An Adaptive Sample Survey Design for the Ivory-billed Woodpecker

Final Report

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The Ivory-billed Woodpecker was once relatively abundant in floodplain forests of the southeastern U.S. By 1900, its range and numbers had declined precipitously due to habitat loss and various types of persecution (Fitzpatrick et al. 2005). The last known population was studied by Tanner (1942) in a remnant patch of old-growth forest known as the Singer Tract in northeast Louisiana in the late 1930's. The tract was subsequently logged, and since that time, numerous individual sightings have occurred, mostly in and near the few remaining large patches of contiguous bottomland forest (Figure 1). Also since that time, however, a number of bottomland forest patches have come under public protection and have grown to mature forests, and others have been reforested under several large-scale conservation efforts (e.g., Twedt et al. 2006).

The Ivory-billed Woodpecker, if extant (Fitzpatrick et al. 2005; Hill et al. 2006; Jackson 2006), may be the most rare and elusive bird species in the United States and thus designing efficient and effective surveys for this species presents a great challenge . The species once existed at low densities in the southeastern U.S. from Florida to Texas and as far North as Illinois and Indiana and is thought to have used extensive forested areas with very large trees and many dead trees (Jackson 2002). In 1938, Tanner (1942) took the last universally accepted photograph of this species in the U.S.; however, intriguing sightings continued throughout the 20th century (Jackson 2002; Fitzpatrick et al. 2005; Hill et al. 2006). Recent evidence that the Ivory-billed Woodpecker (*Campephilus principalis*) persists in both Arkansas (Fitzpatrick et al. 2005) and Florida (Hill et al. 2006) has reinvigorated the hope that this species can be saved from extinction.

Despite historic records and the contributions of Allen and Kellogg (1937), Tanner (1942), and others, we still know very little about Ivory-billed Woodpeckers. Most of the historic information on habitat associations comes from one site (the Singer Tract in Louisiana), which may not be representative of typical Ivory-billed Woodpecker habitat and may poorly reflect historical or current habitat associations. We know even less about the survey effort required to be relatively confident that the bird is not there, although it is probably high given the expected density of the species (1 pair per 16-44 km^2, Tanner 1942).

Recent evidence of the Ivory-billed Woodpecker in the Cache-lower White River Basins initiated a new search effort (Fitzpatrick et al. 2005). The primary objective of the search has been to find the bird and document its existence, mostly searching only those locations that were believed to be optimal based mostly on the limited data provided by Tanner (1942). Meanwhile, other searches were initiated in other locations within the former range where unsubstantiated sightings were reported in recent decades, again focusing on places that were believed to have the best chance of being occupied. Some observations and other promising data have been collected in these places, but many other observations were made in areas that were not consistent with prior expectations (i.e., smaller tracts, few large trees and snags). It is apparent that we have much to learn about the ecology of this species. To this point, significant money and effort have been spent on searching. Although great advances have been made on search techniques and associated technology, little information useful to management and recovery has been obtained.

Fortunately, recent advances in survey design and parameter estimation provide plausible approaches to sampling rare or elusive species (e.g. Thompson 2004). Theoretical advances in sampling designs, specifically adaptive sampling designs (Thompson and Seber 1996), allow for the opportunity to effectively and efficiently estimate population parameters. New approaches in statistical modeling focus on occupancy estimation (MacKenzie et al. 2002, MacKenzie et al. 2006) as the state variable of interest. Using only collections of presence-absence data, these models allow researchers to address specific questions about rare species (e.g. elusive mammals MacKenzie et al. 2005, O'Connell et al. 2006; cryptic insects MacKenzie et al. 2006) while accounting for imperfect detection. Through application of such models within the framework of efficient adaptive sampling design, we develop a spatial two-stage adaptive sampling design (primary stage: river basins, secondary stage: $2km^2$ patches within river basin) for the Ivory-billed Woodpecker with the following objectives: (1) estimate occupancy (proportion of sites in an area of interest that are occupied by a species), use (probability that a randomly selected site is used given animal movement in and out of surveyed area is at random), and detection probability for habitats at two spatial scales within its former range, (2) assess relationships between occupancy, use, and habitat characteristics at those scales, (3) allow the development of a population viability model that depends on patch occupancy instead of difficult-to-measure demographic parameters, and (4) apply newly collected information to the updating of the above models and consequent adaptation of the design into new search locations.

We first provide an analysis using audio evidence of Ivory-billed Woodpeckers to estimate the relationship between habitat and patterns of occupancy and detection, while controlling for the proportion of patch sampled at the Cache and White River National Wildlife Refuges in Arkansas from 2004-2005. Second, we present a two-stage adaptive sampling survey design and field protocol allowing for estimation of occupancy and associated parameters.

Analysis of Audio Evidence of Ivory-billed Woodpeckers

Study site

Our study area encompassed 22 forest patches, ranging in size from 1.2 to 7 km^2 (mean = 2 km^2), within the Cache (35.06°N, 91.33°W) and White River National Wildlife Refuges in Arkansas (34.29°N, 90.08°W). We used natural features and management history (Lower Mississippi Joint Venture *unpubl. data*) to delineate patch boundaries so that patches averaged about 2 km^2.

Acoustic sampling

Autonomous recording units (ARUs) recorded 16,248 hours (2,031 days) of ambient sound throughout the Cache and White River National Wildlife Refuge from December 18, 2004 through May 31, 2005. Each ARU recorded sound for two 4-hr periods; the first period began 30-45 min before sunrise and the second ended 30-45 min after sunset. ARU deployments continued for 6 - 41 consecutive days. Recording sites were selected in an ad hoc manner based on perceived habitat quality (i.e. many large and dead trees) and prior evidence of Ivory-billed Woodpecker presence such as sightings, acoustic encounters, and feeding sign. Within each patch, this ad hoc selection of recording sites resulted in patterns of ARU locations that ranged from evenly distributed to clumped (Fig. 2), thus producing large variation in spatial coverage between patches.

Acoustic analysis

There are two commonly described sounds produced by Ivory-billed Woodpeckers: a kent call and a double knock (Jackson 2002). In 1935, Arthur Allen made the only known recording of a kent call (Allen and Kellogg 1937), a call often described as sounding like a toy trumpet or clarinet. There is no known recording of the Ivory-billed Woodpecker double knock; however, historic descriptions of "double resounding whacks" produced by Ivory-billed Woodpeckers (Allen and Kellogg 1937) agree well with double knocks produced by other woodpeckers in the genus *Campephilus* (Ron Rohrbaugh, Jr. *unpubl. data*).

We first used the XBAT software system (http://xbat.org/) to identify sounds similar to Arthur Allen's recordings of Ivory-billed Woodpecker kent calls and double knocks from Pale-billed Woodpeckers (*Campephilus guatemalensis*) and Powerful Woodpeckers (*Campephilus pollens*). XBAT compares spectrogram cross-correlations between a template and unclassified sounds and retains only sounds with correlations above a specified threshold (henceforth, signals). We used a conservatively low threshold (0.25) to insure that signals were not prematurely removed from consideration. This threshold, however, resulted in hundreds of thousands of signals that were obviously not produced by an Ivory-billed Woodpecker.

In an attempt to exclude false detections, we then subjected signals identified by the XBAT system to a 3-stage review process. First, one of six acoustic analysts reviewed the signals and easily removed most of them (>99%) from consideration due to a strong dissimilarity from historical records of Ivory-billed Woodpecker sounds. Then, at least five acoustic analysts voted on whether the remaining signals are potentially produced by Ivory-billed Woodpeckers. Signals accepted by at least 60% of analysts reached the next level of review (henceforth, detections). A panel of at least three experts outside the acoustic analysis team performed the final review and classified (by consensus) these detections as A2 (rejected), A3 (moderate interest), or A4 (high interest). A3 detections lack "a compelling qualitative resemblance" to Ivory-billed Woodpecker sounds but could not be confidently rejected based on quantitative evidence. A4 detections could not be separated from template sounds based on qualitative or quantitative criteria. Quantitative criteria included double knock interval and fundamental frequency (for kent calls). Qualitative criteria involved the absence of a probable alternative sound source and the general impression of a human observer that a signal sounded like a *Campephilus* woodpecker. We used only detection classified as A4 (high interest) in this analysis.

Vegetation sampling

We used stand-level estimates of big trees/ha (>60.96 cm dbh) and snags/ha from the Lower Mississippi Valley Joint Venture Ivory-billed Woodpecker habitat inventory and assessment to infer a relationship between occupancy and habitat features. Historic accounts of Ivory-billed Woodpeckers typically mention a strong association with many big trees and many dead trees (e.g. Allen and Kellogg 1937; Tanner 1942). In each stand, the Joint Venture randomly selected four 322-m transects. Every 80.5 m along each transect, they estimated the number of big trees and the number of snags within a 16-m radius. Detailed methods for this habitat inventory are available at http://www.lmvjv.org/IBWO_habitat_inventory_&_assessment.htm.

Statistical analysis

We used multi-scale occupancy modeling (Mordecai et al. submitted) to accommodate the hierarchical nature of the data. These models estimate three parameters based on repeated visits at two scales: occupancy (probability of species presence in an area), use (probability of species presence at a smaller scale within that area given occupancy), and detection (probability of detecting a species given use). Because we could not confirm with certainty whether Ivory-billed Woodpeckers were present in any of the patches, we define occupancy as the probability that A4 (high interest) evidence (hereafter; evidence) was present in a stand. We then defined use as the probability that evidence was available to an ARU, given it was present in the stand. Finally, we defined detectability as the probability of detecting such evidence on a given day of the ARU deployment given use during that day.

We corrected for variation in the proportion area sampled among stands by modeling the effect of percent patch surveyed on use; thus linking the availability of evidence to the total area sampled. We used ArcGIS 9.1 (Environmental Systems Research Institute, Redland, California) to place 200-m buffers around each ARU location and calculated percent patch surveyed as the percent of each patch covered by the ARU detection buffers. Buffers of 200 m roughly correspond to the suspected distance at which a signal from an Ivory-billed Woodpecker would likely be detected by an ARU (Ron Rohrbaugh, Jr. *unpubl. data*).

We constructed 32 candidate models based on all possible combinations of density of big trees and density of snags to explain occupancy and detection, and percent area surveyed to explain use. We used mean Akaike's information criterion (AIC, Brooks 2002; Fonnesbeck and Conroy 2004; Conroy et al. 2005) to compare models and used model averaging to calculate parameter estimates (Burnham and Anderson 2002) . To estimate the relative importance of each parameter, we summed the Akaike weight across models in which the parameter occurred (i.e., variable importance weight (v_i), Burnham and Anderson 2002). To test model fit, we compared model-averaged predictions among models with ΔAIC < 4 to stand-level patterns of detections. We considered stands in which the model-averaged prediction of occupancy was greater than 0.5, and there was at least one detection in that stand, as classified correctly.

Using the model with the lowest AIC value, we also calculated the number of 14-day sampling periods required to be 90% confident that a stand was not occupied. The probability of no detections after 14-days of sampling ($period_{14}$), given presence, is the probability that evidence is available during the sampling period (use) multiplied by the probability that the species is not detected over the 14 days ($(1-p)^{14}$). We solved for the number of sampling periods (X) required to be 90% confident that a stand is not occupied by setting the equation $1-(1-period_{14})^X$, the probability that at least one of the sampling periods produces a detection given presence, equal to 0.90.

We analyzed candidate models with the program moBayes (http://code.google.com/p/mobayes/), which uses the Markov chain Monte Carlo (MCMC) toolkit PyMC (http://code.google.com/p/pymc/) to estimate multi-scale occupancy models. In particular, this program uses a Bayesian approach to estimation and thus requires the specification of all information relevant to the problem in the form of a prior distribution around all parameters (Link et al. 2002; Gelman et al. 2003). There was scant prior information regarding occupancy, use or detection for this species, so we used diffuse priors (uniform distribution from -20 to 20 on the logit scale) for all intercepts and (-10 to 10 on the logit scale) for all covariates. We used PyMC to estimate the number of 14-day sampling periods required to be 90% confident the species was not present.

MCMC uses simulation to generate parameter estimates; therefore, determining the number of iterations required to estimate a parameter at a desired level of accuracy is essential. After running a sufficient number of iterations (to achieve the desired accuracy) a parameter is said to have converged (Raftery and Lewis 1992a; Raftery and Lewis 1992b). To ensure convergence of model parameters, we used both visual inspection of simulation values and the methods of Raftery and Lewis (1992a; 1992b) with the default options in CODA (Plummer et al. 2006).

MCMC requires initial values for all parameters to begin the simulation and one fundamental assumption of MCMC is that accepted values do not depend on those initial values (Gelman et al. 2003). Typically, values from early iterations, which may still be dependent, are ignored (also known as burn-in). We used a burn-in period of 5,000 iterations and tested its adequacy using visual inspection and the methods of Raftery and Lewis (1992a; 1992b) with the default options in CODA (Plummer et al. 2006).

Results

Four models had a mean ΔAIC < 2, three of which contained effects of proportion area surveyed on use and big tree density on detection (Table 1). There was no clear, single predictor for occupancy. The null model had a ΔAIC of 4.54 and an Akaike weight of 0.02, indicating that at least one variable was useful for predicting occupancy, use, and/or detection. Model-averaged predictions classified 68% of 22 stands correctly with 5 false positives and 2 false negatives. Percent patch surveyed (v_i =0.61) and the effect of density of big trees on detection (v_i =0.61) had the greatest importance weights, followed by the effect of big tree density on occupancy (v_i =0.54), snag density on occupancy (v_i =0.35), and snag density on detection (v_i =0.23). Although 95% credible intervals (a Bayesian confidence interval, BCI) did not overlap zero for the effect of big tree density on occupancy or detection in most of the top models (Table 1), model-averaged BCIs for the effect of big tree density on occupancy (-0.35, 0.09) and detection (-0.68, 0.60) did. The model-averaged BCI for the effect of percent patch surveyed on use was between -2.33 and 2.23.

Model-averaged predictions of occupancy declined with greater big tree density (Fig. 3), use declined with greater percent patch surveyed (Fig. 4), and detection was relatively unaffected by big tree density (Fig. 5). The number of 14-day acoustic sampling periods required for 90% confidence in detecting evidence given that it is present ranged from 7.4 (95% BCI: 3-12) in low densities of big trees to 360.8 (95% BCI: 3-1158) in high densities of big trees (Fig. 6).

Adaptive-Sample Survey Design

We present a two-stage adaptive cluster sampling survey design occurring at two spatial scales, a primary level and a secondary level (e.g. adaptive cluster sampling occurring at the secondary stage only Salehi and Seber 1997). Following Salehi and Seber (1997), consider the population of spatial units as composed of N primary units from which we take a random sample of n. At the second stage, we take an initial simple random sample of m_i units without replacement from the primary unit i for $i = 1. . . n$ Associated with the jth secondary unit of the ith primary unit is a variable of interest y_{ij}. In this case y_{ij} represents detection of an Ivory-billed Woodpecker from a presence-absence survey. The N primary units are individual river basins within the former range of the Ivory-billed Woodpecker (Figure 7). Many of those can be eliminated from further consideration due to their (believed) complete lack of suitability. River basins with consistent sightings and/or sound recordings (i.e., high quality evidence) will always be selected to survey. At this point those would be the Cache/lower White in Arkansas, the Choctawhatchee in Florida, and the Congaree/Wateree in South Carolina. Other river basins may also be selected non-randomly based on recent historical sightings. Remaining basins in the sampling frame will be randomly selected with weights based on the subjective probability of Ivory-billed Woodpeckers occurring in the area. These selection weights will result in basins with high occupancy probability being frequently selected and those with low occupancy probability being rarely selected. Therefore we will adopt unequal inclusion probabilities for the primary units based on the above criteria.

The M secondary units will be defined as approximately 2-km^2 patches of land within the selected river basins. As individual birds are almost certain to use areas greater than 2 km^2, the secondary level will be estimating probability of a unit being used. These patches can be a consistent square or some other shape in a grid as in Figure 8, or a variable shape and (somewhat) size in order to follow existing features of the landscape such as water features or management compartments. Squares can be problematic, for example, if they include both sides of a watercourse large enough to prevent easy crossing. The 2-km^2 size was chosen because it seems functional and it is currently in use as part of the Lower Mississippi Valley Joint Venture habitat survey (LMVJV refers to these patches as stands, which are subunits of management compartments on public land in the survey).

Again, patches that are inaccessible due to logistics or landowner permission can be omitted from the sampling frame, as will completely unsuitable patches; the resulting system of patches constitutes the sampling frame of the secondary units. Selection of patches will occur in a similar fashion to the primary units except no patches in the sampling frame will be guaranteed selection. Patches will be randomly selected with weights based on the probability of Ivory-billed Woodpecker use.

Patches at the secondary unit-level are adaptively added to the search if the secondary unit (i,j) is said to satisfy the condition of interest D, where $y_{ij} > D$ and $D = 0$. Once the condition of interest has been satisfied additional neighboring units are added to the sample. If any other units in that neighborhood satisfy condition D, then their neighborhoods are also added to the sample. This process is continued until a cluster of units is obtained that contains a "boundary" of units called edge units that do not satisfy D. The final sample then consists of n_1 (not necessarily distinct) clusters. A network of samples, A_i for unit i, is further defined as the cluster generated by unit i but with its edge units removed. The distinct networks are disjoint and form a partition of the M secondary units.

Candidate Estimator

Based on the survey design, a candidate estimator of the total number of detections is

$$\hat{\tau} = \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} \ ,$$

and an estimator for the average number of detections is

$$\hat{\mu} = 1/n_1 \sum_{i=1}^{n1} \frac{1}{m_i} \sum_{j \in A_i} y_j = 1/n_1 \sum_{i=1}^{n_1} w_i \ ,$$

where w_i is the mean of the variable for the i[th] network. Let K denote the number of networks in the sample. Let y_k^* denote the sum of the y-values in the k^{th} network (k = 1,2,…, K) and let x_k denote the number of primary units in the population that intersect the k^{th} network. We define J_k to take the value of 1 with probability a_k if the initial sample of primary units intersects the k^{th} network, and 0 otherwise:

$$a_k = 1 - \left[\binom{N - x_k}{n_1} \Big/ \binom{N}{n_1} \right]$$

and

$$a_{kk'} = 1 - \left[\binom{N - x_k}{n_1} + \binom{N - x_{k'}}{n_1} - \binom{N - x_k - x_{k'} + x_{kk'}}{n_1} \right] \Big/ \binom{N}{n_1}$$

where $a_{kk'}$ is the probability that the initial sample intersects both networks k and k', and $x_{kk'}$ is the number of primary units that intersect both networks, with the convention that $a_{kk} = a_k$. An unbiased estimator of this variance (Thompson and Seber 1996; page 125) is

$$\hat{\mathrm{var}}[\hat{u}] = \frac{1}{M^2 N^2} \sum_{k=1}^{K} \sum_{k'=1}^{K} \frac{y_k^* y_{k'}^*}{a_{kk'}} \left(\frac{a_{kk'}}{a_k a_{k'}} - 1 \right).$$

Adjustment for unequal inclusion probabilities would require a slight modification, but at this time has not been formalized. Smith et al. (1995) used an inclusion probability proportional to available habitat for waterfowl. We hope to do something similar and are currently gathering information from search teams to classify and categorize Ivory-billed Woodpecker habitat, which would permit criteria for ranking potential habitat. We then hope to use this information to define our inclusion probabilities for the primary units.

At this time adjustment for imperfect detection will be done using information from separate independent estimates of detection probability, $\hat{g}_{ij}$, and included into the estimator $\hat{\tau}_0$, which is formed by replacing the actual detection probabilities with the estimated detection probabilities. The new variable of interest, total number of detections adjusted for detection rate, is then estimated by $\hat{u}_{ij} = \frac{y_{ij} z_{ij}}{\hat{g}_{ij}}$ where z_{ij} is an indicator random variable equal to 1 if the *jth* object of the *ith* unit is detected, and 0 otherwise and the new estimator using the sample *u*-variables is $\tilde{\tau} = \hat{\tau}_0\left(\underline{\hat{\mu}_s}\right)$, where $\underline{\hat{\mu}_s} = \{\hat{\mu}_{ij} : i \in s\}$.

Habitat surveys

The habitat protocol stems from the LMVJV habitat measurement protocol, which involves taking many measurements on 4 "transects" of 5 plots each, or n=20 plots per patch. Circular plots are 0.2 acres (0.08 ha) in size, with a 52.7' radius. However, this level of time commitment may not be within the means of all investigators. In this case, a reduced number of measurements can be taken on these plots. We suggest that, as a minimum, density of large (>24" dbh and >36" dbh) trees, density of snags, and dominant tree species should be recorded. Based on feedback from searchers in 2006-07, we believe that most of the data on dominant tree species can be obtained using remotely sensed data, so tree species does not need to be recorded.

However, two additional measurements requiring more precision must be made. Rather than measuring all trees, only trees >24" dbh and >36" dbh and all snags >10" dbh are counted, using one or several 52.7' sections of cord to ascertain the plot boundary, and a Biltmore stick to quickly assess dbh class. We estimate that, with practice, a plot such as this should take < 5 minutes to complete by one person.

The 20 plots per patch should be randomly located and established using a GPS unit. They can be located using simple random sampling or systematic random sampling.

Alternatively, habitat surveys can all be done in the middle of the day at random locations. Once habitat surveys are done for a patch, they do not need to be done again, unless additional or different data are required, or the patch has undergone significant change since the last survey.

Field Protocol

We have classified *D*, the condition of interest, as a trigger and have defined it for visual detections and auditory detections as follows:

Visual detections

A visual detection trigger is any visual detection of category 1, category 2, or category 3 on the Cornell Lab of Ornithology visual encounter ranking system (see below). These visual detection triggers can come from the following sources:

1) a randomly selected patch within the secondary unit sampling frame,
2) a patch triggered for search by a qualifying event in an adjacent patch,
3) a patch searched during the 25% allocated free time in either primary or secondary sampling frame, or outside of the primary sampling frame or,
4) an outsider's report (e.g. hunter) and potentially in a patch not in a primary or secondary unit sampling frame and not originally intended to be surveyed.

Cornell Lab of Ornithology Visual Encounter Ranking System

Any large woodpecker falling into either of the following categories:

Category 1 - an encounter with documentation that can be repeatedly interpreted the same way by independent observers, such as where definitive photographic evidence is collected by the field observer.

Category 2 - an encounter with at least two diagnostic field marks clearly observed and described, and the bird remaining in view long enough for the observer to reconfirm the observed field marks, but no independently verifiable evidence such as a photograph. Diagnostic field marks include:

a. White trailing edge of wing on either the dorsal or ventral surface.

b. White 'shield' formed by folded wings over the lower back of a perched bird.

c. White lines starting behind the eye, continuing down the neck and onto the back of the bird.

d. Black chin

e. Large woodpecker with one of the above diagnostic field marks and clearly heard giving 'kent' calls or double knocks.

Category 3 - an encounter that includes the description of one definitive or several partial or poorly observed field marks.

Auditory Detections

An auditory detection can only be used as a trigger if it meets the following criteria:

1. It is a clear double-knock or kent call, and
2. It was recorded by personnel with extensive experience and training (i.e. member of the search team).
3. It does not displace more than 25% of the search time for the original occupancy protocol.

Auditory detections can be followed at any time during the search period regardless of whether it originates in a selected sample plot or in a plot within the sampling frame, given it meets the above criteria.

Adaptive Field Procedure

Once a detection trigger has been confirmed the protocol will change in the following fashion.

1) The patch containing the trigger and the four adjacent patches in the cardinal directions (North, East, South, and West) will be searched. If the patches are not square, but are of some other shape dictated by landscape features, then the adjoining or most adjacent patch in each of the four cardinal directions should be surveyed (Figures 9 and 10).
2) These five patches (trigger patch plus four adjacent patches) will be visited a total of *five* times instead of the original three visits.
3) Any new trigger detections in the adjacent patches will constitute a new trigger and the three adjacent patches of the new trigger patch will be surveyed a total of *five* times (Figure 11).
4) If at least one more trigger follows the initial trigger, reallocation of search effort will be left up to each search team with the provision that the adaptive protocol is followed. If no additional triggers are found, return to the random patches originally selected for the occupancy model.
5) Continue process to create network of patches until no new triggers have been found resulting in edge patches (Figure 11).
6) Follow the normal occupancy protocol for all other detections.

DISCUSSION

Proportion area surveyed

The influence of the proportion area surveyed, as indicated by its high importance weight in the model set, suggests that availability of a species (or evidence of that species) for detection can be related to the total area sampled even when controlling for sampling effort. Although the credible intervals did overlap zero, there was some evidence that the probability that Ivory-billed Woodpecker evidence was available to an individual ARU increased as the percent patch surveyed declined, while holding survey effort constant. One likely explanation for this relationship is nonrandom sampling. In "hot spots" with much evidence of Ivory-billed Woodpecker presence (e.g. sightings, feeding sign), recording units were generally placed near such evidence. In patches with little evidence, recording units were more evenly distributed; thus, the percent patch surveyed also represents the level of random sampling within the patch. Although multi-scale occupancy modeling allowed us to control for this bias, there was a large amount of uncertainty introduced by statistically controlling it.

The best way to control for sampling bias is to include some random sampling in the design of surveys for rare and elusive species. Such randomization is important even for preliminary or initial surveys. The ideal form of randomization depends on the ecology of the species. We feel our two-stage adaptive sampling design will allow for an increase in estimator performance and potentially eliminate sampling bias associated with non-randomized allocation of sampling effort. Data collected under our new design has just commenced and we anticipate further analyses within the adaptive sampling framework to begin shortly after the 2008 field season.

The 2-km^2 patches in which we analyzed acoustic evidence were much smaller than previously published estimates of Ivory-billed Woodpecker home range sizes. We used each day of recording from an ARU as a repeated sample to estimate the probability of detection. Therefore, because the woodpecker could potentially leave and/or return to the patch during those days, the probability of detection combines the probability of presence during a particular day of deployment and the probability of detection given presence that day. Because we cannot separate these two probabilities, we cannot determine whether habitat influenced the actual use of the area, our ability to detect that use, or both.

One way in which we attempt to separate the probability of presence and the probability of detection given presence for Ivory-billed Woodpecker evidence is by examining occupancy at a larger scale. A range-wide Ivory-billed Woodpecker search began in 2007 that will allow us to examine this relationship at multiple scales while still accounting for imperfect detection. This search should allow us to better understand occupancy, use, and detectability, and in the process obtain indisputable evidence that Ivory-billed Woodpeckers persist in the U.S.

Habitat relationships

Our finding that the probability of evidence being present and/or detection of such evidence increased with declining big tree density may seem counterintuitive. Ivory-billed Woodpeckers are historically associated with areas of large trees, and one might expect dense stands of large trees to attract this woodpecker. Density of big trees (>60.96 cm dbh) in this area, however, decreases with increasing density of even bigger trees (>91.44 cm dbh, M. Lammertink pers. obs.), so the decrease in big tree density probably represents an ecological transition to fewer, but even larger, trees. Unfortunately, we did not have data on the density of trees >91.44 cm for our study area. As all of the stands in our study were older and dominated by big or even bigger trees, further study is needed in younger stands dominated by smaller trees.

If increasing density of big trees represents a transition to fewer and larger trees, there are at least two potential reasons for an increasing probability of detection. First, Ivory-billed Woodpeckers may spend more time in areas with fewer and larger trees. Second, a decrease in big tree density may allow acoustic signals to travel farther, thus improving detectability of an acoustic signal.

There remains much uncertainty as to whether density of big trees affects presence of evidence for Ivory-billed Woodpecker, detection of that evidence, or both. Much of this uncertainty probably results from very low detectability in areas with a high density of big trees, which confounds absence with very low detectability.

Improving survey design

Information on detectability, and particularly how it is related to habitat variables, is extremely valuable in the design of bird surveys. Mackenzie and Royle (2005) discuss how estimates of occupancy and detectability can be used to estimate the optimal number of repeated visits for an occupancy survey. The optimal number of repeated visits decreases with higher detectability and lower occupancy (Mackenzie and Royle 2005). For situations in which occupancy and detectability vary with habitat, such as this study, the optimal number of repeated visits will also likely vary by habitat.

Detectability can also be used to estimate the amount of effort required to demonstrate that a species is not present at a certain level of confidence. When working with endangered species, this quantity can be very important, because it allows natural resource professionals to adopt consistent standards for estimating the presence/absence of a species. When using acoustic surveys for evidence of Ivory-billed Woodpecker, our results suggest that demonstrating absence at a 90% confidence level, even at low densities of big trees, would be difficult. In particular, the lowest estimated effort would require more than 100 days of acoustic sampling per patch and thus analysis of more than 800 hours of recordings. The intensive sampling required and potentially costly analysis of acoustic data suggests that demonstrating absence of evidence at a 90% confidence level within a 2-km^2 patch will not be feasible without more efficient survey methods (i.e., methods with a higher probability of detection).

Although we believe our survey design is appropriate, we anticipate making improvements upon the actual estimator used for occupancy and associated parameters. Ideally, a joint estimator integrating design-based characteristics and model-based characteristics will be the best choice. Currently, we are working on deriving such an approach that combines design-based information from the two-stage adaptive survey design, but also integrates flexible model-based estimates of detection probability and occupancy in a Bayesian formulation. This will eliminate the need of a direct estimator as inference will be derived from the posterior distribution including mean number of detections and an associated variance. This work is ongoing and analyses will require data collected during the field season of 2008.

CONCLUSION

The rediscovery of the Ivory-billed Woodpecker is arguably the most stunning news in wildlife biology in the last few decades. It is imperative that surveys for the species be of rigorous design, allowing investigators to learn the most they possibly can from the survey effort. Although costs may be slightly higher, the benefits in terms of the quality of information obtained will be a substantial improvement over current approaches. We believe that the additional costs will be more than justified by the gain in the quality of inference obtained under this survey sampling design. The approach does not detract from efforts to document the bird's existence; indeed, we believe that our approach may increase the probability of finding birds at multiple locations.

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Table 1. Model selection results for the effect of big tree (B) and snag (S) density on occupancy (ψ) and detection (p), and percent patch surveyed (Sur) on use. Models are ordered by the difference in Akaike Information Criterion (ΔAIC) and Akaike weights (w_i). Superscripts of + or – indicate the direction of the estimate and * indicates 95% credible intervals (Bayesian confidence intervals) that do not overlap zero. Only models with ΔAIC < 4 are shown.

Ψ	**Use**	***p***	**Deviance**	**K**	**ΔAIC**	**w_i**
.	$Sur^{(-)}$	$B^{(-)*}$	106.67	5	0	0.20
$B^{(-)*}$	.	.	109.70	4	1.03	0.12
$S^{(-)}$	$Sur^{(-)}$	$B^{(-)*}$	106.05	6	1.38	0.10
$B^{(-)}$	$Sur^{(-)}$	$B^{(-)*}$	106.53	6	1.86	0.08
$B^{(-)*}S^{(-)}$	.	.	109.27	5	2.60	0.05
.	$Sur^{(-)}$	$B^{(-)*}S^{(-)}$	107.69	6	3.02	0.04
$B^{(-)*}$	.	$S^{(-)}$	109.68	5	3.01	0.04
$B^{(-)*}$	$Sur^{(-)}$	.	109.76	5	3.09	0.04
$B^{(-)*}$	.	$B^{(-)}$	109.80	5	3.13	0.04
$B^{(-)}S^{(-)}$	$Sur^{(-)}$	$B^{(-)*}$	105.98	7	3.31	0.04
$S^{(-)}$	$Sur^{(-)}$	$B^{(-)*}S^{(+)}$	106.60	7	3.93	0.03

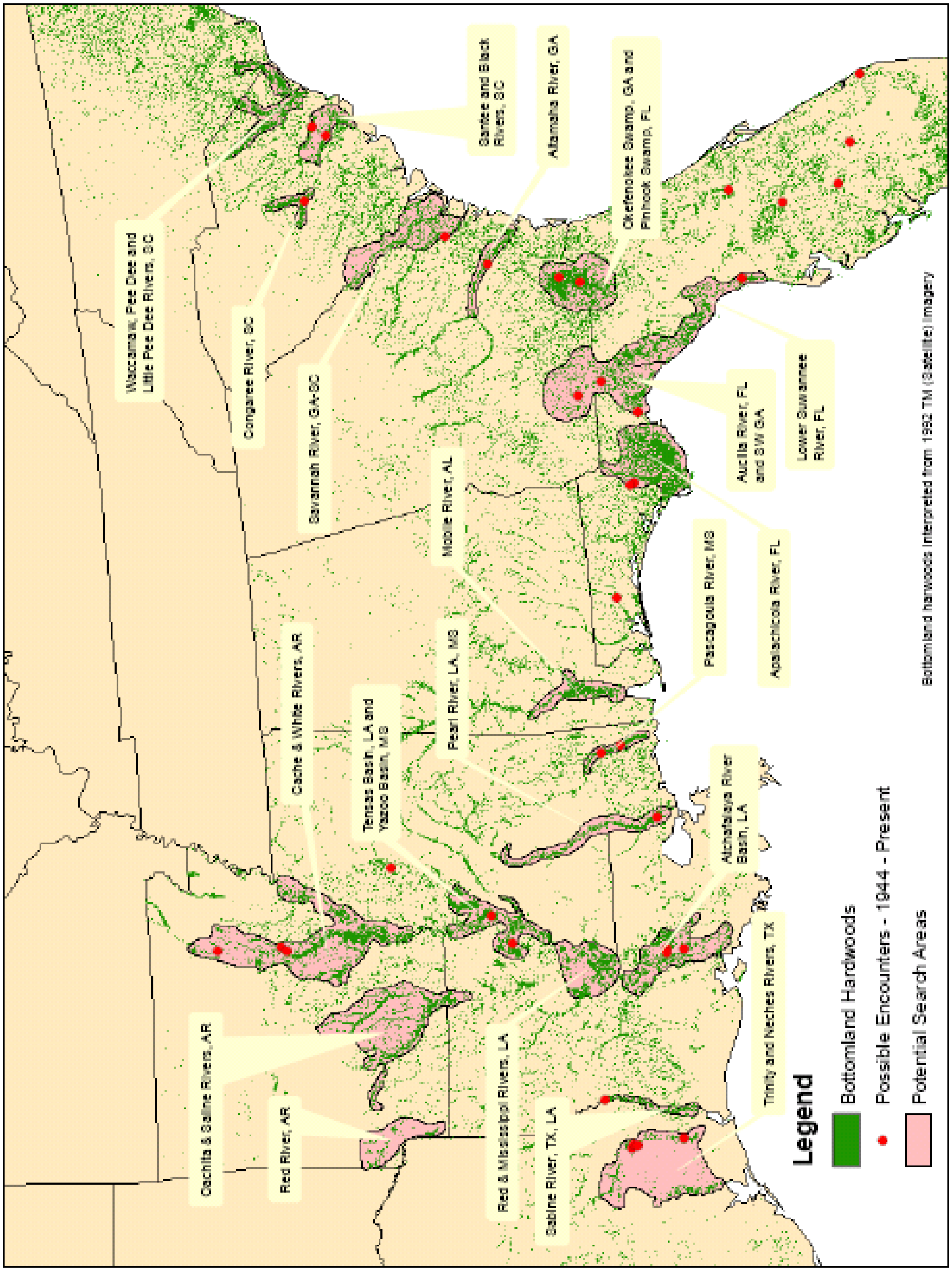

Fig. 1. Possible encounters of Ivory-billed Woodpeckers since 1944 are primarily in large patches of contiguous bottomland forest.

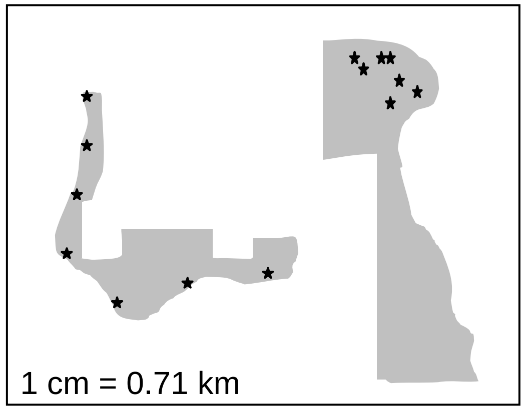

FIG. 2. An example of evenly distributed (left) and clumped (right) ARU locations (stars) within a patch in the Cache River National Wildlife Refuge, Arkansas. Area of each patch is shown in gray.

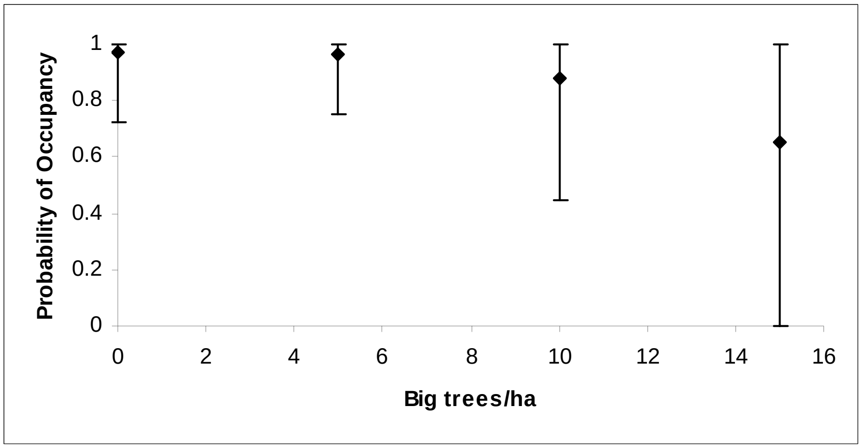

FIG. 3. Model-averaged association between big trees/ha and the probability of occupancy by Ivory-billed Woodpecker (i.e., probability that evidence was present in a stand). Observed values of big tree density ranged from 1-14.5 trees/ha. Error bars indicate 95% credible intervals (Bayesian confidence intervals).

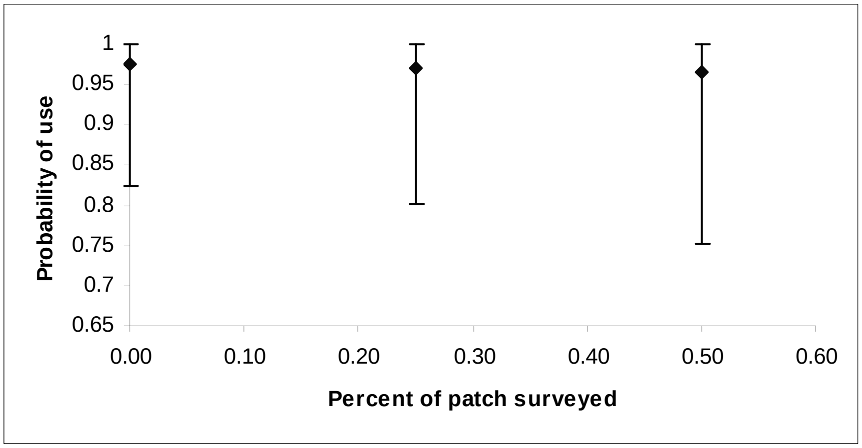

FIG. 4. Model-averaged association between percent of patch surveyed and the probability of use by Ivory-billed Woodpecker (i.e., probability that evidence was present during the deployment of an autonomous recording unit). Observed values of percent patch surveyed ranged from 4.8-47.2%. Error bars indicate 95% credible intervals (Bayesian confidence intervals).

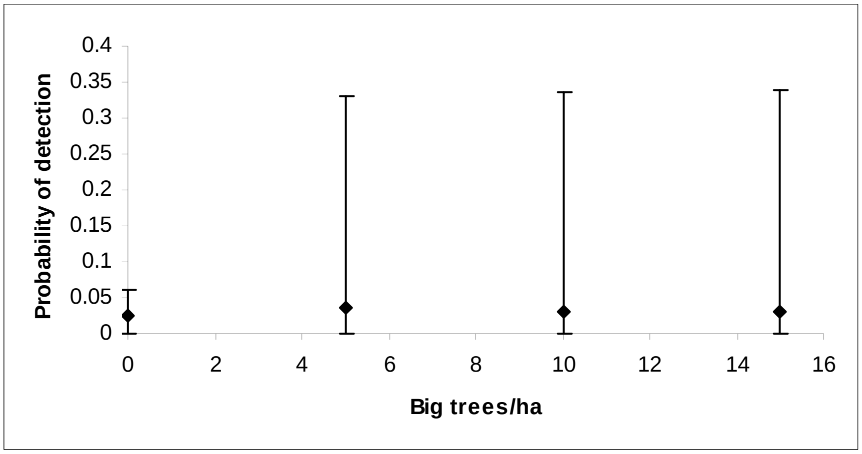

FIG. 5. Model-averaged association between big trees/ha and detectability of evidence for Ivory-billed Woodpecker (i.e., probability of detecting evidence during a one-day deployment of an autonomous recording unit). Observed values of big tree density ranged from 1-14.5 trees/ha. Error bars indicate 95% credible intervals (Bayesian confidence intervals).

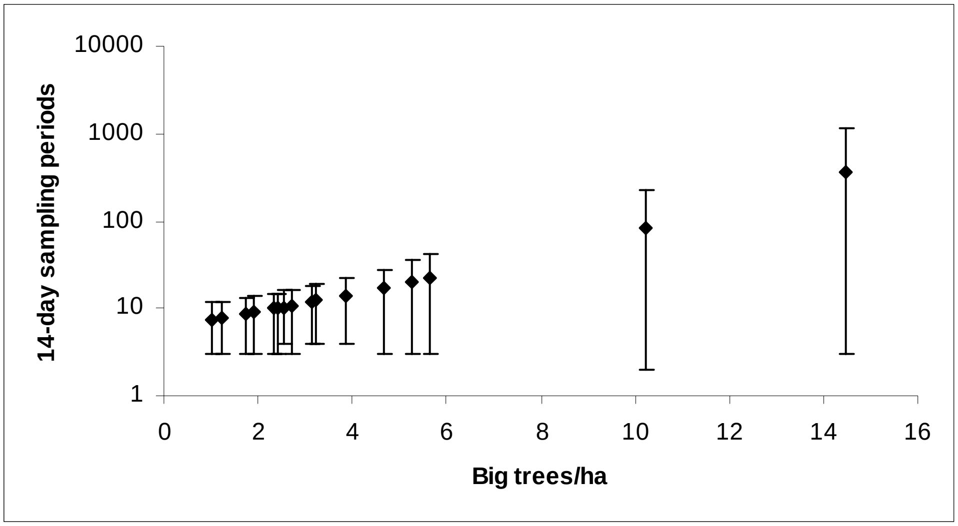

FIG. 6. Number of 14-day sampling periods required to be 90% confident that evidence of Ivory-billed Woodpecker is absent from a stand based on the model with the lowest AIC value. Points correspond to observed values of big trees/ha. Error bars indicate 95% credible intervals (Bayesian confidence intervals). Number of sampling periods is plotted on the log scale.

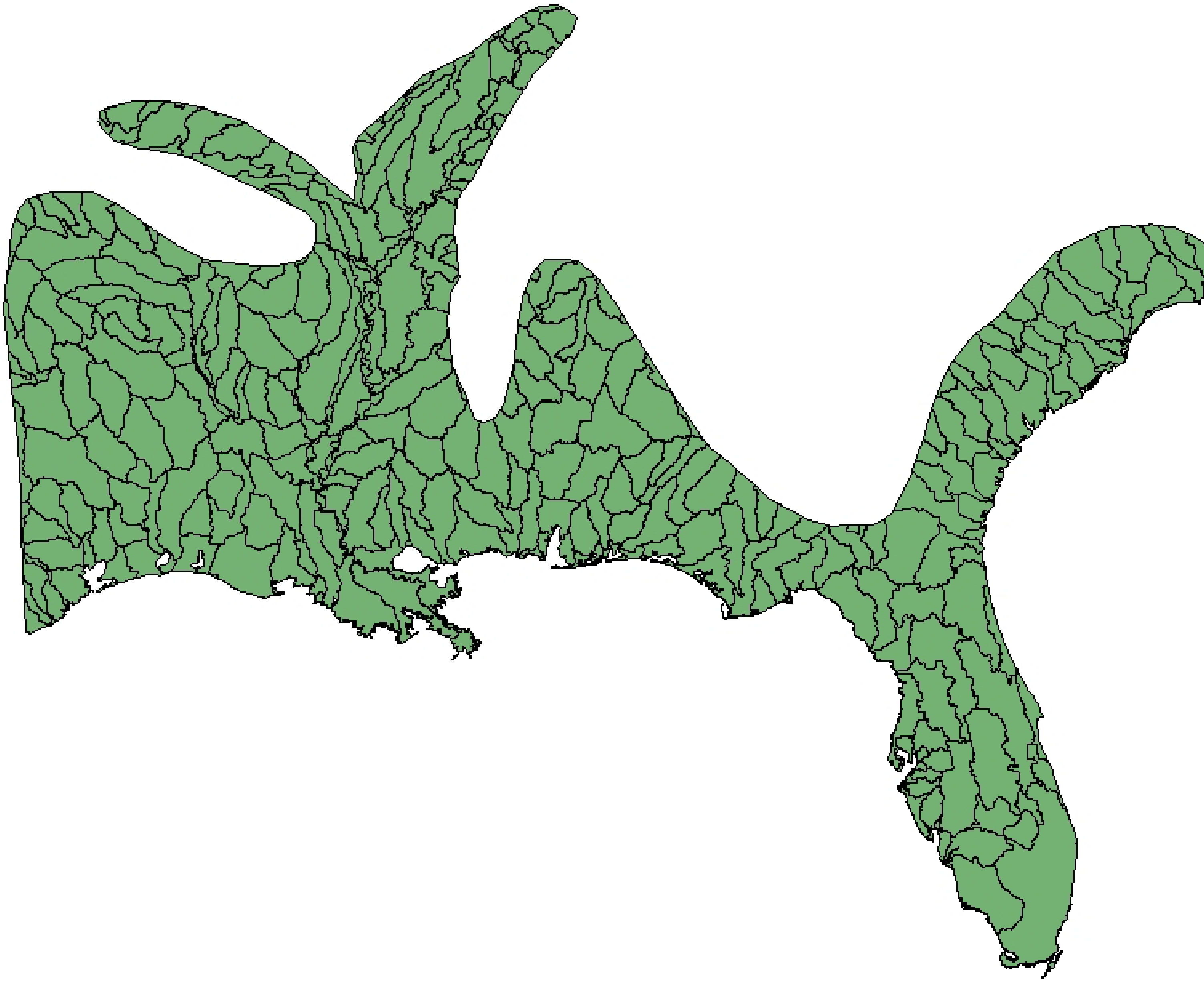

Fig. 7. River basins within the former range of the Ivory-billed Woodpecker.

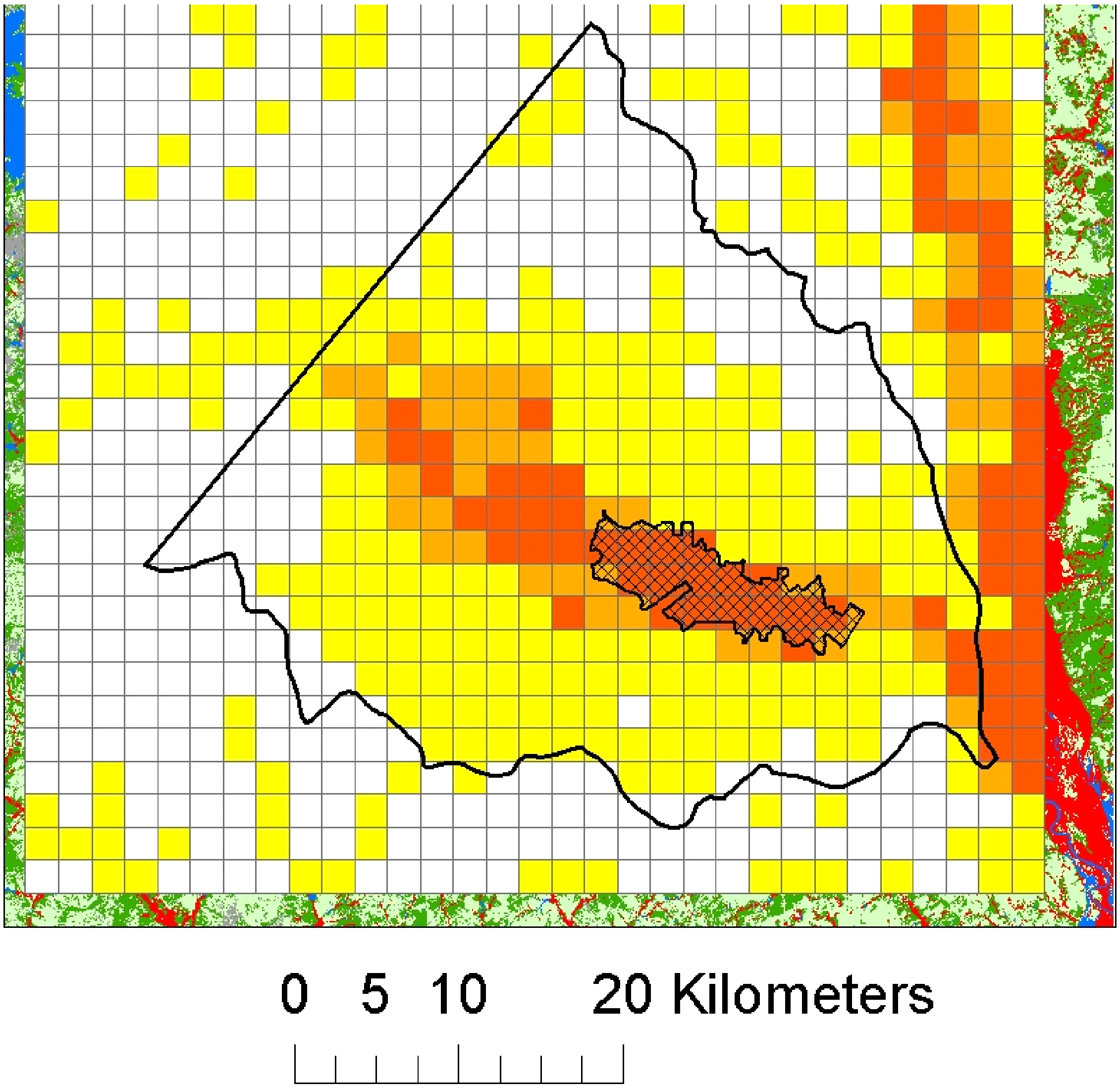

Fig. 8. Example grid of survey units for basin surrounding Congaree National Park, South Carolina. Park boundaries shown as crosshatched area. Colors represent percent of square classified as swamp and/or bottomland hardwood (0-10%: white, 10-40%: yellow, 40-70%: orange, 70-100%: red) by the 2001 National Landcover Dataset (NLCD).

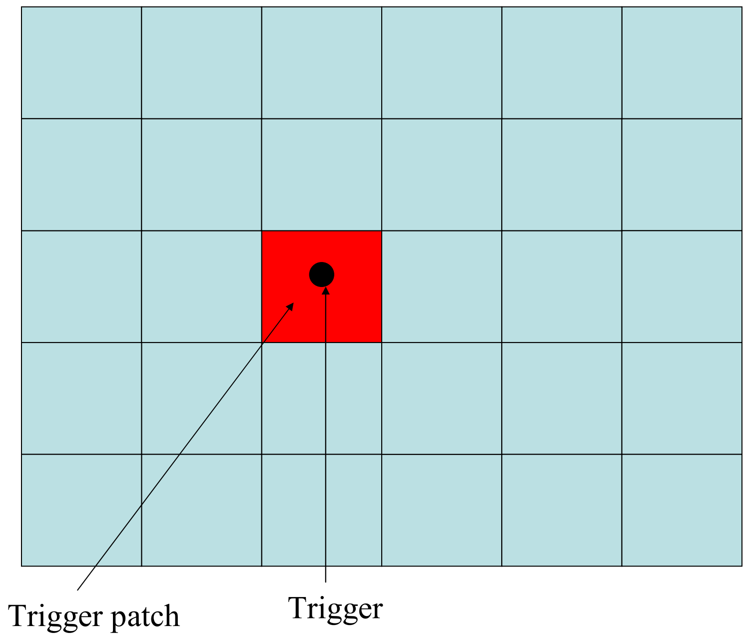

Fig. 9. Example of adaptive survey design for secondary unit of sampling frame where the condition of interest, *D*, (y_{ij}>0), has been satisfied. Condition of interest is referred to as "trigger" and can be either visual or auditory detection of Ivory-billed Woodpecker (see text for more detail).

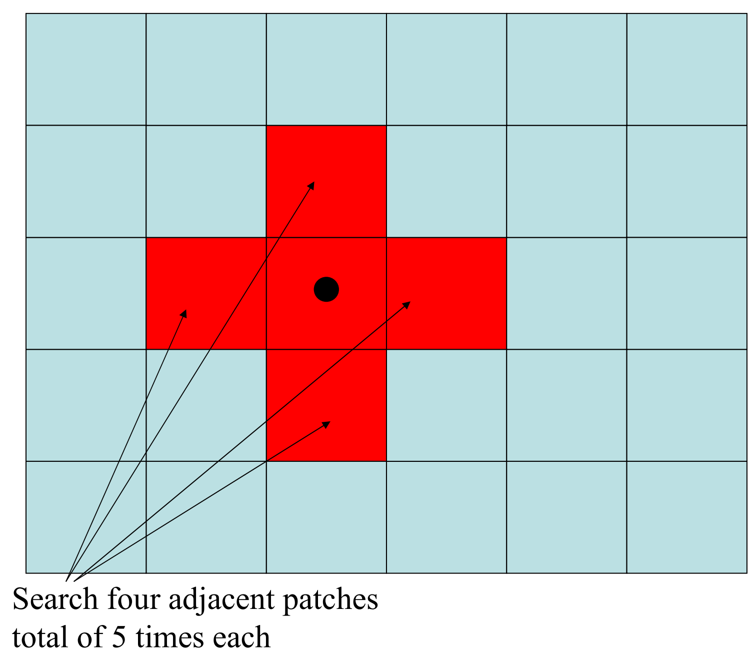

Fig. 10. Example of neighboring units added to the sample frame in adaptive sampling design after initial condition, *D*, has been met. Four adjacent patches plus initial trigger patch are searched five times.

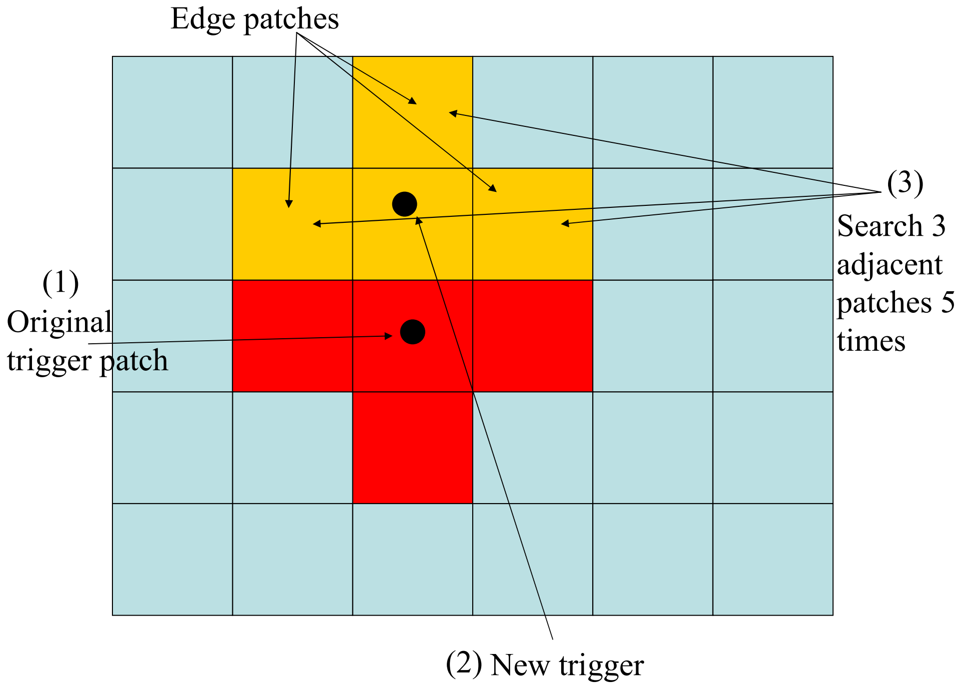

Fig. 11. An example of a neighboring unit (new trigger) satisfying the condition of interest, *D*, (y_{ij}>0), such that additional neighboring units are sampled creating a cluster of units sampled. Process is continued until a cluster of units is obtained that contains a "boundary" of units called edge units that do not satisfy condition *D*.