DEVELOPING METHODOLOGIES FOR PREDICTING THE LOCATIONS OF WOOD DUCK BREEDING HABITAT COMPONENTS IN MINNESOTA

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SUMMARY OF FINDINGS

There have been alterations to both aquatic and terrestrial habitats used by wood duck (*Aix sponsa*) hens and broods in Minnesota and the Upper Midwest during recent decades. We initiated this study to develop methodologies to predict the locations and monitor spatiotemporal changes in the areal extent of wood duck breeding complexes. Specifically, we are exploring the use of Light Detecting and Ranging (LiDAR) data to identify multiple habitat components and to develop this method as a tool to monitor future changes in these components. We also will examine temporal changes in nesting habitat by analyzing Forest Inventory and Analysis (FIA) data with a quantitative method currently being developed to accurately estimate the population variance of stems that may have suitable nesting cavities. Our specific objectives are to (1) develop and evaluate spatial predictive models of habitat components that are important to breeding wood ducks (i.e., tree species [alternatively forest-cover type, deciduous v. coniferous] diameter-at-breast height [DBH], tree canopy density, wetland vegetation type, water depth) based on LiDAR-generated metrics or other sources of spatial data (e.g., National Wetland Inventory [NWI]), existing Geographic Information System [GIS] layers, and aerial photographs, (2) ascertain the optimal point density of LiDAR needed to accurately measure or classify each habitat component of importance to wood ducks, (3) determine the generalizability of the LiDAR-based models for predicting the locations of habitat components by applying algorithms developed from data collected in the main study area (Cass County, Forest Ecological Province) to other sites in the Forest, Prairie, and/or Transition Provinces at which adequate LiDAR data have been obtained, (4) estimate the species- and DBH-specific proportions of trees with suitable cavities and detection probability of suitable cavities from empirical field data, and (5) determine whether there has been a change in the number of potential nest trees since the 1970s based on changes in FIA data.

We conducted vegetation surveys at 677 wetland plots during Summer 2016 and 2017, and 323 forest plots during Fall 2016, Spring 2017, Fall 2017, and Spring 2018. We assigned a habitat classification to 14 types of dominant emergent cover and 6 types of loafing structures during wetland surveys, and 12 cover types to forest plots during nesting habitat surveys, and measured several other habitat variables in each survey. We examined 7,869 trees during forest surveys, and classified 223 cavities as suitable and 111 as marginally suitable for nesting wood ducks. Because data were sparse for relatively large DBH trees of multiple species ($\geq$40 cm for early and mid-successional species, $\geq$50 cm for late successional species), we surveyed additional forest plots to obtain sufficient data on large-DBH trees with suitable cavities.

Flights to collect LiDAR data originally scheduled to occur during Fall 2016 were postponed until Fall 2017. This data became available during Summer 2018, and we began

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associating ground-level aquatic and forest vegetation measurements to LiDAR data during Winter 2019.

We used our probabilities of cavity-occurrence and FIA-based estimates of the populations of stems in corresponding species-DBH-Health Status bins to make an inference about any temporal change in the population of stems with suitable nesting cavities that occurred in Cass County, Minnesota between 1990 and 2014–2018. We initially focused this analysis on 7 tree species that were common in our study area and had some proclivity to produce suitable nesting cavities.

We used and evaluated the accuracy of several approaches to develop models for predicting which forest stands were with or without suitable nesting cavities for wood ducks. We used our empirical forest-plot, LiDAR, and other aerial imagery data in these analyses. The Random-Forest models that best predicted the location of such stands used the presence-absence of cavities as a response variable, and 33 LiDAR-derived metrics, forest cover type, and LiDAR intensity as predictors. The classification accuracy of this model was 74%.

We conducted a preliminary examination of the temporal change in the population of potentially suitable nesting cavities in Cass County between 1990 and 2014–2018 using both FIA and our empirical tree cavity data. Results generally suggest that population decreased during the period of analysis, and that this varied by tree species. In the final analysis, we will attempt to use 1977 FIA data and expand the geographic area of analysis, if we ascertain that these steps will generate reliable results.

INTRODUCTION

Some terrestrial and aquatic habitats used by wood duck (*Aix sponsa*) hens and broods during the pre-nesting, nesting, and brood-rearing life-cycle phases have been altered substantially in Minnesota and the Upper Midwest during recent decades. For example, there were decreases in the areal extent of some classes of aquatic habitats in northcentral Minnesota (Radomski 2006) and in the number of beaver impoundments in the forested portion of Minnesota between the early 1990s and 2002 (Dexter 2002, p. 52), both of which have been used by wood duck broods (see McGilvery 1968, Bellrose and Holm 1994). Although the number of potential nesting trees for wood ducks was projected to increase both in Minnesota (Jaakko Pöyry Consulting, Inc. 1994) and the Upper Midwest (Denton et al. 2012*b*), there has been recent concern among Minnesota Department of Natural Resources (MNDNR) managers that harvesting relatively large diameter-at-breast-height (DBH) trees of economically valuable species (e.g., aspen [*Populus* spp.]) in northern Minnesota will reduce the availability of cavity trees (R. A. Norrgard and D. P. Rave, MNDNR, personal communication) frequently used for nesting by some waterfowl (e.g. wood duck, common goldeneye [*Bucephala clangula*], hooded merganser [*Lophodytes cucullatus*]).

Thus, there is a need to develop methodologies that can be used to predict the locations of the habitat components that compose wood duck breeding complexes (i.e., important habitats used during the pre-breeding to brood-rearing life-cycle phases). These methodologies should have the (A) flexibility to identify both forested and non-forested habitat components that occur at different spatial scales, (B) accuracy and precision to reliably quantify spatiotemporal changes in the characteristics (e.g., areal extent) of habitat components and (C) efficiency to characterize structural (generally vegetation) attributes over large spatial scales. It also would be beneficial to develop such methodologies so that long-term trends in habitat components can be analyzed in a consistent manner.

It is unlikely that all of these needs can be met with a single methodology or existing dataset. Consequently, we will develop 2 methods for obtaining better knowledge regarding spatiotemporal changes in wood duck breeding-habitat components. First, we will develop methodology to identify multiple habitat components and to monitor changes in these components from the contemporary period forward. This will entail building and evaluating spatial predictive models of these habitat components based on LiDAR-generated metrics and other spatial datasets (e.g., satellite imagery, radar data, National Wetland Inventory [NWI]). This methodology also could be used to provide habitat trend information that can be used in MNDNR administrative subsection planning and research efforts (e.g., estimating habitat availability in resource selection studies; see Aebischer et al. [1993]).

Second, we will examine historical changes in potential nesting habitat by analyzing Forest Inventory and Analysis (FIA) data with a quantitative method we are developing. Reliable FIA surveys have been conducted in Minnesota since the 1970s. We will conduct analyses of FIA data to identify spatiotemporal changes in nesting habitat components not characterized by LiDAR, at spatial scales smaller than those of previous investigations (Denton et al. 2012*a*, *b*), and over a greater time period (i.e., since the 1970s, if possible). This method also will provide database queries that can be used in future monitoring efforts, and an insight of whether the predicted trend in the abundance of tree cavities (e.g., Denton et al. 2012*b*) is accurate.

GOALS AND OBJECTIVES

The ultimate goal of this project is to develop methodologies that can be used to predict the locations and monitor spatiotemporal changes in the areal extent of wood duck breeding complexes (i.e., important habitats during the pre-nesting, nesting, and brood-rearing life cycle phases) and perhaps other species that use similar habitat components. Meeting this goal requires that we (1) identify the location and areal extent of breeding-habitat components in our study area, (2) validate the predicted locations of wood duck breeding complexes with independent, empirical data from other sites, and (3) quantify the spatiotemporal trends in potential nesting trees in Minnesota over the long term. We are using multiple sources of data (e.g., empirical field data, FIA, LiDAR, and associated remote sensing imagery) to meet this goal. Our specific objectives are to:

1. Develop and evaluate spatial predictive models of habitat components that are important to breeding wood ducks (i.e., tree species or alternatively forest-cover type, DBH, tree canopy density, wetland vegetation type, and water depth based on LiDAR-generated metrics and other sources of spatial data). This evaluation will include determining the accuracy with which each spatial model can predict the locations of habitat components. Some specific questions we will examine include:
    a) Which specific LiDAR metrics are most important predictors of suitable cavity presence-absence or abundance?
    b) Does including ancillary remotely-sensed data and derived forest inventory attributes as predictors (e.g., satellite imagery, cover-type, timber volume estimates) improve accuracy?
    c) Which spatial scale of analysis produces the most accurate predictions of cavity occurrence (e.g., comparing 5, 10, 20, and 40 m pixels)?
2. Ascertain the optimal point density of LiDAR needed to accurately characterize each habitat component of importance to wood ducks.
3. Determine the generalizability of the LiDAR-based models for predicting the locations of habitat components by applying algorithms developed from data collected in the main study area (Cass County, Forest Ecological Province) to other sites in the Forest, Prairie, and/or Transition Provinces at which adequate LiDAR-cloud data have been obtained (e.g., J. Erb's study areas, MNDNR statewide elevation measurement project).
4. Estimate the species- and DBH-specific proportions of trees with suitable cavities and detection probability of suitable cavities from empirical field data.

5. Determine whether there has been a change in the number of potential nest trees since the 1970s based on changes in FIA data.

METHODS

Study Area

The primary study area encompasses 254,051 ha in northeastern Cass County, Minnesota, and composes 40.6% of this county (Figure 1). Parts of Chippewa Plains, Pine Moraines-Outwash Plains, and St. Louis Moraine Ecological Subsections (Hanson and Hargrave 1996) occur within this area. This study area occurs in Bird Conservation Region 12.

Wetland Surveys

In 2016, we used the available wetland spatial data from NWI (Cowardin et al. 1979, MNDNR 2009) to select 260 sampling plots in the study area. We stratified wetlands contained in the NWI GIS layer by NWI system, subsystem, and class (hereafter, wetland types). Unfortunately, information about NWI subclasses was not available for many wetland types. We calculated the proportion of the 9 major wetland types in the study area: Lacustrine-Littoral-Emergent Vegetation (0.004), Palustrine-Emergent Vegetation (0.102), Lacustrine-Limnetic-Unconsolidated Bottom (0.522), Lacustrine-Littoral-Unconsolidated Bottom (0.020), Palustrine-Forested (0.191), Palustrine-Shrub Scrub (0.130), Palustrine-Unconsolidated Bottom (0.026), Riverine-Upper Perennial-Unconsolidated Bottom (0.003), and Riverine-Lower Perennial-Unconsolidated Bottom (0.002). We then randomly selected 260 2- X 2-m plots from these wetland types: 60 plots from both the Lacustrine-Littoral-Emergent Vegetation and Palustrine-Emergent Vegetation types, and 20 plots each from the remaining types. We selected more plots from the first 2 wetland types because we surmised that these habitats were more likely to be used by wood duck broods (e.g., Grice and Rogers 1965), and that there was a greater likelihood that these habitats would be structurally diverse and thus more difficult to identify from LiDAR signatures. We also specified that plots had to be ≥100 m apart to reduce the likelihood of non-independence among these sampling units (i.e., sampling plots with similar vegetation structure).

Many relatively small, isolated wetlands were not delineated in the NWI GIS layer, so we later selected 50 additional plots in these habitats from the MNDNR Hydrography GIS layer (MNDNR 2015). We randomly selected 1 plot per selected wetland if that wetland was 0.81–8.09 ha, ≤402 m from a road, and adjacent to public land. After initially selecting plots from both layers, we examined aerial photos to assess the accessibility of these locations. We attempted to sample plots that initially appeared accessible.

We changed our approach to selecting wetland and plot locations for the 2017 field season to reduce number of plots located in wetland habitats not likely to be used by wood duck broods and to increase sampling efficiency. Specifically, we selected wetlands classified as either inundation or intermittent water; lake, pond or reservoir; river or stream; shallow water; or wetland from the MNDNR Hydrography GIS layer (MNDNR 2015) that either (1) had a public boat access site or (2) were on public lands and ≤100 m from both a public road and water feature. From sites that met these criteria, we then randomly selected ≤5 sampling locations per wetlands that were ≥4.05 ha, with the- points ≥100 m apart.

Because potential loafing sites were encountered infrequently at randomly selected plots during 2016, we chose to non-randomly select and measure a variety of these structures as encountered so that we could observe the LiDAR signature for each. We also documented and measured these structures at randomly selected points during 2017.

We navigated to the approximate location of each plot center using a Garmin Montana Global Positioning System (GPS) unit, and established a plot center. If the plot center was difficult to access (e.g., because of soft bottom substrate that could not be traversed on foot, dense vegetation that could not be penetrated via boat) or on or near an ecotone, we moved the plot location to a site that was as close as possible to the initial location, accessible, and in the interior of a somewhat homogeneous vegetation patch. Moving plots away from ecotones reduced the likelihood of misclassifying habitats (i.e., habitat misclassifications are more likely to occur near ecotones because the exact location of a sampled plot is difficult to determine with somewhat imprecise GPS units). We also moved some plots located in open water to the nearest vegetated location within the wetland because the former habitat is simple and easily identified with LiDAR data. Instead, we chose to dedicate the greatest sampling effort to vegetated plots.

For each plot, we recorded the date, start time, observers, plot number, whether wood ducks were observed within 100 m of the plot, and if so, provided a count of individuals in each cohort (male, female, brood, unknown). We did not adjust wood duck counts for detectability. We ascertained whether the NWI classification (system, subsystem, class) available on our GIS layer was correct at each plot (i.e., some wetlands may have changed since the original classification or the original classification may have been incorrect), and recorded the appropriate NWI wetland classification to the level of subclass. We classified the types of wood duck loafing structures present within the plot (7 classes: none, rock, log or stump, muskrat lodge, beaver lodge or dam, small island or tussock, barely or lightly vegetated shoreline), as well as the type of beaver modification, if any that had some influence on the plot (6 classes: none, water level, runs, tree removal, dam or lodge, food cache). We also obtained location data for each plot center using a Geneq Sx Blue II GPS unit (15–20 cm accuracy in open habitats when data were obtained at 1 reading / second for 1 minute), and recorded the specific GPS unit used.

At each plot, we placed a 2- X 2-m Daubenmire square (Daubenmire 1959, Gilmore et al. 2008) so its center was located at plot center, and measured several habitat variables within the device. This square had 0.2 m delineations, which facilitated the measurement of several habitat variables. Specifically, we used these delineations to estimate the % coverage (5% increments) of 5 habitat classes (emergent, floating leaf, ground, open water, shrub [woody vegetation ≤1.37 m tall]) that were present at or above the water surface, and of submergent plants, when possible to make reliable observations (i.e., at locations in which water turbidity or sun glare did not substantially hinder observability). Within the Daubenmire square, we also documented the dominant emergent cover type (14 classes: none, alder [*Alnus spp*.], Canada bluejoint grass [*Calamagrostis canadensis*], giant bur-reed [*Sparganium eurycarpum*], cattail [*Typha spp*.], ericaceous shrub, floating-leaf, giant reed grass [*Phragmites spp*.], rush [*Scirpus spp*.], reed canary grass [*Phalaris arundinacea*], sedge [*Carex spp*.], willow [*Salix spp*.], wild rice [*Zizania aquatica*], other), and measured the minimum depth of submergent vegetation and the height of emergent vegetation and shrubs (0.1 m increments) with a 3-m ruler, tree-canopy height (0.1 m increments for woody vegetation ≥1.37 m tall) with a Suunto clinometer or with a 3-m ruler, mean tree-canopy closure with a spherical densiometer, and water depth with either a 3-m measuring pole (0.1 m increments) at relatively shallow plots and an Eagle FishEasy 245DS depth finder (0.03 m increments) at deeper locations.

Within the Daubenmire square, we also estimated vertical vegetation cover and structure using a round Robel pole (Robel et al. 1970) that had alternating 0.1-m white and black bands and narrow, vertical, and contrasting marks at the midpoint of each band. Because it was not possible for personnel to stand at plots in relatively deep water or where the soil substrate was soft, it was necessary to adapt this device so that it could be used by 2 people in a boat. This adaptation consisted of attaching a long wooden pole to the Robel pole in a perpendicular manner. One crew member extended the Robel pole to the corner of the Daubenmire square opposite the other crew member, and oriented this device upright to the water surface. The other crew member placed their sighting eye 0.8 and 1.6 m above the water surface with the aid of the 3-m ruler, and recorded the lowest decimeter or 0.5 dm mark that could be observed from diagonally across the Daubenmire square (2.8 m). Crew members switched assignments and took readings from across the opposite diagonal of the square. This approach generated 2 measurements from each observation height, all of which were averaged together.

Forest Surveys

We first obtained forest spatial data (e.g., forest cover type, stand age and location) of public forest lands from Cass County, State of Minnesota, and U.S. Department of Agriculture (USDA) Forest Service databases. There were slight differences in the manner that these agencies classified forest cover types, so we aggregated appropriate stands (i.e., likely to be used by nesting wood ducks) from each database into 5 basic cover types: aspen-birch, lowland hardwoods, mixed conifer-hardwood, northern hardwoods, and oak. We identified stands on public lands that were likely old enough to have developed cavities suitable for use by nesting wood ducks (i.e., aspen-birch ≥50 years, all other stand types ≥80 years), and constrained the potential sample to stands of these ages or greater. We then stratified stands by cover type and randomly selected 300 forest stands (60 stands of each of the 5 types) to be surveyed.

We then selected plots within these stands with the stipulations that (1) plot centers must be both ≥50 m apart and ≥30 m from the nearest stand boundary and (2) ≤2 plots per stand could be established. We used these selection criteria to increase the likelihood that plots adequately represented the diversity of vegetation structure of each forest type, thus facilitating the development of biologically realistic LiDAR models. We then randomly selected n = 563 plots to be surveyed. It was necessary to remove 19 plots from the sample because of nearby heritage sites or scheduled timber harvests (i.e., interpretation of habitat characteristics would be confounded if harvesting occurred between the times forest surveys were conducted and LiDAR data were collected).

We navigated to the selected plot centers using a Garmin Montana GPS, and established 20-m radius circular plots (0.126 ha) around those points. Plots located near ecotones not indicated on available GIS layers were moved sufficiently into the stand interior as to avoid potential edge effects on vegetation structure. We first recorded the plot identification number, date, start and end times of survey, visit number to the plot (first or second), observers, proportion of visible sky obscured by cloud cover (0.1 increments), and proportion of tree boles covered by snow or obscured by leaf-out (0, 0.01–0.10, 0.11–0.33, 0.34–0.66, 0.67–1.00). We obtained location data for each plot center using Geneq Sx Blue II (0.9–1.8 m accuracy under closed forest canopy when obtaining 1 reading / 5 seconds for approximately 15 min) and Geneq Sx Blue II + GNSS (0.5–0.9 m accuracy under closed forest canopy when obtaining 1 reading / 5 seconds for approximately 15 min) GPS units, and recorded the GPS make, model, and unit number used at each plot. We classified the stand structure following USDA Forest Service (2014) methodology (5 classes: single story, two-storied, multi-storied, mosaic, unknown/unassessable). We assigned all plots to 1 of the 5 general forest cover types (Table 2) and to an Eyre (1980) cover type.

We then examined and measured individual tree stems (both live and dead) within each plot following an established protocol (USDA Forest Service 2014), with some exceptions. Specifically, we surveyed only trees large enough to have cavities used by nesting wood ducks (i.e., ≥22.0 cm DBH [Haramis 1975]), and tall enough for the DBH to be measured (i.e., ≥1.37 m). Starting at the 0° azimuth within each plot, we proceeded clockwise, numbering each suitable tree stem, and recording the following data for each stem: species, DBH (0.1 cm increments), distance (0.1 m increments) and direction (1° increments that were not adjusted for declination) from plot center, health status (following Thomas 1979, Appendix 1), and crown class (5 classes: remnant, dominant, codominant, intermediate, overtopped; U.S. Department of Agriculture Forest Service 2014).

All field crew members (ranging from 2 to 4 per site visit) then circled each stem ≥22.0 cm in the plot, and used binoculars to conduct a preliminary visual search of each tree ≥22.0 cm DBH in the plot to identify cavities that potentially were suitable for nesting by wood ducks. During the preliminary search, personnel ascertained whether the entrance dimensions likely were sufficient to permit a wood duck to pass through (i.e., 6 x 6 cm; Zwicker 1999, cited in Denton et al. 2012*b*) and the bottom of cavity entrance was high enough to be used by nesting wood ducks (i.e., ≥0.6 m above ground level [Strom 1969]). When a potentially suitable cavity was encountered, we used a Pyle Model PLCM22IR remote camera attached via a stiff, braided wire to a 15.2 m Crain CMR Series Measuring Ruler (*sensu* Waldstein 2012) to perform a more careful examination of the entrance and interior of the cavity. We first determined whether cavity entrance dimensions were suitable by attempting to pass a cardboard cut-out of the minimum usable dimensions (i.e., 6 x 6 cm) through the cavity opening. This cut-out was placed on the wire connecting the camera to the measuring ruler. We then examined cavity interiors with the camera to ascertain whether the following conditions had been met: horizontal depth (approximately 10 cm from inner edge of the entrance opening toward the back of the cavity) appeared large enough for hens to move from the entrance to the interior of the cavity, vertical depth (from the bottom of the cavity to the bottom of the entrance) was ≥10.2 cm to 4.5 m; Bellrose and Holm 1994 p. 176) and not hollow to the ground (Robb 1986, cited in Bellrose and Holm 1994, p. 178), nest platform dimensions were ≥14 x 15 cm (Boyer 1974, Haramis 1975, Denton et al. 2012*a*), and the cavity did not contain standing water or excess debris (Sousa and Farmer 1983).

Field personnel used this information to classify the suitability of each examined cavity for wood duck nesting (4 levels: suitable, marginal, unsuitable, unknown). We considered a cavity to be suitable if all these conditions were met. A cavity was classified as marginal if it was unclear whether all dimensional requirements were met (i.e., ≥1 dimensional measurement appeared to be close to some minimum or maximum value). Cavities typically were classified as unknown/unobservable if personnel were unable to completely observe the cavity, either because of cavity height or some structural attribute did not permit observation with the camera system. We considered a cavity to be unsuitable if any dimensional measurement was not met or if there was standing water or excess debris in the cavity. Field personnel also provided a cause for unsuitability (7 classes: entrance dimensions too small, insufficient horizontal depth, insufficient vertical depth, insufficient platform dimensions, too deep or hollow to the ground, standing water in the cavity, excessive debris in the cavity). We classified the reason that a cavity was unsuitable based on the order that structural restrictions would have been encountered as a wood duck entered a cavity (i.e., entrance dimensions, followed by horizontal depth, vertical depth, and finally, dimensions and other characteristics of the platform). Our assessment of the suitability of interior characteristics required some subjectivity because direct measurements could not be made with our camera system.

For each cavity inspected, we recorded tree identification number, cavity entrance type (3 classes: opening on the top, side, combination of top and side openings which are joined on the exterior of the tree), primary and secondary sources of cavity formation (11 classes: split, broken limb, broken top, woodpecker, fire, lightning, insect, logging wound, decay/rot, other, unknown), evidence of animal use (9 classes: eggshell/ membrane, nesting materials, hive or other insect structure, animal present, scratching at entrance, pecking at entrance, other, unknown, none), and animal taxa. We also measured cavity height with either a 15.24 m measuring ruler (±0.1 m), Leupold RX-800i rangefinder (±0.1 m), or Suunto clinometer (±0.5 m).

LiDAR Data Collection and Analysis

The MNDNR Resource Assessment Program (RAP) originally planned to acquire airborne LiDAR and simultaneous 4-band near-infrared imagery data during Fall 2016, but this did not occur until Fall 2017. Data became available for analyses during late Summer 2018. The high-density LiDAR was acquired by a private vendor (Quantum Spatial Inc.), who used a single-photon LiDAR sensor.

We first clipped the LiDAR point-cloud data corresponding to our forest plots using Program FUSION/LDV version 3.80 software (McGaughey 2018). The clipped data of each plot then were summarized into numerous metrics representing canopy-elevation distributions, percent cover, and densities of vertical strata (i.e., slices). These metrics were associated with forest data in each plot for all stems $\geq$22.0 cm DBH. We then developed a Random Forest model (Liaw and Wiener 2002) using these data. We conducted preliminary analyses both to identify important predictors to be used in further analysis and to identify any analytical issues. We used the analytical approach developed by Murphy et al. (2010, p.255–256), in which the number of predictor variables is minimized and the amount of variation explained is maximized via a process of eliminating unimportant variables based on their model improvement ratios. The Random Forest algorithm in the R statistical package (Liaw and Wiener 2002, R Core Team 2020) was used to predict the presence/absence or abundance of a suitable cavity in plots based on the LiDAR metrics and RAP-generated stand-type classifications (i.e., random-forest analyses can be performed in either classification or regression mode [Liaw and Wiener 2002]).

We conducted separate analyses with 3 different response variables derived from our forest and cavity surveys: (1) the presence-absence of suitable cavities, (2) 3 levels of cavity occurrence (none, low [1 suitable cavity per plot], and high [>1 suitable cavity per plot]), and (3) abundance of suitable cavities (0-5 cavities per plot on a continuous scale). We initially included 177 LiDAR-derived metrics that occurred in 40-m grid-cells overlaying the plot locations as potential predictors. The predictors used in the next step of the analysis were 33 metrics related to the intensity of the LIDAR returns (note: these returns were not normalized across the study area) and forest cover-type (classified from Landsat and LiDAR data). After removing collinear variables using QR decomposition (Murphy et al. 2010), 71–78 variables were retained for further analyses.

Random Forest models were run with 10,000 trees 10 separate times, and the accuracy metric was averaged among runs. Murphy et al. (2010) only ran 1 model with 5,000 trees, but we observed that accuracy was variable between model runs without some form of replication.

We then compared the accuracy of Random Forest models for each of the 3 response variables with (1) LiDAR metrics only, (2) LiDAR metrics and the cover type variable, and (3) LiDAR metrics, the cover type variable, and LiDAR intensity metrics. Thus, there were 9 analytical comparisons (i.e., 3 response variables X 3 groups of predictor variables). We also assessed the classification accuracy of response variables (1) and (2) using out-of-bag (OOB) error. OOB is calculated through internal cross-validation in each Random Forest model, with 1-OOB = proportion of correct classification (Cutler et al. 2007). We evaluated response (3) using the proportion of variance explained. Last, we used the rf.modelSel function in the rfUtilities package (Evans and Murphy 2019) in R to rank random-forest models based on performance.

FIA Analysis

We used results from Zlonis et al. (2020) in conjunction with FIA data to infer the extent to which the density and population of suitable nesting cavities changed in Cass County during 1990–2018. Zlonis et al. (2020) found that tree species, DBH, and health status were important predictors on the occurrence of suitable nesting cavities. More specifically, the probability of cavity occurrence among the 7 species examined was greatest in sugar maple, followed by American basswood, red maple, northern red oak, bigtooth aspen, quaking aspen, and finally, paper birch. The probability of cavity occurrence was positively associated with DBH. Suitable cavities were most prevalent in dead stems, followed closely by live health-impacted stems, and finally live healthy trees.

Next, we queried the FIA database to obtain an estimated population of stems that corresponded to the species-DBH-health status bins used in our analysis of empirical data. We limited our query to plots classified as 'timberland' by the U.S. Department of Agriculture Forest Service, which is defined as "forest land capable of producing in excess of 20 cubic feet per acre per year and not legally withdrawn from timber production, with a minimum area classification of one acre" (U.S. Department of Agriculture Forest Service 2019). We used FIA data only from Cass County, Minnesota because it likely had a forest composition and structure (i.e., species, age classes, health condition) similar to that of our study area in the northern portion of this county.

The approaches for applying damage codes (i.e., a metric of health status) to live stems and tallying dead trees changed in FIA over 6 evaluation cycles (i.e., 1977, 1990, 1999–2003, 2004–2008, 2009–2013, 2014–2018). Thus, it was necessary to construct a health-status crosswalk among these evaluation cycles and our cavity survey. Relevant changes in FIA methodology and the data we used are as follows.

The only standing dead stems tallied during the 1977 FIA evaluation cycle were if the mortality of a tree had occurred within the previous 3 years or if it was deemed salvable; thus dead trees during this cycle did not include all of the stems that would have been measured in our empirical study or in subsequent FIA inventories, which had no requirements regarding years since mortality or salvability. Consequently, we did not use data from the 1977 FIA evaluation cycle in the preliminary analysis. A subsample of undisturbed plots were modeled (i.e., not remeasured) during the 1990 FIA evaluation cycle. We included data from this evaluation cycle in the preliminary analysis so that the plausibility of results can be assessed. Another important change in FIA methodology is that all plots in Minnesota were surveyed within approximately 1 year during 1977 and 1990, but only a subset of 20% of available plots were surveyed during any 1 year under the annual evaluation system (i.e., beginning in 1999, all plots in Minnesota are measured in 5 years). Further, damage codes were recorded during 2000–2003 but not 1999. Thus, we decided to include data from the 1999–2003 cycle in the preliminary analysis because of the need for blocks of 5 consecutive years for coverage of all plots in Minnesota.

For each year-group *i*, we summed FIA estimates by species *j*, health status *k* (live-healthy, live-health impacted, dead), and DBH bin *l* to compute estimates of $\widehat{N}_{ijkl}$ (total trees by subgroup) and Var($\widehat{N}_{ijkl}$). We used the cavity model from Zlonis et al. (2020) to estimate the mean probability of a tree in each subgroup having a suitable cavity, E(P), given predictors for species, health status, and DBH bin. We used the product of $\widehat{N}$ and $\hat{P}$ to generate estimates of total potential cavities in each subgroup, $\hat{\tau}_{ijkl}$, and the delta method (Seber 1982, Goodman 1960) to compute Var($\hat{\tau}_{ijkl}$) based on the assumption that $\widehat{N}$ and $\hat{P}$ were independent random variables. We then summed $\hat{\tau}_{ijkl}$ and Var($\hat{\tau}_{ijkl}$) by year and species for investigating temporal changes in suitable cavities over time. Summing variances across the subgroups is based on the assumption that the estimates were independent, which is not true. However, an exploratory Monte Carlo simulation suggested this approach provided a reasonable approximation of the primary sources of uncertainty in the estimation process.

RESULTS

Wetland Surveys

We conducted surveys at 677 randomly selected wetland plots during the late summer and early fall of 2016 and 2017 (Table 1, Figure 2). We classified the dominant emergent cover as alder (0.7%), blue joint grass (0.6%), bur reed (0.3%), cattail *spp* (6.9%), ericaceous shrub (2.2%), floating leaf (18.0%), phragmites *spp* (2.5%), rush *spp* (20.7%), reed canary grass (2.2%), sedge *spp* (8.3%), willow (0.4%), wild rice (31.3%), other vegetation (0.9%), and none (4.9%). We documented tree presence at 10 plots (1.5%), with canopy coverage ranging from 0.05 to 0.85. We observed that 12.3% of randomly selected plots were modified by beaver, wood ducks were present ≤100 m of 9.6% plots, and 4.4% of plots had potential wood duck loafing sites.

The potential loafing structures identified in randomly selected plots were 2 beaver lodges, 6 floating vegetation mats, 4 small islands or tussocks, 14 patches of bare or lightly vegetated shore, 5 logs or stumps, and 1 muskrat house. We observed 6 beaver lodges, 2 logs or stumps, and 1 muskrat house in the 15 non-randomly selected plots.

Forest Surveys

We conducted surveys at 323 forest plots during Fall 2016, Spring 2017, Fall 2017, and Spring 2018 (Figure 3). Of these plots, all stems ≥22.0 cm DBH were examined in 213 and only larger stems were measured in 110.

Most results of the forest surveys were reported in a previous issue of *Summaries of Wildlife Research Findings* and in Zlonis et al. (2020). We reported that the best predictive variables of the presence and absence of suitable nesting cavities were tree species, DBH, and health status. We will use the findings of Zlonis et al. (2020) in follow up analyses of FIA and LiDAR data.

LiDAR Data Collection and Analysis

Single-photon LiDAR data and simultaneous aerial imagery were collected during peak fall color in 2017, usually at about 30 return pulses / m^2 (minimum of 12, up to 40–50; J. Corcoran, MNDNR, unpublished data). Single photon LiDAR operates with green laser and in principle can penetrate the water surface. However, LiDAR data was not as good as anticipated, and did not have bathymetric capability. Thus, identifying the presence/absence and density of submergent vegetation and depth of water in relatively shallow locations likely will not be possible.

Classification accuracy was highest when using all of the predictor variables and the binary cavity presence-absence response variable (74% plots correctly classified; Table 2). This model was better able to classify plots that did not have suitable cavities (80% correctly classified) versus plots that did have suitable cavities (67% correctly classified). When the intensity metrics and the cover type variable were removed consecutively, there was a drop in overall classification accuracy from 74% to 68% to 66%, respectively (Table 2).

Classification accuracy was also lower when using three levels of cavity occurrence (56–59% correctly classified; Table 2). Notably, these models were relatively poor at classifying plots with low and high numbers of suitable cavities (<30% correctly classified for each category). However, when compared to models with a binary response, plots without suitable cavities were correctly classified at a higher rate (85% correctly classified). Generally, regression models did not explain a high percentage of variation in the cavity data (≤21% variance explained; Table 2). Similar to the binary response variable, regression models performed best when using all of the available predictor variables.

FIA Analysis

Preliminary results suggest that there was a substantial decrease in the estimated population of suitable nesting cavities between 1990 and 1999–2003, followed by a rise and approximate stabilization of such stems (Figure 4). However, not all the tree species examined followed this pattern. Further, the estimated proportion of stems with suitable nesting cavities in each health status class appeared to vary among evaluation cycles (Figure 5).

DISCUSSION

Wetland Surveys

Initially, we randomly selected wetlands for sampling to obtain an adequate sample size for each NWI class, with special emphasis placed on those classes that are most likely to have diverse vegetation structure. However, these efforts were confounded in-part by limitations of the existing NWI spatial data. Specifically, we observed during field-data collection that NWI classifications of some plots were incorrect, which we attribute to a combination of misclassification of wetland habitats, habitat changes since the original classification, and projection error. Further, the currently available NWI GIS layer often classifies wetlands only to the level of class, which provides little information regarding vegetation type or structure. Thus, it was not possible to select plots based on subclass or vegetation type and structure. Such limitations of available data contributed to an allocation of sampling locations that were not balanced among the 14 types of emergent covers observed. It is likely, however, that the emergent covers sampled were representative of those available in the study area.

Fortunately, we were able to collect data for a substantial number of plots (1) with structurally similar vegetation types that are difficult to distinguish from aerial photographs (i.e., wild rice v rush *spp*.; (D. Dustin, MNDNR Fisheries, personal communication), (2) dominated by the types of aquatic vegetation that should begin to subside and thus change structure (e.g., floating-leaf plants, wild rice) approximately when LiDAR imagery was obtained (i.e., late September and October), (3) with vegetation types that may be sparse, and (4) with vegetation types that frequently occur in a mix of other types of vegetation (e.g., floating-leaf plants). We anticipate that a substantial amount of data will be needed to develop reliable LiDAR signatures of such sites. Presumably, wetland habitats with no surface vegetation should have a rather simple and readily identifiable LiDAR signature.

Although identifying potential loafing sites for wood ducks using LiDAR imagery was a secondary objective, we were able to locate 6 types of these structures in randomly selected plots and 3 in non-randomly selected plots. These structures likely are a somewhat important habitat component to wood ducks (McGilvery 1968).

LiDAR Data Analysis

We will continue exploring the use of Random-Forest models and LiDAR data to predict the locations of suitable nesting cavities for wood ducks, given the promising preliminary results. Accuracy levels to-date have been acceptable, but could be improved by refining our methods. We will proceed with the binary presence-absence response variable and incorporate a further comparison of accuracy among several pixel sizes of this response (e.g., presence-absence at the scales of 5-, 10-, 20-, and 40-m pixels). Initial forest-inventory modelling using the same LiDAR predictors we used suggests that a pixel size smaller than our plot size (i.e., <40-m pixels) will have greater predictive accuracy (RKD, *unpublished results*). Because of the highlydetailed and fine-scale nature of the LiDAR data, we expect that spatial information would become more generalized at the broader scales examined and predictability would be reduced. Cavities are inherently linked to individual stems, which likely only affect structural attributes of LiDAR data at scales <20 m in the forests of northcentral Minnesota.

We also will incorporate new predictor variables into random-forest models. MNDNR RAP personnel have modelled and mapped 8 common forest inventory metrics that may be useful for predicting suitable nesting cavity locations (i.e., biomass, basal area weighted height, quadratic mean DBH, basal area, site index, trees per acre, volume, cover type; *unpublished results*). We also will explore modelling tree health-status using variables such as snag density and proportion health-impacted trees. With these additional predictors, we would then have 3 metrics that are analogous to forest inventory attributes that have been used to predict suitable nesting cavities (Zlonis et al. 2020). More specifically, the variables cover type, quadratic mean diameter, and proportion health impacted generated by RAP are comparable to the predictors tree species, DBH, and health status, respectively, used by Zlonis et al. (2020), respectively. Finally, a variety of ancillary remotely-sensed data could be used as predictors (e.g., radar). We will restrict the predictors used to those that are available for the entire study area. We plan to continue using QR decomposition and the random-forest model selection function to reduce this large number of potential predictors to a manageable subset. The objective of ascertaining the pulse density needed to accurately classify forest and aquatic vegetation characteristics likely will not be possible because of the characteristics of single-photon linear LiDAR. Last, we are unlikely to use LiDAR intensity to predict cavity presence or absence in the final analysis because this intensity was so uneven across the study area.

We likely will use a similar approach to analyze wetland plot data during the upcoming year. However, it may be necessary to use remotely sensed data to classify wetland habitat if the scattering of LIDAR pulses off the water surface is problematic.

FIA Analysis

Preliminary results suggest that the population of suitable nesting cavities generally decreased between 1990 and 2014–2018. This purported reduction in the population of stems with suitable nesting cavities may be attributed in-part to forest succession, forest practices, and changes in FIA methodology. The idea of forest succession influencing tree-species composition and ultimately the population of stems with suitable cavities is supported by the increase in the estimated population of stems with such cavities in some mid- or late successional species (i.e., red maple, sugar maple) and a decrease in an early successional species (i.e., quaking aspen). We have not examined species-specific removals in FIA data, but will do so to develop a better understanding of whether forest practices may have had had some influence on the population of stems with suitable cavities. The lack of recorded damage codes in FIA during 1999 may partially explain the relatively low population estimate of stems with suitable cavities, especially those that were classified as damaged, during the 1999–2003 evaluation cycle.

During the next year, we will take several steps to complete this phase of the study. Specifically, we will finalize a health-status crosswalk and identify data that warrants inclusion in the final analysis (e.g., additional tree species beyond the 7 examined by Zlonis et al. [2020], evaluation cycles, spatial scales). For example, we will include data from the 1977 and 1990 evaluation cycles if the issues of undercounting dead stems and use of modeled data, respectively, can be resolved. We will use the 2000–2004, 2005–2009, 2010–2014, 2015–2019 time blocks for the final analysis now that 2019 data has become available (i.e., 1999 data will not be used). We also will ascertain whether our findings can be extended reliably into nearby ecological strata (e.g., subsections), based on similarity of forest characteristics at the spatial scales of our study area and those strata.

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Table 1. The National Wetland Inventory classification and sample size of plots surveyed in Cass County, Minnesota, USA during 2016–2017.

National Wetland Inventory system, subsystem, class and subclass of sampled plots [a, b]	Number of plots surveyed
Lacustrine limnetic unconsolidated bottom unknown	1
Lacustrine limnetic unconsolidated bottom sand	3
Lacustrine limnetic aquatic bed rooted vascular	1
Lacustrine littoral aquatic bed unknown	1
Lacustrine littoral aquatic bed rooted vascular	60
Lacustrine littoral aquatic bed floating vascular	5
Lacustrine littoral emergent nonpersistent	233
Lacustrine littoral unconsolidated bottom unknown	12
Lacustrine littoral unconsolidated bottom sand	1
Lacustrine littoral unconsolidated shore unknown	1
Palustrine aquatic bed floating vascular	13
Palustrine aquatic bed rooted vascular	43
Palustrine emergent nonpersistent	130
Palustrine emergent persistent	93
Palustrine emergent *Phragmites australia*	9
Palustrine forested broad-leaved deciduous	1
Palustrine scrub-shrub broad-leaved deciduous	20
Palustrine scrub-shrub broad-leaved evergreen	1
Palustrine unconsolidated bottom sand	3
Palustrine unconsolidated shore organic	1
Palustrine unconsolidated shore sand	5
Riverine lower perennial unconsolidated bottom unknown	2
Riverine lower perennial unconsolidated bottom mud	3
Riverine lower perennial rock bottom unknown	1
Riverine lower perennial emergent nonpersistent	28
Riverine upper perennial aquatic bed rooted vascular	2

National Wetland Inventory system, subsystem, class and subclass of sampled plots [a, b]	Number of plots surveyed
Riverine upper perennial emergent nonpersistent	4

[a] Wetlands in the palustrine system are not assigned a subsystem classification in the National Wetland Inventory classification scheme.
[b] The National Wetland Inventory subclasses of some plots were classified as unknown if distinguishing characteristics were not discernable in the field.

Table 2 The percent (range) of plots correctly classified for the presence/absence or abundance of suitable nesting cavities for wood ducks in 9 different analyses. In these analyses, we used 3 response variables (presence/absence, classes of cavity occurrence (none, low [1 suitable cavity per plot], high [>1 suitable cavity per plot], abundance [0-5 cavities per plot on]) and 3 predictors (LiDAR metrics, LiDAR metrics + forest cover type data, LiDAR metrics + forest cover type data + LiDAR intensity). Plots were 40-m grid cells.

	% Correct classification (range) of plots for 3 groups of predictors		
Response variable	LiDAR metrics	LiDAR metrics + cover type	LiDAR metrics + cover type + intensity
Presence-absence	66% (63–68)	68% (66–69)	74% (69–75)
Three classes – none-low-high	59% (58–62)	57% (56–60)	56% (53–60)
Regression – abundance	9% (7–11)	14% (13–15)	21% (20–21)

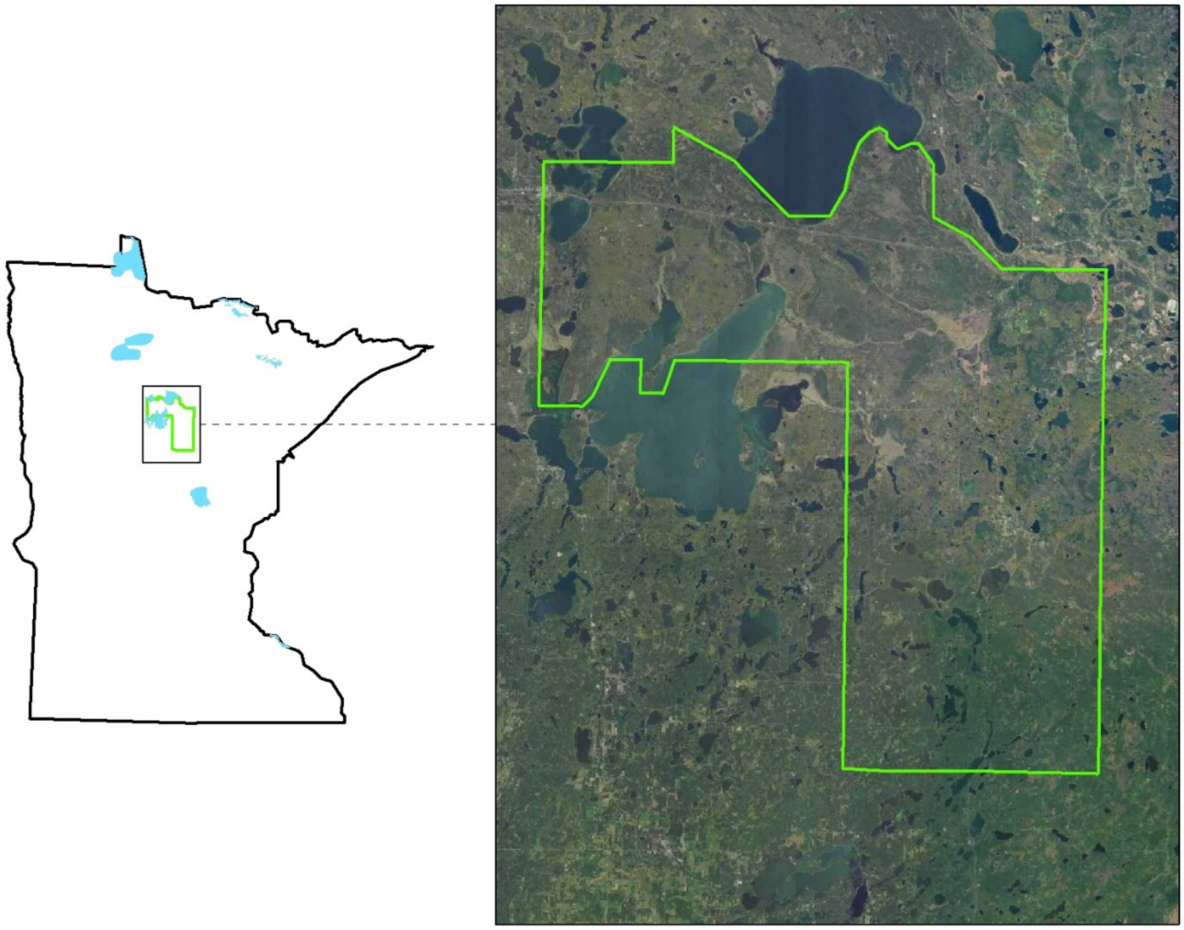

Figure 1. Location of the wood duck-LiDAR project in Cass County, Minnesota, USA.

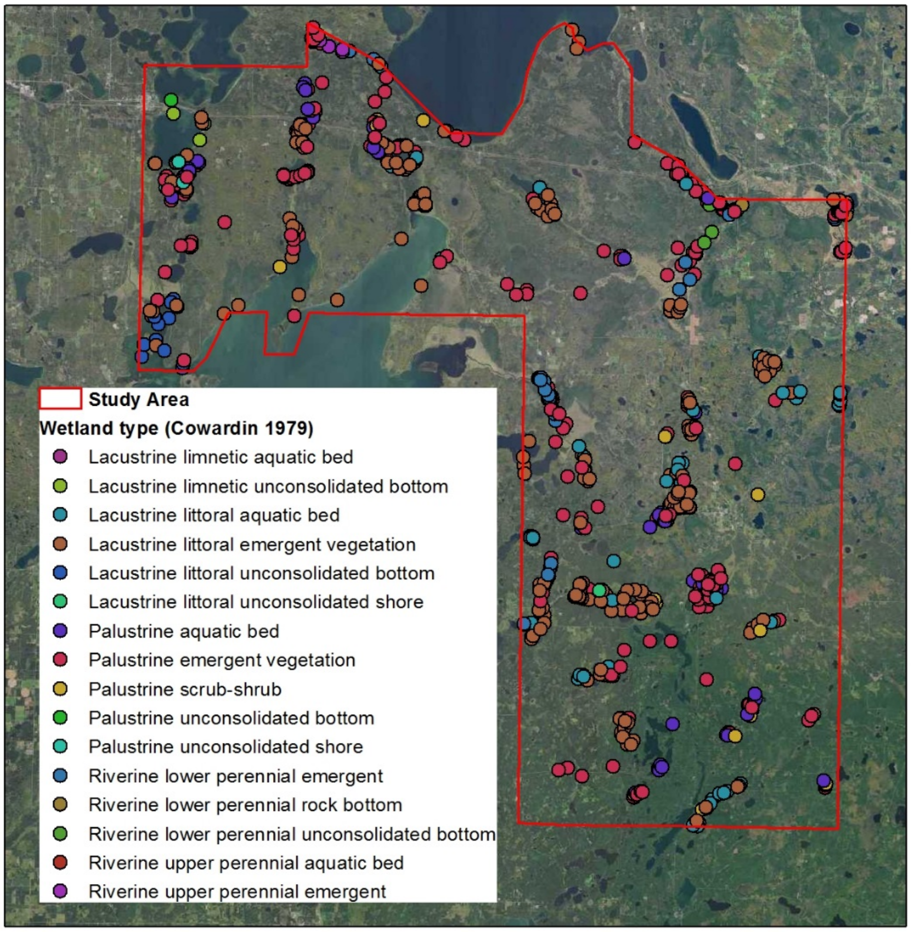

Figure 2. Location of wetland plots of different National Wetland Inventory types (Cowardin et al. 1979) surveyed in in Cass County, Minnesota, USA during Summer and Fall 2016 and 2017.

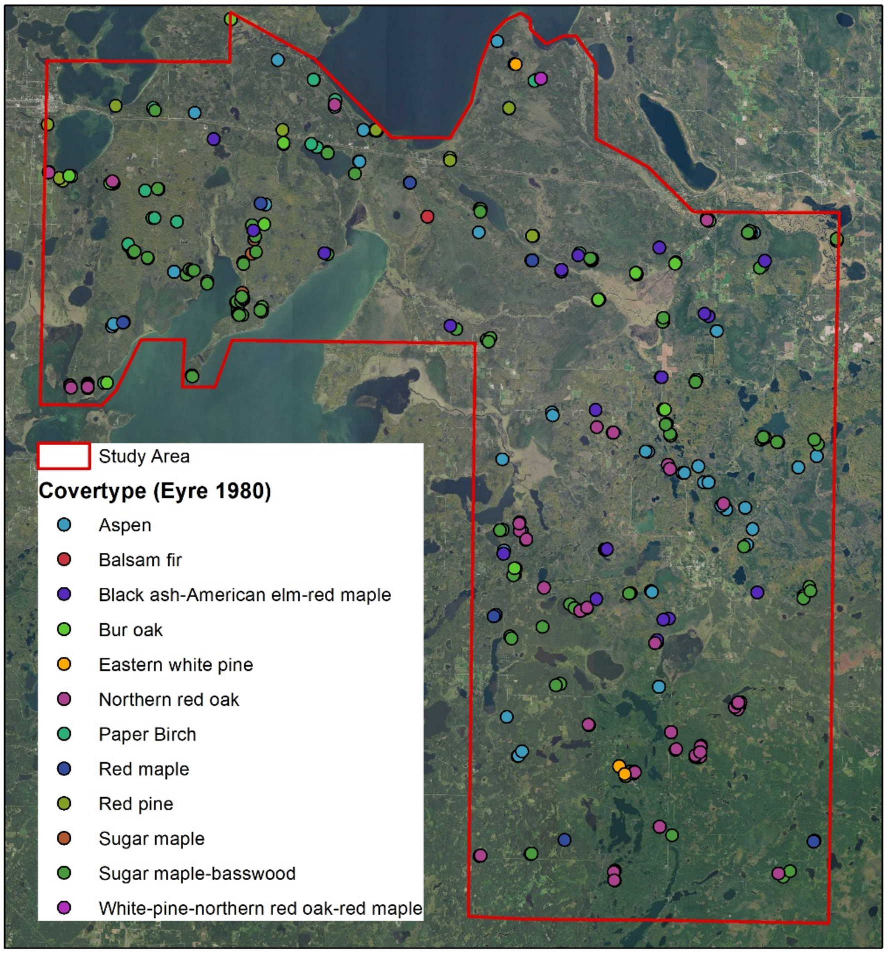

Figure 3. Location of forest plots of different cover types (Eyre 1980) that were surveyed in Cass County, Minnesota, USA during Fall 2016, Spring 2017, Fall 2017, and Spring 2018.

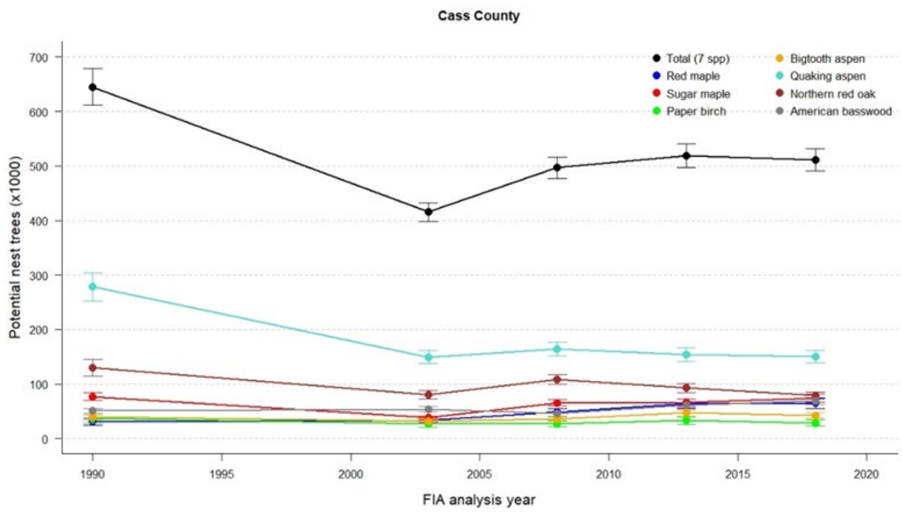

Figure 4. The number of potential nest cavity trees ≥22 cm (8.7”) DBH of 7 species individually and in aggregate in Cass County, Minnesota during 5 FIA survey periods. It is important to note that FIA changed methodology over time. For example, some plots in Minnesota were measured during 1990, except for a subset of plots that had been undisturbed since 1977. Estimates from this subset of undisturbed plots were generated via modeling. Another important methodological change beginning in 1999 was that only about 20% of plots were measured each year, resulting in 5-year evaluation cycles for generating estimates (e.g., 1999–2003, 2004 –2008, 2009–2013, 2014–2018). These cycles are labelled as the last year in the 5-year cycle (e.g, 2003 represents the 1999–2003 cycle).

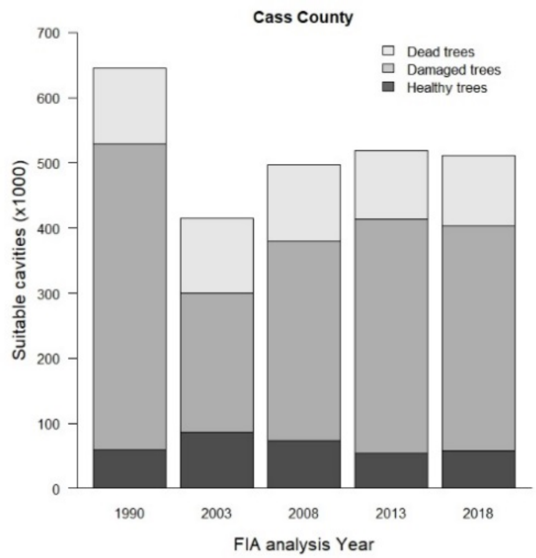

Figure 5. The number of potential nest cavity trees ≥22 cm (8.7”) DBH of 7 species with suitable cavities in Cass County, Minnesota during 5 FIA evaluation cycles. Estimates during each survey period are aggregated into 3 health-status classes: Live-healthy, Live-damaged, and Dead. Some plots were measured during 1990, except for a subset of plots that had been undisturbed since 1977. Estimates from this subset of undisturbed plots were generated via modeling. Beginning in 1999, only about 20% were measured each year, resulting in 5-year evaluation cycles for generating estimates (e.g., 1999–2003, 2004 –2008, 2009–2013, 2014–2018). These cycles are labelled as the last year in the 5-year cycle (e.g, 2003 represents the 1999–2003 cycle). Further, damage codes were not recorded during 1999, which may explain why the number of damaged stems with suitable cavities was relatively low during 1999 –2003.

Appendix 1. Numerical codes used in the classification of the health status of trees (from Thomas 1979).

Health status	Description
1	Live tree that has no defects or injuries that will threaten its long-term health.
2	Live tree with defects that contribute to a decline in health. Indicators may include decay on the bole, fungi, large dead limbs, and substantial cracks.
3	Recently dead tree with bark, limbs, and twigs substantially intact.
4	Dead tree that has lost some limbs and almost all twigs.
5	Dead tree that has lost most limbs and all twigs.
6	Dead tree with a broken top and hard bole wood.
7	Dead tree with a broken top and soft bole wood.