ABSTRACT

Title of Thesis: YOUNG FOREST MANAGEMENT FOR SENSITIVE BIRD SPECIES IN WESTERN MARYLAND

Dylan Maher Taillie, Master of Science, 2020

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Golden-winged warbler, cerulean warbler, and wood thrush populations are in decline in the eastern United States. Golden-winged warblers rely on young forests – such as those created using silviculture – for nesting and early life stages; however, the loss of late-successional forest through timber harvest likely degrades habitat for cerulean warblers and wood thrush. To quantify these complexities, I mapped current habitat quality for these three species in Western Maryland using models based on forest metrics. The creation of young forest through silviculture and field succession scenarios was then simulated to project how modeled changes affect predicted habitat quality. Field succession scenarios and silviculture scenarios both improved predicted habitat quality for golden-winged warblers and wood thrush; however, for cerulean warblers, field succession scenarios improved habitat quality while silviculture scenarios degraded habitat quality. This modeling approach will assist managers in using funds to simultaneously improve habitat quality for multiple sensitive species.

YOUNG FOREST MANAGEMENT FOR SENSITIVE BIRD SPECIES IN WESTERN MARYLAND

by

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Young forest management for sensitive bird species in western Maryland

Dylan Taillie

Abstract

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1. Introduction

North America has lost almost 3 billion birds in the past 50 years, with declines in bird species observed in all major breeding biomes except wetlands (Rosenberg et al., 2019). Forest breeding birds in the eastern United States specifically have seen a decline of close to 20%, much of which can be attributed to loss of habitat in their breeding ranges (Valiela and Martinetto, 2007). Land managers across this region routinely face decisions on how to best create or improve habitat quality to maintain biodiverse communities of birds, plants, insects, and mammals at local and regional scales (Rittenhouse et al., 2010; Dirzo et al., 2014). As highly mobile species, birds rely on specific landscape configurations that provide access to habitat for nesting, foraging, and fledging (James et al., 1984; Wood et al, 2013). Characterizing and managing for these landscape configurations can be a challenge in working landscapes due to multiple land owners, complex land use histories, and unintended disturbances. This study focused on three bird species that are in decline throughout the central Appalachian mountains. The goal of this research was to describe a modeling framework for evaluating the effects of different management options on bird habitat quality. The approach addresses the challenge of managing working landscapes, where successful approaches recognize multiple objectives and the influence of dynamic and complex landscapes on bird habitat.

Wood thrush (*Hylocichla mustelina*), cerulean warbler (*Setophaga cerulea*), and golden-winged warbler (*Vermivora chrysoptera*) are declining in their breeding range across the central Appalachian Mountains (Sauer et al, 2011;Birdlife International, 2020). These species are forest breeding birds; however, they differ in the type and age of preferred forest habitat (James et al., 1984; Wood et al., 2013; Rohrbaugh et al., 2017). Population declines in these three species can be partially attributed to a reduction in habitat within their breeding range (Rohrbaugh et al., 2017). Loss of breeding season habitat for these three species is due to an overall loss of forest in the eastern US, as well as to an increase in the relative abundance of even-aged late successional forest compared with young, early-successional forest. These conditions have been created through the suppression of wildfire and a slowing of timber harvest rates across the Appalachian Montanan region over the last century (Gilbart, 2012). As a consequence of increased forest homogeneity in the Appalachian region, habitat for birds and other animals that rely on early successional forest habitats has decreased (Bakermans et al., 2015).

Reversing this trend, while also maintaining habitat for species dependent on late-successional forest, is challenging because it requires detailed knowledge of the landscape characteristics that define the habitat preferences of multiple bird species. Work defining the habitat preferences of the golden-winged warbler is illustrative of the complex landscape characteristics these birds require. (Birdlife International, 2019). For example, recent radio telemetry results have shown that golden-winged warblers rely on young, early successional forests for early life stages and on late successional forests after fledging, ultimately exploiting a diversity of forest ages proximate to nesting habitat (Streby, 2016; Rohrbaugh et al. 2017; McNeil et al., 2020). Thus, the golden-winged warbler is a species that relies structurally diverse forests, with young forests being a necessary component for nesting and raising young and late-successional forests being important for the post-fledgling life stage. Conversely, wood thrush and cerulean warbler nest in late-successional forests but similarly prefer habitats that exhibit a range of forest age-classes (James et al., 1984; Dellinger et al., 2007; Wood et al., 2013; Nemes and Islam, 2017). Although populations of all three of these species are in decline, public land managers may not be able to justify and fund management actions that benefit only one or a few species. For example, the US National Park Service monitors forest breeding birds and makes landscape management decisions based on improving the bird community index (BCI), an index of ecological condition based on the number of species from diverse bird guilds present (Stohlgren et al., 1995; O'Connell et al., 2000.; Ladin et et al., 2016). However, approaches that consider and increase the complexity of landscapes might be capable of increasing habitat for multiple species and this might be particularly true for mobile bird species that occupy forests of diverse structure throughout the breeding cycle.

A landscape perspective to natural resource management requires the consideration of land-use activities in both private and public lands, and it is therefore advantageous for natural resource managers throughout the eastern US to form partnerships with private land owners to improve habitat outside the boundaries of public land (McShea et al., 2007; Aldinger et al., 2017). Management options for addressing the inequity of forest age structure are available, either through forest harvest or reforestation of croplands and pasture. However, effective approaches require tools to measure landscape structure and estimate how a change in forest structure at a given location might affect landscape characteristics that influence habitat for a range of bird species over a larger area. Of particular interest is the creation of early successional forest and shrubland. A valuable tool for managers looking to manage for a range of species would model the change in habitat quality following a land-cover change scenario that involves the creation of early successional forest. Such a tool would ideally incorporate ongoing changes in land cover due to natural disturbance potentially occurring inside and outside of the area of direct land cover management.

Remote sensing is an effective tool for quantifying land cover and more recently has been used to capture forest structure and higher-resolution landscape characteristics (Ciuti et al., 2017; Fahrig et al., 2010), both of which can be used as predictors in models of habitat quality. Land cover data from optical remote sensing has been used to form metrics of landscape structure, which are widely used to understand fragmentation and habitat connectivity throughout landscapes (Graf et al., 2007; Duclos et al., 2019). As a more recent advancement, Light Detection and Ranging (LiDAR) forest surveys are collected at sufficient detail to quantify vertical canopy structure, and therefore provide critical information for characterizing habitat for birds (Zellweger et al., 2013; Weisberg et al., 2014; Zald et al., 2016). Where possible, the fusion of canopy height data from LiDAR with land cover classifications increases the thematic resolution of resulting forest classifications, potentially useful for the formation of models of habitat quality.

Existing approaches to modeling bird species distributions are generally focused on occupancy (Loman et al., 2017) or abundance (Fink et al., 2020). Each of these approaches serves important needs, but neither makes use of the most recent technologies in remote sensing to capture forest and landscape structure. Furthermore, while abundance models adequately capture the time-varying aspects of abundance due to migration, they do not attempt to characterize changes in habitat quality due to land-cover modification (which have been established here as a management need). For the latter, the same species occurrence data used to fit abundance models must be used with data layers of landscape structure in a way that captures the fine grain and multi-scale determinants of bird habitat. (Shifley et al, 2006; Martin and Fahrig, 2012). Although habitat quality has been modeled for these species (Buehler et al., 2006; Martin et al., 2007; Rittenhouse et al., 2010;), a habitat quality modeling approach combining landscape structure from remote sensing with simulated landscape changes has not been implemented for the bird species introduced herein and has potential to be a powerful management tool for species that use diverse forest habitats. Thus, objectives of this research were to (1) generate geospatial data layers useful for fitting models of habitat quality for the golden-winged warbler, wood thrush, and cerulean warbler in a portion of the central Appalachian mountains; (2) generate a habitat quality model using these data and observations of bird presence; and (3) explore modeled relative habitat quality under scenarios of forest harvest and field succession.

2. Materials and Methods:

2.1 Study area and species

The Appalachian mountain range, including portions of western MD comprises the Eastern stronghold of breeding habitat for our three study species (Buehler et al., 2020, Evans et al., 2020, Confer et al., 2020). Our study area includes the four western-most counties in Maryland: Garrett, Allegany, Washington, and Frederick Counties, henceforth referred to as Western MD (Fig. 1). This area was chosen for several reasons, including historic distribution and nesting of sensitive bird species modeled, availability of accurate LiDAR data used in forest classification and structure mapping, and proximity to the C&O Canal National Historical Park, a large area of public land with specific land management objectives.

Western MD is heavily forested at approximately 58% of the total landscape, with fields (a combination of cultivated crops and pasture and hay) and developed land being the second most common land cover types according to the 2011 National Land Cover Dataset (27% and 12%, respectively, Wickham et al., 2014). The forests of western Maryland are primarily deciduous, with oak-hickory forests representing the dominant forest type (Lefsky et al., 1999). Our study area includes multiple forested and mountainous ecoregions: the Northern Piedmont, Blue Ridge, Ridge and Valley, and Central Appalachians (Johnson and Gates, 2008). Many of the forests throughout Western MD are Federal or State-owned public lands, including Green Ridge State Forest, Savage River State Forest, and much of the Maryland section of the Blue Ridge Mountains (Fig. 2). These large pieces of public land, combined with large areas of privately-owned forests, create semi-continuous forest cover and provide high quality habitat patches for a diversity of wildlife in Western MD.

Forests throughout western MD provide high-quality habitat for many species. However, because much of these forests were harvested approximately 150 years ago, todays forests have regenerated relatively uniformly, resulting in a majority of even-aged, late successional forest (Kays, 1995) (Fig. 2). Although the specific timeframe differs, this historic harvest and homogenization of age-class is often the case with many of the States across the eastern US and many Federal, State and non-profit conservation organizations are working toward creating young forests to increase ecological diversity (Gilbart, 2012).

2.2 Species occurrence data

In the 2002-2006 Maryland and District of Columbia Breeding Bird Atlas, only 6 pairs of golden-winged warblers and 14 pairs of cerulean warblers were confirmed as breeding in Western MD (Breeding Bird Atlas Explorer, 2020). Although cerulean and golden-winged warblers historically have been regularly recorded nesting in western MD, recent declines have led to low numbers of recorded nesting pairs within the study area (Sauer et al., 2011; Bakermans et al., 2015). Due to the rarity of these two species, habitat quality models were fit using bird occurrence data from Pennsylvania where breeding pairs are more commonly reported. This allowed us to increase our presence sample size for all three species. Pennsylvania and western MD have similar climates and forest types, so models that were trained in Pennsylvania can be predicted to western MD without conflicting interpretation for these species due to differences in general ecology of the study areas.

Presence data for wood thrush, cerulean warblers, and golden-winged warblers were acquired from the Second Pennsylvania Breeding Bird Atlas. The breeding bird atlas collects data in 4,937 breeding bird blocks – each about 9.6 square miles wide – across the State, using consistent protocols for counting and assessing bird presence at precise locations during the breeding season (Brauning 1992, Wilson et al. 2012). Presence data for specific survey location (latitude/longitude) within each block were used for modeling purposes to determine precise latitude and longitude for species presence. Only data for confirmed breeding birds were used to fit statistical models and counts of multiple birds in one location were eliminated.

2.3.1 Environmental data – forest structure mapping

Forest structure is consistently recognized as an important determinant for wildlife habitat (Augustynczik et al., 2019; Lesak et al., 2011). Some forest structure associations can be inferred from optical remote sensing data. For example, Landsat data have long been used to differentiate between needle leaf evergreen trees and broad leaf deciduous trees (Shoffner et al., 2018). Associations between forest structure and mobile forest dwelling species such as breeding birds, bats, and small mammals have the potential to provide insights into habitat preference of these species (Bakermans et al., 2012; Zellweger et al., 2013). Forest structure to species relationships can then be projected to areas or situations that lack species occurrence observations. This is the premise of species distribution models, but the usefulness of such models for management depends on the type and scale of predictive data employed. In this work, I sought to use data that represented the forest structure at sufficient detail to separate forest successional stages and the locations of early successional forests in particular.

To classify forest structure throughout western MD, I made synergistic use of Light Detection and Ranging (LiDAR) surveys and the 2011 National Land Cover Datasets (NLCD) derived from medium-resolution optical data (Landsat) (Wickham et al., 2014). While wildlife managers often use NLCD data to understand regional patterns of forested land cover, these data do not characterize local details of vegetation structure, which limits their application to habitat mapping. This project goal was to create a forest classification that combined information on forest types (from NLCD) with estimates of canopy height (derived from LiDAR) thereby allowing the calculation of landscape metrics described in section 2.3.2, which can be useful for identifying habitat requirements for different species at varying scales. As discussed in the introduction, many species such as the golden-winged warbler will use a variety of different forest structure classes (Maier et al., 2008) during different life stages.

The National Land Cover Database uses Landsat imagery to classify land cover throughout the US at 30-meter resolution, and represents a comprehensive raster dataset that allows resource managers to quantify different land cover and land use categories throughout the landscape (Wickham et al., 2014). Raster canopy height data derived from LiDAR were acquired for the Maryland and Pennsylvania region also at 30 meter resolution (Dubayah et al., 2018). These datasets were combined to create 12 forest classes— four height classes crossed with three forest type classes (deciduous, evergreen, and mixed) (Fig. 2). This forest structure classification was adapted from Dickinson et al. (2014), which was conducted in Pennsylvania and guided by forests managers in the region in classifying forests by height and canopy closure, relating canopy height to forest age class (Dickinson et al., 2014). The combination of NLCD and canopy height data amounts to a simple decision tree. For example, all cells in the NLCD class 41 (deciduous forest) are compared against canopy height data and divided up into classes 411 (0.3–9.1m), 412 (9.1–19.8m), 413 (19.8–24.4m) and 414 (>24.4m) based on the maximum canopy height observed in each 30m cell. Our forest classification is a tool for understanding the type and amount of forest in each height class in western MD. In the next section, we use these data to quantify landscape structure at a range of spatial scales.

2.3.2 Environmental data – calculating landscape metrics

As discussed above, there is evidence that mobile species such as birds are sensitive to changes in landscape structure and forest age, structure, and composition (Graf et al., 2009; Zellweger et al., 2013). Landscape structure is defined as the spatial density and configuration of different patches of forest structure (Ciuti et al., 2017). For example, birds that nest in early successional forest may require late-successional forest nearby for their fledglings to find cover and forage. Therefore, suitable habitat for this species would require early successional forest in close proximity to late successional forest. The presence or absence of anthropogenic landscapes, including both urban and agricultural development, is also relevant, as many species are sensitive to non-forest land cover. However, the specific focal distances relevant to each bird species, and parameters such as patch size and shape, are difficult to estimate *a priori*.

Guided by this understanding, the12-class forest structure layer described above was used to generate landscape configuration metrics that quantify aspects of the forest and landscape configuration that may be important for understanding why these study species choose a nesting location. To make this work to be applicable to a wide range of species and to understand what scale is important for each species choosing habitat, I chose to calculate each landscape structure metric at a range of focal distances. Here, the focal distance is the radius of a circle which defines the area from which forest structural data is extracted and used to calculate landscape structure. In landscape ecology this process is often called fragmentation statistics (McGarigal and Marks, 1995). The computational process is to move iteratively through an image, pixel by pixel, and calculate all landscape structure metrics at a range of radii for every pixel in the image (Table 1). This moving window analysis results in a new raster that has the same spatial resolution as the original forest structure classification. For this work that attempts to be useful to a wide variety of species, but especially for songbirds, I chose to calculate all landscape structure metrics at radii of 250, 500, 1000, and 2000 meters. These metrics were chosen to capture the scale at which landscape configuration may be important for these species choosing nesting habitat – such as amount of young forest within 250 meters, diversity of forest classes within 500 meters, or amount of late-successional forest at 2000 meters radius.

2.4 Modeling – variable selection and model fitting

A total of 88 different landscape metrics were calculated (section 2.3), and many of these exhibited a high degree of collinearity. Thus, a variable selection process was necessary for each species-specific habitat quality model to reduce the number of, and collinearity of remaining, landscape metrics used to predict habitat quality. Species with the fewest number of presences require the fewest number of predictor variables to avoid overfitting (Anderson and Gonzalez, 2011; Lesak et al., 2011). This variable selection process was performed in support of another project focused on species distribution modeling in Pennsylvania, but using the same species and the same landscape metrics calculated here (Haydt et al, in preparation). In brief, this involved calculating variance inflation factors (VIF) to reduce multi-collinearity and removing variables with a VIF above 10 as this represented high multicollinearity. Once some variables were removed, the package *xgboost* for R version 3.5.1 was used to iterate through extreme gradient boosting (repeated boosted regression trees) to randomly select variables 15 at a time and iteratively select the most explanatory variables (Haydt et al, in preparation; Tiangi and Guestrin, 2016; Shirley et al., 2013), resulting in a tailored set of final variables used to predict distribution for each bird species (Fig. 4).

To model habitat quality, I fit three models (one for each species) using variables from the aforementioned landscape metrics and bird species occurrence data from the Pennsylvania breeding bird atlas. I fit the three models using presence data and landscape metrics calculated for Pennsylvania. The Pennsylvania landscape was used for model-fitting due to low numbers of confirmed breeding birds documented in western MD, explained in section 2.2. Maximum entropy (Maxent) in the dismo package of the statistical program R (version 3.5.1) was used for fitting and projection (Hijmans et al., 2017). Maxent is regarded as one of the most successful algorithms for fitting habitat quality with low species presence records and without true-absence data (Bellamy et al., 2013). Maxent uses principles of "maximum entropy" to fit a model of estimated species distribution (or habitat quality as expressed here) that deviates as little from a uniform distribution as is required to explain observations (Guillera-Arroita et al., 2014). Maxent does this by using environmental covariates combined with presence-background data to calculate a conditional probability of occurrence given the density of covariates at a presence sight compared to the density of covariates across the study area (Elith et al., 2010). Models were fit using default settings for parameters in maxent, including complementary log-log output and10,000 background points for each species.

2.5 Model evaluation

Models were evaluated for discrimination ability by using presence data withheld from fitting the models and non-detection data, a proxy often substituted for true absence in habitat modeling (Guisan et al., 2017). Thirty percent of presences were withheld when fitting models and then used to compare against predicted presence values to understand the area under the receiver operating curve (AUC of ROC) for each model fit. AUC is a commonly used discrimination metric that compares true positive rates to false negative rates to establish model discrimination – a comparison of true positives and trues negatives to false positives and false negatives (Reese et al, 2005). Absences were used to ensure background points used to fit models were accurately capturing true-negatives and false negatives throughout the landscape.

2.6 Young forest change scenarios

After fitting habitat quality models, I simulated landscape-wide change in realistic, patch-level scenarios that reflect changes that managers across the eastern US are considering when creating young forested habitats (Bakermans et al., 2015; Rohrbaugh et al., 2017). I simulated the change of relatively small (5 – 7 ha) actions in 186 scenarios across the landscape, with 93 forest harvest scenarios and 93 field succession scenarios (Fig. 3). Each scenario involves the digitization of shapefiles and simulated conversion of the current classified landscape within those shapefiles into young forest. Forest harvest scenarios changed the most abundant forest class (deciduous, >24.4 m) into young deciduous forest (0.3 – 9.3 m) (Fig. 2). Field succession scenarios changed pixels classified as either cultivated crops or pasture and hay into young deciduous forest (0.3 – 9.3 m; Fig. 2). Young deciduous forest (0.3-9.3 m) was chosen for the simulation class as it is a realistic timber depiction of forests after harvests used to create habitat for golden-winged warbler in Pennsylvania (Klaus and Buehler, 2001).

Changes across the landscape were spaced 2000m apart using a fishnet to avoid conflicts when recalculating landscape metrics for the entire region and to provide a systematic, un-bias sampling of the landscape. Forest and field simulations were digitized across the landscape, positioning forest scenarios adjacent to roads when possible, considering facilitated access for timber harvest. Field and pasture parcels for succession scenarios were selected along forest edges to model realistic scenarios where only a portion of a field would be reforested. To avoid bias, simulations were placed within each 2000x2000m grid cell at the first available patch of late-successional forest or fields available to be converted according to the rules described above. Grid cells were skipped if the correct landcover did not exist. Once management scenario polygons were selected across the landscape, the total number of scenarios was reduced before simulating land cover change to match number of forest harvest scenarios with number of field succession scenarios (Fig. 3).

2.7 Predicting habitat quality and quantifying change

Models described in section 2.4 were fit and used to predict habitat quality for cerulean warbler, wood thrush, and golden-winged warbler across the western MD landscape in both the existing landscape and landscape change scenarios. Maxent in the *dismo* package (Hijmans et al, 2017) for R version 3.5.1 was used to predict relative habitat quality for all three species for the western MD landscape. Complementary log-log output was used to transform raw values of predicted habitat quality to a 0 – 1 scale, a useful transformation for understanding changes in relative habitat quality for each species (Guillera-Arroita et al., 2014). It should be noted that due to differences in prevalence (presence per available site) for these species, results for predicted habitat quality are not directly comparable between species. Thus, a relative habitat quality of 0.4 for wood thrush is not directly comparable to a habitat quality of 0.4 for golden-winged warbler. However, comparisons of habitat quality for the same species before and after a simulated land cover change are valid. Therefore, I focused my results on summarizing in habitat improvement (or degradation) between current landcover, and field succession or forest harvest scenarios. Results were summarized for amount of habitat change within 1 km of each simulation location, as change outside of 1km was minimal and results are more clearly interpreted at this scale (Fig. 3). When analyzing the results, a "substantial habitat improvement" is defined as pixels with a habitat quality for a species value that increased >= 0.05 and "substantial degradation of habitat" was defined as pixels with a habitat quality decrease <= 0.05. This threshold was created to reduce the influence of the many pixels exhibiting very small (<0.05) changes in habitat quality over broad areas. I wanted to consider more robust changes in quality, presumably exhibited by larger changes in habitat quality typically found clustered within 1km of the simulated land cover change. With these thresholds of improvement in mind, I quantify hectares of improved relative quality vs hectares of degraded relative quality in the results section below.

To obtain a measure of change for each pixel within western MD, original habitat quality was subtracted from the changed landscape to quantify change overall and per pixel with positive values showing habitat quality improvement and negative values showing habitat quality degradation. To understand how landcover surrounding a forest harvest or field succession scenario would impact modeled habitat quality, the effect of total forest area in a 1 km buffer area was evaluated using a linear model to model the effect of landcover variables on changes in relative habitat quality. In analysis of amount of habitat created compared to area directly changed (Fig 6a, 6b), field scenarios and forest change scenarios were reduced to only those which contained greater than 60% forest in the surrounding landscape. Field succession scenarios were reduced from 93 to 61 (66% of original scenarios) and timber harvest scenarios from 93 to 83 (89% of original scenarios) to analyze amount of habitat improved per management change scenario. Without this sub–setting for this analysis, results would be difficult to compare due to inherent differences in the land cover surrounding the typical field and forest scenarios. For the remaining analysis, results were not subset (100% of forest and field scenarios were used).

3. Results

3.1 Golden-winged warbler

Of all three species modeled, golden-winged warbler predicted habitat quality showed the largest response in magnitude of change to the simulated conversion of current land cover to young forest habitat (Fig. 5, Fig 6a, 6b). Both field and forest scenarios resulted in improved habitat quality, both within and surrounding the area of for golden-winged warblers than was changed in simulations (Fig. 6a, 6b). The mean increase in predicted habitat quality for golden-winged warbler within 1km of a field scenario and forest scenario was 0.25 and 0.30, respectively (Fig. 6a, 6b). Overall habitat quality changes were binned to examine how the area of land at each level of relative habitat quality increased or decreased (Fig. 5). From these plots, we learned that for golden-winged warbler over 2000 ha of low-quality lands (< 0.10) were converted to higher quality land, distributed across habitat quality levels from 0.2 to 1.0. In 61 field scenarios 325 hectares of fields were simulated to succeed into young forest and 1994 hectares of habitat improved – improving 8% of area within 1km of a field change scenario for golden-winged warbler or about 4.5 hectares improved per hectare directly changed (Fig. 6a). In 83 forest scenarios 442 hectares of forests were simulated to be harvested and changed into young forest and 3444 hectares of habitat improved – improving 9% of area within 1km of forest change scenarios for golden-winged warbler or about 7.8 hectares improved per hectare directly changed (Fig. 6b). In forest scenarios, predicted habitat quality in 17 hectares – about 0.005% – degraded while the final 91% of habitat showed no substantial change. Increase in average relative habitat quality for golden-winged warbler showed a significant positive linear relationship with amount of surrounding forest cover within 1km in both field and forest scenarios (Fig. 7). The effect of forest area on the change in habitat quality was larger for forest scenarios (Fig 7, r =0.42, $p < 0.01$) than for field scenarios (Fig 7, $r = 0.33$, $p < 0.01$).

3.2 Cerulean warbler

Cerulean warbler predicted habitat quality showed the smallest response in magnitude of change to the simulated conversion of current land cover to young forest habitat. Only field scenarios improved habitat for cerulean warbler. Forest scenarios substantially degraded more habitat for cerulean warbler than was changed in simulations. The average increase in predicted habitat quality for cerulean warbler within 1km of a field scenario was 0.06 while the average decrease in predicted habitat quality in forest scenarios was -0.07. In field scenarios, 8 hectares of habitat improved – improving less than 1% of area within 1km of field change scenarios for cerulean warbler and leaving 99% of surrounding habitat unchanged (Fig 6a). In forest scenarios 327 hectares of habitat degraded – degrading 1% of area within 1km of a forest change scenarios for cerulean warbler and leaving 99% of surrounding habitat unchanged (Fig 6b). For every hectare simulated to be harvested, a loss of 0.75 ha was predicted for cerulean warblers. Increase in average relative habitat quality for cerulean warblers showed a significant positive linear relationship with amount of surrounding forest cover within 1km in only field scenarios (Fig 7, $r = 0.49$, $p < 0.001$).

3.3 Wood thrush

Predicted habitat quality of the wood thrush showed the second largest response in magnitude of change to the simulated conversion of current land cover to young forest habitat. Both field and forest scenarios improved habitat for wood thrush. The average substantial increase in predicted habitat quality for wood thrush within 1km of a both field and forest scenarios was 0.064 (.0641 and .0642, respectively). In field scenarios 2670 hectares of habitat improved – improving 11% of area within 1km of field succession scenarios for wood thrush and leaving 89% of surrounding habitat unchanged, an improvement of about 8.2 hectares of habitat per hectare directly changed (Fig. 6a). In forest scenarios, 6069 ha of habitat improved – improving 16% of area within 1km of a forest change scenarios for wood thrush and leaving 84% of surrounding habitat unchanged, improving about 13.7 hectares of habitat for every hectare directly changed. Increase in average relative habitat quality for wood thrush showed a significant negative linear relationship with amount of surrounding forest cover within 1km in only field scenarios (Fig. 7, $r = -.44$, $p < 0.001$).

4. Discussion

4.1 Interpreting modeling output and assessing significance

Results analyzed above and throughout the discussion section are stated in terms of amount of relative habitat quality improved and/or degraded for each species. Log transforming the raw maxent output in situations where prevalence differs between species leads to the inability to directly relate relative habitat quality to the probability of occupancy (Guillera-Arroita et al., 2014). Therefore, discussion of results is limited to assessment of habitat quality change through forest harvest or field succession, with changes that improve or degrade habitat quality for these species being of most interest. In doing so, I assumed that greater magnitude changes in habitat quality are better for each species, but I did not define a threshold value for "habitat" or "non-habitat". Further, I did not attempt to identify the optimum value of habitat quality that might lead to occupancy over time.

With these caveats stated and understood, the approach I describe using landscape metrics combined with a forest structure classification was successful in modeling realistic habitat preferences of these species. For example, my results cooborated with results from field monitoring that describes the habitat preferences of golden-winged warblers and cerulean warblers (Streby 2016, Wood et al 2013). The use of landscape structure-based metrics afforded model sensitivity to habitat quality outside of where a land cover change was simulated, an aspect of the modeling technique with implications for landscape managers in western MD and throughout the eastern US discussed further below (Fig. 3). Changes were shown to permeate throughout the surrounding landscape, showing improvements in habitat quality for all species within a 1km radius of a management scenario (Fig. 3, Fig 6a, 6b). This aspect of the modeling methods could be applied for other mobile species that rely on diverse forest habitats to spatially capture the best configurations for select management practices such as young forest creation.

As techniques for working with LiDAR data improve and become more accessible, it will be possible to build better habitat models that are more sensitive to specific aspects of forest structure. Studies have done this on a small scale, finding evidence for the use of LiDAR to understand wildlife habitat and using more complex measures of forest structure like canopy gaps, understory height and edge effects (Zellweger et al., 2013). The complexity of forests should not be underestimated when understanding how birds choose nesting habitats, and although integrating these complexities using LiDAR is time consuming, it could make future models more informative.

4.2 Forest harvest scenarios

The conversion of late-successional forest to young forest habitat was most effective at increasing habitat quality for golden-winged warbler and wood thrush (Fig. 5, 6a, 6b). Golden-winged warbler relative habitat quality was improved and the increase in habitat values within 1km averaged 0.3, a higher average magnitude improvement than for any other scenario or species. Forest scenarios were generally surrounded by a more heavily forested landscape, with 89% of forest scenarios surrounded by greater than 60% forest within 1 km. Forest harvest scenarios surrounded by greater than 60% forest led to a more successful creation of habitat for species like golden-winged warbler and wood thrush, species that rely on both young and late-successional forest (Fig 6a, 6b). The literature supports the findings that the creation of young forest through timber harvest in heavily forested areas can successfully improve golden-winged warbler habitat (McNeil et al., 2020; Klaus and Buehler, 2001). Forest harvest for wood thrush was successful in improving habitat quality surrounding a harvest simulation (Fig. 6b). Cerulean warbler lost habitat in forest harvest scenarios, a finding corroborated through previous work by Wood et al. (2006) showing a negative relationship between cerulean warblers nesting success and nearby newly created early-successional habitats. In the research by Wood et al., the early-successional habitats were previously late-successional forest that were cleared for mountain top mining and therefore are similar to a forest harvest scenario such as was simulated in this research. My study simulated only the creation of young forest, a harvest scenario that most closely relates to overstory removal in silvicultural terms and was shown here to negatively impact cerulean warbler habitat quality. However, Wood et al. importantly notes that not all forest harvest scenarios are negative for cerulean warblers as there is much nuance in silvicultural practices, for example shelterwood harvests can increase cerulean density in Appalachian hardwood forests (Wood et al., 2013).

4.3 Field succession scenarios

The conversion of fieldls into young forest habitat was successful at improving habitat quality for all three species, with varied implications for management strategies for each species in western MD. For golden-winged warbler, field conversion to young forest always improved habitat quality. Where habitat quality improved the least, I observed that the surrounding area exhibited lower total forest area (Fig. 7). Since most forest in the region is late-successional, this observation suggests that field scenarios are not as successful in improving golden-winged warbler habitat when there is insufficient late-successional forest in the surrounding landscape to support forage and shelter for fledglings. This finding is supported by previous work that found abandoned agricultural fields bordering older forests created nesting habitat for golden-winged warblers in the Appalachian region of Georgia (Leuenberger et al., 2017; Patton et al., 2010). The relationship between surrounding forest and habitat creation is similar for cerulean warbler; however, field succession scenarios did not degrade any habitat for cerulean warbler in the way that forest harvest scenarios did. Although only 8 hectares of habitat were improved for 328 hectares of habitat changed for cerulean warbler, forest harvest scenarios totaling 442 hectares degraded 327 hectares of predicted habitat quality showing a clear contrast between forest harvest and field succession scenarios for cerulean warbler (Fig. 6a, 6b). This implies that managers can create young forests that benefit cerulean warbler, wood thrush and golden-winged warbler (Fig 6a, 6b), and that multi-species management for these species could be possible with field succession scenarios but not forest harvest scenarios for these species Fig. 6a, 6b).

4.4 Management implications

The incorporation of a canopy height model into the forest classification used in this work was important for fitting and predicting habitat quality models in western MD. However, LiDAR data of similar quality currently do not exist for many areas of the US, and where the data do exist, derived canopy height models have not always been produced. Canopy height models can be time-consuming, difficult to validate, and must consider the relevant scale of observation (Dubayah et al., 2018). For example, a shelterwood harvest might open gaps in the canopy that will only be observed in a LiDAR-derived product when canopy height is modeled at a fine grain. This being said, many resource managers will have access to basic land cover classifications that depict forest and non-forest areas. For this reason, I evaluated habitat quality changes as a function of total forest in the surrounding 1km radius area rather than a certain forest structure class. This approach found evidence that to most effectively improve habitat for cerulean warbler and golden-winged warbler, young forest should be created in regions with >60% forested landcover in the surrounding 1 km (Fig. 7). To improve habitat the greatest for wood thrush in western MD, field succession or forest harvest should be performed in areas with less than 50% forest in the surrounding 1 km (Fig. 7).

This modeling experiment shows that relative habitat quality for mobile species such as birds is influenced by land cover changes up to 1km distant from any location. This suggests that public land managers must consider land cover changes (either intentional or otherwise) in adjacent private lands. Further, models as described here, could be a tool for managers looking to partner with private land owners in the context of young forest creation. More than eighty percent of forests are privately held within the eastern US (Nelson et al., 2010), suggesting public-private partnerships and stakeholder engagement will always be important tools for influencing landscape structure and habitat quality (Gilbart, 2012). Management on public and private lands is often constrained differently, but this study shows that management on any lands (public or private) can improve habitat quality in the surrounding landscape (Fig 6a, 6b). For example, the creation of young forest on a parcel of private land bordering the C&O Canal National Historic Park would increase overall habitat quality within the Park. Alternatively, the creation of young forest on managed public lands like Savage River State Forest and Green Ridge State Forest can influence habitat quality on surrounding private lands that are not being managed for wildlife. This not only improves habitat quality for young-forest dependent wildlife, but may improve visitor experiences through interactions with species that rely on young forest (Fig 6a, 6b). Through consideration of landscape effects on habitat quality, land managers in western MD have the opportunity to leverage limited funding and increase habitat quality over larger areas than can be treated directly (Fig 3, Fig. 6a, 6b).

Prioritizing conservation projects is difficult and weighing the benefits and risks of varying habitat diversification projects can be hard to quantify. One ongoing challenge is managing trade-offs between species, the habitat of which might differentially increase or decrease in quality during forest harvest. In this context, modeling a larger number of species across diverse bird guilds could be more advantageous for a general management approach. While I did model multiple sensitive species, a more comprehensive study would fit models for a larger number of species to understand tradeoffs at play under various forest configurations, ideally optimizing landscapes for a broad array of species. Encompassing more species would shed light on the difficulties around multi-species management and quantify tradeoffs managers face when managing for different bird guilds that often require varied forest configurations.

In addition to expanding the species modeled, this modeling experiment could be integrated into a spatially explicit GIS tool for managers. The tool would be used to understand implications of forest changes in specific polygons across a landscape. As I did in this study, a manager would be able to draw or submit a polygon of an area in which they simulate conversion of current land cover to a type of forest, and use the model to understand how this change affects habitat for the species included in the model. This could be a comprehensive tool, used to understand how the creation of young forest would affect habitat quality and how different types and age classes of forest would affect habitat quality in very specific regions of the landscape. Managers could weigh the benefits of converting one five-hectare patch versus another patch and to quantify how habitat would be improved or degraded in these scenarios of land cover change. Such methods would allow managers to consider the tradeoffs of different management actions, but would require a priori ideas of where harvests might take place. This is in fact often the case, as mangers must also balance economic, access, and other natural resource concerns.

5. Conclusions

I have demonstrated a modeling approach for assessing the relative habitat quality improvement associated with forest harvest and field succession in western Maryland for three sensitive bird species. My specific conclusions are:

- Small changes in the amount of young forest led to an increase in habitat quality for all three species. Because the increase in quality occurred outside of the area of land cover change, land management should consider how landscape structure influences habitat in and around land that is directly managed.
- Field succession that leads to forest growth is preferable for the species I modeled. Loss of late-successional forest negatively impacted cerulean warbler habitat quality, but forest succession following field abandonment increased habitat quality for all three species.
- The greatest average habitat quality improvement was shown for golden-winged warbler and cerulean warbler when surrounding forest cover was greater than 60%, suggesting heavily forested lands should be targeted for habitat improvement.
- Future work should consider integrating these models within a GIS tool that could be used by land managers to model habitat quality for bird species sensitive to forest management and canopy height. Advancing the use of LiDAR to model more nuanced changes in forest structure related to silvicultural practices would also likely improve model performance.

Tables

Metric	Description
Richness	The number of different forest classes
Shannon's Diversity	The proportional abundance of each class
Contagion	Accounts for the proportional abundance and class adjacency type, gives a measure of "clumpiness"
Forest class area	Area of each forest class
Land use class area	Area of each Anderson Level I land use class

Table 1 Landscape metrics calculated at 250, 500, 1000, and 2000 meter radii throughout the western MD region. All of these metrics were not used to predict habitat quality for all species, however it was important to calculate a large variety of metrics to understand what landscape configurations are most important for each species.

Figures

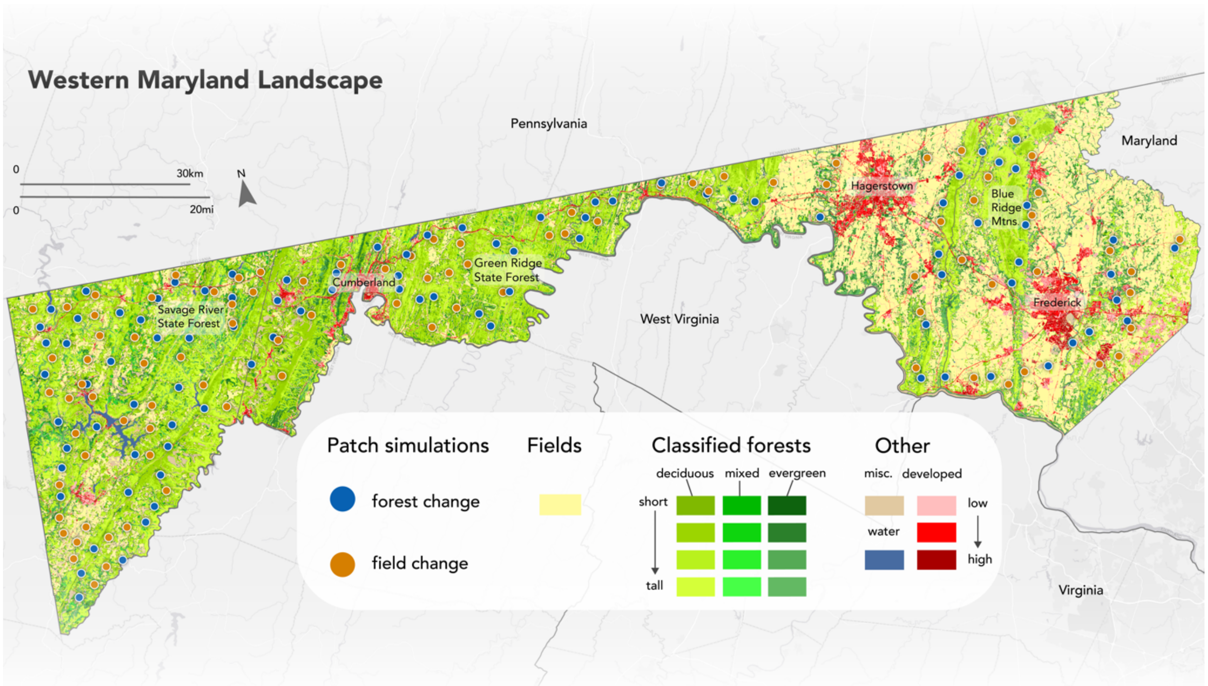


Figure 1 The western Maryland modeling landscape. Dots show places throughout the landscape where change to young forest was simulated. Fields (rust) is defined as a combination of cultivated row fields, pasture, and hay.

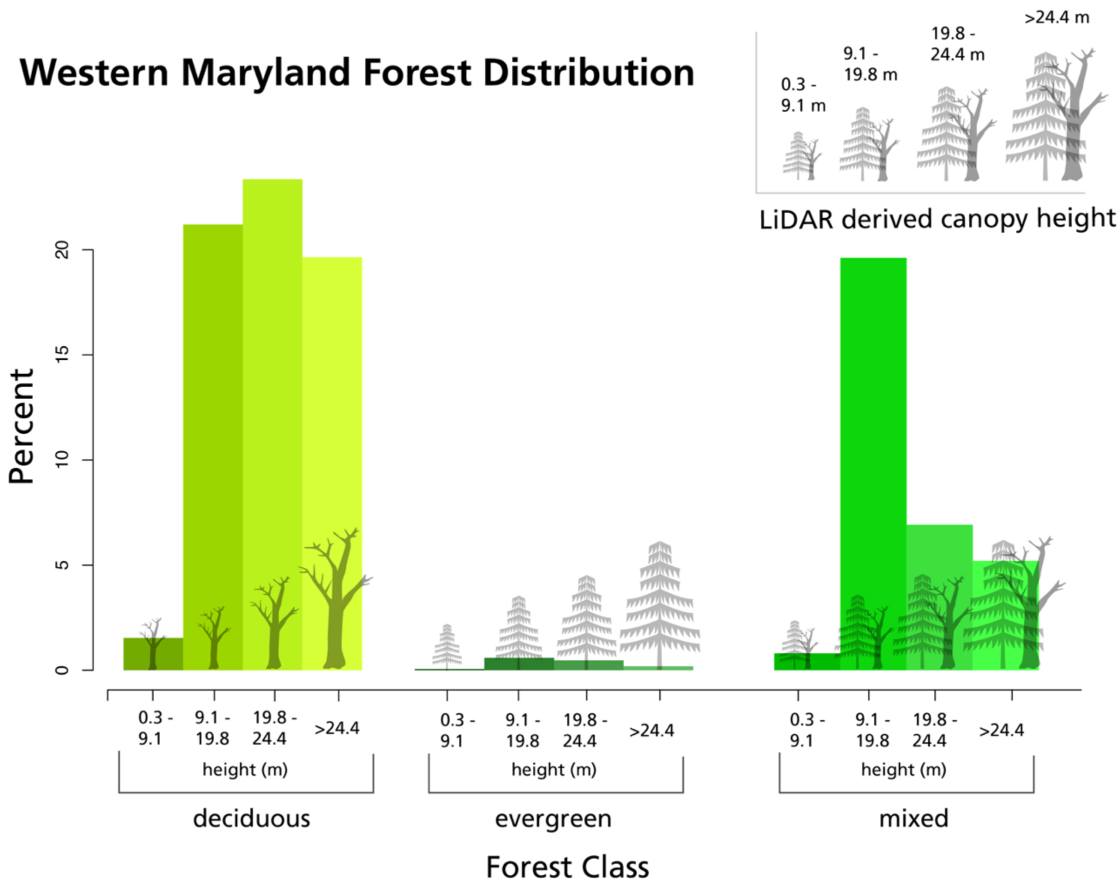


Figure 2 Forest classes throughout western Maryland, classified using a combination of NLCD and LiDAR-derived canopy height data. Western MD is predominately tall (>24.4m) or medium to tall (19.8m – 24.4m) deciduous forest. Young forest (0.3-9.1) for each forest type is the least common age-class.

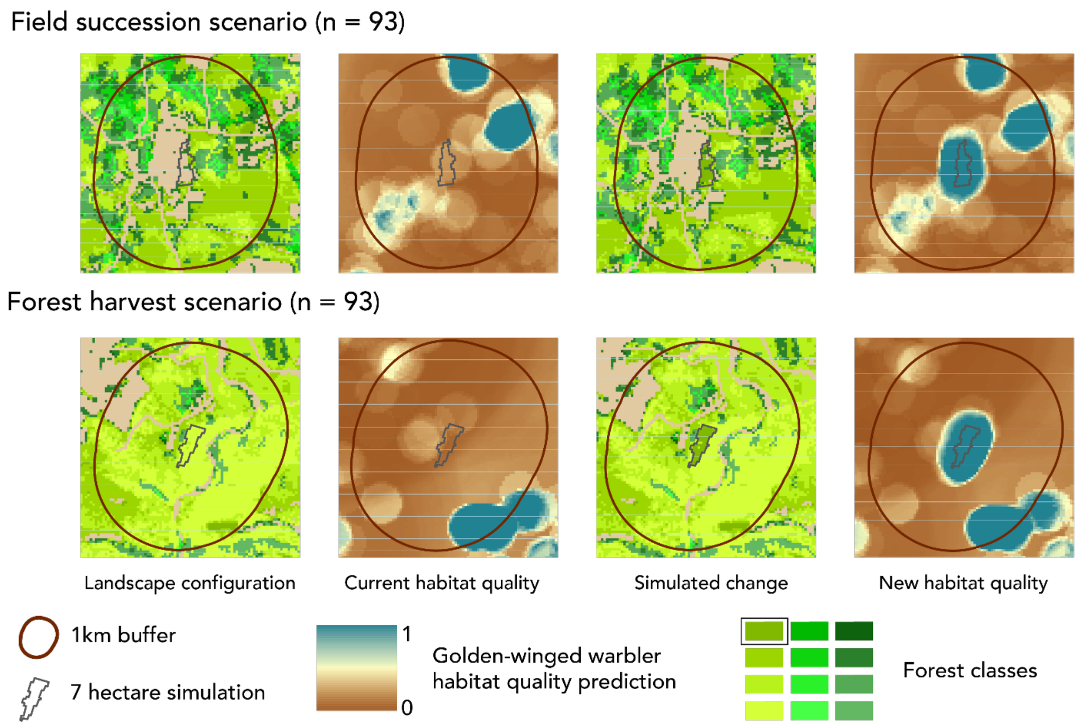


Figure 3 Two example model scenarios for a field succession simulation (top) and a forest harvest simulation (bottom). In each case, I simulated a change from existing land cover to short deciduous forests (i.e., the class outlined in black in the legend). Each simulated change was 7 hectares in area and the habitat quality for the golden-winged warbler is shown before and after the simulated change. The halo effect around the "New habitat quality" images shows habitat quality improved surrounding the simulated change, not just within it.

	Important Variables
Golden Winged Warbler	Amount of 0.3m-9.1m tall deciduous forest within 250m
Presences: 58	Amount of 19.8m-24.4m tall evergreen forest within 2000m
AUC: .85 - .93	Amount of 0.3m-9.1m tall deciduous forest within 2000m
	Amount of 9.1m-19.8m tall deciduous forest within 2000m
	Amount of 0.3m-9.1m tall mixed forest within 2000m
	Amount of 9.1 to 19.8m tall mixed forest within 2000m
Cerulean Warbler	Amount of 19.8m-24.4m tall deciduous forest within 250m
Presences: 191	Amount of 9.1 to 19.8m tall deciduous forest within 1000m
AUC: .84 - .902	Amount of 19.8 to 24.4m tall deciduous forest within 1000m
	Amount of > 24.4m tall deciduous forest within 1000m
	Amount of 9.1-19.8m tall evergreen forest within 2000m
	Amount of LULC cropland within 2000m
	Shannons diversity within 250m
Wood Thrush	Amount of 9.1m-19.8m tall deciduous forest within 250m
Presences: 6,132	Amount of 19.8 to 24.4m tall deciduous forest within 250m
AUC: .67	Amount of 0.3m-9.1m tall deciduous forest within 2000m
	Amount of 19.8 to 24.4m tall deciduous forest within 2000m
	Amount of > 24.4m tall deciduous forest within 2000m
	Amount of 9.1m-19.8m tall mixed forest within 2000m
	Amount of > 24.4m tall mixed forest within 2000m
	Amount of LULC cropland within 2000m
	Shannons diversity within 250m
	Shannons diversity within 2000m

Figure 4 List of selected variables used to fit habitat quality models. Circle sizes represent the radius of the focal area used to calculate each metric. Area under the receiver operating curve (AUC) was used to evaluate model discrimination for each model. Variable selection is described in more detail in section 2.5.

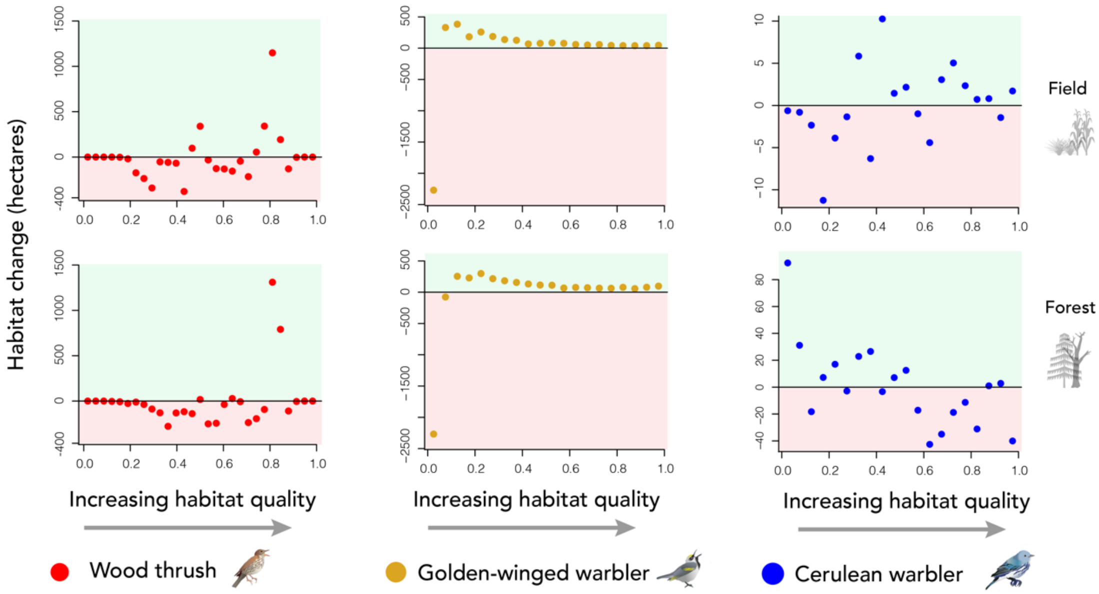
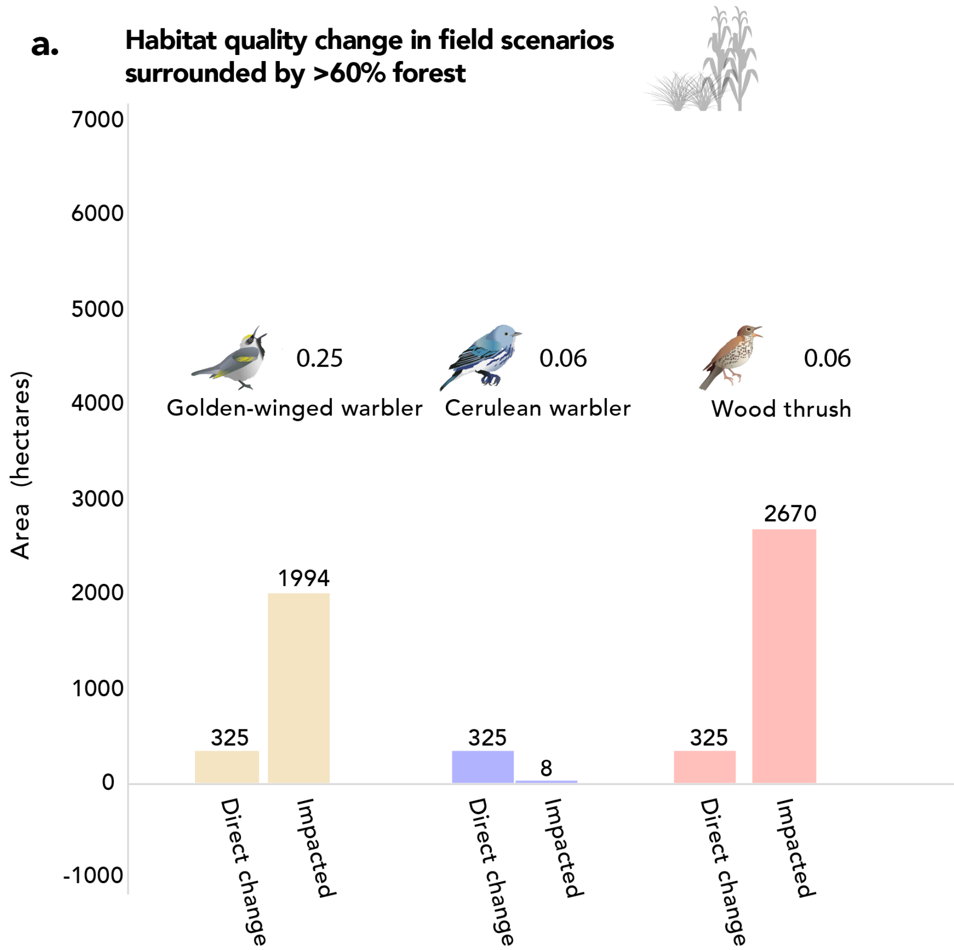


Figure 5 Change in habitat area vs. habitat quality prior to the simulation. Golden-winged warbler shows a large conversion (2500 hectares) of very poor quality lands (0-0.2) into high quality lands (>0.5) in both forest and field scenarios. Habitat generally moved from high quality to low quality in the cerulean warbler forest change scenarios, and from low quality to high quality in field change scenarios (although the changed area was very small).


a.
Habitat quality change in field scenarios surrounded by >60% forest
7000
6000
5000
4000
3000
2000
1000
0
-1000
Area (hectares)
0.25
Golden-winged warbler
0.06
Cerulean warbler
0.06
Wood thrush
325
1994
325
8
325
2670
Direct change
Impacted
Direct change
Impacted
Direct change
Impacted

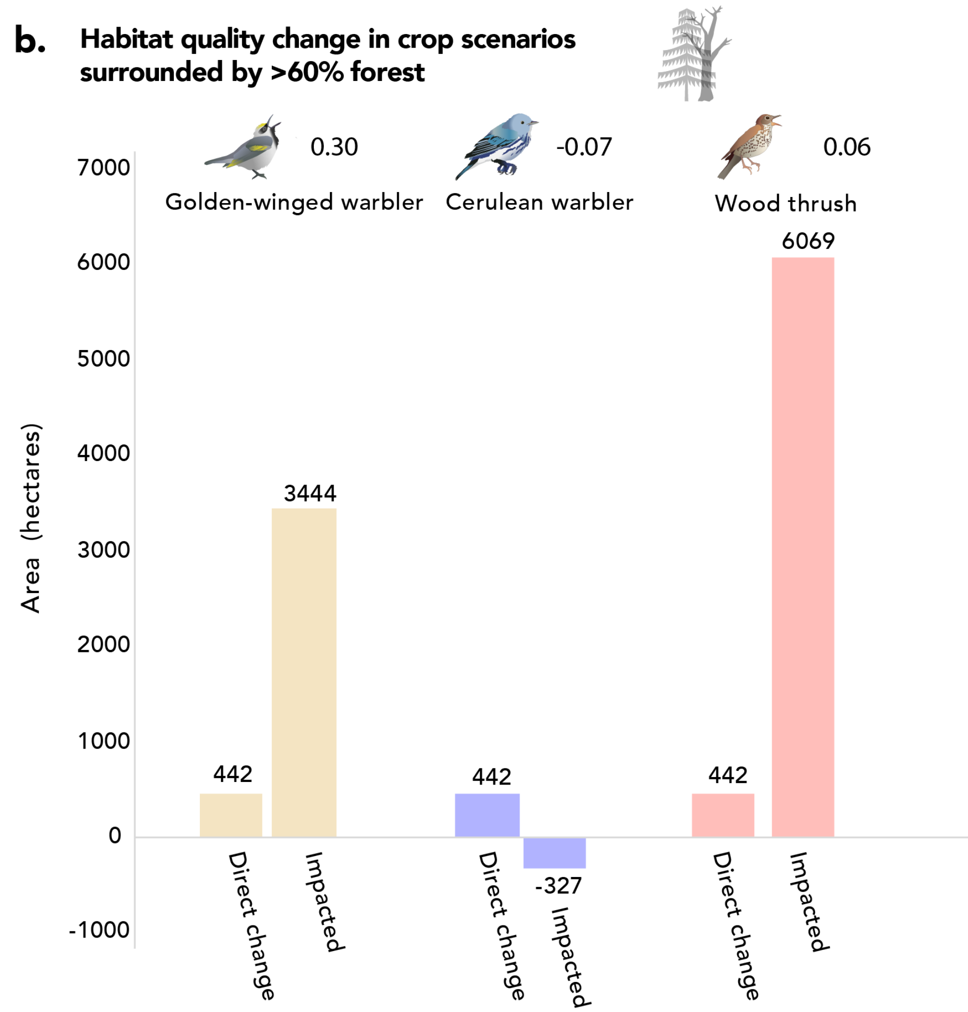


Figure 6 Bar graphs showing area of simulated land cover change and area of habitat improved for each species in (6A) field succession scenarios and (6b) forest harvest scenarios. Only scenarios surrounded by > 60% forest within 1km of the changed land cover are shown. Numbers beside bird icons are average increase or decrease in relative habitat quality for these scenarios.

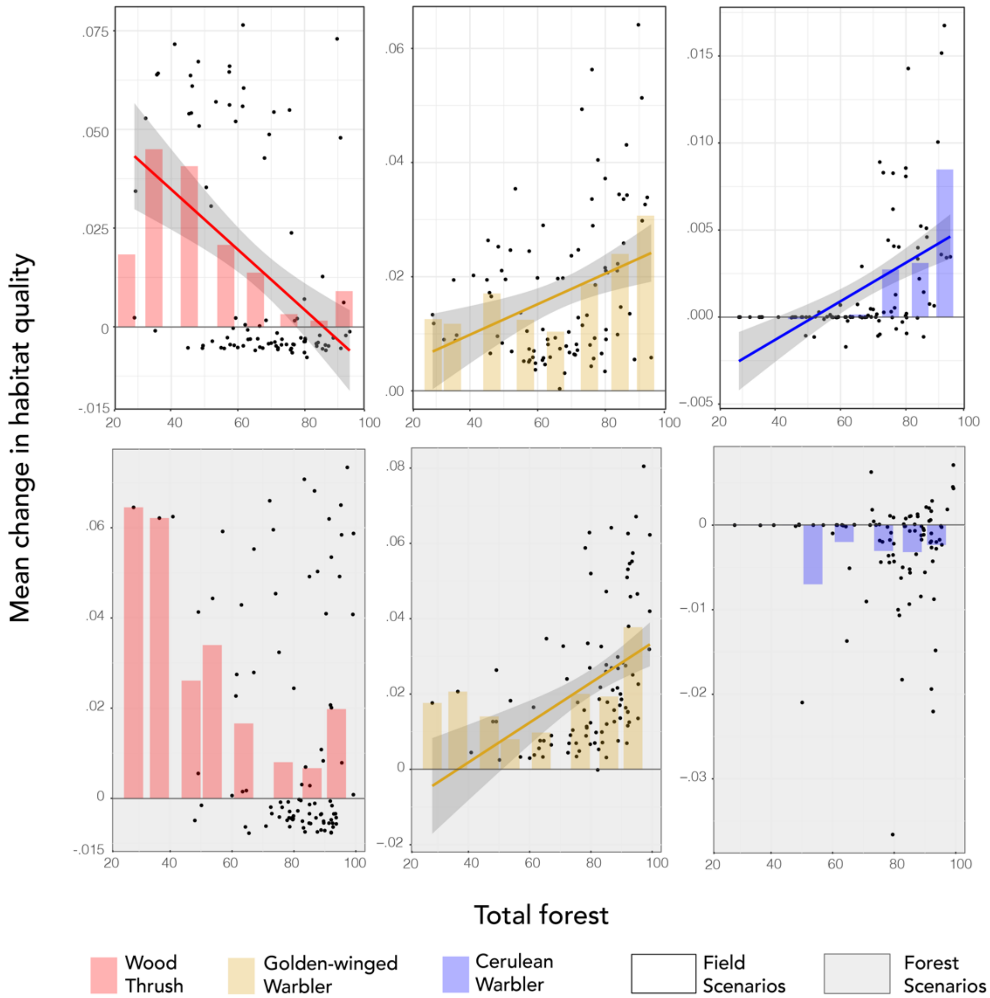


Figure 7 Mean change in habitat quality following each simulated land-cover change vs. total forest area within 1km of the simulation area. Bars show average habitat quality aggregated to 10% bins of total forest (0-100% in 10% intervals). Significant effects of forest area are shown with fitted lines (P < 0.05). Total forest area had the strongest positive effect for golden-winged warbler (both scenario types) and cerulean warbler (field scenarios), indicating that an increase in habitat quality was more likely when the simulated change was surrounded by high total forest area. In field succession scenarios, the increase in wood thrush habitat quality was negatively impacted by increasing forest cover surrounding field scenarios.

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