *Study area*

The study centres on the Moscow Mountain (area ~20,000 ha; latitude 46° 48' N, longitude 116° 52' W) located in north central Idaho, USA. The core study area is forested but largely bounded by croplands associated with dryland agriculture. Major tree species are ponderosa pine (*Pinus ponderosa* C. Lawson var. scopulorum Engelm.), Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco var. glauca (Beissn.) Franco), grand fir (*Abies grandis* (Douglas ex D. Don) Lindl.), western red cedar (*Thuja plicata* Donn ex D. Don) and western larch (*Larix occidentalis* Nutt). The variety of habitat types, stand composition and age structures stemming from forest management serve to diversify forest biophysical settings and successional stages (Falkowski et al. 2009). Major harvest disturbance occurred between 2003 and 2009 including harvest, thinning and prescribed fires (Hudak et al. 2012).

2.2. *Remotely sensed data processing*

LiDAR data were collected during the summers of 2003 and 2009. Mean LiDAR point densities were 0.4 points/m^2 in 2003 and 12 points/m^2 in 2009, while other acquisition parameters were consistent (Hudak et al. 2012). Canopy height and density metrics were

computed across the study area from all returns within 20 m × 20 m grid cells using a script coded in R Development Core Team (2007). The origins of the mapped metrics were defined such that the 2003 and 2009 grid cells exactly overlaid. Tree aboveground biomass was independently mapped in 2003 and 2009 using field plots measured in the same years as the repeat LiDAR surveys (Hudak et al. 2012). Biomass loss of 66 Mg ha^{-1} or greater was considered indicative of forest harvest; all other changes in biomass values were considered non-harvest and representative of natural growth and attrition (Hudak et al. 2012). Because the LiDAR provided only structural and not spectral information, Landsat image data (collected on 3 July 2003 and 3 July 2009) were also used to calculate the normalized difference vegetation index (NDVI), a very broadly applied metric indicative of vegetation greenness found to be useful in prior avian habitat-mapping studies (e.g. Hurlbert and Haskell 2003).

2.3. Bird data collection and modelling

We collected brown creeper data and avian species richness data in the field. Point counts were conducted during 2009 at 151 locations distributed across a range of forest successional stages (Vogeler et al. 2013). The top model for brown creepers included only the percentage of LiDAR hits between 20 and 30 m above ground level (hereafter upper canopy density) and the standard deviation of canopy height (Vogeler et al. 2013). Vogeler (2011) also modelled total species richness (TSR), the species richness of ground/understory nesters (GSR1), the species richness of mid/upper canopy nesters (GSR2) and cavity nesters (GSR3). Top models for TSR and GSR1 both included the understory density metric (i.e. the percentage of LiDAR returns located between 1.0 and 2.5 m above ground level) and NDVI (Vogeler 2011). Similarly, competitive models for GSR2 and GSR3 included the standard deviation of canopy height (m) and NDVI. We used these models to map (1) brown creeper occupancy probabilities, and (2) species richness across the Moscow Mountain from 2009 and 2003 LiDAR-derived metrics using the AsciiGridPredict function in the yaImpute package of R. Changes in avian responses per 20 m × 20 m map cell were then compared by subtracting the 2003 map from the 2009 map, so that increases were expressed as positive and decreases as negative values. We used the Z-test statistic for populations to assess the significance of differences in all mapped responses between 2003 and 2009, and we calculated Spearman's rank correlation (r_s) for the often non-normal distributions in brown creeper occupancy probability and species richness, between 2003 and 2009 at the 151 random stratified field sites. Sample sizes are represented by n.

3. Results

Mapped brown creeper occurrence probabilities differed significantly between 2003 and 2009 ($p < 0.0001$). The change in probability of brown creeper occupancy ranged from 0.00 to 0.95, with a 0.13 mean decrease. There was high spatial correspondence between the magnitude of changes in brown creeper occurrence probability and the harvesting activities mapped by Hudak et al. (2012) (Table 1, Figure 1). Twenty-seven percent of the study was harvested; upon excluding harvest areas, the mean difference across time in non-harvest areas decreased to – 0.05 (Table 1). Spearman's rank correlations between the 2003 and 2009 occupancy maps were over twice as strong at field sites in non-harvest areas ($r_s = 0.87$, $n = 111$) than at field sites in harvest areas ($r_s = 0.39$, $n = 40$; Figure 2(a)).

Table 1. Changes in avian response variables per 20 m × 20 m map cell compared between maps generated using 2003 LiDAR data and 2009 LiDAR data.

	Harvest	Non-harvest	Total
Number of map cells	104,847	379,200	484,047
Mean change in probability of brown creeper occurrence	−0.40 (0.29)	−0.05 (0.15)	−0.13 (0.24)
Mean change in total species richness	−1.67 (1.03)	−0.99 (1.28)	−1.14 (1.33)
Mean change in GSR1	−0.87 (0.70)	−0.80 (1.20)	−0.81 (1.11)
Mean change in GSR2	−1.36 (0.87)	−0.31 (0.46)	−0.54 (0.72)
Mean change in GSR3	0.47 (0.32)	0.10 (0.16)	0.18 (0.25)

Notes: A negative value indicates a decrease from 2003 to 2009. Means are followed by standard deviations in parentheses. GSR1 represents the richness of ground and shrub nesters. GSR2 represents the mid/upper canopy nester richness, and GSR3 represents cavity nester species richness. All comparisons between the 2003 and 2009 maps were significant at the $p < 0.0001$ level.
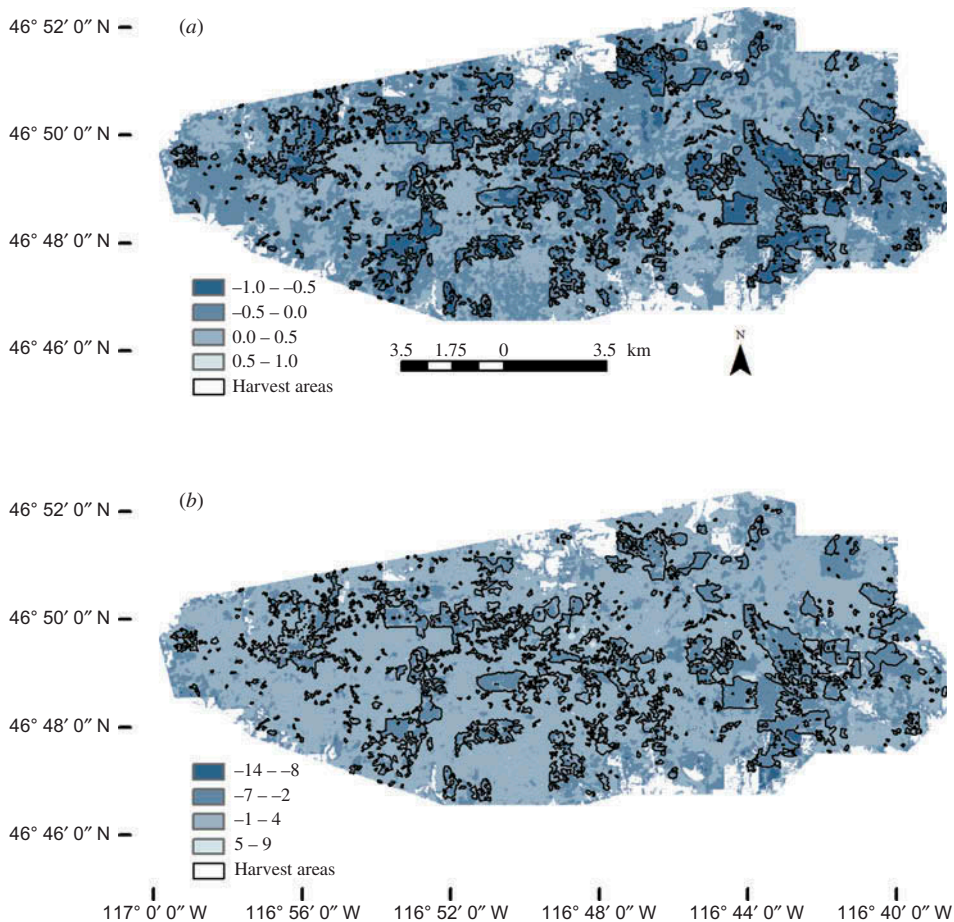
Figure 1. Mapped distributions of (*a*) the change in brown creeper occupancy probability and (*b*) the change in total bird species richness in a mixed coniferous forest. Negative values indicate a decrease from 2003 to 2009. Areas outlined in black represent harvested areas. White areas represent non-forest, and were excluded from the analysis.
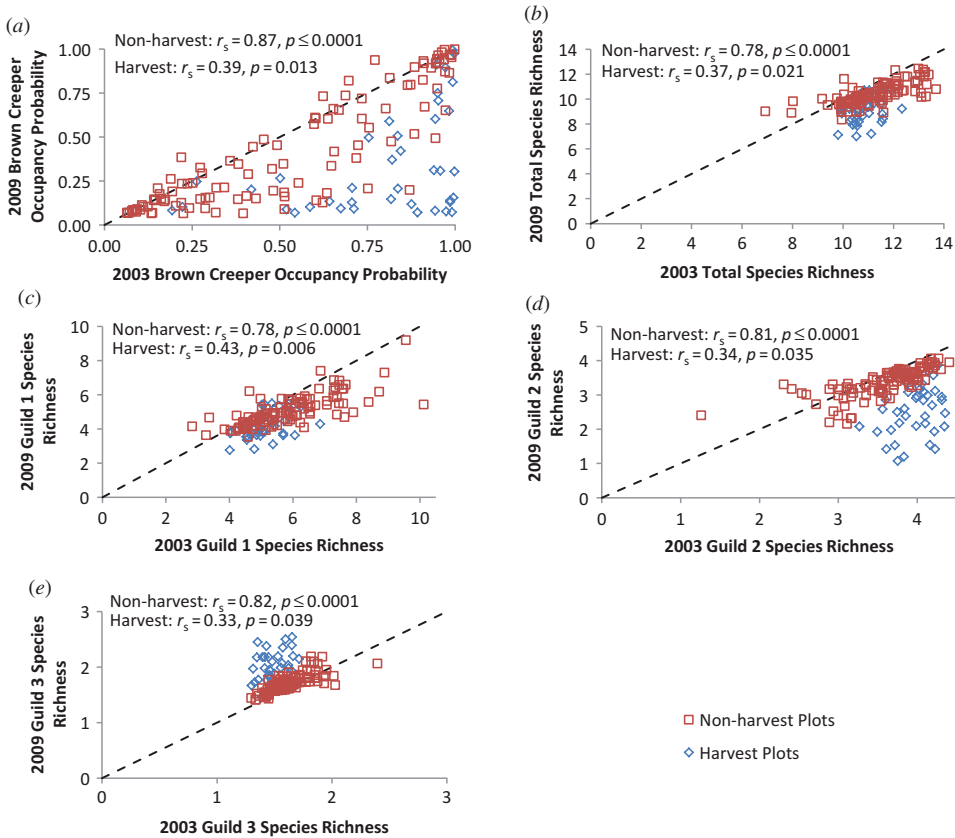
Figure 2.   Scatterplots of 2003 versus 2009 (*a*) brown creeper occupancy probability, (*b*) total species richness, and species richness of (*c*) nest guild 1 (understory nesters), (*d*) nest guild 2 (overstory nesters), and (*e*) nest guild 3 (cavity nesters) at 151 field plots sampled in 2009 that were either not harvested since 2003 (*n* = 111) or harvested (*n* = 40). The 1:1 line, Spearman's rank correlations (r_s), and *p*-values are indicated on each graph.

The magnitude of differences between species richness maps was small, but was statistically significant ($p < 0.0001$) for all comparisons. The maximum number of species categorized in each nesting guild ranged from six (for both mid/upper canopy nesters and cavity nesters) to ten (for the ground/shrub nesters). TSR ($n = 23$) included brown-headed cowbirds (*Molothrus ater*), which were not categorized into a nesting guild because they are brood parasites. Regardless of harvest activity, the mean difference between the 2003 and 2009 maps for TSR was –1.14 species (Table 1; Figure 1). Upon excluding harvest areas, the mean difference between 2003 and 2009 TSR maps was –0.99 species in non-harvest areas. Spearman's rank correlations between the 2003 and 2009 species richness maps were similarly higher ($r_s > 0.78$) for all measures of species richness in non-harvest areas compared to harvest areas, where r_s ranged from 0.33 to 0.43 (Figure 2).

LiDAR metrics differed significantly for all variables examined ($p < 0.0001$), and all metrics with the exception of canopy height variability decreased between 2003 and 2009, regardless of harvest (Table 2). There was a larger decrease in NDVI, upper canopy density and canopy height variability in harvest compared to non-harvest areas. However, understory canopy density decreased more in the non-harvest areas compared to the harvest areas.

Table 2. Mean change between 2003 and 2009 in NDVI and LiDAR metrics used to predict the avian response variables, summarized for harvest and non-harvest areas. Means are summarized from the 75 m radius focal mean values used in predictive models.

	Harvest	Non-harvest	Total
Number of map cells	104,847	379,200	484,047
NDVI	−0.21 (0.13)	−0.05 (0.08)	−0.09 (0.11)
Upper canopy density (%)	−15.2 (11.4)	−1.89 (5.19)	−4.76 (8.89)
Understory canopy density (%)	−0.72 (2.89)	−2.85 (5.41)	−2.39 (5.05)
Canopy height variability (m)	−0.69 (1.71)	0.01 (0.74)	−0.14 (1.07)

Notes: A negative value indicates a decrease from 2003 to 2009. Means are followed by standard deviations in parentheses. All 2003 to 2009 changes are significant at the $p < 0.0001$ level.

4. Discussion

Brown creepers are associated with old and mature forests during their breeding season, and this species is of management concern throughout its range because of habitat loss and degradation (Poulin et al. 2013). This species is generally associated with high amounts of biomass in the upper canopy and large trees that are used for foraging and nesting (Sallabanks, Haufler, and Mehl 2006; Poulin et al. 2013). Brown creepers forage for bark-dwelling insects, and large trees typically serve as foraging sites where this species often gleans and probes for its prey (Farris et al. 2010; Poulin et al. 2013). Large trees and snags are also important as nest sites, and nests are typically constructed underneath loose bark (e.g. Poulin et al. 2013). Because harvest activities often remove larger trees, harvest is likely to influence brown creeper distributions. In our analysis, harvest activity affected distributions in predictable ways; in areas where harvest occurred, brown creeper occupancy decreased markedly and significantly. However, there were also slight yet statistically significant decreases in occupancy probabilities within non-harvest areas. These changes likely reflect the natural processes that can change canopy structure (trees felled by windstorms, pest defoliations, etc.) that are detected by LiDAR yet are too small or subtle within the scale of a 20 m × 20 m map cell to exceed the 'harvested' threshold of disturbance (Hudak et al. 2012). Nevertheless, the absolute change in occupancy probability was relatively small (5%) between 2003 and 2009; therefore, the canopy changes that occurred within non-harvest areas were not sufficiently large to change occupancy map patterns across the approximately 20,000 ha study site (Figure 1).

We utilized different nesting guilds to help understand how changes in component nesting guilds and harvest may influence changes in TSR. In harvested areas, scatterplots show less of a deviation from the 1:1 line (Figure 2) for the shrub nesting guild, GSR1 compared to the other two nesting guilds. Predictably, GSR2 overstory nesting species richness decreased with harvest, which likely decreased nesting habitat. Some cavity nesters prefer open forests (e.g. Vierling, Saab, and Tobalske 2013); assuming suitably sized snags remain after harvest, loss of overstory with a concurrent increase in shrub growth may account for the changes seen in the GSR3 cavity nesting guild (Figure 2).

All of our comparisons were statistically significant, although the magnitude of the changes in species richness were relatively small. Multiple authors have noted that statistical significance and biological significance are not synonymous (e.g. Yoccoz 1991) and analyses based on high sample sizes with high power may be statistically significant but biologically trivial (Steidl, Hayes, and Schauber 1997). Although we found all 2003–2009 differences to be statistically significant, we caution that statistical significance may not equate to biological significance in many cases. The statistically

significant results based on the *Z*-test statistic for populations are in all likelihood misleading because they include not just a large sample but the entire population of forested map cells (Table 1, Figure 2). The relative changes among the mapped 2003–2009 avian-response variables likely have more ecological significance than the absolute differences between 2003 and 2009 maps for any given response variable. Moreover, the mean differences in the mapped responses, even after limiting the 2003–2009 map differences to non-harvest areas, does not factor in uncertainty in the maps themselves. For instance, an uncertainty of ± 1 in TSR in either the 2003 or 2009 maps could be considered acceptable, therefore explaining much of the apparent differences that contribute to statistical significance (Table 1) yet are likely not biologically significant. The same argument could be applied to the LiDAR metrics used as predictors (Table 2), which have their own uncertainties that propagate into the uncertainty and errors in the mapped responses (Table 1), yet are not considered in our analysis. The Spearman correlations between the 2003 and 2009 responses at the 151 field sites are also reported because they provide a much more conservative test of the agreement between the maps (Figure 2). Similar to the *Z*-test statistical results (Table 1), the higher relative significance of the Spearman's rank correlations between the 2003 and 2009 maps in non-harvest areas, compared to harvest areas (Figure 2), is probably a more useful indicator of ecological significance than the *p*-values themselves.

LiDAR data are extremely powerful for wildlife studies because the forest structural attributes of interest (e.g. biomass at a particular canopy height) can be determined *post hoc* as can the spatial extent of the analysis (e.g. Vierling et al. 2008; Swatantran et al. 2012). Tree species composition is not easily detected via LiDAR alone, but when partnered with other sensors, it may be possible to differentiate tree species (e.g. Hill and Thomson 2005). In addition to the differences in time scale between the two acquisitions, the point densities differed. The 2003 LiDAR acquisition had a lower point density; however, Hudak et al. (2012) note that the vertical structure represented by the lower-point density was consistent with the vertical structure represented by the higher density of points in the 2009 dataset.

Finally, it is important to note that these findings are limited at the current time to the avian community in a temperate coniferous forest. It is not clear how changes in forest structure in a 6-year period might influence animals that utilize different components of forest structure at different spatial scales. Bird data in this study were collected within 75 m of a survey point (Vogeler 2011), but the appropriate spatial scale of analysis will depend on the taxa of interest. For instance, other taxa such as arthropods utilize habitat at much finer spatial scales (Vierling et al. 2011), and thus, changes in vegetation that might have negligible effects on bird distributions may have larger effects on arthropods.

5. Conclusion

This study describes how time lags between bird data collection and airborne LiDAR acquisitions might affect wildlife-habitat mapping. Our findings suggest that while a 6-year time difference between a LiDAR acquisition and the collection of bird field data does result in statistically significant differences, the absolute differences in non-harvest locations are nonetheless quite small and therefore may not be biologically significant in this conifer forest. As a result, the temporal mismatch between LiDAR and field-data acquisition would still likely produce avian distribution maps of use to forest managers, despite the time lag. Because this is one case study in one ecosystem, additional work examining the effect of temporal lags between LiDAR- and field-data collection is

warranted under different vegetation growth rates, disturbance and climatic regimes to better understand the influences of data collection time lags on predicting animal distributions.

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