REVISTA DE TELEDETECCIÓN
Spanish Association of Remote Sensing
(2016) 45, Special Issue, 1-14
ISSN 1133-0953
EISSN 1988-8740
http://dx.doi.org/10.4995/raet.2016.3981

INVITED PAPER

A review of the role of active remote sensing and data fusion for characterizing forest in wildlife habitat models

Vogeler, J.C.*[1,2], Cohen, W.B.[3]

[1] *Forest Ecosystems and Society, Oregon State University, 321 Richardson Hall, Corvallis, OR, USA 97331.*

[2] *Department of Forest Resources, University of Minnesota, 115 Green Hall, St. Paul, MN, USA 55108*

[3] *USDA Forest Service, Pacific Northwest Research Station, 3200 NW Jefferson Way, Corvallis, OR, USA 97331.*

Abstract: Spatially explicit maps of wildlife 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. 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. Active remote sensing data from lidar and radar sensors has thus caught the attention of the forest wildlife research and management community in its potential to represent three dimensional habitat features. The purpose of this review was to examine the applications of active remote sensing for characterizing forest in wildlife habitat studies through a keyword search within Web of Science. We present commonly used active remote sensing metrics and methods, discuss recent advances in characterizing aspects of forest habitat, and 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. We also highlight the potential value in data fusion of active and passive sensor data for representing multiple dimensions and scales of forest habitat. While the use of remote sensing has increased in recent years within wildlife habitat studies, continued communication between the remote sensing, forest management, and wildlife communities is vital to ensure appropriate data sources and methods are understood and utilized, and so that creators of mapping products may better realize the needs of secondary users.

Key words: wildlife habitat, forest, lidar, radar, predictive maps.

Revisión de la teledetección activa y la fusión de datos para la caracterización de bosques en modelos especie-hábitat

Resumen: Se ha probado que los mapas que muestran explícitamente las relaciones especie-hábitat constituyen herramientas valiosas en aplicaciones de conservación y gestión, incluyendo la evaluación sobre qué especies y de qué forma se pueden ver afectadas por el cambio climático a gran escala, la fragmentación progresiva del hábitat y los usos del suelo a nivel local. Diversos estudios se han centrado en utilizar la teledetección como herramienta que permite caracterizar la vegetación para el análisis de la selección del hábitat y para cartografiar las relaciones con el entorno natural. Uno de los tipos de hábitats más difíciles de caracterizar mediante teledetección son los sistemas forestales verticales y horizontales complejos. Su caracterización es necesaria para estudiar los aspectos determinantes y/o limitantes para las especies. El uso de la teledetección activa mediante sensores LiDAR y RADAR ha suscitado gran interés en el ámbito de la investigación de especies de fauna silvestre en áreas forestales así como su gestión, dado

* *Corresponding author: jvogeler@umn.edu*

el potencial de esta tecnología para representar características tridimensionales de estos hábitats. El objetivo de este artículo de revisión es analizar las aplicaciones de teledetección activa en los estudios de hábitat de fauna silvestre en zonas forestales a través de búsquedas de palabras claves en la *Web of Science*. Se presentan las métricas y métodos comúnmente utilizados, los avances recientes en la caracterización de hábitats forestales y se recomiendan líneas futuras de investigación en el área de teledetección que podrían beneficiar estudios sobre fauna silvestre en ámbitos forestales que actualmente o no existen o están infrautilizados. También se destaca el valor potencial de la fusión de datos de sensores activos y pasivos para la representación de múltiples dimensiones y escalas del hábitat forestal. Si bien el uso de la teledetección en estudios de hábitat de fauna silvestre se ha incrementado en los últimos años, la comunicación fluida entre las comunidades científicas relacionadas con la teledetección, la gestión forestal y la ecología es vital para garantizar el uso y comprensión adecuados de los datos, permitiendo un mejor conocimiento de las necesidades de los usuarios.

Palabras clave: especie-hábitat, bosque, lidar, radar, mapas predictivos.

1. Introduction

Spatially explicit maps of wildlife 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 (Maclean *et al.,* 2008), ongoing fragmentation of habitat (Osborne *et al.,* 2001), and local land-use practices (Poulin *et al.,* 2008). Relating species distributions to vegetation patterns using field collected data and expert knowledge is far from a new concept, but increasing pressures on wildlife populations through habitat loss and degradation have led to the need for spatially explicit representations of habitat relationships (Scott *et al.,* 1993). 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.

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 resolution and two-dimensional nature of much of the passive remote sensing data have been identified as limitations for capturing some of the important features for wildlife habitat needs (Turner *et al.,* 2003). Most passive sensors collect data using solar reflectance of surface features. While reflectance data from passive sensors may be appropriate for characterizing stand level and compositional attributes such as cover type (Turner *et al.,* 2003), many forest wildlife species also respond to fine-scale three dimensional aspects of the forest (Vierling *et al.,* 2008). Active remote sensing data from lidar and radar sensors has thus caught the attention of the forest wildlife research and management community in the potential to represent these three dimensional habitat features at local scales (Swatantran *et al.,* 2012), although the range and full potential of these applications are still being explored.

Active sensors emit energy pulses and record the return time and amplitude to derive three dimensional vegetation structure (Andersen *et al.,* 2006). In the case of lidar, either the full waveform (waveform lidar) or multiple discrete returns (discrete lidar) are recorded from this returning energy. These sensors may be mounted on aircraft (airborne lidar), on satellite platforms (spaceborne lidar), or on ground-based structures (terrestrial lidar). The majority of the explorations into the value of lidar data for ecological purposes have utilized airborne lidar data for its balance of spatial grain and extent to meet a range of project needs. The ability of the lidar pulses to penetrate canopies and return information from throughout the vertical vegetation profile as well as characterize horizontal heterogeneity of canopy patch/gap dynamics have provided new opportunities for directly characterizing forest structure (Lim *et al.,* 2003). Vertical and horizontal lidar metrics directly derived from the lidar point cloud can also be used to create statistical models for the prediction of additional forest metrics such as biomass (Zhao *et al.,* 2009), basal area (Hudak *et al.,* 2006), and snag and shrub distributions (Martinuzzi *et al.,* 2009).

Radar sensors detect the backscatter from electromagnetic pulses in the microwave spectrum to determine distance and structure of targets (Kasischke *et al.,* 1997). Different radar sensors are characterized by the wavelength of the emitted energy. Interferometric synthetic aperture radar (InSAR) is a common approach utilized for forest mapping purposes which involves comparing the variance in the returning energy from two or more synthetic aperture radar (SAR) images (Baltzer, 2001). Studies have demonstrated the utility of radar for forest mapping 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).

A long running tool in wildlife ecology and management are habitat suitability models that quantify wildlife species habitat relationships and can be used to predict other potentially suitable patches. These models come in many forms, but some of the more well known in the management community are the U.S. Fish and Wildlife Service habitat suitability models (HSMs; USFWS, 1980). The models can then be used to assign unknown areas a habitat suitability index (HSI) on a scale of 0 (unsuitable) to 1.0 (highly suitable) based on the defined habitat parameters in the HSM (USFWS, 1980). The next step for translating these types of models into tools applicable to a wider range of management and conservation purposes is the creation of habitat suitability maps using spatial datasets that represent drivers of wildlife species distributions and habitat needs. Many studies have pointed out the value of active remote sensing for characterizing forest patterns and features important to wildlife and the exploration into directly relating these features to species distributions is rapidly increasing (see reviews by Vierling *et al.,* 2008; Merrick *et al.,* 2013). The production of spatially explicit representations of these habitat relationships, in the form of habitat suitability or predicted habitat maps, is still limited.

The purpose of this review was to examine the applications of active remote sensing for characterizing forest in wildlife habitat studies through a keyword search within Web of Science. We present commonly used active remote sensing metrics and methods and discuss recent advances in characterizing key aspects of forest habitat. We also highlight the value in data fusion of active and passive sensor data for representing multiple dimensions of forest habitat. We conclude by discussing additional metrics/methods for charactering forest systems using active remote sensing or the fusion of active and passive data that are not yet represented or underutilized within the wildlife habitat literature that could benefit forest wildlife studies by advancing opportunities for mapping predicted habitat.

2. Review of active remote sensing of habitat

We conducted a keyword search within the Web of Science database using the phrases “lidar AND habitat AND forest” and “radar AND habitat AND forest”. We reviewed studies from the resulting pool of literature that actually utilized lidar or radar to characterize forest for habitat modeling and/or mapping purposes. We excluded studies that only discussed the potential applications without actually relating the data to habitat modeling/mapping applications. The reviewed studies either incorporated wildlife data sets by directly modeling habitat relationships, or utilized remote sensing data to map previously published HSMs. We compiled the types of lidar/radar sensor data employed, comparing the use of directly derived remote sensing metrics (primary metrics) or more difficult to represent forest features that were modeled using calibration field data (secondary metrics). We noted the focal taxa (bird *vs.* mammal) and whether the study took a species specific, community, or diversity analysis approach. We also report the proportion of studies that used the fusion of passive and active remote sensing to characterize the habitat, highlighting any value that may have been found from such an approach.

Our literature search returned 59 studies that met our review criteria (53 lidar, 5 radar, and 1 that incorporated both lidar and radar; Table 1). The majority of the studies focused on birds (77%) and spanned 15 countries with the majority covering areas of the U.S. (47%). Over half of the studies (57%) employed field data in addition to active remote sensing products for either calibration of secondary metrics, supervised classifications of passive data, validation efforts, or to quantify additional model metrics. Only 17% of the studies used these field data to calibrate secondary active remote sensing metrics. Some studies investigated both species specific habitat as well as diversity patterns, others focus on one or the other, where 56 studies included a species specific modeling approach, 11 studies incorporated a diversity or species richness measure, and one study took a community analysis approach.

Table 1. Breakdown of active remote sensor and data types used in the reviewed wildlife habitat studies.

	Number of Studies	Percent of Studies [b]
Lidar		
Terrestrial	2	3
Airborne		
Discrete (DSL)	43	73
Waveform (WF)	7	12
DSL/WF	1[a]	2
Spaceborne		
GLAS/WF	1	2
Total	54	92
Radar		
Airborne	2[a]	3
Spaceborne	4	7
Total	6	10

[a] One study (Swatantran *et al.* 2012) incorporated waveform and discrete airborne lidar as well as airborne radar data. The study is included in counts in both the lidar and radar sections.

[b] Percent values are calculated using a total study count of 59 due to one study incorporating both lidar and radar.

2.1. Lidar wildlife habitat studies

A total of 54 studies in our review incorporated lidar data in their examination of forest wildlife habitat or diversity measures. The majority of the studies utilized data from airborne lidar sensors (96%), where 44/54 lidar studies used discrete, 7/54 used waveform, and one study compared the two (Swatantran *et al.,* 2012; Table 1). The typical measures derived from both discrete and waveform airborne lidar were comparable, usually characterizing some aspect of canopy height, density, or the distribution of vegetation within specific height strata. The only study exploring spaceborne lidar for habitat assessment applications was Vierling *et al.* (2013) who compared the utility of discrete airborne lidar metrics with those derived from satellite-based Geoscience Laser Altimeter Systems (GLAS) lidar for quantifying red-naped sapsucker habitat relationships. The study found weak results for GLAS habitat modeling efforts compared to airborne lidar-derived metrics and suggested that the resolution and accuracy of the data may be inadequate at this time to represent important 3-D habitat features for many wildlife species (Vierling *et al.,* 2013). Two studies employed terrestrial lidar for characterizing fine-scale forest architecture (Michel *et al.,* 2008; Yang *et al.,* 2013). 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. Sub-canopy vegetation was characterized using terrestrial lidar by Yang *et al.* (2013) to examine bat flight patterns. Terrestrial 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.

The majority of reviewed lidar studies characterized the forest habitat through primary metrics that were either from, or comparable to, those available through the frequently used FUSION lidar processing software (McGaughey, 2009). These included (but were not limited to) raster binned summary statistics at multiple spatial scales of: canopy height and densities; percentiles of heights; and the density of lidar returns within specific height strata. There was a particular focus on the architecture of the understory stratum. Several studies used multi-temporal lidar, although these opportunities are rare, conducting lidar flights during leaf on and leaf off season either to better penetrate the canopy and characterize understory architecture (Broughton *et al.,* 2012), or to try and differentiate between deciduous *vs.* coniferous components of the canopy (Garabedian *et al.,* 2014).

Our definition of active remote sensing secondary metrics included those calibrated with field-collected data. Only 8/54 of our reviewed lidar studies incorporated such secondary forest metrics. Martinuzzi *et al.* (2009) modeled and mapped snag and shrub distributions using primary lidar metrics along with secondary maps of basal area and forest succession stage. These maps of snags and shrubs facilitated the mapping of previously published habitat suitability models for four avian species (Martinuzzi *et al.,* 2009). A set of secondary lidar metrics including biomass, basal area, vegetation volume, stand density index, along with other lidar modeled forest attributes were related to Mount Graham red squirrel distributions to create habitat suitability maps (Hatten, 2014). Secondary mapping products were created using primary lidar metrics in the study by Coops *et al.* (2010) which focused on forest stand metrics previously found to be important for winter mule deer habitat including canopy closure and an overall stand structure classification.

The value of lidar for forest wildlife habitat modeling applications goes beyond providing continuous representations of habitat metrics previously sampled through field efforts. The continuous 3-D data also allows for the examination of previous unquantifiable, or extremely difficult to quantify, vertical and horizontal elements of forest structure (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 an 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 vertical foliage layers which lidar is able to quantify. 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 as opposed to field sampled vegetation data also allows for extraction of landscape metrics in studies examining relationships at larger habitat selection scales (Nelson *et al.,* 2005).

2.2. Radar wildlife habitat studies

In our Web of Science review, we found only six studies that utilized radar for characterizing forest in the examination of wildlife habitat, with one of the studies including both lidar and radar metrics (Swatantran *et al.,* 2012). All of these studies focused on bird species and included multiple primary radar metrics of band values and combinations to represent measures of forest structure and heterogeneity. The majority (4/6) of studies used data from spaceborne as opposed to airborne radar sensors. Imhoff *et al.* (1997) related the SAR bands in their study to forest metrics using field-collected vegetation data to help interpret the modeled bird habitat relationships, where the C-band was influenced by the forest canopy, L-band was related to branch attributes, and the P-band was linked to stem attributes.

Two of the radar studies incorporated biomass, a frequently modeled secondary metric for forest applications, along with Landsat-derived landcover (Bergen *et al.,* 2007; Culbert *et al.,* 2013). Biomass in conjunction with landcover types can be indicative of forest height, age and tree density (Bergen *et al.,* 2007). Culbert *et al.* (2013) compared the influence of vertical and horizontal structure on bird species richness measures across the U.S. using three national datasets: the Breeding Bird Survey; National Landcover Dataset (NLCD); and the National Biomass and Carbon Dataset (NBCD). The NBCD canopy height and biomass metrics are modeled using radar, elevation, and Landsat-derived landcover calibrated with a national field vegetation survey dataset (USDA Forest Inventory and Analysis). The study found promise in both remote sensing datasets for explaining species richness patterns, where the vertical structure had the strongest influence complemented by horizontal structure (Culbert *et al.,* 2013). Although biomass may be indicative of forest characteristics of importance for a wide range of wildlife species, few studies have directly explored the relationship between biomass and habitat selection. Biomass is difficult to quantify across large areas using field methods alone and thus may have been passed over for more field accessible forest metrics in traditional wildlife habitat studies (e.g. forest height, ocular estimations of canopy cover, tree density). As biomass maps become more available through remote sensing methods such as radar (Baltzer, 2001), there could be value in further exploring the utility for representing wildlife distributions across multiple scales of habitat selection. During our review, we found several studies that used ground radar stations for detecting bird migrations, but as they did not use the radar for characterizing forest habitat, they were not included in the review.

2.3. Predicted habitat maps

While all of the studies we reviewed focused on spatial predictor data, only 42% of these translated their models into predictive maps. The predicted habitat maps included HSI comparable maps, predicted foraging areas, or diversity patterns depending on the focus of the study. Several of the studies did not directly relate habitat metrics to wildlife distributions and instead mapped previously published habitat relationships. Two of these created spatial representations of USFWS HSI models (Nelson *et al.,* 2005; Martinuzzi *et al.,* 2009) and an additional two mapped previously noted habitat components from other literature sources (Coops *et al.,* 2010; Pistolesi *et al.,* 2015).

As the availability of forest remote sensing metrics increases, it is important to investigate how and which of these metrics are relevant in explaining species distributions and diversity patterns as well as to explore opportunities to characterize the habitat in new ways. While understanding these relationships is a vital first step, it is also important to exploit the full value of the spatial predictors by translating these relationships into usable tools for broader applications in the form of maps. Predicted habitat 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 models identifying potential impacts of climate change (Maclean *et al.,* 2008), the prioritization of conservation resources (Graf *et al.,* 2005), trade-off analyses for landscape planning, monitoring habitat change through time (Davis *et al.,* 2015), local scale management planning (Graf *et al.,* 2009), among many other potential applications (Figure 1).

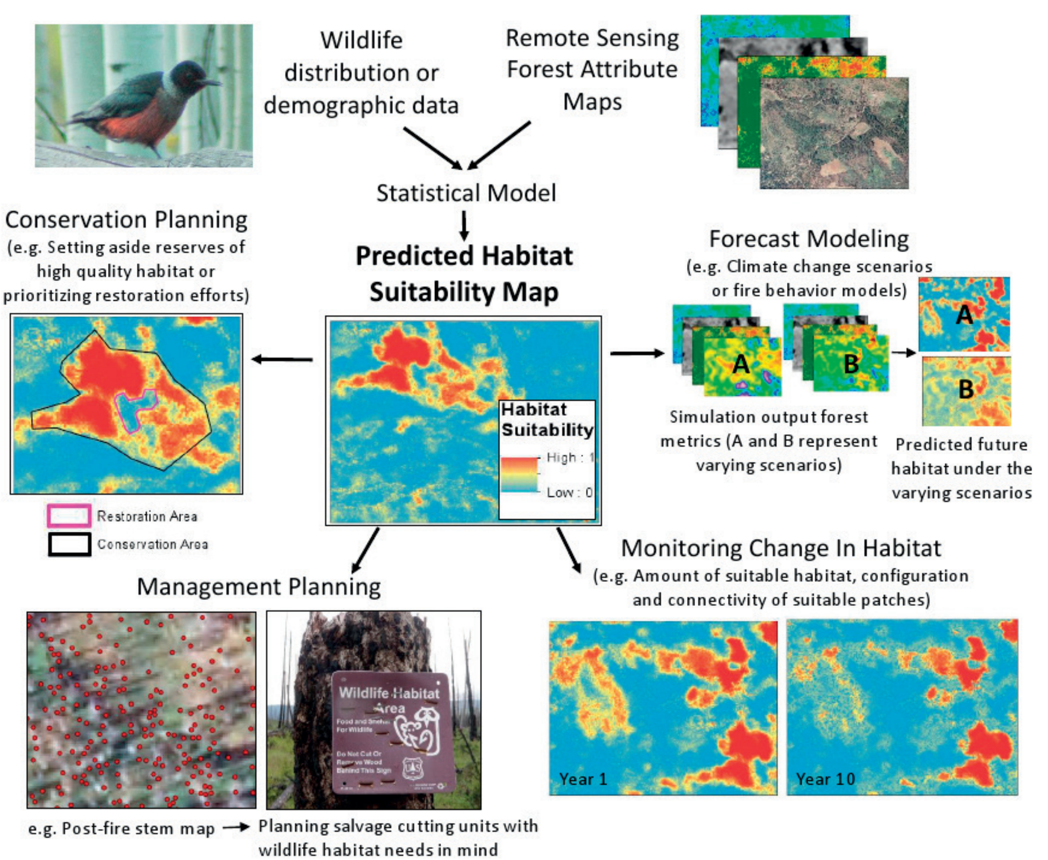

Figure 1. Conceptual figure on the creation of predicted habitat maps using remotely sensed forest predictors and potential management and conservation applications.

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 such as climate change impacts and fragmentation of landscapes, fine grain predictions 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 decision making or planning efforts.

2.4. Comparisons and limitations

The reviewed studies exhibited promise in both the use of radar and lidar for representing aspects of forest habitats relevant to species distributions and diversity patterns, although with varying success and ranges of metrics able to be derived. Swatantran *et al.* (2012) compared the utility of radar, waveform and discrete lidar, and Landsat imagery for predicting the prevalence of eight avian species. When compared separately all of the data sets showed promise, although metrics derived from the Uninhibited Aerial Vehicle Synthetic Aperture Radar explained the least variance for all but one species, while lidar preformed the best for all but one species, and waveform and discrete sensor metrics had comparable predictive performance (Swatantran *et al.,* 2012).

While the range and detail of forest attributes available through lidar often exceeds those able to be derived from radar sensors, lidar is far more limited spatially and temporally (Andersen *et al.,* 2006). Spatial and temporal limitations of airborne lidar data may be alleviated with comparable 3-dimensional datasets from a satellite sensor, although a comparable spaceborne lidar sensor is currently not available. The satellite based GLAS lidar sensor collected swaths of data from 2003 to 2009, although little support has been found for the ability of the data to represent forest wildlife habitat (Vierling *et al.,* 2013). NASA's Ice, Cloud and Land Elevation Satellite-2 (ICESat-2) is planned to be launched in 2017 (http://icesat.gsfc.nasa.gov/icesat2/mission_overview) although it is unknown whether this satellite will provide improvements to wildlife habitat mapping efforts. More promising for providing measures of forest architecture is the proposed Global Ecosystems Dynamics Investigation (GEDI) lidar mission scheduled for 2018 which has the goal of providing terrestrial vegetation information focusing on forest systems (http://science.nasa.gov/missions/gedi/). GEDI data will still be limited spatially, but will provide consistent samples of a wider spread of forest types and potentially provide new opportunities to scale up to more continuous sensor data.

Studies have found varying degrees of promise in the potential of scaling up lidar forest metrics with satellite based radar or passive sensors (Andersen *et al.,* 2012, Pflugmacher *et al.,* 2014). Andersen *et al.* (2012) utilized a multi-scale/sensor sampling approach to model and map forest biomass in a remote area of interior Alaska. The first level of the study modeled field sampled biomass using strips of coinciding lidar data, which was then scaled up to the landscape level using a combination of Landsat TM and ALOS PALSAR dual-polarization synthetic aperture radar (PolSAR) satellite imagery (Andersen *et al.,* 2012). Historic biomass and the change in forest biomass were mapped using a similar multi-level approach by Pflugmacher *et al.* (2014). The study used lidar estimates of biomass calibrated with field data, which was then modeled using Landsat time series disturbance and recovery products (Pflugmacher *et al.,* 2014). The resulting Landsat time series biomass model was then able to be scaled back in time for historic biomass and to estimate the change in biomass (Pflugmacher *et al.,* 2014).

2.5. Fusion of active and passive remote sensing data

Passive remote sensing was frequently incorporated in the examination of habitat selection and diversity patterns (45% of lidar studies and all of the radar studies). The majority of the data fusion studies incorporated data from one of the Landsat sensors (16 studies) or aerial photos (11 studies). The addition of passive data was often to represent compositional elements and/or patch dynamics to complement the forest structure represented by the active remote sensing metrics. Several of the studies compared leaf-on and leaf-off passive sensor images to differentiate between deciduous and coniferous forest patches (Goetz *et al.,* 2010; Swatantran *et al.,* 2012; Farrell *et al.,* 2013). Data fusion is not always limited to one active and one passive sensor. Swatantran *et al.* (2012) compared the performance of radar, lidar, and passive imagery as discussed above, as well as investigating the value of data fusion for predicting bird species prevalence. The combination of the data for predictive modeling improved the performance on average by 25% over radar-only, 15% for Landsat, and 4% for lidar (Swatantran *et al.,* 2012). The results of data fusions for forest metrics outside of the wildlife literature vary (Popescu *et al.,* 2004; Vogeler *et al.,* 2016), but there is a consistent trend of improved model performance through active and passive data fusion as the metrics available from the different sensors are often complementary as opposed to overlapping.

Habitat selection occurs at a hierarchy of spatial scales (Johnson, 1980). At larger spatial scales, passive remote sensing may be able to capture drivers of species distributions while vertical forest structure from active remote sensing may be needed to quantify local scale habitat relationships. Due to the temporal limitation of lidar data collections for many study areas, there may be value in creating passive remote sensing based habitat maps for monitoring efforts (Davis *et al.,* 2015). While these models may often exhibit lower accuracies and spatial precision, studies have found promise in their ability to quantify the overall amount of suitable habitat for species (Ackers *et al.,* 2015) that may prove useful for monitoring habitat loss through time in between lidar data collections.

3. Future Suggestions: Additional Forest Habitat Metrics

While it is becoming more common for wildlife studies to incorporate active remote sensing, there are yet underutilized or unrealized opportunities for characterizing aspects of the forest for wildlife habitat modeling. 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 secondary users. Better communication between disciplines may help shorten the gap between data creation and validation and the adoption of the data products by users such as the wildlife community.

While only included in a handful of reviewed studies, recent advances in lidar modeling and mapping of stem densities of particular size classes (Ackers *et al.,* 2015), snag distributions (Vogeler *et al.,* 2016), and the availability of a shrub layer (Wing *et al.,* 2012) may provide valuable resources for future wildlife habitat mapping (Table 2). We reviewed the published USFWS HSI models for wildlife species utilizing forest habitat for some portion of their life history needs (USGS, 2015). While we acknowledge this set of habitat models is a small sample of available wildlife models, we feel they cover a suite of wildlife species, forest habitats, and required habitat metrics to illustrate the opportunities to provide habitat maps through the use of remote sensing metrics (Table 2). In this section we will discuss some of the more difficult to represent components of forest habitat included in these models that are available through active remote sensing or the fusion of remote sensing datasets, although their incorporation into habitat mapping efforts are still limited.

Information about the spatial arrangement of specific tree resources and/or densities is included in many wildlife habitat models (Table 2). Lidar has shown promise for providing such information at scales relevant to many habitat modeling applications (Duncanson *et al.,* 2014, Ackers *et al.,* 2015). Although our review did include several studies that explored the utility of lidar for stem mapping purposes (García-Feced *et al.,* 2011; Swatantran *et al.,* 2012; Ackers *et al.,* 2015), additional wildlife studies may benefit from such products. Techniques/software such as TreeVaW (Popescu, 2004) and FUSION's canopy height maxima function (McGaughey, 2009) use lidar derived canopy height models to look for local peaks in the model to map individual dominant tree crowns. Using data from local forests on dbh/height relationships, stem maps of trees of particular size thresholds are increasing in availability (Kankare *et al.,* 2014; Ackers *et al.,* 2015).

Standing dead trees are of particular importance for a suite of wildlife species for nesting, roosting, and foraging resources (Haggard and Gaines, 2001). 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). Studies have begun to explore the utility of lidar for mapping

Table 2. Summary of forest metrics included in USFWS Habitat Suitability Models for forest wildlife species (USGS, 2015).

	Summary of U.S. Fish and Wildlife Service Habitat Suitability Model Components							
Species	Composition [a]	Landcover [b]	Canopy Closure	Canopy Heights	Stem Maps [c]	Snags	Shrubs	Ground Cover [d]
Bald Eagle		x			x			
Barred Owl			x		x			
Black-capped Chickadee			x	x		x		
Beaver	x		x		x		x	
Black Bears	x	x	x		x			
Blue Grouse	x	x	x	x			x	
Northern Bobwhite	x		x	x	x			x
Downy Woodpecker					x	x		
Ferruginous Hawk					x		x	
Fisher	x		x		x			
Fox Squirrel	x	x	x		x		x	
Gray Squirrel	x		x		x			
Hairy Woodpecker	x		x		x	x		
Lewis's Woodpecker	x		x			x	x	
Marten	x		x		x			x
Mink	x	x	x				x	
Moose	x		x	x	x		x	
Pine Warbler	x		x		x			
Pileated Woodpecker			x		x	x		x
Southern Red-backed Vole	x		x		x			x
Ruffed Grouse	x			x	x		x	
Spotted Owl	x		x		x			
Veery	x		x	x			x	
Wild Turkey	x	x	x	x	x		x	
Williamson Sapsucker	x		x		x	x		
American Woodcock					x		x	x
Yellow Warbler							x	

[a] Composition metrics may differentiate between coniferous and deciduous canopy, specific tree or shrub species, or to specify the presence of hard or soft mast producing species.
[b] Landcover refers to general cover types such as forest and non-forest, not specific species.
[c] The stem map category of metrics includes tree specific measurements such as diameter at breast height (dbh) thresholds as well as stand summary metrics such as average dbh, basal area, stem density, and succession stage.
[d] Ground cover metrics include downed wood, stumps, grass cover, and litter.

deadwood although these efforts and range of snag characteristics and study systems are still limited. Martinuzzi *et al.* (2009) and Vogeler *et al.* (2016) mapped snags of particular sizes to provide comparable information included in habitat suitability models. Martinuzzi *et al.* (2009) incorporated these snag products into the mapping of previously published HSI models for three avian cavity nesting species (Sousa, 1983; Schroeder, 1983; Sousa, 1987). Vogeler *et al.* (2014) included a large snag map created using the fusion of lidar and Landsat time series products in their examination of habitat selection for the Lewis woodpecker, a species of conservation concern. The value of radar for forest structure measurements seems to lie in the ability of wavelengths to penetrate cloud cover and the continuous nature of sensors for height and biomass estimations (Baltzer, 2001), while exhibiting more limited contributions in multi-sensor mapping efforts of specific forest features such as standing deadwood (Huang *et al.,* 2009).

In areas with tree canopy cover, it is difficult to directly utilize the lidar point cloud to extract reliable information on shrub specific components of 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 shrub components *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.,* 2009). 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 (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). It is important for future research to explore the value of shrub maps in depicting the important aspects of the understory that actually drive habitat selection by wildlife species.

While it was common for the reviewed studies to incorporate both active and passive remote sensing data in their wildlife habitat models, the majority of these data fusion studies utilized basic land-cover and/or productivity metrics derived from Landsat sensors. New advances in the processing of Landsat time series image stacks may provide additional information useful to wildlife mapping efforts such as disturbance histories (dates, intensities, and trends), 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 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 or active remote sensing, there is promise in the use of Landsat time series data for such purposes (Cohen *et al.,* 2010; Kennedy *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 magnitude of change from the fire event and current lidar structure/topography data has facilitated the mapping of important post-fire forest habitat elements including snags of varying sizes and shrub distributions (Vogeler *et al.,* 2016). 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 (e.g. salvage logging; Schroeder *et al.,* 2012). Incorporating disturbance and recovery products available through Landsat time series methods may provide valuable complimentary habitat information to the structure data available through active sensors.

4. Conclusions

Active remote sensing has expanded the opportunities for modeling wildlife distributions and diversity, and for spatially mapping those relationships providing management and conservation resources. Forest remote sensing is a rapidly advancing field, thus communication is vital for the exchange of knowledge between the pioneers of mapping products and secondary users that may also benefit from advances in the technology.

Ultimately, no one sensor will provide information on all aspects of vegetation structure and composition important in wildlife habitat selection. The fusion of multiple complementary sensors may better represent the range of forest metrics required to model wildlife habitat. It is important to continue to test different sensors ability to represent aspects of forests that drive wildlife distributions and update/validate previously created habitat models as new information and spatial datasets become available. Predicted habitat maps are important for: understanding current distributions (Vogeler *et al.,* 2013); managing lands for multiple uses including providing wildlife habitat and timber resources; setting aside conservation areas or prioritizing restoration efforts for species of conservation interest (Graf *et al.,* 2005; Graf *et al.,* 2009); and for monitoring changes in the landscape, habitat, and habitat patch connectivity (Osborne *et al.,* 2001). Continuous remote sensing data also facilitates characterizing the vertical and horizontal distribution of habitat in new ways creating opportunities to expand on our understanding of drivers of habitat selection and species distributions at multiple scales. Future studies should continue to expand the species and geographic range of habitat modeling efforts using geospatial datasets including those derived from active remote sensing.

Acknowledgements

Our review was funded by the National Aeronautics and Space Administration, Carbon Cycle Program (NASA Grant 10-CARBON10-45).

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