AN ABSTRACT OF THE DISSERTATION OF

Jody C. Vogeler for the degree of Doctor of Philosophy in Forest Ecosystems and Society presented on December 8, 2014.

Title: The Use of Remote Sensing for Characterizing Forests in Wildlife Habitat Modeling.

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Warren B. Cohen

Spatially explicit maps of habitat relationships have proven to be valuable tools for conservation and management applications including evaluating how and which species may be impacted by large scale climate change, ongoing fragmentation of habitat, and local land-use practices. Studies have turned to remote sensing datasets as a way to characterize vegetation for the examination of habitat selection and for mapping realized relationships across the landscape. Although the use of remote sensing in wildlife studies has increased in recent years, the use of these datasets is still limited and some data sources and methods are yet to be explored. The overall goal of this dissertation was to look at the state of the wildlife ecology discipline in the use of geospatial data for habitat mapping, and to advance this area through the fusion of remote sensing tools for the mapping of previously difficult to characterize forest metrics for inclusion in avian cavity-nester habitat models.

Chapter 2 reviewed over 60 years of selected wildlife literature to examine the wildlife ecology disciple through historic trends and recent advances in the use of remote sensing for habitat characterization focusing on aspects of scale and the use of available technology. We discuss commonly used remote sensing data sources, point out recent advances in the use of geospatial data for characterizing forest wildlife habitat (the use of lidar data and the creation of spatially explicit habitat prediction maps), and provide future suggestions for increased utilization of available datasets (secondary lidar metrics...
and time series Landsat data). In chapters 3 and 4 we explored the use of remote sensing for characterizing forest components previously difficult to map across landscapes at scales relevant to local wildlife habitat selection. Chapter 3 found promise in the fusion of lidar structure and Landsat time series disturbance products in the modeling and mapping of post-fire snag and shrub distributions at fine scales and at size/cover thresholds relevant for habitat mapping applications for many wildlife species. The study was conducted within the 2003 B&B Fire Complex in central Oregon. Using 164 field calibration plots and remote sensing predictors, we modeled the presence/absence of snag classes (dbh ≥40cm, ≥50cm, and ≥75cm) and woody shrub cover resulting in 10m output predictive grid maps. Remote sensing predictors included various lidar structure and topography variables and Landsat time series products representing the pre-fire forest, disturbance magnitude, and current forest conditions. We were able to model and map all habitat metrics with acceptable predictive performance and low-moderate errors. The utility of these snag and shrub metrics for representing important nesting habitat features for a cavity-nesting species of conservation concern, the Lewis's Woodpecker (*Melanerpes lewis*), was demonstrated in Chapter 4. We were able to model nesting habitat with good accuracies according to multiple performance measures and then map realized relationships for this species of conservation concern in an identified source habitat type, providing a potential resource for local scale conservation and management efforts and adding to the regional knowledge of habitat selection for the Lewis's Woodpecker. To our knowledge, these chapters represent first attempts to fuse lidar and time series Landsat disturbance metrics in a post-fire landscape and for the mapping of snag and shrub distributions at scales relevant to avian cavity nesting habitat.
The Use of Remote Sensing for Characterizing Forests in Wildlife Habitat Modeling

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Jody C. Vogeler

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Jody C. Vogeler, Author
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THE USE OF REMOTE SENSING FOR CHARACTERIZING FOREST IN WILDLIFE HABITAT MODELING

CHAPTER 1: INTRODUCTION

Understanding drivers of wildlife species habitat selection is the basis for many efforts evaluating how and which species may be impacted by large scale climate change (Maclean et al. 2008), ongoing fragmentation of habitat (Saunders et al. 1991), and local land-use practices (Poulin et al. 2008). Spatially explicit maps of habitat relationships have proven to be valuable tools for such conservation and management applications (Graf et al. 2009). Studies have turned to remote sensing datasets as a way to characterize vegetation for the examination of habitat selection and for mapping realized relationships across the landscape (Clawges et al. 2008, Vogeler et al. 2013).

Previously published habitat suitability models (HSMs) are also starting to be mapped using remote sensing representations of habitat selection drivers and important thresholds in order to assign habitat suitability index values across landscapes (Martinuzzi et al. 2009a). While studies are finding great promise in the ability of remote sensing to represent the vegetation at scales relevant to habitat selection for species, it is also important to validate that the characterization of habitat features by remote sensing are actually depicting the features of interest for the species.

The use of remote sensing in wildlife studies has significantly increased in recent years, although there may be data sources and/or methods that are still in their infancy or yet to be explored for wildlife research and management purposes. The second chapter of this dissertation reviews over 6 decades of selected wildlife literature to examine historic trends, acknowledge recent advances in wildlife studies attributed to geospatial datasets, and identify remote sensing datasets or methodologies that are yet to be represented or still in their infancy within the wildlife literature. We focused our historic trends review on forest avian studies within two long running wildlife journals, *Journal of Wildlife Management* (JWM, http://www.bioone.org/loi/wild) and *Ecology* (ECO, http://www.esajournals.org/loi/ecol), from 1950 to 2014. We reviewed aspects of spatial
scale and the use of technology for characterizing forest structure and/or composition. We also included the journal *Remote Sensing of Environment* (RSE; http://www.journals.elsevier.com/remote-sensing-of-environment) in our review starting at the initiation of the journal in 1969, to also sample trends in wildlife studies utilizing remote sensing datasets within the remote sensing literature. To identify early representations of remote sensing data for characterizing forest structure or composition in the literature not restricted by journal or taxa, as well as to identify recent advances in the field, we conducted an additional, broad literature review using keyword searches within Google Scholar. To identify promising data sources and/or methods for characterizing forests that are not yet represented or may have additional untapped value for wildlife habitat studies, we reviewed literature from the remote sensing and forest research disciplines. We present several of these data sources and methods and discuss how they may advance efforts for understanding or depicting wildlife habitat relationships.

Some fine-scale forest attributes important to a variety of wildlife species have been found to be difficult to map using remote sensing technology due to the spatial resolution and the two-dimensional nature of many of the satellite based data sources. Examples of these difficult to map local scale forest features include woody shrub cover and snag distributions of varying size thresholds, both of which provide nesting/roosting, foraging, and concealment substrates for a variety of wildlife species in many forest habitats (Hagar 2007, Brown 2002). It has been estimated that 2/3 of all wildlife species use standing deadwood or woody debris for some part of their life cycle (Brown 2002). In post-fire systems, snags are of particular importance for providing resources for the complex cavity-nesting communities often closely linked to these burned forests (Haggard and Gaines 2001). As management activities and changing fire patterns alter the availability and spatial arrangement of snags, there is increasing concern for cavity-nesting communities (Martin & Eadie 1999). Another important aspect of post-fire areas that impact wildlife species utilization include a woody shrub component for increasing invertebrate abundance, soft mast production, nesting substrates, and concealment from predators (Nappi et al. 2004). In these post-fire areas conflicts pertaining to the
management of land for multiple purposes, including wildlife habitat and timber production, lie in understanding three-dimensional aspects of the landscape and the distribution of specific structural elements such as snags of various sizes, decay stages, and densities, and the availability of a woody shrub component.

Three-dimensional lidar structure data and time series Landsat disturbance and recovery products have begun to show promise in their ability to provide information about standing dead components of forested systems (Martinuzzi et al. 2009a, Pflugmacher et al. 2012). Martinuzzi et al. (2009a) found promise in the utility of lidar structure and topography data for the modeling and predictive mapping of snags of varying size thresholds in an unburned mixed conifer forest in Idaho. Standing dead wood is often represented in remote sensing studies as dead biomass (Kim et al. 2009) or the proportion of trees in a general dead condition class (Bater et al. 2007). Pflugmacher et al. (2012) were able to utilize time-series Landsat data for providing historic disturbance and recovery trends to aid in the prediction of current forest conditions including the distribution of dead biomass. While these studies point out the potential of these data for depicting the distribution of dead forest components, to our knowledge specific snag mapping products have not been validated for use in habitat studies by ground wildlife data, nor have specific snag size classes been modeled with remote sensing data in post-fire landscapes.

The ability of lidar to model shrub distributions has also been explored, although studies and forest types are limited and the importance of the resulting maps have yet to be validated on the ground with wildlife datasets (Martinuzzi et al. 2009a, Wing et al. 2012). While some lidar pulses may penetrate the canopy to return information on the structure of the lower strata of a forest, especially in more open stands or in post-fire areas with high canopy mortality, it is difficult to directly map shrub layers with lidar point-cloud data alone (Martinuzzi et al. 2009a). By calibrating the lidar data with onsite field-data, models can be created to predict the distribution of woody shrub cover across a study area (Martinuzzi et al. 2009a).

As mapping products representing important habitat components of post-fire systems increase in availability, detail, and accuracy, new opportunities arise to map
habitat for forest species of conservation concern. One such species is the Lewis's Woodpecker (*Melanerpes lewis*), which is a species of conservation interest in multiple U.S. states and areas of Canada, including being listed as a sensitive species with a critical status by the Oregon Department of Fish and Wildlife (ODFW 2008), with habitat loss and degradation proposed as contributing factors in the species decline (Vierling et al. 2013). In the context of source-sink meta-populations, the high reproductive success of post-fire habitats have led them to be considered as population sources for the Lewis’s Woodpecker (Gentry and Vierling 2007, Saab and Vierling 2001), thus representing critical habitat for this species of concern. Previous Lewis's Woodpecker breeding season habitat studies, including the published Habitat Suitability Model (HSM), have identified the importance of a woody shrub component along with moderate canopy cover and a density of large snags (Sousa 1983, Witt 2009; Zhu et al. 2012), although these relationships have not been calibrated and mapped across a post-fire landscape.

Some studies have found promise in the combination of remote sensing datasets, namely lidar and time series Landsat products for characterizing forests (Pflugmacher et al. 2012), but to our knowledge these methods have not yet been explored in post-fire landscapes or for the modeling of specific snag resources or shrub distributions for inclusion in habitat mapping efforts. The objectives of chapter 3 and 4 of this dissertation were to 1) explore the fusion of lidar structure information with Landsat time series disturbance products for the modeling and mapping of post-fire snags and shrub distributions; and 2) evaluate the utility of these remote sensing products for characterizing post-fire Lewis's Woodpecker nesting habitat, a species of conservation concern in many western states and provinces.
CHAPTER 2: THE ROLE OF REMOTE SENSING FOR CHARACTERIZING FOREST IN WILDLIFE HABITAT MODELS: HISTORIC TRENDS, RECENT ADVANCES, AND FUTURE SUGGESTIONS

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ABSTRACT

Understanding wildlife habitat relationships is important for management and conservation efforts for predicting how and which species may be negatively impacted by large scale climate change, ongoing fragmentation of habitat, and local land-use practices. Depicting habitat relationships and predicting responses to environmental change require datasets characterizing habitat patterns and features that may be of importance to species at hierarchical levels of habitat selection. The purpose of this paper is to discuss the characterization of forests for understanding wildlife habitat relationships through historic trends, recent advances, and future directions with an emphasis on the utilization of remote sensing data. We reviewed over 6 decades of selected wildlife literature to look for trends in the scales at which forest habitat were characterized and at which relationships were analyzed within these studies, as well as the use of different remote sensing datasets for characterizing forest structure and composition as related to wildlife habitat. Our review focused on three aspects of scale: observation (scale at which vegetation was sampled); modeling (scale at which analyses were conducted); and geographic (spatial extent of the study). We discuss commonly used remote sensing data sources, point out recent advances in the use of geospatial data for characterizing forest wildlife habitat (the use of lidar data and the creation of spatially explicit habitat prediction maps), and provide future suggestions for increased utilization of available datasets (secondary lidar metrics and time series Landsat data). The use of remote sensing has significantly increased in recent years, although there still may be additional applications and opportunities to represent habitat features yet to be realized. Continued communication between disciplines is important in the exchange of knowledge as forest ecology and remote sensing research identify promising ways of representing forest structure and composition that may aid in wildlife research and management.
1. INTRODUCTION

Wildlife populations are faced with the challenge of persisting in a complex environment of multiple natural and anthropogenic stressors, often acting with synergistic impacts (Theobald et al. 1997). Understanding wildlife habitat relationships is therefore important for management and conservation efforts (Wintle et al. 2005, Graf et al. 2009). Recently there is even greater pressure to provide spatially explicit broad scale information on drivers of species distributions. Such information has great value for predicting how and which species may be negatively impacted by large scale climate change (Maclean et al. 2008), ongoing fragmentation of habitat (Saunders et al. 1991), and local land-use practices (Poulin et al. 2008).

The challenge of understanding species distributions and potential impacts of a changing environment is a complex one involving a variety of factors acting on multiple scales (Clawges et al. 2008). Wildlife species select their habitat in a hierarchy of scales starting with the species geographic range (1st order), individual selection of a home range (2nd order), important patches for life history needs within the home range (3rd order), and ultimate resources such as foraging/nesting substrates (4th order; Johnson 1980). Metapopulation ecology incorporating population dynamics and the spatial arrangement of habitat patches has also become a focus in wildlife research and conservation (Hanski 1998). Anthropogenic impacts such as urban and energy development that lead to habitat fragmentation and other disturbances that disrupt and restrict the movement of species and connection of habitat patches, increases the complexity of, and concern for, the issue of species persistence (McKinney 2002). To be able to predict how changes in the environment may impact species, we must first have a sound understanding of the drivers of species habitat relationships at these levels of selection, as well as other factors limiting dispersal and ultimate distributions of populations.

An important piece of the puzzle in understanding habitat relationships and predicting responses to environmental change are datasets characterizing habitat patterns and features that may be of importance to species at the above levels of selection. A
rapidly growing body of literature has found promise in the utility of remote sensing for characterizing vegetation patterns and important features for ecological research (Kerr and Ostrovsky 2003, Fassnacht et al. 2006, Vierling et al. 2008). Potentially one of the more difficult habitat types to try to characterize with remote sensing are the vertically and horizontally complex forest systems. Characterizing this complexity is needed to explore which aspects may represent driving and/or limiting factors for wildlife species (Vierling et al. 2008).

The purpose of this paper is to discuss the characterization of forests for understanding wildlife habitat relationships through historic trends, recent advances, and future directions. We reviewed over 6 decades of selected wildlife literature to look for trends in the scales at which forest habitat were characterized and at which relationships were analyzed within these studies, as well as the use of different remote sensing datasets for characterizing forest structure and composition as related to wildlife habitat. We then reviewed recent advances in wildlife habitat studies that can be attributed to geospatial data. Finally, we provide suggestions for future research in the area of new remote sensing data/techniques that could benefit forest wildlife studies that are currently not represented or may be underutilized within the wildlife literature.

1.1. Remote Sensing for Forest Habitat Applications

Wildlife species have been shown to respond to vertical and horizontal aspects of forest structure and composition (Sallabanks et al. 2006, Clawges et al. 2008). The ability of remote sensing to characterize these aspects of forest structure has been well documented in the remote sensing and forest ecology literature (Appendix A). The value of spatial datasets depicting important aspects of forest systems at scales relevant to wildlife species and populations have caught the attention of the wildlife community and have increased in habitat modeling applications in recent years (Clawges et al. 2008, Goetz et al. 2010, Vogeler et al. 2013). Continued communication between disciplines is important in the exchange of knowledge as forest ecology and remote sensing research identify promising ways of representing forest structure and composition that may aid in wildlife research and management.
2. METHODS

2.1. Forest Wildlife Literature Review 1950-2014

To evaluate historic trends in remote sensing forest habitat applications and the scales at which habitat is represented and relationships examined, we selected two long-running journals to focus this section of our review: *Ecology* (ECO, http://www.esajournals.org/loi/ecol) and *Journal of Wildlife Management* (JWM, http://www.bioone.org/loi/wild). While we acknowledge that these two journals may or may not represent the trends that exist in the wildlife literature as a whole, focusing our review on a sample of the literature allowed us to evaluate trends over a span of 6 decades. The remaining sections of our review beyond looking at historic trends, utilize a more broad Google Scholar search. For this historic trends section, we further narrowed the scope of review by focusing on a single animal taxon, birds, which are well documented in the literature, and represent a wide range of spatial scales and preferred nesting and foraging substrates. We reviewed studies from 1950-2014 within JWM and ECO that utilized some aspect of forest structure, composition, or configuration in relating bird species distributions and/or demographic data to occupied habitat. Since the focus of this paper is in the area of species habitat relationships, we excluded broad diversity studies and only reviewed those examining habitat for individual bird species or groups of species that share nesting and/or foraging preferences (guilds). Due to the large amount of studies that meet these criteria in the JWM, we reviewed every other issue within a given year. We focused on aspects of spatial scale and the use of technology for characterizing forest structure and/or composition. We also included the journal *Remote Sensing of Environment* (RSE; http://www.journals.elsevier.com/remote-sensing-of-environment) in this historic trends review, to ensure that we were not missing a significant boom in wildlife literature utilizing remote sensing datasets by limiting ourselves to these wildlife-specific journals. This review began at the initiation of the journal in 1969.

2.1.1. Spatial Scale
The concept of scale has been identified as an important consideration in both the remote sensing and wildlife habitat literature (Johnson 1980, Woodcock and Strahler 1987); but when working across disciplines, it is important to clarify definitions and concepts. Wu and Li (2009) proposed 6 types of scale to consider in scientific research which pertain to both the remote sensing and wildlife habitat disciplines: observation, modeling, operational, geographic, policy, and cartographic. We will only discuss the first 5 here. The observation scale pertains to the scale at which the data is sampled or in the case of remote sensing, the spatial, temporal, and spectral resolution of the dataset. The modeling scale is the scale at which the statistical analyses is conducted. The operational scale refers to the scale at which natural processes occur such as the orders of wildlife habitat selection. The extent of the research area evaluated is the geographic scale. The policy scale ties in the scales at which conservation and management decisions are made and implemented.

We chose to focus our review on observation, modeling, and geographic scales, although operational and policy scales were inherently included in some of the classifications used when describing the three focal scales (figure 2.1). The observation scale, or scale at which vegetation was sampled, was classified as either tree or patch level. The modeling scale at which analyses were conducted was divided into small, moderate, and large modeling scales. Included in the small modeling scale are those analyses at the tree or plot specific level (with an arbitrary cutoff of 100m plot radius). The moderate modeling scale was subdivided into a animal driven class (breeding season territory) and a vegetation driven scale (homogenous forest stand). The large modeling scale was subdivided into the animal driven year-round home range, and a user-defined landscape. The animal driven modeling scales, breeding season territory and year-round home range, can also be consider operational scales at which natural processes occur (territories and home ranges represent 3rd and 2nd order habitat selection, respectively; Johnson et al. 1980). The last type of scale that we focused on in our review was the geographic scale, or the spatial extent covered by the study. We created classifications for this type of scale that are also related to policy scales depending on the borders crossed and areas included in the geographic scale category. These included sub-state, regional,
and national geographic extents. The sub-state geographic scale may include multiple counties, ownerships, and forests, although these studies were often conducted within the boundaries of one state or national forest. The regional extent may not exhaustively cover a state, but crosses state boundaries. The national geographic scale includes those studies that sample across the majority of a country or at least the geographic range of a species within that country. Studies conducted at each of these extent levels have their own set of policy and administrative considerations. When considering the combination of scales for a project/purpose it is important to match the observation data to the modeling approach and aim to capture the operational scales within the models (Wu and Li 2009).

2.1.2. Technology

In our review of each paper, we recorded the technology/source used to collect the vegetation data, including field-measurements, aerial photography, satellite imagery, and active remote sensing (i.e. airborne lidar). Some studies were not explicit in the source of data used to determine metrics, but in many of those cases we were able to decipher the data source through context clues or cited sources. We noted the first appearance of a data source in the reviewed journal, and then summarized the proportion per decade of reviewed papers utilizing the data sources as well as the aspects of scale discussed above.

To identify early representations of remote sensing data for characterizing forest structure or composition in the literature not restricted by journal or taxa, we conducted an additional, broad literature review using keyword searches within Google Scholar. These studies along with other key dates relating to the origin of different remote sensing data and other important developments facilitating the analysis and utilization of geospatial data, were plotted on a time line.

2.2. Review of recent advances in characterizing forest habitat for wildlife and suggestions for future research

In addition to our review of forest bird habitat studies within ECO, JWM, and RSE, we also wanted to expand our search beyond birds and these three journals to evaluate more general advances in characterizing forest habitat for wildlife studies. We
used keyword searches related to forest wildlife habitat and the span of remote sensing datasets within Google Scholar. After reviewing recent publications in the area of geospatial data applications in wildlife habitat studies from this more broad review, we chose a few what we considered recent advances that are greatly expanding the understanding of habitat relationships and the representation of that information for conservation and management purposes. To identify promising data sources and/or methods for characterizing forests that are not yet represented or are underutilized in the wildlife literature, we reviewed literature from the remote sensing and forest research disciplines. We present several of these data sources or methods and discuss how they may advance efforts for understanding or depicting wildlife habitat relationships.

3. LITERATURE REVIEW RESULTS

3.1. ECO and JWM (1950-2014) and RSE (1969-2014) Review

We reviewed 266 articles that met the criteria for our forest bird habitat studies review in ECO (85 articles) and the JWM (169 articles) since 1950, and RSE (12 articles) since 1969 (Appendix B). The majority of the studies were at least partially conducted within North America (245/266), with a handful of studies on other continents including South America (5), Africa (1), Europe (8), Asia (1), and the Australia and Oceania region (7). It was common for studies to cover multiple land cover types, but they all included at least some aspect of forest composition or structure in the examination of avian habitat relationships to be included in the review.

3.1.1. Aspects of scale review

The smallest extent at the sub-state level was the most common geographic scale including 86% of the reviewed studies (figure 2.2a). These studies were usually conducted within a single forest or park, occasionally covering several parks or national forests, with 3 studies that examined forest avian habitat relationships across all forests within a state. The regional extent was examined in 34 of 266 studies. Due to our definitions for the categories of extent, a study at the regional scale may not necessarily
cover a significantly larger area than some of the sub-state extent studies. Due to the additional considerations required when working across state boundaries, this factored into how we defined regional extents. There was an increase in studies covering regional extents in more recent decades of our review but not necessarily a steady trend (figure 2.2a). This increase could be attributed to advances in technology and vegetation datasets with more broad spatial coverage, although we only found 3 studies that covered a nation-wide extent.

The need for large scale wildlife monitoring has motivated efforts such as the North American Breeding Bird Survey (NA BBS; https://www.pwrc.usgs.gov/bbs), providing larger extent wildlife datasets. NA BBS was established in 1966 growing to almost 2000 survey routes by 1968 (Ziolkowski et al. 2010). Currently there are approximately 3700 BBS routes in North America with the highest concentration of routes in New England, Mid-Atlantic states, and southern Canada (Ziolkowski et al. 2010). Larger extent wildlife datasets such as BBS data along with remotely sensed vegetation maps have opened the doors for examining wildlife habitat relationships across larger scales facilitating new studies exploring the potential impacts of climate change or other expansive drivers of wildlife species distributions and for the monitoring of populations. We found both regional and national extent studies in our historic trends review that utilized NA BBS data along with Landsat derived landcover maps (Vance et al. 2003, Tittler et al. 2006, Jones et al. 2007).

There were a variety of modeling scales utilized in the reviewed studies. Examples at the smallest end of the small modeling scale were studies modeling important variables of specific nesting or foraging trees. At the upper end of the small-scale class were studies examining relationships between species occurrence or density and summarized forest structure/composition within 100m of the location. Common summary vegetation variables included stem densities of specific tree species and sizes, canopy height, mean canopy cover, mean shrub cover, and foliage profiles. These metrics could be considered 3rd or 4th order habitat selection depending on the particular study.

The moderate modeling scale was subdivided into a vegetation driven class, the level of homogenous forest stands, and an animal driven class, breeding season
territories. The majority of these studies could be considered 3rd order of habitat selection. Studies using stands as the modeling scale defined stands as patches of forest with homogenous structure and composition with edges defined where the pattern of structure or composition changed. These studies included those that looked at differences in densities of a bird species within different types of stands, general stand type associations of species, and those evaluating the impact of fragmentation. Fragmentation metrics included in this stand scale were related to patch size, length of edge, or amount of core habitat (area of stand buffered from the edge). When a breeding season territory was used as the modeling scale, the vegetation structure and composition and/or the variability of, was summarized within the territories. Mean values for vegetation variables were often summarized across all territories of a species to look at preferences or thresholds for that species.

Large modeling scales included studies using user defined "landscapes" or animal defined home ranges encompassing the year-round range of individuals of a species. Home ranges were often determined using radio telemetry to identify boundaries. Landscapes were either an arbitrarily-defined distance around sample locations to look at the composition and configuration of habitat patches surrounding locations, or distances were chosen to match average areas of home ranges to create random "availability" comparisons to those of “used” home ranges following a use/availability statistical approach. The studies utilizing home ranges could be considered 2nd order of habitat selection.

Some studies spanned multiple modeling scales and thus levels of habitat selection. When subcategories of animal and vegetation defined boundaries were consolidated, the only consistent trend observed was an increase in the proportion of studies including a large modeling scale (home range or landscape; figure 2.2b). This could be due to the greater availability of remotely sensed vegetation datasets that facilitate landscape level variables such as the amount of core habitat in a larger area, habitat connectivity, diversity of landcover types, or other aspects of landscape configuration that may drive or restrict wildlife distributions and movements. Open source landscape analyses software such as FRAGSTATS (McGarigal et al. 1995), may
have also aided in an increase in this type of variable in the habitat models. There has also been greater awareness of the importance of looking at multiple scales for understanding wildlife habitat as well as the importance of a landscape context in understanding wildlife distributions and metapopulation dynamics in more recent decades. Advances in spatial statistics have also risen to the occasion to be able to attempt multi-scale habitat relationship models.

When the subgroups at the moderate and large modeling scales are divided, home range and territory scales track each other in a steady although slow increase throughout the review (figure 2.2c). This could be a product of better and more available radio telemetry data allowing for easier mapping of individual animal movements for the mapping of breeding season territories and year round home ranges. There was an obvious bump in landscape variables in the 1990s, independent of the other large scale home range metric, which once again may note the release of FRAGSTATS (McGarigal et al. 1995) and advances in spatial statistics.

The observational scale of the vegetation data required to represent important drivers of wildlife distributions is an important consideration when determining if remote sensing datasets may be appropriate for characterizing habitat. While some studies contained metrics at both the tree and the patch observational scale, we found 62% of studies contained variables at the tree scale, and 77% of studies used vegetation metrics at the patch scale. There was a slight trend observed of an increase in patch and decrease in tree observational scale metrics, but it is difficult to tell if the trend is deliberate or will continue (figure 2.2d). This could be the result of a shift towards patch scale remote sensing as opposed to tree level data which is difficult to collect outside of the field.

3.1.3. Technology trends in wildlife literature (ECO and JWM 1950-2014)

Throughout the duration of the review, 36% and 34% of the ECO and JWM articles utilized remote sensing, respectively. Regardless of the inclusion of other data sources, the majority of the reviewed studies utilized field methods to collect at least some portion of their vegetation data (figure 2.3). Wildlife disciplines are traditionally and will potentially always be rooted to field collected data. Most wildlife distribution
and demographic data with the exception of some radio telemetry-based information can only be collected in the field. It has also been well documented that many wildlife species are influenced by some aspects of fine-scaled structural features that are difficult or impossible to quantify without field data. Examples of such metrics include: the distribution and abundance of a variety of vegetation produced food sources (soft and hard mast); specific nesting substrates such as snags of varying decay stages for cavity nesters or adequate foliage concealment for ground and understory nests; the availability of downed hollow logs; the density of understory shrubs; and specific ground cover attributes.

The sensors used in at least one study in our JWM and ECO review included various forms of aerial photography, satellite sensors (IKONOS, QuickBird, Landsat MSS, TM, and ETM+), and one lidar study (Goetz et al. 2010). Studies were rarely explicit on remote sensing processing or data source details, although we attempted to deduce or follow citations to as many data sources at possible which only left a few where we were unsure of the sensor used for mapping. Aerial photos first appeared in ECO in 1970 to characterize cover composition in a red-tailed hawk (Buteo jamaicensis) nesting study (Luttich et al. 1970) and as a part of two studies in JWM in 1972 (Nicholls and Warner 1972, Martinka 1972). Nicholls and Warner (1972) utilized aerial photos in conjunction with field visits to map cover types for a study on barred owls (Strix varia). Blue grouse (Dendragapus obscurus) territories were mapped onto aerial photos in the study by Martinka (1972) which acted as boundaries for characterizing vegetation. Other common uses of aerial photos in the reviewed studies included: marking bird or nest locations and then characterizing surrounding habitat type; percent of cover types within territories; delineating stand boundaries and calculating area and length of edge; and for measuring distance to water from nest sites.

The majority of studies that utilized satellite-derived metrics used one of the Landsat sensors (i.e., Landsat MSS, TM, and ETM+) for characterizing habitat through the use of landcover maps (such as NLCD), calculating percent forest cover, or to derive forest stand age maps. Landsat was first observed in our review in JWM in 1992 to characterize canopy closure in a pileated woodpecker (Dryocopus pileatus) study (Bull et
Stouffer and Bierregaard (1995) first utilized Landsat within ECO to map the
distribution of disturbances in a multi-species study looking at the effect of isolation of
forest fragments on species abundances.

Beyond the Landsat series of satellite sensors, IKONOS and QuickBird imagery
was utilized to characterize forest metrics in one study each in our ECO and JWM
review. Singleton et al. (2010) looked at barred owl habitat selection using 60cm
resolution QuickBird imagery to map overstory canopy closure and diameters of
overstory tree crowns in ECO. IKONOS derived maps of cover types were used to
calculate landscape metrics within FRAGSTATS in a multi-species study by Schlesinger
et al. (2008) in JWM.

Lidar data only appeared once during this trend review within JWM and ECO, but
will be discussed further in the next section. Published in ECO, Goetz et al. (2010) used
waveform lidar to derive canopy height and complexity metrics in conjunction with two-
date Landsat-derived normalized difference vegetation index (NDVI) to predict breeding
season habitat of the black-throated blue warbler (*Dendroica caerulescens*). No other
types of active remote sensing were represented in the ECO and JWM review.

3.1.4. **RSE review of technology in wildlife habitat studies**

Our review of RSE found only 12 articles since 1969 that utilized remote sensing
technology in the examination of forest avian habitat relationships (AppendixB), with the
first study in this group not published until 1997 (Imhoff et al. 1997). The main
difference between the wildlife studies reviewed in RSE and those from JWM and ECO
is that many of the RSE forest wildlife studies combined multiple sources of remote
sensing data, as well as consistently being more explicit in reporting data sources,
processing methods, and discussing map accuracies. Remote sensing data sources
included aerial photography, IKONOS, QuickBird, Landsat, MODIS, AVHRR, lidar, and
radar.

3.1.5. **Timeline of important dates in remote sensing and wildlife habitat applications**
Through our more broad literature research through Google Scholar, we plotted early applications of remote sensing for characterizing forest habitat in wildlife studies on a timeline with the initiation dates of remote sensing datasets and their use in forestry applications (figure 2.4). Time lags were observed between the initiation of remote sensing technologies and their adoption into the wildlife literature although this may be expected within any secondary users of mapping products and appropriate considering the advantage of allowing the remote sensing and forestry realm to first test and validate the utility of these datasets for characterizing aspects of forest structure and composition that may contribute to wildlife habitat modeling purposes. While there are examples of wildlife studies utilizing many of the remote sensing mapping products, there may still be room for increased communication between the disciplines to further advance wildlife habitat mapping applications and to provide feedback as to the needs of the wildlife community for map creators.

3.2. Recent advances and applications of remote sensing in avian habitat studies

Our review of more recent literature not restricted by journal or taxa showed a substantial increase in the use of remote sensing in more recent wildlife habitat modeling efforts. The use of GIS and spatial datasets is becoming the norm. In our broad Google Scholar review of recent wildlife habitat literature, we identified two geospatial related topics, one data source and one geospatial map product, that have recently boomed. The first is the adoption of lidar data to characterize vegetation in wildlife habitat studies. The second is a product of wildlife habitat modeling using geospatial data, the creation and publication of spatially explicit habitat prediction maps (Graf et al. 2005, Martinuzzi et al. 2009a, Vogeler et al. 2013).

3.2.1. Lidar for Characterizing Habitat

The resolution and the two-dimensional nature of many of the satellite based data sources has been identified as a limitation for capturing some of the important features for wildlife habitat needs. While coarser grain data for characterizing stand level attributes such as cover type may be adequate for some purposes, many forest wildlife
species respond to fine-scale three dimensional aspects of the forest including (but not limited to): foliage height diversity (Clawges et al. 2008); the presence and densities of particular forest strata such as the understory and the upper canopy (Clawges et al. 2008, Vogeler et al. 2013); the distribution of snags and downed wood (Bull and Meslow 1977); and stem densities of varying sizes (Sallabanks et al. 2006). The fine-scale, three-dimensional nature of lidar data has thus caught the attention of the forest wildlife research and management community in its potential to represent these habitat features at local scales.

While the first study using lidar data to model wildlife species habitat appeared in 2002, utilization has only recently become more commonly recognized by the wildlife community. The first use of lidar data in species habitat modeling was Hinsely et al. (2002), who related lidar-derived canopy height to habitat quality for Great Tits and Blue Tits. Vierling et al (2008) reviewed early explorations into the use of lidar for habitat modeling. They found that studies discussed the potential of lidar to advance wildlife habitat mapping, but only a handful of studies at that time had actually utilized lidar to characterize forest metrics for inclusion in wildlife habitat modeling efforts. Since the review by Vierling et al. (2008), lidar has begun to appear more frequently in the wildlife literature, although still only representing a small proportion of wildlife habitat studies and only one study in our ECO and JWM review (Goetz et al. 2010). More recently, Merrick et al. (2013) conducted an updated review on applications of lidar data in wildlife habitat assessments. They too found that the majority of studies with lidar and wildlife habitat as the topic (n=154) discussed the potential value of lidar for wildlife studies while few studies directly utilized lidar for that purpose (n=18; Merrick et al. 2013).

The value of lidar goes beyond the ability to characterize fine-scale habitat features previously sampled using field-based methods. The continuous 3-D data allows for the characterization of vegetation in ways either only able to be collected in small field-based samples or unable to be collected using field-based methods at all. In doing so, lidar is advancing wildlife habitat studies by allowing for the examination of previous unquantifiable, or extremely difficult to quantify, habitat features (Clawges et al. 2008,
Vogeler et al. 2013). For example, there has been a long understood relationship between wildlife species and foliage height diversity although this metric is extremely labor intensive to collect using manual methods even on small scales (MacArthur and MacArthur 1961). Studies have found great promise in the ability of lidar to represent foliage height diversity in a ecologically meaningful way for multiple wildlife species as well as allowing for the mapping of this metric across whole landscapes (Clawges et al. 2008). In addition to diversity in foliage heights, some wildlife species respond to specific foliage layers within the forest. Lidar facilitates the mapping of specific forest strata to test for relative importance of certain layers for species. Vogeler et al. (2013) found the upper canopy as represented by lidar, to be the driving factor in the occupancy of a late-seral specialist, the brown creeper (*Certhia americana*). The continuous nature of lidar data across landscapes as opposed to field sampled vegetation data also allows for extraction of landscape metrics in studies examining habitat relationships at larger habitat selection scales (Nelson et al. 2005).

As the range and diversity of methods and variables for describing forest structure and complexity across multiple scales increases, it is important to expand the exploration into which of these approaches or maps show the most promise for depicting the drivers of wildlife habitat selection. We know that species select their habitat at multiple scales with the important drivers and thresholds for resource availability and configurations of habitat patches potentially variable depending on the spatial scale and the level of detail at which the habitat features are classified.

3.2.2. Predicted Habitat Maps

The increase in the availability of spatially explicit vegetation datasets and geospatial data processing capabilities has led to a major advancement in the field of wildlife habitat for the purpose of management and conservation efforts: prediction maps. Prediction maps provide a valuable tool for management and conservation planning (Mason et al. 2003). Maps highlighting important areas for species distributions may be useful for forecast modeling efforts identifying potential impacts of climate change, the
prioritization of conservation resources, trade-off analyses for landscape planning, and for local scale management plans.

Habitat mapping is not a new concept, but advances in the abundance, availability, and resolution of the spatial data have increased mapping opportunities. A long time tool in the wildlife community for management and conservation efforts are habitat suitability index (HSI) models. HSI models are created through the synthesis of known habitat drivers for a given species derived from the available literature and expert knowledge which are then scaled from 0.0 (unsuitable habitat) to 1.0 (optimal habitat). Models for species habitat can only be used to create predicted habitat maps if the components of the models are available in spatial datasets (Martinuzzi et al. 2009a). Remote sensing and other mapped environmental data began to be utilized to map habitat models in the 1980s (Donovan et al. 1986, Palmeirim 1988). The challenge of habitat modeling/mapping is balancing generality, detail, and accuracy (Mason et al. 2003). While general coarse grain maps may be appropriate for large scale planning (climate change, fragmentation, etc.), fine grain prediction maps may be needed for local scale land management decisions. The acceptable level of accuracy is also project-specific and therefore limitations and biases of predictive maps should be evaluated and understood before use in decisions or planning efforts.

Utilizing a combination of remote sensing data may allow for addressing both large and fine scale conservation concerns and planning. Graf et al. (2005) produced predictive maps for an endangered forest-specialist grouse species, the Western Capercaillie (*Tetrao urogallus*), across the Swiss Alps using Landsat data. These maps allowed for the identification of a high quality area of habitat to set aside as a conservation reserve (Graf et al. 2005). Later efforts were then able to use lidar data within the relatively high quality habitat reserve to identify areas to concentrate fine scale restoration efforts (Graf et al. 2009).

The USGS GAP analysis project ([http://gapanalysis.usgs.gov](http://gapanalysis.usgs.gov)) is a national effort with the goal of maintaining biodiversity through the mapping of species distributions in relation to protected areas and other owner/management regimes. The motto of GAP is “keeping common species common”. Their broad scale species distribution maps, while
perhaps lacking in local scale precision, aid in identifying species that may be at the greatest risk of habitat loss due to limited habitat within protected areas. Species maps are created by reviewing available literature on known species habitat relationships to link the species to Landsat derived landcover and other remotely-sensed topographic and vegetation datasets to create national range and distribution maps for that species. Land ownership layers can then be added to the maps to assess the amount of potential habitat on protected lands for that species. Efforts can then be prioritized for species at the greatest risk of habitat loss due to little or no potential habitat on protected lands. There are ongoing efforts by the GAP project and collaborators to expand the available species distribution maps and to improve the quality of existing maps (Martinuzzi et al. 2009b).

While not a part of this review, it should also be noted that many of the advances in vegetation and predicted habitat mapping is not limited to the availability of remote sensing datasets. Advances in statistical methodology for spatial datasets and modeling along with computer power, storage capabilities, and the creation of software facilitating data processing and statistical analyses for less computer savvy users (wildlife ecologists as opposed to computer programmers), share in this advancement.

3.3. Suggestions for additional remote sensing applications or increased utilization in wildlife habitat studies

While it is becoming more common for wildlife studies to incorporate remote sensing into their studies of habitat relationships, there are yet underutilized or unrealized opportunities to advance the field with additional datasets. With the magnitude and multitude of forces working to disrupt wildlife populations and distributions, examining habitat relationships at the levels of selection at which wildlife select their habitat and being able to represent these relationships in a spatially explicit manner may provide invaluable tools for future monitoring, management, and conservation efforts. Continued communication between the remote sensing, forest management, and wildlife communities is vital in the exchange of knowledge so that appropriate data sources and methods are understood and utilized, and so that creators of mapping products may better realize the needs of the users.
3.3.1. Lidar technology and forest metric advancements

While lidar has been shown to be able to represent habitat features important to wildlife species, most studies have limited their analyses to the metrics able to be directly mapped (or results of simple computations/ratios) from lidar point clouds, such as vegetation heights and ratios of height measures (Goetz et al. 2010) and stratum specific cover/densities (Vogeler et al. 2013). Merrick et al. (2013) discuss these as "primary" lidar vegetation metrics. There is also value in relating primary lidar metrics to field-collected vegetation features to create secondary lidar metrics unable to be directly mapped from lidar point clouds (Merrick et al. 2013). Secondary lidar metrics include (but are not limited to) shrub cover, snag distributions, forest biomass, stem maps/densities, and forest succession stages. All are important features for wildlife that have previously been unable to be remotely sensed with reasonable accuracies or at fine spatial grains relevant to many species. Although the value of these secondary metrics for wildlife habitat mapping purposes has been pointed out in habitat prediction efforts (Martinuzzi et al. 2009a, Garabedian et al. 2014) few wildlife studies have directly related these metrics/maps to actual ground-based wildlife datasets. Therefore, we want to discuss a few of the secondary lidar-modeled forest metrics available in the forest remote sensing literature to point out potential opportunities for inclusion in wildlife habitat research and management purposes. We also present a handful of the wildlife studies that have begun to explore these possibilities.

In areas with overstory cover, it is difficult to directly utilize the lidar point cloud to extract reliable information on the understory (Maltamo et al. 2005, Su and Bork 2007), an important forest stratum for many wildlife species for nesting, foraging, and concealment (Hagar 2007). While lidar point clouds may not directly depict understory structure per se, aspects of canopy density, stand characteristics, and topography which are able to be mapped from lidar point clouds, influence shrub distributions, thus providing predictive information for creating shrub models and for mapping their predicted distributions across landscapes (Martinuzzi et al. 2009a). Martinuzzi et al. (2009a) utilized primary lidar variables along with lidar-derived basal area and
succession maps (Hudak et al. 2008, Falkowski et al. 2009) to model the presence/absence of deciduous shrub cover across Moscow Mountain in north-central Idaho. The best model was then applied to the lidar area to create spatially explicit predictive maps of shrub distributions across the landscape for inclusion in wildlife habitat prediction efforts (Martinuzzi et al. 2009a). In addition to information about the 3-dimensional location of lidar pulse returns, sensors also record information about the intensity of energy returned. Until recently, this data is often variable across acquisitions and difficult to calibrate although newer lidar sensors are starting to track the intensity gain of emitting pulses for later calibration efforts, advancing the potential to extract useful spectral information about laser vegetation and ground return data (Wing et al. 2012). Either in raw intensity form or through project specific normalization efforts, studies have still found utility (with varying success) in the un-calibrated intensity data for the mapping of understory components (Wing et al. 2012), coniferous vs. deciduous vegetation (Wing et al. 2010), and live vs. dead biomass (Kim et al. 2009). Wing et al. (2012) utilized intensity metrics along with height and density lidar point cloud data in a series of processing steps to map understory vegetation cover in a ponderosa pine forest of northeastern California. These efforts to utilize lidar to map understory components of the forest are limited and thus further exploration is needed across forest and disturbance types. It is also important for future research to explore the value of these maps in depicting the important aspects of the understory that actually drive habitat selection by wildlife species.

Standing dead wood has been identified as an important resource for a wide range of wildlife species. It has been estimated that 2/3 of all wildlife species use standing deadwood or woody debris for some part of their life cycle (Brown 2002). Previous 2-D remote sensing methods have had difficulty modeling snag distributions with any great detail or accuracy (Frescino et al. 2001) for local scale habitat applications. The 3-D nature of lidar data has shown promise in modeling (Martinuzzi et al. 2009a, Bater et al. 2009) and more recently even direct mapping of standing dead wood (Wing et al. In Review). Martinuzzi et al. (2009a) had promising results while modeling the distribution of snag size classes of importance to 3 cavity nester species (downy woodpecker, hairy
woodpecker, and Lewis's woodpecker) using primary lidar vegetation metrics and topography with models segmented by lidar-derived forest succession stages (previously mapped by Falkowski et al. 2009). Snag class accuracies ranged between 73% and 95% (Martinuzzi et al. 2009a). The lidar-derived coefficient of variation of height was the best predictor of stand-level tree decay classes by Bater et al. (2009), which included a standing dead wood category (r=0.85, p<0.001, RMSE=4.9%).

Stem densities within a stand are an important factor in determining habitat use by many species. Dense forest stands of varying ages may either be avoided due to restriction of movement, or selected for to aid in concealment depending on the wildlife species of interest (Sallabanks et al. 2006). Stem densities of various tree size classes can also help predict the availability of resources that may be important for wildlife species such as trees of a particular size threshold (Bull and Meslow 1977), or a generally open stand with low stem densities for ease of aerial foraging (Sousa 1983). Estimation of stand stem densities as well as the more detailed stem mapping, has been explored in recent forest lidar research (Lee and Lucas 2007, Hudak et al. 2014). Lee and Lucas (2007) stem mapped individual trees using a lidar-derived crown-openness index in Queensland, Australia in mixed and open forests. When aggregated up to stand level tree densities, calibrated lidar products were comparable to field measurements (Lee and Lucas 2007). Hudak et al. (2014) compared the imputation of stand and sub-stand forest attributes sampled in the field including stem density using Landsat and lidar data. Lidar-derived maps consistently outperformed Landsat imputed forest attribute maps with relatively good accuracy at the stand level (Hudak et al. 2014).

Forest landscapes are most often a mosaic of stands of various ages, structure, and disturbance history. Not only have many wildlife species been found to be associated with particular succession stages due to the related structure and available resources (Sallabanks et al. 2006), but the configuration of stands of various stages across the landscape can also be drivers or inhibitors of movement and selection (O'Brien et al. 2006). Maps of forest succession thus has value to wildlife research and management planning across landscapes. Falkowski et al. (2009) created forest succession maps across a single mountain in north-central Idaho (~30,000ha of mixed-conifer forests) utilizing
lidar-derived forest metrics. A variety of height and density metrics were utilized to create a resulting map with an overall accuracy >95% (Falkowski et al. 2009). These maps improved the snag modeling efforts of Martinuzzi et al. (2009a) as a source for segmenting the snag models discussed above, as well as acting as the stratification base map for bird survey locations used in the modeling of brown creeper habitat (Vogeler et al. 2013) and bird/guild species richness (Vogeler et al. 2014).

Lidar is not the answer to all wildlife habitat modeling needs. While there are some uses of lidar that are limited or absent from the wildlife literature, there will continue to be wildlife habitat modeling needs that will not be solved with airborne lidar data alone. Studies have found promise in the combination of lidar data with satellite imagery to help negate some of these limitations such as determining forest composition (Clawges et al. 2008, Goetz et al. 2010). There also may be potential in the use of newly available calibrated lidar intensity data for differentiating between coniferous and deciduous vegetation cover (Wing et al. 2010). While a major drawback of lidar data is the limited spatial coverage, some studies have explored the use of statistical methods to scale up fine scale data with limited spatial coverage to coarser grained datasets with broad coverage (Pflugmacher et al. 2014). There are also continuing efforts to expand the spatial coverage of lidar datasets.

The expense of lidar acquisition not only limits the spatial coverage, but also results in infrequent data collection of the same area. Vierling et al. (2014) explored the "shelf-life" of lidar datasets for the mapping of wildlife habitat using two flights of the same study area with a six year time difference (2003 and 2009). Brown creeper habitat models were created using lidar data acquired the same year as the bird surveys (2009; Vogeler et al. 2013). The habitat models were also mapped using the 2003 lidar data, examining the resulting change in habitat mapped as suitable for the species. They found little change with the six year time lag, with hardly any change if known harvest areas were removed (Vierling et al. 2014). These results show promise in the utility of lidar to provide valuable information for habitat models for a time period beyond the acquisition year, increasing the value of individual lidar datasets.
Spatial and temporal limitations of lidar data may be alleviated if able to produce comparable 3-dimensional datasets from a satellite sensor. The satellite based GLAS sensor collected swaths of data from 2003 to 2009 (Vierling et al. 2013). A habitat study on red-naped sapsuckers by Vierling et al. (2013) found weak results for GLAS habitat modeling efforts compared to airborne lidar-derived metrics. They suggest that the resolution and accuracy of the data may be inadequate at this time to represent important 3-D habitat features for wildlife species (Vierling et al. 2013). A new spaceborne lidar mission, Global Ecosystems Dynamics Investigation (GEDI) lidar, is scheduled to be completed in 2018, with the hope of providing data for forest carbon and biomass mapping (NASA 2014) that may also create new opportunities for species habitat mapping applications.

Some fine scale features such as individual tree structure (i.e. size, detailed foliage profiles, bark texture) that are important to wildlife species that are currently not able to be mapped with airborne lidar, may be captured using ground-based terrestrial lidar (T-lidar). While the original value of T-lidar may have been as a way to collect comparable field plot data more quickly than manual efforts, it is now being recognized that the data may also be able to characterize the sub-canopy in new ways unable to be mapped with manual methods (Dassot et al. 2011). One of these advantages may be the ability to take a detailed 3-D snapshot of what a plot looks like and then observe through time for subtle changes and growth that may be less accurate or not possible with manual methods (Dassot et al. 2011). Only a small handful of wildlife studies have explored the utility of T-lidar for characterizing habitat. Two studies have utilized T-lidar to characterize sub-canopy vegetation structure to examine flight (Yang et al. 2013) and foraging patterns (Aschoff et al. 2007) of bat species. Michel et al. (2008) mapped habitat surrounding nests of two New Zealand bird species as well as control points to detect fine-scale differences in species nesting habitat selections. T-lidar data has similar issues as manually collected field plots in that the isolated data coverage makes it unusable for mapping the realized relationships across landscapes, but the information still may aid in understanding fine scale drivers of species distributions and habitat needs that may be
important in management planning. Opportunities may increase and/or improve as terrestrial lidar units become more portable and economical.

3.3.2. Landsat, the underutilized tool

Landsat has been adopted by the wildlife community due to its relatively fine-moderate spatial and temporal scales. While it has mostly been utilized for classifying cover types, there is more untapped or at least underutilized value for wildlife habitat studies. A few wildlife studies have used two-date Landsat to look at change detection or identification of deciduous cover through leaf-on and leaf-off images (Goetz et al. 2010). New advances in the processing of time series Landsat image stacks has provided information useful to wildlife mapping efforts such as disturbance histories (dates, intensities, and trends) and the ability to scale back in time (Pflugmacher et al. 2014) or to update older maps to match available wildlife datasets.

Some wildlife species are known to be associated with agents of forest disturbance such as fire, insect infestations, wind-throw, and timber harvest. While these events may be difficult to detect or assign a specific disturbance agent using single date Landsat imagery, there is much promise in the use of time-series Landsat data for such purposes. LandTrendr is one such algorithm that utilizes spectral trends in a stack of Landsat images to identify abrupt disturbances and slower forest processes (Kennedy et al. 2010). Utilizing the long-running rich history of Landsat images allows for better characterization of forest structure and composition at a single point in time (Pflugmacher et al. 2012) as well as facilitating monitoring through time (Pflugmacher et al. 2014, Ohmann et al. 2014). In the case of post-fire landscapes, an important habitat for many wildlife species, a stack of pre-fire Landsat images can provide information about the structure and composition of the forest before the fire event. This information in conjunction with details of burn intensities across the fire matrix may allow for predictive mapping of important post-fire forest habitat elements such as snags of varying sizes and conditions. Landsat images following a fire event provide spectral trajectory information that may be associated with field data to map post-fire natural recovery or further disturbance (i.e. salvage logging; Schroeder et al. 2012). These time series processing
methods can also be applied for monitoring changes in predicted habitat or forest disturbance and recovery through time for inclusion in wildlife research and management planning. The Northwest Forest Plan, a set of policies guiding land-use on federal Pacific Northwest forest lands, utilized gradient nearest neighbor (GNN) imputation techniques and LandTrendr products to monitor for change and to assess the amount of available habitat at each monitoring interval over the region covered by the plan for changes in late-successional/old-growth habitat (Davis et al. 2011). LandTrendr algorithms were then utilized to look at disturbances each year to identify agents of habitat change and to assist in monitoring efforts (Davis et al. 2011).

Remote sensing datasets and maps that are difficult or expensive to acquire and therefore only periodically created, may still be utilized by wildlife modeling efforts out of necessity. Biases in using these older datasets may be mitigated by scaling back in time using a temporally continuous dataset such as Landsat, in order to identify areas that may have been disturbed since the creation of the other mapping product. Re-sampling efforts could then be concentrated in these areas, or they may be removed to avoid biases.

4. CONCLUSION

Understanding wildlife habitat relationships at the varying levels of habitat selection is important for management and conservation in the face of a changing environment. Continuous spatially explicit remote sensing datasets allow for wildlife habitat relationships to be mapped across the landscape, providing useful resources for planning and monitoring efforts. Although the use of remote sensing has significantly increased within the wildlife research and management community in recent years, there may still be room for further utilization and opportunities to represent habitat features within forests yet to be realized. The reality is that we cannot be experts of all aspects of forest ecology and management; therefore there are major advantages in interdisciplinary efforts for opening communication lines and advancing research more quickly beyond the methods and knowledge of one discipline. Continued communication can assist in even further shortening time lags between the creation and validation of remotely sensed vegetation metrics by the remote sensing and forest ecology community to the inclusion
of those data into forest wildlife studies and management efforts. Feedback by end users such as the wildlife community is also useful for map developers in understanding the needs and effectiveness of the data in habitat mapping applications.

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Figure 2.1. Examples of the scales reviewed in *Journal of Wildlife Management*, *Ecology*, and *Remote Sensing of Environment*. Geographic scales are related to the spatial extent of the study; modeling scales are those at which analyses are conducted; and the scales at which the vegetation was sampled are the observation scales. The broad modeling (small, moderate, and large) scales have sub-classes: A - tree; B - plot (radius ≤ 100m); C - breeding season territory; D - homogenous forest stand; and E - either animal-driven year-round home range or user-defined landscape. Within the observation scale categories, patch may refer to a homogenous patch of vegetation and/or structure, or to a pixel within gridded remote sensing mapping products.
Figure 2.2. Scale review results combined for *Journal of Wildlife Management* and *Ecology* from 1950-2014 and *Remote Sensing of Environment* from 1969-2014. (a) Proportions of studies for each of the geographic scales adding to 1.0. (b) Proportions of studies using tree and patch observation scales. (c) Modeling scales consolidated to proportions of studies modeling at small (tree and plot), moderate (breeding season territory and forest stand), and large (year-round animal home range and landscape) modeling scales. (d) Proportions of studies using modeling scales with subdivided moderate and large scales. Graph (b), (c), and (d) proportions may add to greater than one if studies utilized more than one scale during that decade.
Figure 2.3. Proportion of forest avian habitat studies within *Journal of Wildlife Management* and *Ecology* from 1950-2014 that utilized remote sensing for characterizing forest in habitat models. Proportions of studies that used field work compared to specific sources of remote sensing data (aerial photos, satellite, and lidar) are shown with separate lines in the figure as well as an overall category representing the proportion of studies that utilized at least one remote sensing sensor. Some studies included multiple sources of data so proportions for decades may add to more than 1.0, except when comparing only the field data category and the overall remote sensing category which do add to one.
Figure 2.4. Timeline of dates related to the initiation of remote sensing data sources and their adoption into wildlife literature located through a broad keyword search within Google Scholar. We also highlighted first dates within our focal wildlife journals, *Journal of Wildlife Management* (JWM) and *Ecology* (ECO).
CHAPTER 3: MAPPING POST-FIRE HABITAT CHARACTERISTICS THROUGH THE FUSION OF REMOTE SENSING TOOLS

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ABSTRACT

Post-fire snags provide important resources for cavity nesting communities as well as being subject to timber removal through salvage logging practices. Tools that can characterize their distributions along with other features important as wildlife habitat, would be useful for research and management purposes. Three dimensional lidar data and time series Landsat disturbance products have both shown varying promise in the ability to characterize aspects of dead biomass, but studies have yet to fuse these datasets to map specific snags at varying size thresholds or the distribution of woody shrubs. The purpose of this study was to 1) explore the fusion of remote sensing products for the modeling and mapping of snag size classes and shrub distributions across a post-fire complex in central Oregon that burned in 2003; and 2) compare the individual performance of the Landsat and lidar datasets. Using 164 field calibration plots and remote sensing predictors, we modeled the presence/absence of snag classes (dbh ≥40cm, ≥50cm, and ≥75cm) and woody shrub cover resulting in 10m output predictive grid maps. Remote sensing predictors included various lidar structure and topography variables and Landsat time series products representing the pre-fire forest, disturbance magnitude, and current forest condition. A top model was chosen for mapping purposes using AIC model selection and then by comparing leave-one-out-cross-validation error matrices to choose among competing models. We were able to model and map all habitat metrics with acceptable predictive performance. All snag size class top models were considered to have "good" predictive performance as indicated by area under the curve values (0.74 - 0.90), with percent correctly classified values ranging from 69-81% when balancing false positive and false negative errors. Landsat and lidar metrics were found to be significant predictors of shrub cover with an adjusted R² value of 0.55. When a threshold was chosen to map moderate (30% threshold) and high (50% threshold) shrub cover, we found percent correctly classified rates of 79% and 84%, respectively. Landsat models outperformed lidar structure models, although when compared separately, Landsat-only models had fair predictive power at best, often with high errors. The ability to map the
habitat metrics with relatively low-moderate errors and acceptable accuracies was through the fusion of these remote sensing datasets.

1. INTRODUCTION

Fire patterns are currently in the spotlight due to the concern over deviations from historical fire regimes and potential future climate change impacts (Dale et al. 2001). Fire events and post-fire systems are important in their evolutionary tie with ecosystem functioning and turnover, and wildlife life history strategies (Weber & Flannigan 1997). They are also of societal and management interest in areas of human-wildland interface (Radeloff et al. 2005) and as managers guide their plans and efforts with multiple uses in mind including the natural system, providing timber resources, and minimizing damage to human infrastructures.

Tools that allow for the characterization of these systems, their distribution across the landscape, and the availability of habitat resources within, would be useful for managers and others interested in the patterns and functioning of these areas. Remote sensing has a long running history in providing information about wildland fire trends and spatial patterns (Lentile et al. 2006). At the regional and national scales, Landsat provides information about temporal and spatial arrangement of fire events through openly available products such as delta normalized burn ratio (dnbr) maps of fire severities (Escuin et al. 2008). The 30mx30m spatial and 16 day temporal resolutions of Landsat reflectance data allow for the monitoring of fire events (intensity at time of fire), size (boundaries and year burned), and severity patterns across fire complexes (Lentile et al. 2006).

At the local-scale, conflicts pertaining to the management of land for multiple purposes lie in understanding three-dimensional aspects of the post-fire landscape and the distribution of specific structural elements such as snags of various sizes, decay stages, and densities, and the availability of a woody shrub component. Post-fire landscapes are important habitats for a variety of wildlife species while also subject to timber removal on many public (Eklund et al. 2009) and private lands. More specifically, post-fire snags provide important resources for cavity-nesting communities as foraging, nesting, and
roosting substrates (Haggard & Gaines 2001). Selection of a snag for life history needs may vary by the snag size, species, decay stage, and surrounding landscape properties (Saab et al. 2004). As management activities and changing fire patterns alter the availability and spatial arrangement of snags, there is increasing concern for cavity-nesting communities (Martin & Eadie 1999). Another important aspect of post-fire areas that impact wildlife species utilization include a woody shrub component for increasing invertebrate abundance, soft mast production, nesting substrates, and concealment from predators (Nappi et al. 2004). Information about the spatial arrangement of snag classes and woody shrub cover may assist in post-fire research and management efforts.

The ability of airborne light-detecting-and ranging (lidar) for representing various aspects of three-dimensional forest structure has been established, but its utility in providing information about specific snag resources is more limited (Martinuzzi et al. 2009a; Wing et al. 2010). Standing dead wood is often represented in lidar studies as dead biomass (Kim et al. 2009) or the proportion of dead trees (Bater et al. 2007). Studies evaluating the utility of lidar for mapping specific snag distributions often focus on the vertical/horizontal accuracy of locating specific trees (Wing et al. 2010; Yao et al. 2012), but few studies have looked at the modeling and mapping of snags of specific diameter sizes (Martinuzzi et al. 2009a), an important component of wildlife habitat selection and management planning. Martinuzzi et al. (2009a) found promise in the utility of lidar structure and topography data for the modeling and predictive mapping of snags of varying size thresholds in an unburned mixed conifer forest in Idaho. To our knowledge, such efforts have not been explored in a post-fire landscape.

A woody shrub layer provides wildlife with cover and nesting substrates, and provides direct and indirect foraging opportunities (Hagar 2007), although understory forest strata are difficult to directly map with remote sensing. Spatially explicit information about shrub distributions may provide an important resource for wildlife habitat mapping efforts as well as aiding in the understanding of post-fire vegetation patterns and assessing impacts of salvage logging. While some lidar pulses may penetrate the canopy to return information on the structure of the lower stratum of a forest, especially in more open stands or in post-fire areas with high canopy mortality, it is
difficult to directly map shrub layers with lidar point-cloud data alone (Martinuzzi et al. 2009a). By calibrating the lidar data with onsite field data, models can be created to predict the distribution of woody shrubs across a study area (Martinuzzi et al. 2009a).

While lidar may provide unique three-dimensional remote sensing products, there is still great value in the spectral reflectance that sensors such as Landsat can provide, especially when tapping into the value of the long-running dataset. Time series Landsat products provide information on disturbance and recovery events, durations, and magnitudes (Kennedy et al. 2010). While these data are often used for regional monitoring and assessments (Hudak et al. 2013), there may be underutilized value for these products within local scale disturbance events as well. Schroeder et al. (2012) used a multi-step mapping approach to identify overlap between previously mapped fire perimeters and Landsat time series-derived harvest areas to map post-fire salvage logging across a single Landsat scene in boreal forests of Saskatchewan with high map accuracy (kappa=0.91). Pflugmacher et al. (2012) found value in time-series Landsat data for providing historic disturbance and recovery trends to aid in the prediction of current forest conditions.

The purpose of our study was to evaluate the utility of fusing multiple remote sensing data sets for the modeling and mapping of snags and shrub distributions across a post-fire complex in central Oregon. Lidar and time series Landsat products were calibrated with field-collected data to produce maps of important post-fire wildlife habitat components including snags of varying sizes and the availability of a woody shrub layer. A secondary objective was to compare the individual performance of the Landsat and lidar datasets to highlight the value, if any, in the combination of multiple types of remote sensing products for predicting the distributions of difficult to map forest habitat resources.

2. METHODS

2.1. Study Area
Our study was conducted in the B&B Fire Complex within the Deschutes National Forest located in the Cascade Mountains of central Oregon (figure 3.1). The fire complex was created when two fires, the Bear Butte Fire and the Booth Fire that ignited on the same day in the summer of 2003, burned together to cover 36,732 hectares (90,769 acres) with a mosaic of fire severities. Our study area is constrained to coinciding lidar coverage within the fire perimeter that covers about a 28,000 hectare area which includes the majority of the fire complex on the east side of the Pacific Crest. Elevations ranged from 822-2182 meters, with higher elevations occurring within the Mount Jefferson Wilderness Area. The mixed conifer forest was dominated by the wet and dry varieties of several previous mapped plant association groups (PAG): ponderosa pine (Pinus ponderosa), mixed-conifer, lodgepole pine (Pinus contorta), and mountain hemlock (Tsuga mertensiana). The most frequently observed shrub genus within our field surveys were Ceanothus (Ceanothus sp.), willow (Salix sp.), and manzanita (Arctostaphylos sp.).

2.2. Identifying Important Habitat Components

To identify important snag size classes utilized by the cavity nesting community within the B&B Fire Complex, we conducted cavity nest surveys for 18 avian species of primary cavity excavators (PCE; species that create cavities), weak cavity excavators (WCE; may utilize pre-existing cavities or excavate when suitable snags are available and/or cavity resources are limited), and secondary cavity users (SCU; utilize pre-existing cavities) during the 2012 breeding season. We monitored 148 nests every 3-6 days until fledge or fail. Following the breeding season, we sampled all nest trees and determined thresholds that represent size classes utilized in higher proportions than their availability on the landscape as determined from sample plots (figure 3.2). We identified three snag size classes to include in our modeling efforts: snags with a diameter at breast height (dbh) ≥ 40cm, ≥50cm, and ≥75cm (table 3.1). We also included woody shrub cover (Shrub%) in our modeling efforts, which has also been noted as important for post-fire wildlife communities (Raphael et al. 1987).
2.3. Field Vegetation Data Collection

Vegetation data was collected at 164 15-meter (m) radius field plots during the summers of 2012 and 2013. Plots were stratified by the dominant PAG and fire severity. We collapsed the PAG polygons down to three main classes for a simpler stratification: ponderosa pine, mixed-conifer, and an alpine category that included the higher elevation lodgepole pine and mountain hemlock zones. A previously created Landsat dnbr fire severity dataset was used for the purpose of stratification using the classes of unburned, low, moderate, and high severities. We used a Trimble GeoExplorer GPS unit to record the location of plot centers. A minimum of 150 logged points were collected by the GPS and later differentially corrected using online base station files resulting in a horizontal accuracy of <1 meter for the majority of our plot locations. All trees ≥12cm dbh within a 15m radius of plot center were included in data collection. One crew member recorded all measurements while stem mapping trees from plot center using an Impulse Laser Rangerfinder for distance and a compass for bearings, while a second crew member collected at-tree measurements. For all trees we measured height (using rangefinder), dbh, decay stage, top condition (broken top vs. intact), percent remaining bark, species if identifiable, and number of cavities present. We used a designation of 0 (live) to 5 (severely burnt and misshapen with spongy wood) decay stage for the snags, with the middle stages associated with the proportion of primary (large) and secondary (fine) branches remaining and the snag top condition. Within 5-m radius center subplots, we collected maximum shrub height and ocular estimations for shrub cover, ground cover characteristics, and seedling/sapling counts by species for each subplot quadrant which we later averaged.

Stem-mapping the field plots allowed flexibility in the scale at which to summarize the habitat metrics for applicability in multiple projects. For the purpose of this study, we chose a 5.64m radius summary scale to represent the fine-scale variability in the distributions of focal snag and shrub variables and to correspond to 10m predictor grids of remote sensing data used for later mapping steps and explained in more detail below.
2.4. Lidar Acquisition and Processing

Lidar data was provided as part of a larger Deschutes National Forest data acquisition by Watershed Sciences flown between 2009 and 2010 depending on area of interest. The northwest portion of our study site was flown on July 25, 2010 with the remaining area covered in October 2009 flights. The Leica ALS50 Phase II and ALS60 sensors had a pulse rate of >105 kHz, average pulse density of 8.6/m^2, and an average accuracy of 0.04m. Plot and grid lidar metrics were processed with FUSION software (McGaughey 2009). We used cylinders representing plot radii to clip the lidar data and calculate height, density, and intensity cloud metrics. Gridmetrics allowed us to calculate corresponding rasters at a 10x10m grid size, representing the same spatial area as a 5.64m radius circular plot. Height and density metrics were summarized using lidar returns above 1m, and canopy cover with returns over 2m (table 3.2). We clipped the lidar grids by the B&B Fire boundary and filled in nodata with zero values using a constant mask raster matching the lidar grids in ArcGIS 10.1. These nodata cells were a product of lower height thresholds in the lidar processing and thus represent areas without vegetation cover above these thresholds. Also in ArcGIS, we aggregated 1m lidar Bare Earth grid rasters delivered by Watershed Sciences to 10m grids of elevation, percent and degree slope, and aspect. From these grids, we produced frequently used aspect transformations with raster calculator (table 3.2).

2.5. Landsat Processing

In the processing of time series Landsat image stacks, we used a cloud mask to make an annual composite for all years leading up to, and following the fire event. We calculated tasseled-cap brightness, greenness, and wetness metrics for all yearly composite images (Crist 1985). For the remainder of the analyses, we chose to focus on only a few of the possible Landsat time-series products (see Pflugmacher et al. 2014 for potential time-series metrics). Our focal metrics included: the year prior to the fire (2002) to represent pre-fire condition; the change in tasseled-cap values from the pre-fire condition to the year following the fire event (due to the timing of the fire, the
disturbance was either detected as 2003 or 2004); and the tasseled-cap values from the 2010 composite image to coincide with lidar data collection and represent current conditions. We used the change in tasseled-cap pre- and post-disturbance to represent continuous measures of fire magnitude and vegetation change as a result of the fire event. The goal of this study is to model and map the habitat metrics at a small enough scale to provide flexibility in applications, the ability to represent fine-scale variability, and to facilitate opportunities to create density measures of the snag size thresholds by aggregating to project-specific scales (demonstrated in Chapter 4). Initial explorations into the field plot data identified 10m grids (and associated 5.64m radius plots) as a focal scale where snags at the dbh thresholds were only found in low numbers (range between 0-5, although majority were between 0-2 for a single 5.64m radius plot), and at which the dataset reflects relatively well balanced presence and absence ratios for logistic regression analyses. This scale also closely matches that of the field-collected shrub data. We hoped that the combination of lidar structure data processed at this fine-scale in conjunction with Landsat data representing the slightly larger area, would provide the opportunity to model these focal features at the smaller lidar scale. We therefore resampled the Landsat grids to match the 10m lidar grids.

2.6. Statistical Models and Predictive Mapping

Zonal statistics within ArcGIS 10.1 were used to extract Landsat predictor grid summary metrics for the plot areas using a 5.64m radius buffer around field plot centers. The average value of predictor metrics within the plot buffers from the zonal statistics tables were used from this point forward in statistical analyses. (Lidar metrics provided during the cloudmetrics step described above). Highly correlated variables were removed, resulting in the exclusion of some lidar structure variables and all tasseled-cap brightness values, but retaining all greenness and wetness metrics and a variety of lidar height, density, cover, intensity, and topography metrics (table 3.2). We used logistic regression with a binomial error distribution and a logit link function to model the relationship between the occurrence of snags within a snag class and the Landsat and lidar vegetation and topography metrics. Models were created using the glm function (MASS package;
Venables & Ripley 2002) in the statistical software program R (R Development Core Team 2014) and top models were selected following a stepwise forward and backward AIC model selection approach. A similar model selection approach was used for percent shrub cover, which we transformed to a proportion for the sake of modeling, then applied general additive models within the gamlss package in R (Rigby & Stasinopoulos 2005), using a beta inflated distribution to best match the distribution of the shrub field data (figure 3.3). Model runs were conducted for each habitat metric using the combined predictor set, a Landsat-only set, a lidar structure-only set, and a lidar-derived topography set in order to compare predictive performance and to evaluate any model improvements by using the combined remote sensing metrics. Each predictor set represents different aspects of the forest system, potentially providing unique information for modeling the distribution of snag and shrubs. Landsat time series products capture the before, during, and after dynamics of the major disturbance even. Lidar data provides 3-dimensional data on the current forest structure. Topography may capture composition variation due to elevation and aspect, as well as impacts that slope may potentially have on shrub distributions (Martinuzzi et al. 2009) and snag fall rates (McComb and Ohmann 1996).

Accuracy and error values were calculated using leave-one-out-cross-validation (loocv) prediction values for all habitat metrics. For the snag class presence/absence models, we created confusion matrices and associated statistics including: percent correctly classified (PCC), false positive rate (FPR), false negative rate (FNR), and kappa statistic (Fielding & Bell 1997). While kappa is a useful measure of how well the model can predict over what is predicted by chance, evaluating the rates of false positive and negative errors can also help us match the appropriate model for project specific objectives where one type of error may be more or less acceptable given the application. We considered kappa values between 0.4 and 0.75 as acceptable and values over 0.75 as excellent model performance (Luck, 2002).

We assessed false negative (omission) and false positive (commission) error rates using four possible methods for selecting an optimal threshold at which to assign presence/absence predictions to the probability of occurrence model outputs, all of which were available methods within the PresenceAbsence package in R (Freeman & Moisen
threshold at which false negative and false positive errors are balanced; where kappa is maximized; and where PCC is maximized. Project goals determine the level and type of error appropriate and thus which threshold will best meet that purpose. Receiver operator curves (ROC) were created in R (Sing et al. 2005) for the top combined model for each habitat metric. Area under the curve (AUC) values were calculated as an additional way to evaluate model predictive performance regardless of threshold chosen (Guisan & Zimmermann 2000). AUC values can range between 0.5 depicting no model discrimination to 1.0 representing perfect model performance. We followed the interpretations presented by Pearce & Ferrier (2000) where AUCs between 0.7-0.9 represent reasonably good model discrimination appropriate for most purposes, and AUCs >0.9 reflecting excellent model performance. Accuracy measures from logistic regression can be inflated by highly unbalanced presence/absence datasets (Freeman & Moisen 2008). Due to large number of absence plots for the snag class dbh≥75cm, we took a random subset the absence plots using the regsubsets function in R (Lumley 2013), reducing the total to reach a minimum balance ratio of 0.3 between presence and absence. For the percent shrub cover metric modeled with general additive models, we tested for model and variable significance using a confidence threshold of 0.05. We also plotted predicted values from the loocv vs. observed field values to estimate $R^2$ s for the loocv predictions as a way to evaluate predictive performance.

2.7. Predictive Mapping

The rgdal package in R was used to apply top models for the habitat variables to the 10m predictor grids to create probability of occurrence maps for the snag classes and percent shrub cover for the Shrub% response metric. We chose the probability of occurrence threshold for each snag class where false positive and false negative errors were balanced to map presence/absence. As shrub distributions were converted to proportion of cover for modeling purposes, we multiplied predictive maps by 100 to return to percent shrub cover. We also demonstrate how this percent shrub cover map can be used to extract cover thresholds for habitat mapping applications, including a moderate and high shrub cover class.
3. RESULTS

We were able to model and map the distribution of snags and shrubs in a post-fire landscape through the fusion of Landsat, lidar, and field-collected data with acceptable predictive performance (table 3.3). Logistic regression model accuracies were the highest for the largest snag class, with tradeoffs for false positive and false negative error rates and overall correct classification accuracy for the different size classes depending on the optimal threshold method chosen to designate presence and absence (table 3.4). Landsat and lidar metrics were found to be significant predictors of woody shrub cover with an adjusted $R^2$ value of 0.55 (table 3.3).

Within the combined model runs including Landsat and lidar metrics, Landsat tasseled-cap metrics from 2010 were found in top models for all variables (table 3.5). TCG_2010 displayed a significant positive relationship in all top models, while TCW_2010 had significant negative influences on the presence of all snag size classes (table 3.5). Pre-fire Landsat tasseled-cap metrics were included in several variable top models. TCG_PRE negatively influenced shrub cover while TCW_PRE was positively related to the occurrence of snags with dbh≥40cm (table 3.5). The disturbance change in tasseled-cap metrics were only significant in top models for Shrub% where there as a negative relationship with TCG_CHANGE.

The only lidar structure metric that was included in more than one snag or shrub variable top model was STRAT5 (20-30m stratum) although only a significant predictor of the largest dbh size class (table 3.6). As the proportion of lidar returns increased in STRAT5, so did the probability of occurrence of snags dbh≥75cm (table 3.5). That is not to say that there were not multiple significant relationships between lidar structure metrics and the habitat features in the lidar only runs, but these relationships seemed to be masked by the importance of the time series metrics in the combined models. Elevation was a significant predictor in top models for snags≥75cm and shrub cover (table 3.6), where the probability of occurrence for snags dbh≥75cm and the percent of shrub cover decreased as you move up in elevation (table 3.5).
When categories of predictor variables were separated into individual model runs, Landsat-only models outperformed lidar structure models for all variables (table 3.3). For snags with dbh≥40cm and dbh≥50cm, the top Landsat-only model was even competitive with the combined run following AIC model selection where models with ΔAIC <2 are considered competitive (table 3.3). Topography was the worst predictor set for all variables, although there were fewer topography metrics than in the other model sets (table 3.1). In the lidar structure-only model runs, COVER was a significant negative predictor in top models for all variables.

Spatially continuous Landsat and lidar predictor variables allowed us to map realized relationships within the top model for the snag (figure 3.4) and shrub (figure 3.5) habitat metrics across the post-fire landscape. We found that the threshold chosen to designate presence and absence for the snag classes had varying impacts on the false negative and false positive predictive errors and overall accuracies depending on the habitat metric (table 3.4). We plotted the thresholds where false negative and false positive errors were balanced for each snag class model onto the ROCs (figure 3.6), our chosen threshold for depicting the presence and absence of the snags from the probability of occurrence maps.

Maps of percent of shrub cover allow habitat mapping users to chose important cover thresholds for a particular organism of interest. We demonstrated this ability through the mapping of moderate shrub cover (30% threshold) and high shrub cover (50%) thresholds (figure 3.5) with percent correctly classified rates of 79.3% and 84.2%, respectively.

4. DISCUSSION

The combination of passive Landsat reflectance data through time along with current fine-scale structure and topographic data provided by lidar allowed us to map important habitat components including the availability of snag size classes and woody shrubs across a post-fire landscape. Although Landsat time series models outperformed lidar structure models when compared independently, Landsat-only models had fair predictive power at best, often with higher error rates. The ability to map the habitat
metrics with relatively low-moderate errors and acceptable accuracies was through the fusion of these remote sensing datasets. Our results add to a growing body of literature exhibiting the value in combining multiple remote sensing datasets with corresponding field data to model forest systems (Dalponte et al. 2008; Goetz et al. 2010; Hudak et al. 2006), although few studies have explored this utility to map fine-scale post-fire structure components (Bishop et al. 2014; Wulder et al. 2009).

Standing dead wood is a critical habitat component for many wildlife species, although difficult to map through remote sensing methods. Snags of varying size thresholds provide nesting substrates for cavity nesting communities as well as provide foraging, roosting, and perching sites for a whole suite of other species (Ohmann et al. 1994). Dead wood also play a vital role in ecosystem functioning as carbon stores and through nutrient cycling (Stevens 1997). Spatially explicit information about fine-scale distributions of snag size classes can provide valuable resources for post-fire management and monitoring efforts. Studies have begun to explore the utility of lidar data in the mapping of dead wood distributions with varying accuracies (Bater et al. 2007; Martinuzzi et al. 2009a). Through the combination of Landsat time series and lidar, we were able to predict the distribution of moderate to large snags in a post-fire landscape with only slightly lower overall accuracies (percent correctly classified ranging from 69-81%) compared to those of Martinuzzi et al. (2009a) which included more inclusive snag size classes within an unburned coniferous forest (overall accuracies of 86%-88% when models were segmented by forest succession classes). Few studies have attempted to map snag distributions at fine-scales in a post-fire forest system using remote sensing (Wing et al. 2010). Wing et al. (2010) manually located trees within lidar point clouds in a post-fire landscape by focusing in on known tree locations. The study found good support for the ability of lidar to accurately locate trees and extract heights as well as condition (live vs. dead; Wing et al. 2010b). To our knowledge, our work represents the first demonstration of the utility of fusing remote sensing data calibrated with field plots to map the distributions of snags specifically at varying size thresholds in a post-fire forest at a fine 10m grid scale.
Although an important structure component of forest systems, directly mapping woody shrub distributions even with three-dimensional lidar data can be difficult in areas of high canopy cover and where the understory is made up of other non-shrub components (Martinuzzi et al. 2009a). Fire events often reduce the canopy cover allowing more lidar pulses to reach lower strata of the forest, but increased down wood and regenerating trees make it difficult to extract shrub specific components of the understory. Wing et al. (2012) was able to map fine-scale post-fire shrub distributions through a filtration method utilizing lidar point intensity information to remove points not associated with understory vegetation. The resulting Understory Lidar Cover Density (ULCD) metric was highly correlated with field shrub cover ($R^2 = 0.74$; Wing et al. 2012). In our 9 or 10 year post-fire study area, there was significant amounts of down wood and coniferous re-growth, but our results also showed some promise in our model's ability to pick out shrubs from these other components with an $R^2$ of 0.55, although our lidar intensity metrics did contribute to the top model.

While lidar has become an attractive option for mapping structural habitat components, recent improvements in extracting the full value of time series Landsat stacks are also advancing the mapping of forest systems appropriate for wildlife habitat purposes. Spectral information about pre-disturbance forest in conjunction with magnitude of change and current spectral properties were important predictors for many of the habitat metrics in this study. Characteristics of pre-disturbance forest condition can help predict what may remain following the disturbance event, especially when paired with information about the magnitude of change (Pflugmacher et al. 2012). When considering the occurrence of larger snags following a fire, there must first have been mature enough pre-fire forest conditions to contain larger trees. Variations in the magnitude of change may help us predict crown mortality, and thus the chance of standing dead trees following the event. Pflugmacher et al. (2012) examined the importance of disturbance and recovery information from time series Landsat for predicting current forest structure conditions compared to lidar and single-date Landsat imagery. Of note, the study found time series disturbance and recovery metrics were better predictors of aboveground dead biomass than current lidar structure data.
Pflugmacher et al., 2012). Utilizing time series methods can also aid in long term monitoring efforts for forest conditions and changes in wildlife habitat (Davis et al. 2011).

Lidar data is limited in spatial and temporal coverage; therefore there is value in being able to extract spatially continuous habitat components and change through time using Landsat products. Ideally, the temporal and spatial availability of lidar datasets will improve so that we can utilize the full range of existing remote sensing technology including important structural information from lidar, in creating the best habitat monitoring and management products possible. The rich structure data, acquisition costs, and processing time lead to the utilization of lidar datasets for years following the actual year of collection. In our study there was a 2-4 year time lag between lidar acquisition and field surveys depending on the particular plot and which flight covered that location. While all salvage logging had been completed prior to this time, snag fell rates increase with time since fire (Everett et al. 1999), and thus could add to model errors in relating lidar structure data with field collected metrics. The Fire and Fuel Extension to the Forest Vegetation Simulator for this region assign a per year fall rate for snags ranging from a rate of 0.065/year for smaller snags to 0.01/year for larger snags in their simulation modeling of stand dynamics incorporating wildfires and prescribed fire events (Reinhardt and Crookston 2003). While the larger snags modeled in this study are more likely to persist on the landscape than smaller snags, model predictive performance may have been impacted by some snag falls during the lidar and field data collection time lag.

Habitat suitability models (HSMs) are a frequently used tool in the wildlife research and management community (Donovan 1987). HSMs take existing information about habitat selection for a species and create a scale, the habitat suitability index (HSI), for assessing available habitat across landscapes and for monitoring change through time. The habitat components of the HSMs are often represented as critical thresholds to meet life history needs (Sousa 1983). Being able to provide maps of similar components allow for these models to be mapped and validated, and ultimately improved. We demonstrated the ability to create a continuous shrub cover map and extract important thresholds similar to those used in HSMs (Sousa 1983). Spatial information about the occurrence of
large snags, an important nesting component for many species, are also useful for HSM efforts and for mapping realized or previously noted species habitat relationships (Martinuzzi et al. 2009a). The probability of occurrence maps created for our snag size classes allow for some prioritizing or adapting for particular project needs. By maximizing overall accuracy through the max percent correctly classified and max kappa optimal threshold methods for assigning presence and absence values, there are often tradeoffs for either increased false positive or false negative errors. Decisions such as the optimal threshold methods for the probability of occurrence predictive maps and the amount of error acceptable for a particular application bring up an important point in the secondary use of mapping products for management or research purposes: communication. The creators of map products are intimate with the map limitations and intended applications, as well as tradeoffs in errors. Communicating these limitations to secondary users is crucial in ensuring mapping products are utilized appropriately and that results and limitations are interpreted correctly. Feedback from users also helps to improve future mapping products and technology.

5. CONCLUSION

Our models for snag size classes and shrub distributions fall in the acceptable predictive range as quantified by the calculated predictive accuracies (i.e. AUC and kappa) and provide important information about critical fine-scale components of habitat, representing one of the first explorations into the fusion of remote sensing datasets to map these components in a post-fire landscape. We demonstrate the ability to use moderate resolution data in conjunction with detailed structure data to map resources at fine scales. These fine scales provide flexibility in the species mapping applications and allow for the aggregating of presence/absence data to represent density measures of particular snag size classes (demonstrated in chapter 4 of this dissertation). While our study area covered a range of forest vegetation zones along an elevation gradient, these models were still created in a single fire complex and post-fire time period. Future research should expand these efforts to additional fire complexes and along a post-fire chronosequence.
ACKNOWLEDGEMENTS

Our research was funded by the National Aeronautics and Space Administration, Carbon Cycle Program (NASA Grant 10-CARBON10-45). We thank our field technicians for assisting in data collection and Keith Olsen for initial assistance in lidar processing methods.
Figure 3.1. B&B fire complex (2003) located within central Oregon and the mosaic of fire severities represented by the previously mapped dnbr for the area of overlap between the fire complex and coinciding lidar coverage.
Figure 3.2. Histogram of field sampled snag diameter at breast heights (dbh) from 164, 15 meter radius field plots collected in the B&B Fire Complex, Oregon, in the summers of 2012 and 2013. All snags ≥12cm dbh were sampled and included in the above histogram.
Figure 3.3. Histogram of percent shrub cover sampled in 5 meter radius subplots at 164 locations within the B&B Fire Complex, Oregon. Data was collected in the summers of 2012 and 2013.
Figure 3.4. Probability of occurrence maps for snag size classes modeled with field data collected 9-10 years post-fire and mapped through the fusion of Landsat time series and lidar data for the 2003 B&B Fire Complex in central Oregon.
Figure 3.5. Predictive map for percent shrub cover created using time series Landsat products and lidar structure and topography metrics and field plots sampled 9-10 years post-fire for the 2003 B&B Fire Complex located in central Oregon. Also shown are the extracted threshold presence/absence maps for moderate shrub cover (>30%) and high shrub cover (>50%), with percent correctly classified rates of 79.3% and 84.2%, respectively.
Figure 3.6. ROC curves for the top models for snag size classes containing both Landsat and lidar predictor variables for the B&B Fire Complex modeled 9-10 years post-fire. The threshold at which false positive and false negative error rates are balanced for each model are marked on the ROC curves. Area-under-the-curve (AUC) rates are reported for each snag class model.
Table 3.1. The observed use by cavity nesters and availability of snags at dbh size thresholds as sampled in field plots within the central Oregon B&B Fire Complex 9-10 years post-fire. Cavity nesting groups include primary cavity excavators (PCEs), weak cavity excavators (WCEs), and secondary cavity users (SCUs). Nest proportions reflect the proportion of nests surveyed within the respective cavity nester groups for each snag size class. Plot tree values represent the proportion of trees measured in that size class within 164 field plots where all trees ≥12cm dbh were sampled within a 15m radius.

<table>
<thead>
<tr>
<th>Percent Use/Availability of Snags</th>
<th>all nests</th>
<th>PCEs</th>
<th>SCUs</th>
<th>WCEs</th>
<th>Plot Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>dbh≥40cm</td>
<td>77.6</td>
<td>96.6</td>
<td>70</td>
<td>42.9</td>
<td>21.9</td>
</tr>
<tr>
<td>dbh≥50cm</td>
<td>55.9</td>
<td>70.7</td>
<td>48.8</td>
<td>42.9</td>
<td>10.4</td>
</tr>
<tr>
<td>dbh≥75cm</td>
<td>19.6</td>
<td>17.2</td>
<td>20</td>
<td>28.6</td>
<td>2.3</td>
</tr>
</tbody>
</table>
Table 3.2. Model metric descriptions and abbreviations including the response habitat metrics summarized from 5.64m radius field plots and the groups of remote sensing predictor datasets remaining after the removal of highly correlated variables in an initial exploratory analyses step.

<table>
<thead>
<tr>
<th>Model Metric Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Presence/Absence Response Variables</strong></td>
</tr>
<tr>
<td>Snag≥40cm Snags ≥ 40cm dbh</td>
</tr>
<tr>
<td>Snag≥50cm Snags ≥ 50cm dbh</td>
</tr>
<tr>
<td>Snag≥75cm Snags ≥ 75cm dbh</td>
</tr>
<tr>
<td><strong>Continuous Response Variable</strong></td>
</tr>
<tr>
<td>Shrub% Mean percent of woody deciduous shrub cover</td>
</tr>
<tr>
<td><strong>Landsat Predictor Variables</strong></td>
</tr>
<tr>
<td>TCG_PRE Tasseled cap greenness value the year prior to fire even</td>
</tr>
<tr>
<td>TCW_PRE Tasseled cap wetness value the year prior to fire even</td>
</tr>
<tr>
<td>TCG_CHANGE Change in tasseled cap greenness values before and after fire event</td>
</tr>
<tr>
<td>TCW_CHANGE Change in tasseled cap wetness values before and after fire event</td>
</tr>
<tr>
<td>TCG_2010 Tasseled cap greenness value from 2010 yearly composite</td>
</tr>
<tr>
<td>TCW_2010 Tasseled cap wetness value from 2010 yearly composite</td>
</tr>
<tr>
<td><strong>Lidar Structure Predictor Variables</strong></td>
</tr>
<tr>
<td>COVER Percent canopy cover above 2 meters</td>
</tr>
<tr>
<td>HTMEAN Mean height of lidar vegetation returns above 1 meter</td>
</tr>
<tr>
<td>HTSTD Standard deviation of heights for lidar returns above 1 meter</td>
</tr>
<tr>
<td>HTCV Coefficient of variation of height of returns above 1 meter</td>
</tr>
<tr>
<td>CRR Canopy relief ratio = (mean height-minimum height)/(max height-minimum height)</td>
</tr>
<tr>
<td>INTMEAN Mean of lidar return intensity</td>
</tr>
<tr>
<td>INTSTD Standard deviation of lidar return intensities</td>
</tr>
<tr>
<td>STRAT2 Stratum 2 = proportion of lidar returns between 1 and 2.5 meters aboveground</td>
</tr>
<tr>
<td>STRAT3 Stratum 3 = proportion of lidar returns between 2.5 and 10 meters aboveground</td>
</tr>
<tr>
<td>STRAT4 Stratum 4 = proportion of lidar returns between 10 and 20 meters aboveground</td>
</tr>
<tr>
<td>STRAT5 Stratum 5 = proportion of lidar returns between 20 and 30 meters aboveground</td>
</tr>
<tr>
<td>STRAT6 Stratum 6 = proportion of lidar returns between 30 and 40 meters aboveground</td>
</tr>
<tr>
<td>STRAT7 Stratum 7 = proportion of lidar returns &gt;40 meters aboveground</td>
</tr>
<tr>
<td><strong>Lidar Topography Predictor Variables</strong></td>
</tr>
<tr>
<td>ELEV Lidar derived elevation</td>
</tr>
<tr>
<td>SLOPE Lidar derived degree slope</td>
</tr>
<tr>
<td>ASPECT Transformed lidar derive Aspect = COS*[45-Aspect(degrees)]+1</td>
</tr>
<tr>
<td>SSINA Percent slope * SIN * Aspect(degrees)</td>
</tr>
<tr>
<td>SCOSA Percent slope * COS * Aspect(degrees)</td>
</tr>
</tbody>
</table>
Table 3.3. Model statistics for top models following a stepwise AIC model selection approach for each habitat metric and predictor set modeled within the central Oregon B&B Fire Complex. Combined model runs are those incorporating both lidar and Landsat metrics. Models in bold represent the top model and any model considered as a competing model following AIC model selection. Indicators for varying levels of significance for parameters include: *** <0.001, ** <0.01, * <0.05, . <0.1.

<table>
<thead>
<tr>
<th>Presence/Absence Response</th>
<th>Best Model Variables</th>
<th>AIC</th>
<th>Kappa</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined</td>
<td>TCW_PRE (*), TCG_2010 (<strong>), TCW_2010 (</strong>), HTSTD ()</td>
<td>178.43</td>
<td>0.4226</td>
<td>0.77</td>
</tr>
<tr>
<td>Landsat</td>
<td>TCW_PRE (<strong>), TCG_2010 (</strong>), TCW_2010 (**), HTSTD ()</td>
<td>180.06</td>
<td>0.4232</td>
<td>0.73</td>
</tr>
<tr>
<td>Lidar Structure</td>
<td>COVER (**), HTSTD (*)</td>
<td>193.03</td>
<td>0.2463</td>
<td>0.64</td>
</tr>
<tr>
<td>Lidar Topography</td>
<td>Intercept only</td>
<td>202.02</td>
<td>0.1344</td>
<td>0.55</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Snag50cm</th>
<th>Best Model Variables</th>
<th>AIC</th>
<th>Kappa</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined</td>
<td>TCW_PRE (*), TCG_2010 (<strong>), TCW_2010 (</strong>), STRAT5 ()</td>
<td>209.09</td>
<td>0.4287</td>
<td>0.74</td>
</tr>
<tr>
<td>Landsat</td>
<td>TCW_PRE (*), TCG_2010 (<strong>), TCW_2010 (</strong>), HTMEAN (), STRAT2, STRAT5 ()</td>
<td>210.03</td>
<td>0.3784</td>
<td>0.72</td>
</tr>
<tr>
<td>Lidar Structure</td>
<td>COVER (**), HTMEAN (), STRAT2, STRAT5 ()</td>
<td>221.92</td>
<td>0.2948</td>
<td>0.69</td>
</tr>
<tr>
<td>Lidar Topography</td>
<td>ELEV (*)</td>
<td>226.82</td>
<td>0.1853</td>
<td>0.50</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Snag75cm</th>
<th>Best Model Variables</th>
<th>AIC</th>
<th>Kappa</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined</td>
<td>TCG_CHANGE (), TCG_2010 (<strong>), TCW_2010 (</strong>), CRR(), INTSTD (), STRAT2, STRAT5 (), STRAT7, ELEV ()</td>
<td>93.12</td>
<td>0.5925</td>
<td>0.90</td>
</tr>
<tr>
<td>Landsat</td>
<td>TCG_PRE (), TCG_CHANGE (), TCW_2010 (), HTMEAN ()</td>
<td>112.87</td>
<td>0.3985</td>
<td>0.80</td>
</tr>
<tr>
<td>Lidar Structure</td>
<td>COVER (**), HTMEAN ()</td>
<td>118.34</td>
<td>0.4468</td>
<td>0.77</td>
</tr>
<tr>
<td>Lidar Topography</td>
<td>ELEV (**), SLOPE</td>
<td>120.18</td>
<td>0.2406</td>
<td>0.68</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Continuous Response</th>
<th>Best Model Variables</th>
<th>Adjusted R²</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined</td>
<td>TCG_PRE (<strong>), TCW_PRE (*), TCG_CHANGE (</strong>), TCG_2010 (**), ELEV (*)</td>
<td>-44.63</td>
<td>0.5491</td>
</tr>
<tr>
<td>Landsat</td>
<td>TCG_PRE, TCW_PRE, TCG_CHANGE (*), TCW_CHANGE, TCG_2010 (**), SCOSA(,)</td>
<td>-39.69</td>
<td>0.5140</td>
</tr>
<tr>
<td>Lidar Structure</td>
<td>COVER (**), HTCV, INTSTD ()</td>
<td>21.5</td>
<td>0.1760</td>
</tr>
<tr>
<td>Lidar Topography</td>
<td>ELEV (<strong>), SLOPE (</strong>)</td>
<td>31.68</td>
<td>0.0865</td>
</tr>
</tbody>
</table>
Table 3.4. Associated errors and accuracy rates of four example methods for choosing the optimal threshold for designating presence/absence from the probability of occurrence snag class maps created using Landsat and lidar data in the Oregon B&B Fire Complex. The default threshold remains fixed at 0.5, but all other thresholds are model specific including the threshold where false positive and false negative error rates are balanced (FPR=FNR), where the kappa statistic is maximized (MaxKappa), and the threshold at which the percent correctly classified is maximized (MaxPCC).

<table>
<thead>
<tr>
<th>Response</th>
<th>Method</th>
<th>Threshold</th>
<th>PCC</th>
<th>FPR</th>
<th>FNR</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snag≥40cm</td>
<td>Default</td>
<td>0.50</td>
<td>75.61</td>
<td>0.63</td>
<td>0.08</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>FPR=FNR</td>
<td>0.71</td>
<td>68.90</td>
<td>0.31</td>
<td>0.31</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>MaxKappa</td>
<td>0.66</td>
<td>74.39</td>
<td>0.33</td>
<td>0.23</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>MaxPCC</td>
<td>0.43</td>
<td>78.05</td>
<td>0.65</td>
<td>0.03</td>
<td>0.37</td>
</tr>
<tr>
<td>Snag≥50cm</td>
<td>Default</td>
<td>0.50</td>
<td>67.07</td>
<td>0.31</td>
<td>0.35</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>FPR=FNR</td>
<td>0.49</td>
<td>67.07</td>
<td>0.34</td>
<td>0.32</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>MaxKappa</td>
<td>0.43</td>
<td>71.34</td>
<td>0.42</td>
<td>0.15</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>MaxPCC</td>
<td>0.43</td>
<td>71.34</td>
<td>0.42</td>
<td>0.15</td>
<td>0.43</td>
</tr>
<tr>
<td>Snag≥75cm</td>
<td>Default</td>
<td>0.50</td>
<td>84.62</td>
<td>0.06</td>
<td>0.48</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>FPR=FNR</td>
<td>0.29</td>
<td>81.20</td>
<td>0.19</td>
<td>0.19</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>MaxKappa</td>
<td>0.28</td>
<td>82.91</td>
<td>0.19</td>
<td>0.11</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>MaxPCC</td>
<td>0.52</td>
<td>84.62</td>
<td>0.06</td>
<td>0.48</td>
<td>0.52</td>
</tr>
</tbody>
</table>
Table 3.5. Top combined model results for each habitat metric mapped within the central Oregon B&B Fire Complex. Results include parameter estimates and 95% confidence intervals (CI lower, CI upper). Indicators for varying levels of significance for parameters include: *** <0.001, ** <0.01, * <0.05, . <0.1.

<table>
<thead>
<tr>
<th>Response</th>
<th>Parameter</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>CI lower</th>
<th>CI upper</th>
<th>zvalue</th>
<th>sig</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snag≥40cm</td>
<td>(Intercept)</td>
<td>-6.7780</td>
<td>1.7300</td>
<td>-10.3953</td>
<td>-3.5645</td>
<td>-3.9400</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>TCW_PRE</td>
<td>0.0015</td>
<td>0.0006</td>
<td>0.0004</td>
<td>0.0026</td>
<td>2.6040</td>
<td>**</td>
</tr>
<tr>
<td></td>
<td>TCG_2010</td>
<td>0.0028</td>
<td>0.0006</td>
<td>0.0016</td>
<td>0.0041</td>
<td>4.4760</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>TCW_2010</td>
<td>-0.0037</td>
<td>0.0008</td>
<td>-0.0055</td>
<td>-0.0022</td>
<td>-4.4190</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>HTSTD</td>
<td>0.1371</td>
<td>0.0803</td>
<td>-0.0169</td>
<td>0.2999</td>
<td>1.8630</td>
<td></td>
</tr>
<tr>
<td>Snag≥50cm</td>
<td>(Intercept)</td>
<td>-7.0923</td>
<td>1.7832</td>
<td>-10.8473</td>
<td>-3.8182</td>
<td>-3.9770</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>TCW_PRE</td>
<td>0.0010</td>
<td>0.0005</td>
<td>0.0000</td>
<td>0.0020</td>
<td>1.9160</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TCG_2010</td>
<td>0.0029</td>
<td>0.0006</td>
<td>0.0017</td>
<td>0.0041</td>
<td>4.6340</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>TCW_2010</td>
<td>-0.0032</td>
<td>0.0009</td>
<td>-0.0050</td>
<td>-0.0016</td>
<td>-3.6350</td>
<td>***</td>
</tr>
<tr>
<td></td>
<td>STRAT5</td>
<td>0.0479</td>
<td>0.0288</td>
<td>-0.0068</td>
<td>0.1085</td>
<td>1.6630</td>
<td></td>
</tr>
<tr>
<td>Snag≥75cm</td>
<td>(Intercept)</td>
<td>-18.7500</td>
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Table 3.6. Parameters and associated significance for the selected top combined model for each habitat variable in the B&B Fire Complex, Oregon. Indicators for varying levels of significance for parameters include: *** <0.001, ** <0.01, * <0.05, . <0.1, ns = not significant but included in the top model.

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CHAPTER 4: PRIMARY AND SECONDARY REMOTE SENSING PRODUCTS PREDICT POST-FIRE LEWIS'S WOODPECKER NESTING HABITAT

Authors: Vogeler, Jody. C.\textsuperscript{a}, Zhiqiang Yang\textsuperscript{a}, Warren. B. Cohen\textsuperscript{a, b}

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\textsuperscript{b} USDA Forest Service, PNW Research Station
ABSTRACT

As remote sensing mapping products representing important habitat components increase in availability, detail, and accuracy, new opportunities arise to map habitat for forest species of conservation concern. One such species is the Lewis's Woodpecker which is a species of conservation interest in multiple states and areas of Canada with habitat loss and degradation proposed as contributing factors in the species decline. The purpose of this study was to model and map Lewis's Woodpecker nesting habitat using primary (directly derived or simple ratios of raw data) and secondary (modeled and mapped using ground calibration data) remote sensing products. We found promise in the utility of lidar and Landsat time series modeled snag and shrub products in conjunction with lidar-derived canopy cover, vegetation height variability, and topographic slope for modeling and mapping nesting habitat for the Lewis's Woodpecker across a post-fire landscape. All of the 26 Lewis's Woodpecker nests located succeeded during the breeding season (2012), adding support to the previous studies suggesting the importance of post-fire areas as population sources for the species. Our top model contained additional variables (variability in canopy cover and topographic slope) to those included in the previously published habitat suitability model (HSM) for the species (canopy cover, shrub cover, and density of large snags). A model with comparable metrics to those in the HSM was competitive although with the lowest predictive capabilities and the highest errors among the models. When we applied the actual HSM with pre-designated parameter values, we found the model to have poor predictive performance for our local scale post-fire study area. Our snag metric also utilized a larger snag size threshold than included in the HSM (50cm vs. 30.5cm). Our results add to the studies displaying the importance of a 50cm dbh snag threshold for Lewis's Woodpeckers, suggesting that the HSM may be too liberal in the utilized snag size. We were able to utilize the remote sensing products to map realized habitat relationships for this species of conservation concern in an identified source habitat type, providing a potential resource for local scale conservation and management efforts and adding to the regional knowledge of habitat selection for the Lewis's Woodpecker.
1. INTRODUCTION

As the availability of fine- to moderate-scale remote sensing data characterizing vegetation patterns has increased, spatially explicit maps of suitable habitat for wildlife species have emerged as a critical resource for conservation purposes (Graf et al. 2009). While broad scale maps of species distributions are readily available through efforts such as USGS Gap Analysis (GAP; Gergely & McKerrow 2013), maps depicting local scale habitat relationships are often lacking. One reason for this may be the complexity of vegetation structure and composition to which wildlife species respond (MacArthur and MacArthur 1961) that can be difficult to represent with remote sensing data. Studies have begun to explore the use of three-dimensional data from Light Detection and Ranging (lidar), sometimes fused with other remote sensing products and/or ground plots for calibration, to bridge this gap in accurate local scale representations of vegetation structure and patterns for inclusion in wildlife habitat mapping (Martinuzzi et al. 2009a; Smart et al. 2012; Tattoni et al. 2012). Such efforts are still limited and many species of conservation concern are still lacking in validated spatially explicit maps of critical habitat such as nesting sites.

One such species of conservation concern yet to be represented in validated local fine-scale habitat maps is the Lewis's Woodpecker (*Melanerpes lewis*). The Lewis's Woodpecker is a species of conservation interest in multiple U.S. states and areas of Canada, including being listed as a sensitive species with a critical status by the Oregon Department of Fish and Wildlife (ODFW 2008), with habitat loss and degradation proposed as contributing factors in the species decline (Vierling et al. 2013). Unlike many woodpecker species, Lewis's feed mainly on free ranging insects during the breeding season as opposed to bark associated beetles (Vierling et al. 2013). As aerial foragers they prefer open habitats including cottonwood and aspen riparian forests, open ponderosa pine stands, and disturbed pine and fir forests with an adequate shrub layer for insect production (Witt 2009). Lewis's Woodpeckers prefer to nest in large snags, often utilizing or modifying existing cavities due to their limited excavating capabilities (Gentry & Vierling, 2007). In the context of source-sink meta-populations, the high
reproductive success of post-fire forests have led them to be considered as population sources for the Lewis's Woodpecker (Gentry & Vierling 2007, Saab & Vierling 2001), thus representing critical habitat for this species of concern. Previous Lewis's Woodpecker breeding season habitat studies, including the published Habitat Suitability Model (HSM; Sousa 1983), have identified the importance of a woody shrub component along with moderate canopy cover and a density of large snags (Witt 2009; Zhu et al. 2012), although these relationships have not been calibrated with nesting locations and mapped across a post-fire landscape.

Remote sensing metrics can be thought of as primary (directly derived or relatively simple computations) or secondary (modeled and mapped using ground calibration data; Merrick et al. 2013). Studies have begun to explore the use of lidar and/or the fusion of lidar with other remote sensing data to map important yet difficult to characterize habitat components (Smart et al. 2012; Tattoni et al. 2012). Among these are the fine-scale distributions of snags of varying size thresholds and woody shrubs (Martinuzzi et al. 2009a). Martinuzzi et al. (2009a) included the Lewis's Woodpecker in the set of species which they explored the utility of such metrics for mapping previously published habitat suitability models in an unburned mixed-conifer forest at the 1-hectare scale, although the incorporation of these secondary predictor grids into habitat mapping efforts are still in the early stages and have yet to be validated with on the ground occurrence or nesting data or explored in a post-fire landscape. As previously noted habitat components of importance to the Lewis's Woodpecker, information on the spatial distribution of large snags and woody shrubs along with directly-derived canopy cover should facilitate the modeling and mapping of suitable post-fire nesting habitat (Sousa 1983).

The purpose of this study was to incorporate primary and secondary remote sensing data in the fine-scale modeling and predictive mapping of Lewis's Woodpecker nesting habitat in a 9-year post-fire landscape in central Oregon. We also compared models created with the onsite Lewis's nesting data to the predictive performance of the existing habitat suitability model (Sousa 1983) to evaluate the general habitat model's ability to distinguish suitable nesting patches within our post-fire study area. Habitat
relationships identified and mapped within this post-fire area may provide local conservation resources for a species of conservation concern in an identified source habitat type.

2. METHODS

2.1. Study Area

We focused our study on a 9-year post-fire complex in the East Cascades of Oregon. The B&B Fire Complex is located in the Deschutes National Forest and is the combination of the Bear Butte and Booth Fires which ignited on the same day in the summer of 2003 and burned together resulting in 36,732 hectares (90,769 acres) of post-fire landscape with a mosaic of fire severities. The fire burned across multiple forest zones including ponderosa pine (*Pinus ponderosa*), mixed-conifer, lodgepole pine (*Pinus contorta*), and mountain hemlock (*Tsuga mertensiana*) dominated plant association zones. Our study was limited to the ponderosa pine-dominated and mixed-conifer zones of the fire landscape. The dominant shrubs included Ceanothus (*Ceanothus sp.*), willow (*Salix sp.*), and manzanita (*Arctostaphylos sp.*).

2.2. Nest Surveys

We conducted surveys for cavity-nesters in the breeding season of 2012. From May through August a nest crew surveyed sites that covered the range of fire severities and pre-fire forest succession stages and represented both unlogged and salvaged stands. Nests were also found opportunistically while in transit between survey sites. We located and monitored nests for 18 primary and secondary cavity-nesters although this study focuses on the data collected for the Lewis's Woodpecker. Once located, a nest was monitored every 3-6 days until evidence of fledge or fail. We used observational cues through adult behavior and activity at the nest (i.e. food carries to the nest, fecal sac removals, loud nestlings, fledglings on nest tree) to estimate nest stage at each visit. If no activity was observed for 30 minutes, we visited the nest for at least one more 30 minute period to validate no activity at the nest, denoting a fledged or failed nest.
depending on the stage at last visit of activity. We took the midpoint between the last visit with activity and the first visit with no activity to assign a fledge/fail date. We used the nesting period of 54 days utilized by Zhu et al. (2012) to back date from the time of fledging to the estimated nest initiation date.

2.2. Tree Data

Following fledge/fail, nest tree and cavity data were collected and the snag location was recorded with a Trimble GeoExplorer GPS unit. We also selected non-use plots to represent absence within modeling efforts that were at least 200 meters from a Lewis's nest or another non-use plot. To select these non-use plots, we identified nest survey sites in which we did not observe Lewis's Woodpecker activity during the 2012 breeding season, and randomly selected points within these stratified by fire severity. We located these random points within the non-use areas in the field, then selected the nearest snag containing a cavity as the center of our non-use plot. For each nest and non-use tree, we recorded diameter at breast height (dbh), tree and nest height using an Impulse Laser Rangefinder, decay stage, top condition, tree species if identifiable, and the abundance of cavities. For each nest cavity, we determined cavity orientation, visually estimated size using 3 size classes (small, medium, and large), and noted whether excavated or modified in the current year or if it was a pre-existing cavity.

2.3. Habitat Predictor Maps

We included primary and secondary remote sensing metrics in our evaluation of Lewis's Woodpecker nesting habitat selection. Primary metrics were directly derived from lidar data acquired in 2009/2010 by Watershed Sciences using a Leica ALS50 Phase II and a ALS60 sensor with a pulse rate of >105 kHz and an average pulse density of 8.6/m². We processed lidar las tiles in FUSION 3.4 at a 10 meter scale using gridmetrics (McGaughy 2009). Final metrics included in our model represented previously noted habitat features important to Lewis's Woodpeckers and/or other post-fire cavity-nesting species including: canopy cover (over 2m); standard deviation of canopy cover; standard deviation of height; and the degree slope.
Studies utilizing remotely sensed variables in wildlife habitat selection studies have expressed the need for fine scale information about snag densities and woody shrub distributions, both of which have been shown to be important for Lewis's Woodpecker nesting habitat (Sousa 1983; Zhu et al. 2012). We used previously created maps of the probability of occurrence of snags ≥50cm dbh, the size threshold containing all but 3 of our Lewis's nests, and a map of mean shrub cover, both at the 10meter grid scale. The maps were created using the fusion of lidar structure and topography data with time series Landsat products representing the pre-fire forest, magnitude of change from the fire event, and current reflectance properties. Field data stratified by plant association group and fire severity were used to calibrate the models and map the relationships across the lidar/fire overlap area. Percent shrub cover was mapped in addition to the probability of occurrence of snags of varying size classes including those with a dbh≥50cm. Probability of occurrence maps are on a scale of 0, denoting no probability of occurrence, to 1.0, representing the highest probability of occurrence. The threshold chosen to designate a pixel as presence or absence impacts the accuracy and associate error structure of the predictive map. We chose the threshold for the probability of occurrence map of snags ≥50cm dbh where the false negative and false positive error rates were balanced (threshold=0.49) and mapped the predicted presence and absence of the large snags.

Similar to previous Lewis's Woodpecker nest patch studies, a 50 meter radius buffer was created around the nests and non-use snags to evaluate relationships between Lewis's Woodpecker nest patch selection (Vierling et al. 2009) and a variety of previously noted habitat features of importance to Lewis's (Zhu et al. 2012) and/or other cavity-nester species at this scale. We summed the number of pixels within the nest or non-use patch that was predicted to contain a snag with dbh ≥50cm and divided by the total number of pixels to create a large snag density metric (the proportion of snags within a path predicted to contain a snag≥50cm dbh). Zonal stats within ArcGIS 10.1 was used to extract means and standard deviations of the other habitat metrics. After initial exploratory analyses including testing for high collinearity and evaluating variable interactions, we included the following metrics in the statistical analyses: mean canopy cover (COVER%); standard deviation of canopy cover (COVER_SD); standard deviation
of the lidar-derived 10m mean height raster to represent the variability in heights across the patch (HEIGHT_SD); degree slope (SLOPE); mean shrub cover (SHRUB%); and density of snags ≥50cm dbh (SNAGS; table 4.1).

2.4. Statistical Models

We created 20 ecologically meaningful candidate models including a null intercept-only model (table 4.2) to evaluate the relationship between Lewis's Woodpecker nest patch selection and the remote-sensing habitat metrics. We ran generalized linear models using the GLM function with a binomial family and a logit link function in the statistical software package R (R Development Core Team 2014). To evaluate the relative performance of candidate models and to help in identifying a top model for mapping purposes, we used an Akaike (1973) information criterion (AIC) selection approach where the model with the lowest AIC and all those with a delta AIC ≤2 are considered competing models (Burnham and Anderson 2004). For all competing models we plotted Receiver-Operating-Curves (ROC) and calculated the Area-Under-the-Curve (AUC) as a further assessment of model performance, where AUC values between 0.7 and 0.9 denote a model with good model discrimination and excellent models are represented by AUC values >0.9 (Pearce & Ferrier 2000). We chose the threshold for the Lewis's Woodpecker nesting patch probability of occurrence for designating predicted presence and absence where positive and negative predictive errors were balanced. This allowed us to compare the error structure for each of the competing models. We also calculated model and parameter Akaike weights (Johnson and Omland 2004) to examine top parameters in the prediction of nest patches. Ultimately the competing model with high overall predictive capabilities while minimizing the prediction errors was selected as the top model to move forward with mapping steps.

2.5. Sousa (1983) Habitat Suitability Model Comparison

We used the defined habitat variable relationships from the published Lewis's Woodpecker HSM (Sousa 1983) in conjunction with our shrub, canopy cover, and large snag density maps to test the capability of this existing breeding season model for
distinguishing between nest patches and non-use plots within our post-fire landscape. The output from the HSMs are habitat suitability indices ranging from 0-1 rating the suitability of a patch for the species of interest and are comparable to the 0-1 probability of occurrence measure calculated from our modeling approach. We used the model to predict our observed presence and absence patches and then calculated similar classification accuracy and error measures for this HSM, and then compared the predictive performance to that of our selected top model.

2.6. Predictor Maps

As a first step for mapping our top Lewis's Woodpecker nesting patch model, we clipped the predictor grids to only include the portion of the fire occurring below 1300m elevation, a slightly higher elevation threshold than noted by previous literature (Cooper & Gillies 1999: 1100m) but containing all nests and Lewis's Woodpecker activity observed in our study area. This area was dominated by the dry and wet varieties of the ponderosa pine and mixed-conifer vegetation zones, previously noted vegetation zones for Lewis's during the breeding season (Cooper & Gillies 1999). We used focal statistics within ArcGIS 10.1 to recalculate the remote sensing predictor grids at the 10m grid scale to represent the summary of the individual metrics in the surrounding 50m radius buffer to match the predictor variables used in the modeling methods. To create the focal grid for snag densities, we used the focal statistic that sums the pixels within the buffer, and then divided that by the average number of pixels that occurred in the 50m radius buffers (79) within the Spatial Analyst Raster Calculator. We mapped the top model across the landscape using these focal predictor grids and the rgdal package in R at a 10m grid size (although representing the surrounding 50m radius) to maintain the fine grain of the data and allow further spatial flexibility in identifying key patches of habitat for management and conservation purposes. Resulting maps occurred on a 0-1 probability of occurrence scale. Consistent with above, we chose the probability of occurrence threshold where the positive and negative predictor errors were balanced to designate 10m pixels representing the center of a suitable 50m radius nesting patch for the Lewis's Woodpecker.
3. RESULTS

3.1. Nest Tree and Cavity

Of the 26 active Lewis's Woodpecker nests that we located, all succeeded. Two of the nests were located in the same tree, so only 25 nest trees and patches were used in analyses. In the majority of the nests we observed 1-3 fledglings on or near the nest tree giving solid evidence that they were successful. At other nests there were large nestlings sticking out of the cavity on last visit with activity and then two 30 minute periods of no activity on later days therefore we assumed the nest fledged at least one young. All nests fledged between July 22nd and August 13th, with the majority between July 31st and August 6th. We therefore estimated the nest initiation dates between May 29th and June 20th with the majority initiating between June 7th and June 13th. During nest surveys, we witnessed two independent Lewis's Woodpeckers modifying existing cavities but never saw further evidence of incubating or nesting activity on future visits so we did not consider them as nesting attempts. We observed several aggressive interactions between European Starlings and Lewis's, where the woodpecker always seem to dominate the interactions resulting in the starlings leaving the tree of conflict or area.

We often observed Lewis's modifying existing cavities although it was difficult to determine exactly how many of the nest cavities were fully created or were modified existing cavities as many of the nests were located after initiation. All of the cavities had evidence of fresh excavation activity and little wear leading us to deduce that all were at least modified that nesting season. Lewis's were found to nest in the large size class of cavities 73% of the time, and in medium cavities 27% of time. The breakdown of proportions of nest cavity azimuths included: NE = 57.7%; NW = 19.2%; SE =11.5%; SW= 11.5%. The majority of nest trees included at least one other cavity (64%).

All nests were in broken top snags. Most often nests occurred within the top quarter of the snag (84%), with an average nest height of 17.0m (SE = 1.2m). The average nest snag dbh and height was 71.0cm (SE = 3.1cm) and 21.6m (SE = 1.4), respectively. Tree species identification can be difficult in older burns as snags progress in decay, although we found ponderosa pine were usually still recognizable and
represented 64% (n=16) of our nest trees. We found four nests in identified Douglas-fir, and 5 were in snags of unknown species. As ponderosa pine were often identifiable even when heavily decayed, these unknowns were most likely Douglas-fir or another conifer species. Nests were often in snags of higher decay stages (80% of nests) although not completely charred and misshapen and usually retaining a few stubby branches to serve as perches but not enough to obstruct flight. We found 20% of the nests in less decayed snags still with a broken top but with a significant amount of larger branches still intact. We did not find any nests in highly intact snags where the majority of primary (large) and secondary (fine) branches remained, or in extremely decayed snags that were charred and misshapen. The majority of nests were within 150 meters of another Lewis's nest (58%).

3.2. Nest Patch/Plot

We found models of primary and secondary remote sensing metrics as good predictors of Lewis's Woodpecker nest patch selection (table 4.3). Several of the competing models (model with the lowest AIC value and those with delta AIC ≤2) had comparable AUC values, so we chose the model that minimized the false positive and false negative predictor errors as the top model, containing the following habitat metrics: COVER%, COVER SD, SLOPE, SNAGS, SHRUB% (table 4.3). Although COVER%, COVER SD, and SLOPE were significant predictors when related to nest patch selection independently (table 4.4), only SNAGS was a significant predictor in the top model (table 4.3) and exhibited the highest parameter Akaike weight (table 4.4). In single variable candidate models, COVER%, COVER SD, and SLOPE had significant negative relationships and SNAGS had a significant positive influence on the probability of Lewis's selecting a nest patch (table 4.4). This was also represented by the significantly lower COVER%, COVER SD, and SLOPE at nest plots than non-use plots (table 4.5). Nest plots were also characterized by a significantly higher SNAGS than non-use plots (table 4.5).

We created a ROC curve for the top model and plotted the threshold on the curve where false positive and false negative errors were balanced to use for designating presence/absence (figure 4.1). This was the threshold that was then applied to the
probability of nest occurrence map to represent the predicted suitable nest patches in the B&B Fire Complex (figure 4.2).

3.3. Sousa (1983) Habitat Suitability Model Comparison

Although a model containing the same three metrics as the HSM, but calibrated and modeled with local Lewis's nest patch use data was selected as a competing model, the actual HSM using the model parameters presented in Sousa (1983) had poor predictive performance for our B&B Fire Lewis's Woodpecker nesting population. The percent correctly classified was 45.8% compared to the 83.3% found with our B&B Fire top model, with kappa and AUC values corresponding to poor predictive capabilities (table 4.6). At the threshold where prediction errors were balanced, the HSM model exhibited a false positive and false negative error rate of 0.54. When a threshold was chosen to assess classification errors where the percent correctly classified was maximized, the HSM model had an extremely high false positive error rate (0.75), indicating poor capabilities of distinguishing used nest patches from non-use plots.

4. DISCUSSION

Through the use of primary and secondary remote sensing products, we were able to successfully model and map Lewis's Woodpecker nesting habitat. To our knowledge, this represents the first time fine-scale secondary snag products have been used in the modeling and mapping of cavity-nester habitat using known nesting locations, and we found promise in this application. Martinuzzi et al. (2009a) modeled shrub and snag size classes in an unburned mixed-conifer forest in Idaho for inclusion in mapping previously published habitat suitability models for four avian species including the Lewis's Woodpecker and two other cavity nester species at a 1-hectare grid scale. While the study provided an important initial demonstration into the use of secondary snag products for such purposes, the next step was to calibrate and validate habitat mapping efforts using such products paired with on the ground nesting data and locations which we have demonstrated. Importantly, we have created fine-scale predictive maps for nest patches for a species of concern in an identified source habitat type, a potentially valuable tool for
local conservation efforts and adding to the regional knowledge of species distributions and habitat utilization.

In agreement with previous studies, we found high reproductive success for the Lewis's Woodpecker in a post-fire landscape. While we did not observe any nest failures, that does not mean they did not occur at our study area for this species. Our nests represent a sample of the population and we may have failed to detect some failures by not locating all nests in the initiation stage. Nest predators had re-inhabited the B&B fire complex and caused nest failures for other cavity nesting species in the area. We observed the Lewis's Woodpecker to be aggressive towards potential predators and European Starlings, a possible nest usurper, and the adults frequently guarded nest trees which may have attributed to the higher nest success than other species in the 9-year post-fire landscape. Nests were high in relatively tall snags which has also been found to reduce nest predations (Li & Martin 1991). Similar to previous studies, we often observed our Lewis's nests to be spatially clumped in areas of suitable habitat (Cooper & Gillies 1999).

The previously published habitat suitability model for the Lewis's Woodpecker included canopy cover, shrub cover, and the density of large snags (Sousa 1983). Our top model contained additional variables, but a candidate model with comparable metrics to those in the HSM was also competitive based on the AIC, although with the lowest predictive capabilities and the highest errors among the competing models. When the actual parameters from the published HSM were applied to our study area to predict nest patch use, the model performed poorly and was unable to adequately distinguish nest patches from non-use plots. Lewis's Woodpeckers utilized several different open forest types as nesting habitat. The Sousa (1983) HSM was created as a general model applicable to the suite of forest types. Our results indicate that on this local scale in a single post-fire landscape, the HSM may not be suitable for identifying areas of actual use and non-use. The model may be better suited for evaluating habitat patches on a more broad scale, or for applications involving a variety of forest types, although future studies should test this further. Our snag metric also utilized a larger snag size threshold than the one used in the published HSM (50cm vs. 30.5cm; Sousa 1983). Not only did this
threshold contain the majority of our nest trees, which ranged from 46.7cm - 94.7cmdbh, and was our most important predictor variable, but it has also been found to be an important threshold for Lewis's in other studies and habitat types (Zhu et al., 2012), suggesting that the HSM may be too liberal in the utilized snag size threshold.

In addition to comparable metrics to those found in the HSM, our top model also contained the standard deviation of canopy cover and the degree slope, where Lewis's nest patch selection was negatively related to both. Variability in the 10-m grid canopy cover metric within the 50m radius nest patch could represent areas with complex vertical and horizontal distributions of a range of snag sizes and heights including a mid canopy layer that may impede aerial foraging. Although shrub cover was included in the top model, it was not significant at the 0.05 level. This could suggest that shrub cover was not a limiting resource in our study area. The lower elevations of the 9-year post-fire landscape had abundant shrub growth. Perhaps in older burns where the understory has had a chance to re-establish, yet prior to the stage of a closed canopy of young trees, shrubs may be less of a limiting resource than other habitat components such as the density of large snags.

The density of snags ≥50cmdbh had a strong positive relationship with the probability of nest occurrence. While Lewis's Woodpeckers have been found to inhabit and even prefer partially salvaged post-fire stands (Saab et al. 2007), an important management consideration is the retention of large enough snags to meet habitat needs. In our study area we observed Lewis's nests in both salvaged and unlogged units, although the majority of nests were in unlogged stands or along the edge of salvaged and retention patches. As time since fire progresses, snag fall rates increase, with fall rates lower for larger snags (Raphael & Morrison 1987). In our 9-yr old burn, snags have begun to fall opening up stands than may have been unfavorable for Lewis's Woodpeckers in the early years post-fire, yet retaining the preferred and longer lasting larger snags. Some salvage logging guidelines utilize a lower snag size threshold than those selected as nest trees in our study as criteria for snag retention (i.e. 23 cm dbh, Saab et al. 2007). The removal of large snags could have negative impacts for this species of concern which has shown a preference for snags ≥50cmdbh within several studies (Zhu et al. 2012) including this
The Decayed Wood Advisor for Managing Snags, Partially Dead Trees, and Down Wood for Washington and Oregon (DecAID) is a management tool that in addition to other utilities, provides dead wood management guidelines for a suite of species associated with these forest resources using existing wildlife datasets (Mellen-Mclean et al. 2012). DecAID reports that at the ≥50cm dbh snag size threshold, 50% of the Lewis's individuals included in their synthesis of datasets were found in areas with a density of 6.2 snags/ha, with 85% of Lewis's utilizing areas with ≥40.3 snags/ha at this 50cm dbh snag threshold. The majority of the data included in this synthesis originated from a group of burned forests in southwestern Idaho (Saab & Dudley 1998, Saab et al. 2009, Saab et al. 2011). These results in addition to our own suggest that in these post-fire landscapes, management plans that identify and protect large snag resources during salvage operations may benefit Lewis's Woodpecker nesting habitat.

5. CONCLUSIONS

While our models identified the density of snags as the strongest predictor of nesting patches with canopy cover, variability, slope, and shrub cover also included in the top model, these relationships may vary along a post-fire chronosequence and in other unburned Lewis's Woodpecker breeding season habitats. Our study demonstrated the utility of secondary remote sensing metrics such as fine-scale snag distributions in predicting nesting habitat for this species, although future studies should test and validate these relationships with Lewis's Woodpecker nesting locations in other forest types and explore the utility for mapping habitat relationships for additional post-fire wildlife species. While we found 50cm dbh as an important threshold for Lewis's Woodpecker nesting snags, this threshold may vary between regions and among forest types (Sousa 1983). Therefore further studies are needed to identify other drivers for habitat selection that may impact the size of snags suitable for nesting, an important management and conservation consideration as the concern for this species continues to increase due to habitat loss and degradation.
ACKNOWLEDGEMENTS

Our research was funded by the National Aeronautics and Space Administration, Carbon Cycle Program (NASA Grant 10-CARBON10-45). We thank our field technicians for assisting in data collection.
Figure 4.1. ROC plot for the top model chosen for mapping purposes containing the remotely sensed predictors COVER%, COVERσ, SLOPE, SNAGS, and SHRUB% and created using predictions from leave-one-out-cross-validation. The 0.54 threshold where false positive and false negative errors were balanced in the top model is shown on the curve and represents the threshold at which we mapped suitable Lewis Woodpecker nest patches from our probability of occurrence maps of the study area in the B&B Fire Complex in central Oregon.
Figure 4.2. Map of predicted nest patch suitability for the Lewis's Woodpecker within the central Oregon B&B Fire Complex. Presence and absence mapped using a threshold of 0.54 for probability of occurrence. This is the threshold where false positive and false negative errors are balanced. Maps are restricted to elevations below 1300m which included all observed Lewis's activity in our study.
Table 4.1. Primary and secondary remote sensing predictor metric descriptions. Primary metrics are those able to be directly derived or simple computations of remote sensing data. Secondary metrics are those that have been calibrated with field data through modeling efforts to represent additional vegetation features unable to be directly detected. All metrics were mapped at the 10meter grid scale and summarized within a 50meter radius buffer around all nest and random snags.

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Abbreviation</th>
<th>Metric Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary lidar-derived</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean canopy cover</td>
<td>COVER%</td>
<td>Percent of lidar returns above 2 meters aboveground</td>
</tr>
<tr>
<td>Variability in canopy cover</td>
<td>COVER_SD</td>
<td>Standard deviation of canopy cover above 2 meters</td>
</tr>
<tr>
<td>Variability in vegetation height</td>
<td>HEIGHT_SD</td>
<td>Standard deviation of vegetation heights</td>
</tr>
<tr>
<td>Degree slope</td>
<td>SLOPE</td>
<td>Topographic slope in degrees</td>
</tr>
<tr>
<td>Secondary lidar and Landsat-derived</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Density of snags ≥50cm dbh</td>
<td>SNAGS</td>
<td>Proportion of pixels within buffer predicted to contain ≥50cm dbh snag</td>
</tr>
<tr>
<td>Mean woody shrub cover</td>
<td>SHRUB%</td>
<td>Mean predicted woody shrub cover</td>
</tr>
</tbody>
</table>
Table 4.2. List of 20 ecologically meaningful candidate models for predicting the selection of a nesting patch by the Lewis's Woodpecker in a 9-yr post-fire landscape.

<table>
<thead>
<tr>
<th>Candidate Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept only (null)</td>
</tr>
<tr>
<td>COVER%</td>
</tr>
<tr>
<td>COVER_SD</td>
</tr>
<tr>
<td>HEIGHT_SD</td>
</tr>
<tr>
<td>SLOPE</td>
</tr>
<tr>
<td>SNAGS</td>
</tr>
<tr>
<td>SHRUB%</td>
</tr>
<tr>
<td>COVER% COVER_SD</td>
</tr>
<tr>
<td>SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD</td>
</tr>
<tr>
<td>SLOPE SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER% SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE SNAGS</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE SHRUB%</td>
</tr>
<tr>
<td>COVER% COVER_SD SLOPE SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER% HEIGHT_SD SLOPE SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER_SD HEIGHT_SD SLOPE SNAGS SHRUB%</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE SNAGS SHRUB%</td>
</tr>
</tbody>
</table>
Table 4.3. Competing models for predicting Lewis's Woodpecker nest patches. Threshold specific errors and accuracies were calculated using leave-one-out-cross-validation and the threshold where false positive and negative errors are balanced. Wi are the model specific akaike weights; AUC is the area under the curve calculated using Receiver Operating Curves; the Threshold is the model-specific value for the probability of occurrence where false positive and negative errors are balanced; PCC is the percent correctly classified; FPR is the false positive rate; FNR is the false negative rate. The model in bold was chosen for mapping of suitable nest patches.  *Lowest AIC value = 51.601.

<table>
<thead>
<tr>
<th>50m Radius Competing Model Sets</th>
<th>ΔAIC</th>
<th>Wi</th>
<th>AUC</th>
<th>Threshold</th>
<th>PCC (%)</th>
<th>FPR</th>
<th>FNR</th>
<th>kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVER_SD HEIGHT_SD SLOPE SNAGS SHRUB%</td>
<td>0.000*</td>
<td>0.182</td>
<td>0.88</td>
<td>0.59</td>
<td>77.1</td>
<td>0.208</td>
<td>0.250</td>
<td>0.542</td>
</tr>
<tr>
<td>COVER% HEIGHT_SD SLOPE SNAGS SHRUB%</td>
<td>0.084</td>
<td>0.174</td>
<td>0.88</td>
<td>0.59</td>
<td>79.2</td>
<td>0.208</td>
<td>0.208</td>
<td>0.583</td>
</tr>
<tr>
<td>COVER% COVER_SD SLOPE SNAGS SHRUB%</td>
<td>0.150</td>
<td>0.169</td>
<td>0.88</td>
<td>0.54</td>
<td>83.3</td>
<td>0.167</td>
<td>0.167</td>
<td>0.667</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE SNAGS</td>
<td>0.529</td>
<td>0.139</td>
<td>0.87</td>
<td>0.59</td>
<td>75.0</td>
<td>0.250</td>
<td>0.250</td>
<td>0.500</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE</td>
<td>1.161</td>
<td>0.102</td>
<td>0.85</td>
<td>0.59</td>
<td>79.2</td>
<td>0.208</td>
<td>0.208</td>
<td>0.583</td>
</tr>
<tr>
<td>COVER% COVER_SD HEIGHT_SD SLOPE SNAGS SHRUB%</td>
<td>1.383</td>
<td>0.072</td>
<td>0.89</td>
<td>0.60</td>
<td>83.3</td>
<td>0.167</td>
<td>0.167</td>
<td>0.667</td>
</tr>
<tr>
<td>COVER% SNAGS SHRUB%</td>
<td>1.983</td>
<td>0.067</td>
<td>0.85</td>
<td>0.54</td>
<td>75.0</td>
<td>0.250</td>
<td>0.250</td>
<td>0.500</td>
</tr>
</tbody>
</table>
Table 4.4. Parameter estimates, standard errors, confidence intervals, and significance levels for parameters from single variable glm models along with parameter-specific Akaike weights representing the relative importance of predictor variables for predicting Lewis's Woodpecker nesting patches in the B&B Fire Complex, Oregon. Indicators for varying levels of significance for parameters include: *** <0.001, ** <0.01, * <0.05, <0.1.

<table>
<thead>
<tr>
<th>Single Variable Models</th>
<th>Parameter Estimate</th>
<th>Standard Error</th>
<th>Lower Confidence Interval</th>
<th>Upper Confidence Interval</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>COVER%</td>
<td>-0.127</td>
<td>0.056</td>
<td>-0.254</td>
<td>-0.037</td>
<td>0.023 *</td>
</tr>
<tr>
<td>COVER_SD</td>
<td>-0.212</td>
<td>0.083</td>
<td>-0.396</td>
<td>-0.066</td>
<td>0.011 *</td>
</tr>
<tr>
<td>HEIGHT_SD</td>
<td>0.373</td>
<td>0.209</td>
<td>-0.016</td>
<td>0.817</td>
<td>0.074</td>
</tr>
<tr>
<td>SLOPE</td>
<td>-0.216</td>
<td>0.101</td>
<td>-0.457</td>
<td>-0.052</td>
<td>0.032 *</td>
</tr>
<tr>
<td>SNAGS</td>
<td>1.758</td>
<td>0.793</td>
<td>0.260</td>
<td>3.401</td>
<td>0.027 *</td>
</tr>
<tr>
<td>SHRUB%</td>
<td>-0.014</td>
<td>0.012</td>
<td>-0.040</td>
<td>0.009</td>
<td>0.255</td>
</tr>
</tbody>
</table>
Table 4.5. Means and confidence intervals (+/- 2 standard error) for predictor metrics summarized for the 50m radius buffers compared between Lewis's Woodpecker nest and non-use patches within the B&B Fire Complex in central Oregon.

<table>
<thead>
<tr>
<th></th>
<th>COVER%</th>
<th>COVER SD</th>
<th>HEIGHT SD</th>
<th>SLOPE</th>
<th>SNAGS</th>
<th>SHRUB%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Present</td>
<td>6.477</td>
<td>6.992</td>
<td>7.067</td>
<td>4.590</td>
<td>0.730</td>
<td>30.436</td>
</tr>
<tr>
<td></td>
<td>(4.652, 8.303)</td>
<td>(5.719, 8.264)</td>
<td>(6.581, 7.554)</td>
<td>(3.804, 5.376)</td>
<td>(0.576, 0.884)</td>
<td>(22.867, 38.005)</td>
</tr>
<tr>
<td>Absent</td>
<td>14.811</td>
<td>10.954</td>
<td>6.254</td>
<td>8.002</td>
<td>0.470</td>
<td>38.574</td>
</tr>
<tr>
<td></td>
<td>(9.282, 20.339)</td>
<td>(8.665, 13.243)</td>
<td>(5.536, 6.973)</td>
<td>(5.549, 10.455)</td>
<td>(0.313, 0.627)</td>
<td>(26.574, 50.575)</td>
</tr>
</tbody>
</table>
Table 4.6. Comparison of predictive accuracies and error rates between the top model selected in our Lewis's Woodpecker nest patch modeling efforts for 9-year post-fire B&B Fire Complex in central Oregon and the previously published Lewis's Woodpecker habitat suitability model (HSM; Sousa 1983), reported for the threshold where errors are balanced. Accuracy rates include percent correctly classified (PCC), kappa statistic, and area under the curve (AUC, not threshold specific). Error rates include false positive errors (FPR) and false negative errors (FNR).

<table>
<thead>
<tr>
<th>Predictive Model</th>
<th>Threshold</th>
<th>PCC (%)</th>
<th>FPR</th>
<th>FNR</th>
<th>Kappa</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>B&amp;B Top Model</td>
<td>0.54</td>
<td>83.3</td>
<td>0.167</td>
<td>0.167</td>
<td>0.667</td>
<td>0.88</td>
</tr>
<tr>
<td>HSM (Sousa 1983)</td>
<td>0.27</td>
<td>45.8</td>
<td>0.542</td>
<td>0.542</td>
<td>-0.083</td>
<td>0.51</td>
</tr>
</tbody>
</table>
CHAPTER 5: CONCLUSIONS

The overall goal of this dissertation was to look at the state of the wildlife research discipline in the use of geospatial data for habitat mapping, and to advance this area through the fusion of remote sensing tools for the mapping of previously difficult to characterize habitat metrics for inclusion in avian cavity nesting models. Chapter 2 reviewed over 60 years of selected wildlife literature to evaluate historic trends in the use of spatial scales and technology in the representation of forests for habitat modeling, identifying recent advances in the wildlife discipline attributed to geospatial data products, and providing suggestions for future improvements through the utilization of unrepresented or underutilized remote sensing datasets for habitat characterization. Chapter 3 found promise in the fusion of lidar structure and Landsat time series disturbance products in the modeling and mapping of post-fire snag and shrub distributions at fine scales and size/cover thresholds relevant for habitat mapping applications for many wildlife species. The utility of these metrics for representing important habitat features for a cavity nesting species of conservation concern, the Lewis's Woodpecker, was demonstrated in Chapter 4. These chapters represent first attempts to fuse lidar and time series Landsat disturbance metrics in a post-fire landscape and for the mapping of snags and shrub distributions at scales relevant to avian nesting habitat. We found promise in these methods and the resulting habitat modeling for a cavity nester of conservation concern in an identified source habitat type.

The primary objectives of Chapter 2 were to 1) review historic trends in remote sensing and the scales of wildlife studies in forest systems; 2) review literature for recent advances in wildlife habitat studies that can be attributed to geospatial data; and 3) provide future suggestions for remote sensing sources that are underutilized or yet to be represented in the wildlife literature. We reviewed 266 articles in the historic trends portion of our review that met the criteria for our forest bird habitat studies review within *Ecology* (ECO, http://www.esajournals.org/loi/ecol; 85 articles) and the *Journal of Wildlife Management* (JWM, http://www.bioone.org/loi/wild; 169 articles) since 1950, and *Remote Sensing of Environment* (RSE; http://www.journals.elsevier.com/remote-
sensing-of-environment (12 articles) to identify trends in the use of spatial scales and technology for characterizing forest for species habitat modeling within these journals.

Remote sensing was utilized to characterize forest for avian habitat modeling efforts in 36% and 34% of the ECO and JWM articles, respectively. Regardless of the inclusion of other data sources, the majority of the reviewed studies utilized field methods to collect at least some portion of their vegetation data. Sensors represented in at least one study within ECO and JWM included various forms of aerial photography, satellite sensors (IKONOS, QuickBird, Landsat MSS, TM, and ETM+), and one lidar study (Goetz et al. 2010). The review of RSE found only 12 articles since 1969 that utilized remote sensing technology in the examination of forest avian habitat relationships, with the first study in this group not published until 1997 (Imhoff et al. 1997). The main difference between these studies and those in JWM and ECO were that RSE studies were consistently more explicit in reporting data sources, processing methods, and discussing map accuracies which was limited within the other two journals.

Our review focused on three aspects of scale: observation (scale at which vegetation was sampled); modeling (scale at which analyses were conducted); and geographic (spatial extent of the study). The smallest extent at the sub-state level was the most common geographic scale including 86% of the reviewed studies, with these studies were usually conducted within a single forest or park. There was an increase in studies covering regional extents in more recent decades of our review but not necessarily a steady trend. This increase could be attributed to advances in technology and vegetation datasets with more broad spatial coverage. The need for broad scale wildlife monitoring has motivated efforts such as the North American Breeding Bird Survey (NA BBS; https://www.pwrc.usgs.gov/bbs), providing larger extent wildlife datasets. Large scale wildlife datasets in conjunction with remotely sensed vegetation maps allow for wildlife habitat relationships to be examined on scales relevant for assessing potential impacts of climate change and other large scale drivers of wildlife species distributions. There was also an observed increase in the proportion of studies within JWM and ECO that incorporated a large modeling scale. This could be due to the greater availability of
remotely sensed vegetation datasets that facilitate landscape level variables such as the amount of core habitat in a larger area, habitat connectivity, diversity of landcover types, or other aspects of landscape configuration that may drive or restrict wildlife distributions and movements. Open source landscape analyses software packages such as FRAGSTATS (McGarrigal et al. 1995), may have also aided in an increase in this type of variable in the habitat models.

In addition to reviewing historic trends in the wildlife literature, Chapter 2 also discussed commonly used remote sensing data sources, pointed out recent advances in the use of geospatial data for characterizing forest wildlife habitat (the use of lidar data and the creation of habitat prediction maps), and provided future suggestions for increased utilization of available datasets (secondary lidar metrics and time series Landsat data). We discussed the value of continued communication between disciplines for assisting in even further shortening time lags between the creation and validation of remotely sensed vegetation metrics by the remote sensing and forest ecology community to the inclusion of those data into forest wildlife studies and management efforts. Feedback by end users such as the wildlife community also provides useful information for map developers in understanding the needs and effectiveness of the data in habitat mapping applications.

In the attempt to improve available mapping products relevant to habitat modeling needs, Chapter 3 examined the utility of remote sensing datasets calibrated with field data for mapping post-fire snag and shrub distributions. The primary objectives of chapter 3 were to 1) test the utility of data fusion for modeling snag distributions of important thresholds for cavity nesting communities and woody shrub cover; 2) evaluate any model improvements with the fusion of datasets compared to individual lidar and Landsat models; and 3) map realized relationships across a post-fire landscape. We identified important snag size thresholds using breeding season nest tree data for the local cavity nesting community, resulting in the focal size thresholds of snags with dbhs ≥40cm, 50cm, and 75cm. Through the fusion of field plot data, various lidar structure and topography metrics, and time series Landsat disturbance products representing pre-fire forest, disturbance magnitude, and current forest condition, we were able to model and
map the fine scale (10m grid) presence/absence of the above snag size classes and the percent of woody shrub cover, with acceptable map accuracies. All snag size class top models were considered to have "good" predictive performance as indicated by area under the curve values (0.74 - 0.90), with percent correctly classified values ranging from 69-81% when balancing false positive and false negative errors. Logistic regression accuracies were highest for the largest size class containing snags with dbh ≥75cm (AUC of 0.90). Landsat and lidar metrics were found to be significant predictors of woody shrub cover with an adjusted $R^2$ values of 0.55. We demonstrated the ability to chose cover thresholds for habitat mapping using the percent cover shrub maps through the mapping of moderate shrub cover (30% threshold) and high shrub cover (50% threshold) and reported associated classification accuracies and errors. We found percent correctly classified rates of 79% and 84% for moderate and high shrub cover, respectively.

The importance of the remote sensing predictors varied for the habitat metrics in the combined Landsat and lidar model runs, although Landsat current forest condition metrics were found in top models for all variables. When categories of predictor variables were separated into individual lidar structure, lidar topography, and Landsat only model runs, Landsat models outperformed lidar structure models for all habitat metrics. For the snag classes with dbhs ≥40cm and ≥50cm, the top Landsat models were even competitive with the combined top models following AIC model selection. Although Landsat time series models outperformed lidar structure models when compared independently, models had fair predictive power at best, often with high error rates. The ability to map the habitat metrics with relatively low-moderate errors and acceptable accuracies was through the fusion of the remote sensing datasets. These results add to the growing body of literature exhibiting the value of combining multiple remote sensing datasets with corresponding field data to model forest systems (Dalponte et al. 2008; Goetz et al. 2010; Hudak et al. 2006), although few studies have explored this utility to map fine scale post-fire structure components (Bishop et al. 2014; Wulder et al. 2009).

Chapter 4 found promise in the utility of the above snag and shrub maps in conjunction with lidar-derived canopy cover and vegetation height variability for modeling and mapping nesting habitat for a post-fire species of conservation concern.
The primary objectives of chapter 4 were to 1) model Lewis's Woodpecker nesting habitat using remote sensing map products; 2) compare top models to the previously published Lewis's Woodpecker habitat suitability model (HSM); and 3) map the top habitat model across a post-fire landscape which has been identified as a source habitat type for this species. All of the 26 Lewis's Woodpecker nests we located succeeded during the breeding season (2012), adding support to the previous studies suggesting the importance of post-fire areas as population sources for the species (Saab and Vierling 2001, Gentry and Vierling 2007). We found models of primary (directly derived or relatively simple computations of raw data) and secondary (modeled and mapped using ground calibration data; Merrick et al. 2013) remote sensing metrics as good predictors of Lewis's Woodpecker nest patch selection. The previously published HSM for the Lewis's Woodpecker included canopy cover, shrub cover, and the density of large snags (Sousa 1983). Our top model contained additional variables (variability in canopy cover and topographic slope), but a candidate model with comparable metrics to those in the HSM was also a competing model following AIC model selection, although with the lowest predictive capabilities and the highest errors among the competing models. When the actual parameters from the published HSM were applied to our study area to predict nest patch use, the model performed poorly and was unable to adequately distinguish nest patches from non-use plots. The Sousa (1983) HSM was created as a general model applicable to the suite of forest types that Lewis's utilize. Our results indicate that for our local scale application in a single post-fire landscape, the HSM may not be suitable for identifying areas of actual use and non-use. The model may be better suited for evaluating habitat patches on a more broad scale, or for applications involving a variety of forest types, although future studies should test this further. Our snag metric also utilized a larger snag size threshold than included in the HSM (50cm vs. 30.5cm; Sousa 1983). Not only did this ≥50cm dbh snag class contain the majority of our nest trees and was found as our most important predictor variable with a positive relationship, but it has also been found to be an important threshold for the Lewis's nest trees in other studies and habitat types (Zhu et al. 2012), suggesting that the HSM may be too liberal in the utilized snag size threshold for some forest types. Importantly, we were able to utilize the
remote sensing products to map realized habitat relationships for this species of 
conservation concern in an identified source habitat type, providing a potential resource 
for local scale conservation and management efforts and adding to the regional 
knowledge of habitat selection for the Lewis's Woodpecker.

Overall, we were successful in meeting all objective of this dissertation. This 
work provides an important review of historic trends in wildlife literature, acknowledging 
recent advances through the use of remote sensing products, and providing directions for 
future work, supporting continued communication and collaborations between 
disciplines. We follow up this review by utilizing remote sensing datasets identified as 
underutilized in our review, to model and map important yet difficult to represent wildlife 
habitat metrics including snag and shrub distributions. These snag and shrub mapping 
products in conjunction with other lidar structure metrics were able to successfully model 
and map preferred nesting habitat for the Lewis's Woodpecker, improving upon 
previously published HSMs and providing an important management resource for this 
species of conservation concern. To our knowledge, this work represents the first study to 
 fuse lidar and time series Landsat products for the fine scale mapping of snag size class 
and shrub distributions, and to explore the utility of these metrics for a cavity nesting 
species of concern validated with corresponding nesting data for the study area. While 
our study area represents a range of pre-fire forest types along a elevation gradient and a 
mosaic of fire severities, it still is a single study area within one post-fire time period. 
Future work should explore these methods in other forest types along a post-fire 
chronosequence, and for mapping other identified forest habitat features of importance to 
wildlife species.
BIBLIOGRAPHY


management of species and habitats at risk. LM Darling (editor). Kamloops, BC (pp. 423-428).


Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. BioScience 52: 19-30.


Witt, C. (2009). Quantification of Lewis’s Woodpecker habitat using Forest Inventory and Analysis data. McWilliams, Will; Moisen, Gretchen; Czaplewski, Ray, comps in 2008 Forest Inventory and Analysis (FIA) Symposium; October 21-23, 2008: Park City, UT.


Appendix A. Background on remote sensing technology commonly used for characterizing forest systems.

We use remote sensing data to extract information from a distance about an object of interest (Jenson 2000). Forest characterization and mapping applications range from ground-based sensors such as spectroradiometers for investigating forest canopies and terrestrial laser scanners providing plot-level tree data, to satellite based sensors such as Landsat which utilize the multi-spectral reflectance of the sun from earth features to detect patterns and attributes associated with various landcover classes/types. In this section, we will briefly describe some of the most commonly used remote sensing technology for forest research and management applications and which have shown promise in representing aspects of forest habitat for wildlife research.

One of the longest running sources of remote sensing data in forest ecology is aerial photography. Depending on the complexity and detail of the photogrammetric sensor, information such as forest stand boundaries, forest type, and individual tree crowns can be mapped. Aerial photographs were first adopted by the US Forest Service for forest survey techniques in 1946 (LaBau et al. 2007) and are still utilized for many forest research and management purposes (Wulder et al. 2004). More recently, they are often used in conjunction with other remote sensing datasets to verify stand boundaries (Næsset 2002) and train/validate satellite data in classification efforts (Wickham et al. 2004). Historical analog photos can be scanned to convert to orthophotos while more recent acquisitions are done with digital photographic sensors of varying complexity (Wulder et al. 2004).

Numerous satellite sensors have been utilized to characterize forest biophysical properties, patterns, and for monitoring change, all important information in understanding forest wildlife habitat distributions. Information about the resolutions of the sensors is important in determining which sensor may be appropriate for a particular project or application including: radiometric resolution (the dynamic range and precision of the recorded reflectance across a variety of spectral bands); spectral resolution (the widths and number of spectral bands recorded); spatial resolution (the smallest spatial detail represented by the image pixel size), and the spatial extent of the data; and
temporal resolution (how often the data collected for a particular area) and extent (Lefsky and Cohen 2003). In addition to the resolution considerations, the economic cost to a project is also an important factor. The series of Landsat sensors have emerged as a front runner in the diversity and abundance of applications in forest ecology including wildlife habitat research most likely due to the availability of free (or low cost/area) widespread and long running datasets at moderate-high spatial resolutions. In 2008 USGS opened the Landsat archive, dating back to 1972, making high quality, standard calibrated data accessible for free to the general public (Woodcock et al. 2008). The 30m spatial resolution of Landsat multispectral data along with the temporal resolution of 16 days (or 8 days, considering that most often there were two satellite simultaneously in orbit over most of Landsat’s history; Roy et al. 2014) provides data appropriate for many applications of depicting aspects of forest habitat including forest age, composition, condition, and change (Cohen and Goward 2004). Landsat data in conjunction with other mapping products and field based vegetation survey plots have also proven promising for the regional scale mapping of difficult to characterize forest structure and composition elements through imputation statistical methods (Ohmann and Gregory 2002). For further information on the Landsat program and data see previous reviews by Roy et al. (2014), Cohen and Goward (2004), and Wulder et al. (2004).

Landsat and other passive satellite sensors are able to provide important information about horizontal forest structure and configuration; unfortunately these data are lacking in 3-dimensional detail needed to characterize vertical forest structure, an important component of wildlife habitat. Airborne lidar is an active remote sensing technology that fills this gap through the mapping of vertical and horizontal forest structure at scales relevant to many wildlife species (Vierling et al. 2008). Lidar data are derived from information about the time that it takes for a laser pulse to be emitted, hit features on the ground, and then return to the sensor (Lefsky et al. 2002). Knowing the speed of light, flight details, and the time of emission and echo of multiple laser pulses per second, 3-D data can be extracted about the ground topography, vegetation height, and density of foliage within different vegetation height strata (Lefsky et al. 2002). These data has been used to characterize multiple aspects of forests habitat including canopy
cover and gaps (Lefsky et al. 1999), understory distributions (Martinuzzi et al. 2009a), foliage height profiles and diversity (Clawges et al. 2008), and forest successional stages (Falkowski et al. 2009). Limitations of airborne lidar data include limited spatial coverage, the lack of multispectral information, weather restrictions, high data acquisition and processing costs, and lack of historic record. The Geoscience Laser Altimeter System (GLAS), the first satellite based lidar sensor on the Ice, Cloud and land Elevation Satellite (ICESat), collected swaths of data from 2003 to 2009 (Vierling et al. 2013). Studies have found promise in the satellite's ability to represent canopy heights (Sun et al. 2008), although the data are not spatially continuous (collected in transects) and are limited in the vertical structure information able to be extracted.

Active radar technology is a form of remote sensing which senses backscatter from electromagnetic pulses in the microwave spectrum to determine distance and structure of targets (Kasischke et al. 1997). InSAR is a form of radar which utilizes a narrow range of the spectrum with two receivers at the ends of a baseline (Treuhaft et al. 2004). The differences in the phase and amplitudes received by the two sensors provides better information on the position, structure, and biophysical properties of the target landscape than classic radar technology (Baltzer 2001). Studies have demonstrated the utility of InSAR for forest applications such as landcover classification including some limited structural information, biomass mapping, and monitoring of change and temporal processes on the landscape (Kasischke et al. 1997, Baltzer 2001). Space-borne InSAR missions expand the availability of structure data over airborne lidar by providing global datasets not impacted by clouds or weather (Baltzer et al. 2001). Unfortunately, products are at a coarser scale with lower spatial accuracy and do not provide complete vertical profile information comparable to lidar data (Treuhaft et al. 2004), although there has been some exploration into the fusion of the two data sources to mitigate some of the limitations of both (Hyde et al. 2007). Currently, the value of InSAR data for habitat mapping may be restricted to more homogenous forest types at larger habitat selection scales.
APPENDIX B. Forest bird habitat studies included in Chapter 2 historic trends review ordered by journal and then year of publication.

*Ecology 1950-2014*


*Journal of Wildlife Management 1950-2014 (every other section per year reviewed, alternating between odd and even sections)*


Gysel, L. W. 1961. An ecological study of tree cavities and ground burrows in forest stands.


Ellison, L. N. 1976. Winter food selection by Alaskan spruce grouse


Smetzer, J. R., D. I. King, and S. Schlossberg. 2014. Management regime influences shrubland birds and habitat conditions in the northern Appalachians, USA.


