

**Quantifying methods to improve statistical power in grassland and passerine bird
nesting studies**

by

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The student author and the program of study committee are solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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ABSTRACT

Studying nests of grass- and ground-nesting birds is challenging because nests can be rare on the landscape and camouflage can make them difficult to locate. Yet, large sample sizes are needed understand complex interactions between nests and their environments. In this thesis, I present research on two technological approaches for addressing these challenges: thermal-imaging cameras for locating nests and thermal data loggers for monitoring nests.

In Chapter 2, I examine the use of a thermal-imaging camera for increasing the detection probability of warm bird nests against cooler background temperatures. Carrying the imager while searching for nests and using it when thermal conditions allowed did not result in a greater detection probability for bird nests. I believe this was due to prevailing sunny conditions obscuring the thermal signal from nests during the majority of the surveys, as well as dense vegetation blocking the thermal signal in much of the habitat we searched. Some study systems may benefit from use of a thermal imager, but I found the money used to purchase the device would have been better invested in additional technician hours searching for nests with traditional methods.

In Chapter 3, I describe a study where I tested (1) the impact of iButton® thermal data loggers on hatching success in grass- and shrub-nesting passerines overall and (2) as separate groups for species that either accept or reject brown-headed cowbird (*Molothrus ater*) eggs. I also tested (3) the difference between estimating daily survival rates of nests using data derived from in-person visits and data derived from iButtons. In addition, I present a simulation study to provide a general description of differences observed between in-person

visits and iButtons for estimating daily survival rate. I found that iButtons did not affect hatching success probability for grass- and shrub-nesting passerines overall or for nest parasite egg-accepting and egg-rejecting species as separate groups. I did see a trend in the data to suggest nest parasite egg-rejecting species' nests that received iButtons hatched at a lower rate, but the sample size was not sufficient to reach a definitive conclusion. Using iButtons to estimate success or failure dates in real nests of three species resulted in 0.3–0.9% higher estimates of daily survival rate, 12.2–15.3% larger sample sizes, and 2.0–6.3% reduced standard errors. The direction and trend of these measures was supported by the simulation study, although the magnitude of the effect was much smaller in the simulated data, possibly due to lower variation in the simulated data.

These studies of thermal-imaging cameras and iButton thermal data loggers provide guidance to researchers regarding available technological solutions for two common challenges in conducting bird nest studies. Research funds may be better spent on technician hours than on thermal-imaging cameras for most nest studies for ground-nesting birds, and iButton thermal data loggers represent an efficient method for increasing sample sizes and decreasing standard errors when estimating daily survival rates.

CHAPTER 1: INTRODUCTION

Land cover in Iowa in the mid-1800's was approximately 80% tallgrass prairie (Gallant et al. 2011). Over the last 150 years, Iowa's landscape has been systematically altered to promote agricultural productivity and is now composed of 65% row crop agriculture and only 5% grassland (Iowa State University Extension and Outreach 2017). Today Iowa is a powerhouse agricultural producer, leading the nation in corn, hog, egg, and ethanol production (National Agricultural Statistics Service 2015), but this transformation has had profound impacts on water quality and wildlife habitat. The percentage of water

bodies in Iowa impaired by poor water quality has been increasing for the last decade (Fig. 1.1). A contributing factor to this is storm runoff from agricultural fields that washes soil and nutrients into nearby waterways, increasing turbidity and promoting algal and bacterial growth (Carpenter et al. 1998). This addition of suspended soil and nutrients impairs the natural functions of waterways in Iowa and eventually contributes to the hypoxic zone in the Gulf of Mexico (Alexander et al. 2008).

Another consequence of the transformation of the landscape from prairie to agriculture is that grassland

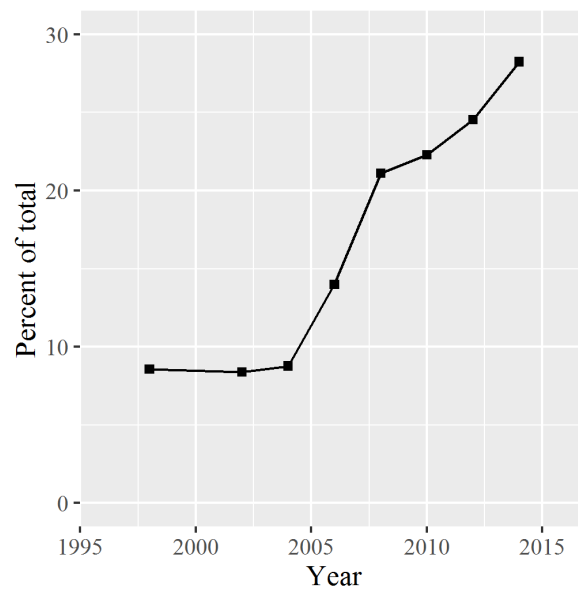


FIGURE 1.1 IOWA IMPAIRED WATER BODIES

Percentage of Iowa water bodies listed as U.S. Environmental Protection Agency category 4 & 5 for years 1998–2014 (Iowa Department of Natural Resources 2017).

habitat that supports wildlife adapted for life in the tallgrass prairie has plummeted from 10.2 million ha in the mid-1800's to 0.68 million ha in 2013, a loss of over 93% (Iowa State University Extension and Outreach 2017).

In 2005, a large multi-disciplinary team of scientists, educators, and extension specialists based out of Iowa State University formed the STRIPS (Science-based Trials of Row-crops Integrated with Prairie Strips) research group to investigate a new conservation method called prairie strips. Prairie strips are contour buffer strips of diverse native perennial vegetation expected to reduce water and nutrient runoff and soil erosion, as well as provide a number of other ecosystem services such as aesthetic value and habitat for pollinators and wildlife. Results from research conducted at Neal Smith National Wildlife Refuge (NSNWR; Jasper County, IA, USA) starting in 2007 showed that strategically positioning prairie strips on 10–20% of a corn or soybean field could reduce nitrogen runoff by up to 84% (Zhou et al. 2014), phosphorous runoff by up to 90% (Zhou et al. 2014), and sediment runoff by up to 96% (Helmets et al. 2012). Additionally, the abundance of birds in fields with prairie strips was 1.5–2.9 times higher (Schulte et al. 2016) than in fields without prairie strips. These early results point to a promising new method for combating several landscape-level conservation challenges in Iowa, but more research is needed, especially in the area of the ability of prairie strips to provide suitable wildlife habitat. The experimental fields at NSNWR ranged in size from 0.55–3.24 ha and were embedded in a matrix of wildlife refuge lands dominated by natural habitats, which is not representative of the landscape in Iowa, which is dominated by agricultural production lands (Schulte et al. 2016). These small experimental fields allowed more careful control of conservation measures than would be expected on a full scale commercial farm. The bird abundance data, however, may have been

affected by birds entering the experimental fields from the surrounding prairie and woodland matrix. To address these concerns, the STRIPS team began conducting water, soil, insect, and wildlife research on large-scale commercial farms across Iowa in 2015.

The Landscape Ecology and Sustainable Ecosystem Management lab at Iowa State University, under the direction of Dr. Lisa Schulte Moore, is investigating the potential of prairie strips to serve as wildlife habitat on commercial farms across Iowa. Studies were initiated to compare the occupancy and density of birds in fields with and without prairie strips, compare the occupancy of reptiles, amphibians, and small mammals in prairie strips and other grass areas on farms, and compare bird nest survival in prairie strips to other areas on farms.

Iowa has one of the highest percentages of privately-owned land in the United States. As a private land conservation practice, prairie strips could serve as important nesting habitat for grassland birds whose populations in North America have seen an almost 40% decline between 1968–2011, with 75% of obligate grassland species in decline over the same period (Sauer et al. 2013). To determine if prairie strips serve as quality nesting habitat or are functioning as ecological traps for birds, important demographic data from nesting attempts are needed.

Studying bird nesting is challenging for several reasons, including nests that are rare or cryptic and difficult to locate, the potential for the presence of an observer to influence the outcome of the nest, and the need for large sample sizes to model complex interactions. Compounding these general challenges of bird nesting studies, my study required locating a significant number of nests within a relatively small area of prairie strips, with the area available for study totaling only 14.8 ha in 2016. To maximize the statistical power of my

study, I needed to find a high percentage of the nests present within the prairie strips at my study sites and extract as much information from them as possible.

Bird nests may be difficult to find for multiple reasons. First and most simply, nests may be difficult to find if they are rare on the landscape. This is often the case for nests of species that are of management interest due to declining populations. For these species, it is critically important to find a large proportion of the nests present (i.e. a detection probability near 1.0) and to collect as much information from each nest found as possible, while avoiding undue disturbance to the nest. Nests of birds in grasslands may also be difficult to locate because they nest in the open and rely heavily on camouflage to avoid predation. The cryptic nature of these nests means significant effort and disturbance is required to locate them (Winter et al. 2003). For example, Winter et al. found 2,075 nests of several species over four field seasons, which is a large enough sample size to meet in-depth study objectives. Unfortunately, accomplishing this required 13–14 people per year, which is out of the budget range for many worthy projects.

Once nests are located, they need to be monitored periodically to determine if they are still active. The Mayfield method for estimating daily survival rate of nests (Mayfield 1961) forms the basis for more recent maximum likelihood methods of studying bird nest survival (Dinsmore et al. 2002). These methods recommend an observer nest visit interval of 2–4 days to obtain as precise a failure date as possible (Martin and Geupel 1993). In a recent meta-analysis, Ibáñez-Álamo et al. (2012) showed that there was no evidence for a negative impact of researcher visits on nest success across six avian orders when analyzed as a group, however there was some evidence for an observer effect on passerines when tested separately ($P = 0.058$). Ibáñez-Álamo et al.'s finding for passerines is in contrast to Götmark (1992),

who found 21% of studies showed a negative observer effect on passerines. To take a conservative approach, the need for frequent nest visits should be balanced against the possibility that frequent visits by a human observer may influence nest outcome. As an additional consideration, frequent nest visits can also impose logistical constraints on the study design by requiring an observer to return to each nest site often.

Finally, finding a large number of nests is important because factors that affect their survival are complex and operate at many scales on the landscape, requiring substantial statistical power to interpret. Factors that have been shown to influence nest survival include abundance of food items near the nest (Shochat *et al.* 2005), timing of the nesting attempt (e.g. Moynahan *et al.* 2007), the micro-habitat of the nest site (e.g. Dinsmore & Dinsmore 2007), the position of the nest within a patch (e.g. Winter *et al.* 2006), and landscape composition around the nest patch (e.g. Stephens *et al.* 2005). Large sample sizes are needed whether researchers are interested in an exploratory analysis determining all the factors affecting daily survival rate, or if they just need to control variation produced by extraneous variables to explain the effect of only a single factor of interest.

There are many technological and methodological tools available for these challenges, but my study focuses on two technological solutions that have shown promise: the use of a thermal-imaging camera to locate nests (Chapter 2) and the use of thermal data loggers to precisely estimate nest failure dates when estimating daily nest survival rates (Chapter 3). Using these two technologies, I attempted to maximize the number of nests found and the information provided from each nest for my study of prairie strips serving as nesting habitat for birds.

CHAPTER 2: THERMAL-IMAGER AVAILABILITY DOES NOT IMPROVE NEST DETECTION PROBABILITY

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ABSTRACT We conducted a designed experiment to test if having a thermal-imaging camera available increased researchers' nest detection rates when searching for bird nests in an agricultural landscape. With known active nests present, naive observers searched for nests with and without a thermal imager available for use and we found no difference in detection probabilities. Extraneous heat signatures from reflected solar radiation and dense vegetation were the key factors limiting the usefulness of thermal imagers for locating nests.

KEY WORDS detection probability, grassland birds, nest searches, nest survival, prairie strips, sample size, thermal imager.

Studies of nest success for birds are frequently used to provide demographic data necessary for developing conservation or management plans for species of interest. However, birds that nest on the ground often rely on camouflage to protect their nests, making the nests difficult

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for researchers to locate. Thermal imagers are hand-held cameras that have a sensor that detects emitted or reflected thermal infrared radiation (i.e. heat) and displays it as an image. By highlighting warm objects against cooler backgrounds, thermal imagers might enable researchers to locate cryptic bird nests that contain incubated eggs or nestlings. Indeed, thermal infrared-imaging cameras have been explored as a method for locating warm bird nests since at least 1995 (Boonstra et al. 1995). Previously, researchers have explored the use of thermal-imaging cameras for locating nests of cavity nesters, Arctic-nesting birds, grassland-nesting ducks (Boonstra et al. 1995), grassland-nesting sparrows (Galligan et al. 2003), and ground-nesting forest songbirds (Mattsson and Niemi 2006) with mixed success; yet, all the studies published to date have relied entirely on qualitative methods. To the best of our knowledge, no researchers have quantitatively compared nest detection probabilities when a thermal imager is available to detection probabilities without a thermal imager.

In this study, we searched standardized plots for bird nests with and without the availability of a thermal imager with the goal of estimating increases in nest detection probability when a thermal imager is available for use. Improving the detectability of cryptic bird nests in grass would allow researchers to increase sample sizes and thus statistical power to answer study questions.

STUDY AREA

Our study was conducted on 7 farms in central Iowa, USA in the summer of 2016 (Appendix A). Nest searches were conducted as part of a larger study examining nest survival in contour buffer strip conservation features composed of diverse native vegetation, hereafter referred to as prairie strips (Schulte et al. 2016). Farms were selected for the presence of prairie strips and other grass conservation features and were located within 100 km of Ames, Iowa. Farms

were managed for corn and soybean production and incorporated soil and water conservation features such as: grass waterways, grass back-slope terraces, grass contour buffer strips, prairie strips, cover crops, and no-till fields.

METHODS

We searched for bird nests on 125 randomly selected plots at our 7 study sites. Search plots were stratified by property and land use with 25 plots per land use: row crop with no cover crop (20×100 m), row crop with cover crop (20×100 m), narrow (5.6–10.4 m in width) prairie strips, wide (15.2–77.7 m in width) prairie strips, and exotic cool-season grass strips (7.7–71.7 m in width). Search plots in linear grass features were defined by the width of the feature and a variable length (7.4–178.2 m) to standardize the area at 0.1 ha. Crop plots were anticipated to have lower densities of nests so were created larger (20×100 m, 0.2 ha) to increase the probability of non-zero nest counts and were placed at least 50 m from a field edge.

The thermal infrared-imaging camera used was a FLIR[®] E8 handheld model (FLIR[®] E8[™], FLIR Systems, Inc., Nashua, New Hampshire, USA), sensitive to 7.5–13 μm thermal radiation at a resolution of 320×240 pixels. It was sensitive to differences of $<0.06^{\circ}\text{C}$, had an accuracy of $\pm 2^{\circ}\text{C}$, and weighed 0.575 kg with a battery life of about 6–8 hours of intermittent use. It retailed for \$3,995.

A pair of observers searched for nests in each plot for 3 minutes per 0.1 ha once per week, alternating weeks with a second pair of observers. Searches were conducted by systematically walking through the plot and disturbing vegetation with a sweeping stick while watching for flushing adult birds (Martin and Geupel 1993, Winter et al. 2003). Once a flush was observed, indicating the presence of a nest, a secondary search of the area around

the flush was conducted to locate the nest. One pair of observers carried a thermal-imaging camera and used it for secondary searches whenever environmental conditions allowed a warm nest to be distinguished from the thermal background (i.e. very early in the morning or when the sky stayed overcast through the morning). Start time and cloud cover were recorded for all plot searches, and the pair of observers carrying the thermal imager also recorded maximum temperature displayed by the thermal imager. Visual-obstruction readings were taken at the beginning and end of the field season to determine vegetation density in every plot.

Nests located by one pair of observers were not marked or revealed to the second pair so that each pairs' searches were independent. A high-precision GPS unit (Trimble® GeoXT™ 2005 Series, Trimble Inc., Sunnyvale, California, USA) was used to record the location of nests and a small autonomous thermal data logger (iButton® ThermoChron® DS1921G, Maxim Integrated, San Jose, California, USA) was placed in the nest to monitor temperature as a proxy for nest activity (Hartman and Oring 2006). The GPS coordinates, nest substrate, and presence of a temperature logger in the nest were used to match nests found by both pairs. After plot searches were complete at a site for the day, each pair of observers conducted nest visits to determine if nests they had found the previous week were still active and were available for discovery by the other pair of observers.

Because plots were searched only once per week, nests located by one pair had to survive for 6 days to be available to be discovered by the second pair. Nests that were known to be active due to discovery and subsequent checks by the first pair at the time when a search was conducted by the second pair were considered to be an “eligible trial” (Smith et al. 2009).

All eligible trials were then classed as either a miss or a discovery and used as categorical response variables in logistic regression models. Likelihood ratio tests (LRT) were used to test for significance compared to models with fewer parameters. Eligible trials were first tested for an effect from availability of a thermal imager versus the null model. A model containing a factor for thermal-imager treatment and a grouping factor for species was also tested against a model containing only a thermal-imager factor.

Direct sunlight was likely to affect the ability of an observer to differentiate the thermal signal given by a warm nest and thermal signals created by reflected solar rays. To account for this, we tested a model with main effects for thermal-imager availability and minutes elapsed since sunrise plus an interaction term against a model containing only a factor for thermal-imager use.

Because vegetation density in search plots was also likely to impact the effectiveness of the thermal imager, we modeled detection as a function of thermal imager-use plus average early-season visual-obstruction readings across each search plot compared to thermal-imager use alone. All analyses were conducted with the statistical software R (Version 3.2.5, www.r-project.org, accessed 4 Apr 2016).

RESULTS

We conducted 842 plot searches between 10 May 2016 and 27 June 2016, averaging 6.7 searches per plot over 7 weeks. Air temperature during searches varied from 6.0–34.1° C and cloud cover averaged 36.8% with a median value of 20.0%. Searches were conducted between 0.5 hours before sunrise to 11 hours after sunrise, with the mean start time of 3.5 hours after sunrise.

We located 39 nests during plots searches. Using Program MARK (White and Burnham 1999), nests were estimated to have a daily survival rate of 0.89–0.90, which predicts that only 51–53% of them would survive the 6 daily intervals between the first and second checks. Indeed, based on information from the first pair of observers, only 24 nests were known to be present and active when the second pair of observers conducted a search, forming an eligible trial (Table 2.1).

TABLE 2.1. ELIGIBLE TRIALS OF THERMAL-IMAGER AVAILABILITY FOR IMPROVING NEST DETECTION PROBABILITY

Number of eligible trials for determining the effect of availability of a thermal imager on detection probability of bird nests by species, search method, and outcome. Eligible trials are defined as an opportunity by one pair of observers to locate a nest that was known to be present and active based on information from a second pair of observers. Trials were conducted on commercial farms in central Iowa, USA in the summer of 2016.

Species	Treatment	Re-detection	Miss
Dickcissel (<i>Spiza americana</i>)	Thermal imager	1	2
Dickcissel (<i>Spiza americana</i>)	Traditional	1	3
Killdeer (<i>Charadrius vociferus</i>)	Thermal imager	0	1
Killdeer (<i>Charadrius vociferus</i>)	Traditional	0	0
Red-winged blackbird (<i>Agelaius phoeniceus</i>)	Thermal imager	2	3
Red-winged blackbird (<i>Agelaius phoeniceus</i>)	Traditional	0	2
Vesper sparrow (<i>Pooecetes gramineus</i>)	Thermal imager	0	4
Vesper sparrow (<i>Pooecetes gramineus</i>)	Traditional	0	5

We found no differences between availability and no availability of a thermal imager (LRT: $X_{23}^2 = 21.627$, $P = 0.348$). We were unable to test for differences in detectability between species (dickcissel [*Spiza americana*], killdeer [*Charadrius vociferus*], red-winged blackbird [*Agelaius phoeniceus*], and vesper sparrow [*Pooecetes gramineus*]) due to having no re-detections for killdeer and vesper sparrows. We therefore assumed that detectability was not different between species for subsequent tests.

Because the thermal signals from warm nests were clearer early in the morning, we also tested a model which included main effects and the interaction between thermal imager availability and time since sunrise against a model with thermal imager availability alone. We found no evidence for an interaction between thermal-imager availability and time since sunrise (LRT: $X_{21}^2 = 19.819$, $P = 0.169$).

We were unable to test visual-obstruction reading as a fully interactive effect with thermal-imager availability because the model did not converge. Visual-obstruction reading as an additive effect did not improve the thermal imager availability model (LRT: $X_{22}^2 = 20.747$, $P = 0.764$).

DISCUSSION

Bird nests in grass areas are often cryptic difficult to locate. In previous studies, the effectiveness of thermal-imaging devices for locating bird nests has been evaluated in a qualitative manner, but no studies have been published that used a rigorous designed experiment. We conducted such an experiment to test if having a thermal imager available for use under appropriate thermal conditions (early in the morning or under heavy cloud cover) improved detection rates for nests. We found no support to indicate that detection probabilities were different when a thermal imager was available for use.

The results from previous qualitative studies on use of thermal imagers to improve nest detection rates have been mixed. Boonstra et al. (1995) were unable to locate the nests of two grassland-nesting ducks (*Anas carolinensis*, *Anas platyrhynchos*) whose approximate location was known, until they were within a meter of the nest. They found the nests of Arctic tundra birds such as Lapland larkspurs (*Calcarius lapponicus*) and pectoral sandpipers (*Calidris melanotos*) to be obvious once the general area was known from traditional

methods. Galligan et al. (2003) found a thermal imager to be useful in pinpointing the location of nests of extremely cryptic *Ammodramus* sparrows once the general area was known from an adult flushing in response to rope dragging. Mattsson and Niemi (2006) found 2 of 19 ovenbird (*Seiurus aurocapillus*) nests using a thermal imager. Both nests were located when the opening of the domed ground nests were oriented toward the observer using the imager. They did not have success using the thermal imager to locate any nests of other ground-nesting forest songbirds. Mattsson and Niemi (2006) found the thermal imager gave no advantage for finding nests when the adult birds did not give a behavioral cue to narrow the search area and the telescope-like design of the imager they used limited its usefulness. Boonstra et al. (1995), Galligan et al. (2003), and Mattsson and Niemi (2006) all describe direct sunlight and obstruction by vegetation as factors limiting the usefulness of the imager for finding nests.

Our results included only 4 re-detections from 24 eligible trials. This relatively small, unbalanced data set made interpreting results difficult, but we believe the thermal imager did not yield an improvement in detection rates for three reasons. First, only 40% of our plot searches and 46% of our eligible trials were conducted within 2 hours of sunrise or under greater than 90% cloud cover. Reflected solar infrared rays under commonly sunny conditions made it very difficult to distinguish actual nests from background thermal noise (Fig. 2.1).

Secondly, an unobstructed line of sight was required between the nest and the thermal imager for the heat signature to be detected. Our search plot treatments had a range of vegetation densities (Fig. 2.2) measured as visual-obstruction readings in May, with median values varying between 10 cm for the crop field plots and 33.3 cm for the cool-season

contour strip plots. Vegetation density in the grass and prairie strips was relatively low at the beginning of the season, but increased substantially as the season progressed, especially in the prairie strips. However, many of the prairie strips were recently established and thus mowed partway through the season for weed control, making visual-obstruction readings taken late in the season difficult to interpret.

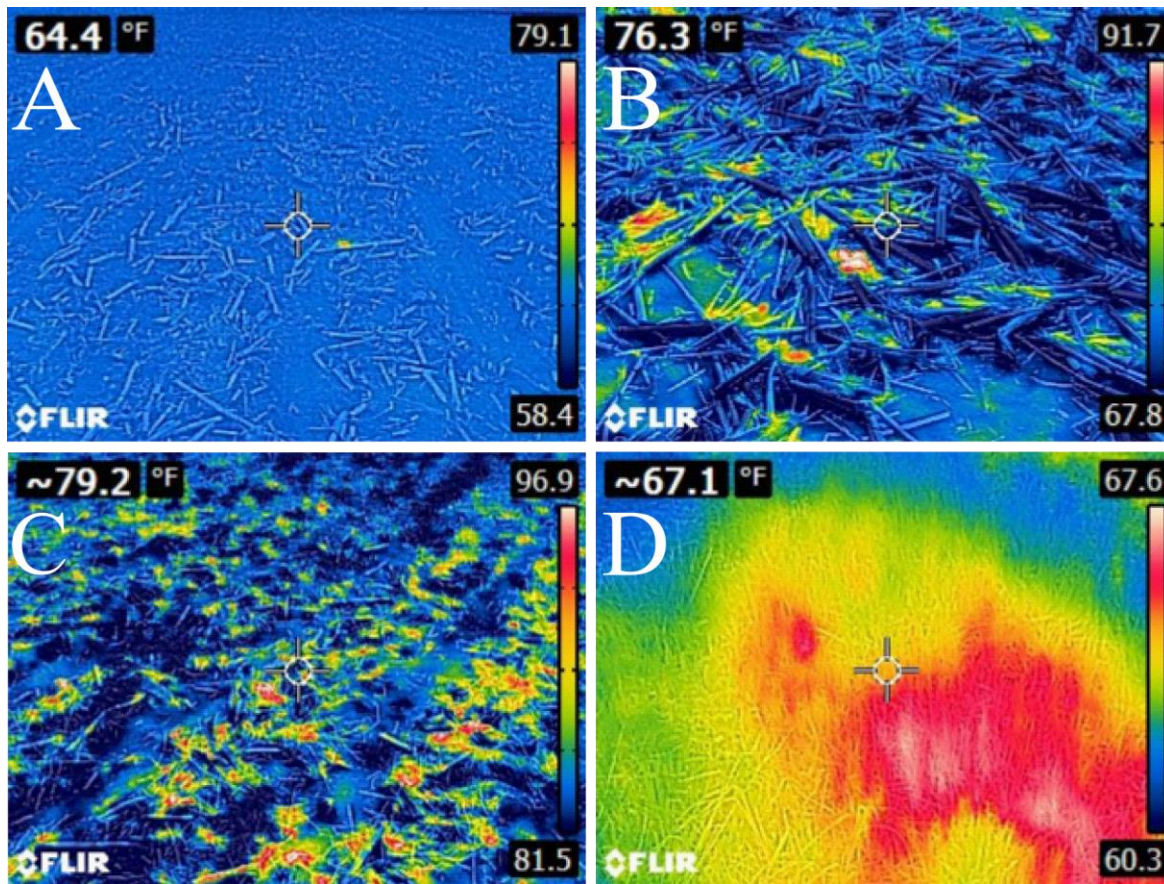


FIGURE 2.1. EXAMPLE VIEWS THROUGH A THERMAL IMAGER

The temperature in the upper left is a measurement of the thermal energy being emitted or reflected from the object in the crosshairs, not the ambient air temperature. The red–blue scale on the right of each image shows the range of emissivity values represented within the field of view. A) Vesper sparrow nest (just right of cross hairs) in a barren agricultural field before dawn. B) Killdeer nest (just below and to the left of cross hairs) in a barren agricultural field within an hour after dawn. C) Direct sunlight early in the morning reflects off many surfaces, creating a confusing image. There is no nest in this view. D) Smooth brome grass monoculture with strong reflected solar rays in the early afternoon. There is no nest in this view. (Figure best viewed in color.)

Finally, our study was designed as a practical test of the effectiveness of adding a thermal imager to our toolbox of existing nest-locating techniques and not a test of its effectiveness only under ideal conditions. If we had tested only under ideal conditions, it is possible that nest detection probabilities would have been higher using the thermal imager, but we would not have adequately addressed the overall impact on nests found. Because our motivation behind using a thermal-imaging device was to increase our sample size, we did not find the thermal imager to be an efficient use of research funds.

The thermal imager in our study cost nearly \$4000. Instead of purchasing a thermal imager to increase the number of nests in our sample, we could have instead spent the same amount of money and hired an additional research technician for 400 hours. During two field seasons in 2015 and 2016, our field crew spent a total of 3,520 hours with the primary goal of locating nests. During that time we located 537 nests for our larger study. This equates to locating nests at a rate of 1 nest per 6.5 hours of technician time (including transportation to and from sites and other

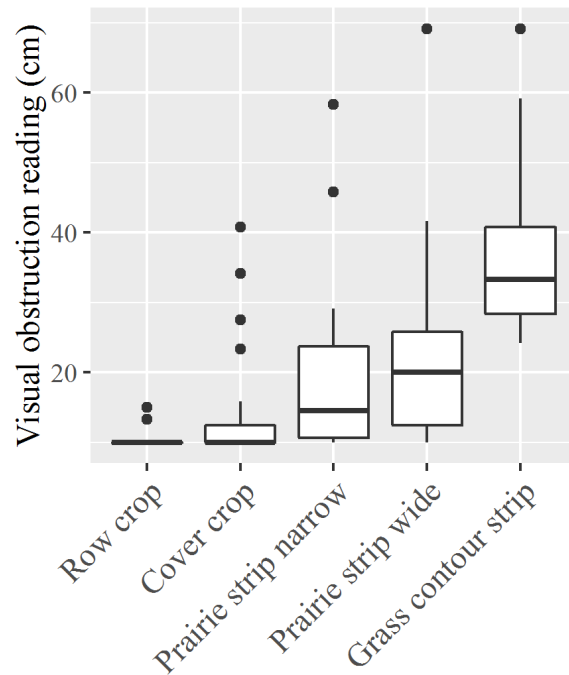


FIGURE 2.2. SEARCH PLOT VEGETATION DENSITIES

Vegetation densities measured in visual-obstruction readings (VOR) by plot type. VOR was measured in May of 2016 to estimate vegetation density at the start of the nesting season. Many of the prairie strip plots were newly established and were mowed for weed control the previous year, accounting for the relatively low VOR readings. Boxes represent the inter-quartile range (IQR), lines indicate mean values, whiskers indicate values within ± 1.5 IQR, and dots are outliers beyond those values.

non-searching tasks), or 61.5 nests per 400 technician hours. Even when considering that the thermal imager could be used across multiple field seasons, the additional technician hours would have had a much larger impact on our sample size than purchasing a thermal imager for use only when searching conditions were ideal.

While neither minutes elapsed since sunrise (representing the strength of reflected solar radiation) nor visual-obstruction readings were significant effects in our models, our experience operating the imager suggested that direct sunlight and visual obstruction were the two key limiting factors for pinpointing bird nests. This conclusion is consistent with the qualitative descriptions given by Boonstra et al. (1995), Galligan et al. (2003), and Mattsson and Niemi (2006).

While acknowledging that our sample size was somewhat small, we did not find that having a thermal imager available increased nest detection probabilities. A thermal imager may prove a valuable research tool in other study systems where observers spend more time searching for nests with no direct sunlight, such as before sunrise, under heavy cloud cover, under tree canopies, or in shaded valleys, or in areas with very low vegetation, such as tundra or sparsely vegetated forest floors. Further quantitative studies are needed to determine if study niches exist where the thermal environment is more favorable for use of a thermal-imaging device in locating bird nests.

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CHAPTER 3: IBUTTON® TEMPERATURE DATA LOGGERS INCREASE SAMPLE SIZE AND PRECISION WHEN ESTIMATING DAILY SURVIVAL RATE FOR BIRD NESTS

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ABSTRACT

Nest studies of many bird species are complicated by nests that are rare on the landscape or difficult to find. To minimize observer effects and maximize statistical power, methods are needed that minimize disturbance to nests while still yielding as much information per nest as possible. One approach to meeting these objectives is to use iButton® thermal data loggers to precisely determine nest success or failure dates without frequent, potentially disruptive in-person visits. Our study objectives were to determine (1) if iButton placement in nests of grass- and shrub-nesting passerines affected hatching probabilities overall and (2) if iButtons affected nest parasite egg-accepting and egg-rejecting species differently. We also studied (3)

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the effect of using iButton data versus in-person visits on sample size (nest exposure-days), estimated daily survival rate, and associated precision when analyzing nest data in Program MARK. We compared these two approaches to building nest histories with both real nest data and a simulation study.

We found no evidence that placement of an iButton in nests of grass- and shrub-nesting passerines affected hatching rates overall ($OR_{iButton} = 0.813$, $CI_{iButton} = 0.477-1.377$). We also found that iButtons did not affect hatching rates when nest parasite egg-accepting and egg-rejecting species' nests were analyzed separately ($OR_{iButton:accepting} = 0.594$, $CI_{iButton:accepting} = 0.082-3.819$), although the sample size was small and further research may be warranted. Nest histories created from iButton data instead of in-person visits had 12.2–15.3% more nest-observation days, 0.3–0.9% higher estimates of daily survival rate, and 2.0–6.3% decreased standard errors. Our simulation study showed increases in sample size and decreases in standard error, with larger differences for larger visit intervals, although the magnitude of the effect was much smaller than with real data.

Our findings confirm studies from previous authors that found no evidence that iButton thermal data loggers affect nest success for most passerine species, although a trend present in the data indicates caution should be used before placement in nests of species that reject eggs of nest parasites. We also found that use of iButtons increased the contribution to statistical power from each nest monitored, thus increasing the precision of estimates. We therefore suggest researchers consider their use when designing nest studies for passerine species.

KEY WORDS

Brown-headed cowbird, grassland birds, iButton, nest survival, passerine, precision, sample size, simulation, statistical power, thermal data logger.

INTRODUCTION

Bird nests are commonly located and studied to provide demographic information to understand and manage bird populations, especially those in decline. Obtaining robust estimates of nest survival can be challenging, however, because nests can be cryptic and difficult to locate (Martin and Geupel 1993), frequent visits by observers may influence the outcome of the nest (Götmark 1992, Ibáñez-Álamo et al. 2012), and large sample sizes are needed to quantify complex interactions between survival and environmental factors.

iButton® thermal data loggers (iButton ThermoChron® DS1921G, Maxim Integrated, San Jose, California, USA) may help overcome these challenges by allowing researchers to obtain more information from each nest through fewer visits, thus offering the opportunity to attain larger sample sizes required to suitably parameterize demographic models.

Finding an adequate number of nests can require significant searching effort. For example, in a grassland bird study, Winter et al. (2003) found 2,075 passerine nests over four field seasons, but required 13–14 people per field season to accomplish this. Each observer averaged only 4 nests per week. Many grassland bird nest searching strategies require an adult to flush from the nest to provide the initial indication that a nest is nearby. Giovanni et al. (2011) found that western meadowlarks (*Sturnella neglecta*) only flushed from the nest on 19% of trials when a rope was dragged over them. This example demonstrates that even when significant labor resources are available, nest detection probability can still be low, resulting in a low percentage of nests found. Because of the difficulty of locating nests, every

nest that is found should provide the maximum amount of information possible and observer effort should be focused on locating new nests rather than frequent visits to known nests.

Nest survival analyses using the Mayfield method (Mayfield 1975) or more recent maximum likelihood methods (Dinsmore and Dinsmore 2007) implemented in Program MARK (White and Burnham 1999) require that observers have periodically re-visited nests to determine the date the nest either succeeded or failed. This information can then be used to determine the average daily survival rate for a population of nests. When conducting nest survival studies, investigators are often encouraged to keep visit intervals as small as possible to reduce uncertainty in the success or failure date (Martin and Geupel 1993). However, re-visiting nests too frequently carries the risk of influencing the fate of the nest, either positively or negatively (Götmark 1992, Ibáñez-Álamo et al. 2012) as well as requiring more effort on the part of the researcher that might otherwise be spent on finding more nests and increasing sample size.

Many factors influence bird nest survival on scales varying from the micro-habitat around a nest (<1 m) to landscape scales (>1 km) and large sample sizes are needed to tease apart these complex interactions. Factors that have been shown to influence nest survival include abundance of food items near the nest (Shochat et al. 2005), timing of the nesting attempt (e.g. Moynahan et al. 2007), the micro-habitat of the nest site (e.g. Dinsmore and Dinsmore 2007), the position of the nest within a patch (e.g. Winter et al. 2006), and landscape composition around the nest patch (e.g. Stephens et al. 2005). Sample units in nest studies are nest-exposure days, or the number of days nests are under observation. Each nest provides a variable contribution to overall sample size depending on how long it is observed before succeeding or failing.

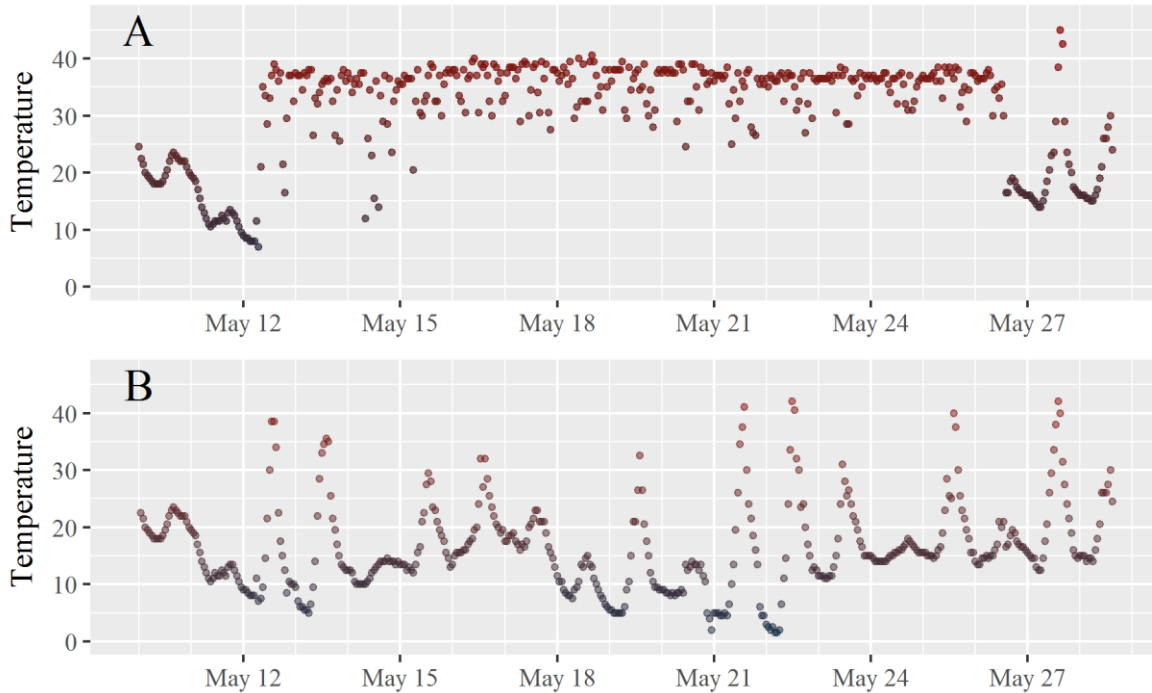


FIGURE 3.1. EXAMPLE iBUTTON NEST TEMPERATURE DATA

Temperature data recorded (A) inside the nest and (B) directly outside the nest of a vesper sparrow in 2015 in central Iowa, USA. The iButton® was deployed when the nest was discovered shortly after the last egg was laid on the morning of 12 May and removed after nest failed on 28 May. Active nests generally show a steady high temperature compared to iButtons monitoring the environmental temperature outside the nest, with a clear return to a daily high–low pattern after nest failure.

Temperature can be used as an indicator of biological activity in nests because incubated eggs and living nestlings create a warmer, less variable thermal environment than the area outside the nest (Fig. 3.1 and 3.2). Portable temperature probes have been used to remotely monitor nest failure times since at least 2000 (Jackson and Green 2000), but more recently cost and size have been reduced enough to make them a practical option for most nest studies.

iButton-brand thermal data loggers represent an improvement over past temperature monitoring devices because they are small (=17.35 mm diameter \times 5.89 mm thick), rugged, and autonomous. They have been used since 2003 to autonomously monitor adult activity at

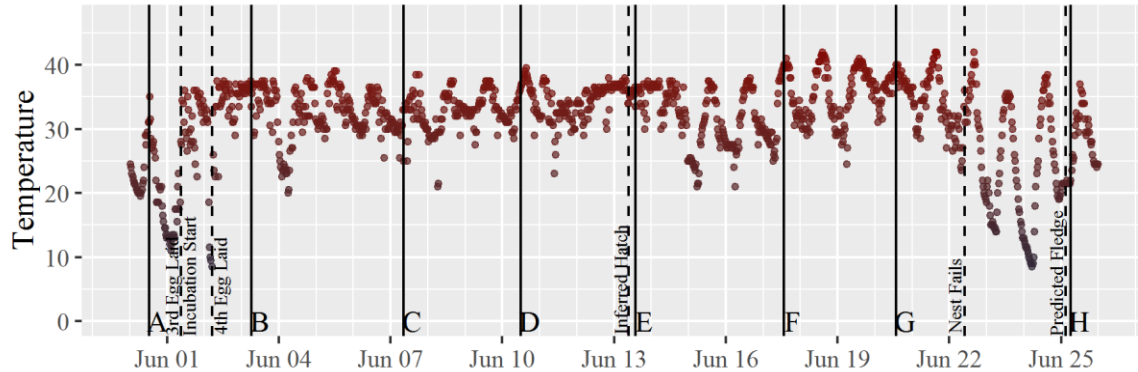


FIGURE 3.2. EXAMPLE iBUTTON DATA WITH NEST STATUS CHANGES AND IN-PERSON VISITS NOTED

Example of iButton temperature data from a red-winged blackbird nest in 2016 in central Iowa, USA. In-person visits are marked by letters and solid lines and dashed lines indicate a transition in nest state. A) 31 May: iButton is inserted when nest contains a single blackbird egg. A second egg is laid 31 May and incubation begins after the laying of the third egg on 1 Jun. A fourth egg is laid 2 Jun. B) 3 Jun: Nest contains 4 eggs. C) 7 Jun: Nest maintains 4 eggs. D) 10 Jun: Nest maintains 4 eggs E) 13 Jun: Nest contains 3 young and 1 egg. Young are still wet from hatching that morning. F) 17 Jun: One young has been predated, two remain. G) 20 Jun: Second young has disappeared, one remains. H) 25 Jun: Nest is empty. Last young predated 22 Jun. Fledge date predicted from hatch date was 25 Jun.

nests (Badyaev et al. 2003) and since 2006 to monitor nest temperatures as a proxy for nest survival (Hartman and Oring 2006). Hartman and Oring (2006) first used iButtons to monitor the timing of predation in 39 of 78 long-billed curlew (*Numenius americanus*) nests; Schneider and McWilliams (2007) monitored 13 of 46 piping plover (*Charadrius melodus*) nests with iButtons; and Sutti and Strong (2014) monitored 34 of 161 nests of 16 species of riparian forest-, edge-, and scrub-nesting birds with iButtons. The results of these studies suggest iButtons do not impact nest success, but robust conclusions were limited by the small number of studies evaluating their impact and small sample sizes within those studies. Furthermore, Sutti and Strong (2014) were the only investigators we are aware of that have evaluated iButton impacts on passerine nests, and they did not address potential differences between bird species that accept or reject eggs of nest parasites such as brown-headed

cowbirds (*Molothrus ater*). This is an important distinction because the appearance of brown-headed cowbirds eggs in a nest are known to cause some species to abandon their nesting attempt (Lowther 1993).

Brown-headed cowbirds are nest parasites that reproduce by laying eggs in host nests so that the host bird does the work of raising the parasite's young. At least 144 passerine species have been known to accept cowbird eggs and raise them to fledging (Lowther 1993). Cowbird eggs and young usually develop faster than the host species and frequently the cowbird young outcompete the host young for food (Lowther 1993), reducing the chance of the host young successfully fledging. However, some passerine species have the ability to identify and reject foreign eggs in their nest as a defense against nest parasitism (Lowther 1993). iButton temperature data loggers are small, circular, and dull in color and could be interpreted by birds as a foreign egg and thus could cause an increased level of abandonment when inserted into the nest of a nest parasite egg-rejecting species. We were unable to locate any prior studies which examined differences in nest success between nest parasite egg-accepting and egg-rejecting species when iButtons were used.

We conducted a designed experiment to determine the extent to which the presence of an iButton in nests of grass- and shrub-nesting passerines during the egg laying or incubation stages affected egg hatching rates of (1) all bird species combined and (2) nest parasite egg-accepting versus egg-rejecting species differently. Our final objective was (3) to quantify differences in estimates of daily survival rates between nests visited by an observer every 3–4 days and nests monitored daily with an iButton, using both real nests and a simulation study. Our goal was to determine the safety and utility of iButton thermal data loggers for use in passerine nest survival studies.

MATERIALS AND METHODS

We conducted searches for nests of grass- and shrub-nesting birds on 7 farms in central Iowa, USA in the summers of 2015 and 2016. Nest searches were conducted as part of a larger study examining nest survival in contour buffer strip conservation features composed of diverse, native vegetation, hereafter referred to as prairie strips (Schulte et al. 2016). Farms were selected for the presence of prairie strips and other grass conservation features and were located within 100 km of Ames, Iowa, USA (Appendix A). Farms were managed for corn and soybean production and utilized soil and water conservation features including grass waterways, grass back-slope terraces, exotic cool-season grass contour buffer strips, diverse prairie strips, cover crops, and no-till fields. Landscapes surrounding the farms were dominated by row crop agriculture growing corn and soybeans with some pastures and woods.

Areas with perennial vegetation, fencerows, and row crop fields were searched for bird nests by 2–4 observers walking abreast and watching for birds flushing from nests. In 2016, when we located a passerine nest with eggs or young we flipped a coin to determine if it received an iButton thermal data logger or was held as a control. Nests of non-passerines (e.g. shorebirds, gallinaceous birds) were monitored, but were not included in this study because they were few in number and are not targeted by cowbirds. In 2015, most nests encountered were monitored with an iButton as part of the larger prairie strips study, but assignment of an iButton was not randomized. Data from those nests were only included in our investigation of differences between in-person visits and monitoring with iButtons, and not included in our investigation of iButton impact on hatching success. We attempted to visit all nests every 2–4 days regardless of iButton presence.

iButton thermal data loggers are small, water-resistant (IP56 rated), autonomous devices that record temperatures at a constant interval between 1–255 minutes. We used model DS1921G, which is accurate to $\pm 1^{\circ}\text{C}$ at temperatures between -30°C to $+70^{\circ}\text{C}$ with a resolution of 0.5°C , and has memory to store 2048 temperature readings. We programmed them to record the temperature every 20 minutes, which allowed the units to operate for 28.4 days before running out of memory.

iButtons can be ejected from nests by adult birds and must be securely fastened in the nest. To accomplish this, iButtons were first activated and programmed with a start time and recording interval using software provided by the manufacturer (Maxim Integrated, San Jose, CA, USA). Next, monofilament lines with two long (15–20 cm) strings were attached to the iButton using hot melt adhesive thermoplastic to provide a method of securely tying the unit inside a nest. Finally, the iButtons, with monofilament ties, were dipped into clear PlastiDip® brand liquid plastic coating (Plasti Dip International, Blaine, Minnesota, USA) to provide additional weatherproofing (Roznik and Alford 2012), and improve the attachment of the hot glue and monofilament line to the steel case. The overall finished color was dull grey. The two monofilament lines could be passed through the wall of a nest with a 10 cm drapery sewing needle and securely tied inside the bowl of the nest with the iButton in contact with the eggs or young. For ground nests with minimal nest structure we prepared iButtons by affixing them to a 7.6 cm metal spike with hot glue and dipping them in PlastiDip. This allowed them to be anchored directly to the ground instead of tied to the nest substrate.

To meet our first objective of assessing the effect of iButtons on hatching success among all species, we analyzed data using a logistic regression model with the statistical

software R (Version 3.2.5, www.r-project.org, accessed 4 Apr 2016). Hatching success was a binomial response variable and a factor for iButton presence was the main effect. We report the odds ratio (OR) and a 95% confidence interval (CI) for all analyses.

To meet our second objective, we tested whether installation of an iButton affected hatching success differently between nest parasite egg-accepting or egg-rejecting species by adding a main effect for an egg-accepting or egg-rejecting factor and an interaction term to the previous model. We also applied a contrast for nest parasite egg-accepting or rejecting status to a linear model of hatching success as a function of iButton treatment plus species with an interaction term, using only species for which there was at least one hatched and one failed nest for the two iButton treatments: American robin (*Turdus migratorius*), eastern/western meadowlarks (*Sturnella spp.*), dickcissel (*Spiza americana*), and red-winged blackbird (*Agelaius phoeniceus*). We then predicted the hatching rate of nest parasite egg-accepting and egg-rejecting species with and without an iButton to look for biologically significant trends in the data to inform future investigations.

To investigate our third objective of iButton impact on sample size, estimated daily survival rate, and the precision of that estimate, we analyzed both real nest data and created a simulation study. Using our real nest data for species with more than 30 nests, we created two sets of encounter histories for all nests monitored with an iButton in 2015 and 2016. The first encounter history was based only on data obtained from in-person visits made to the nest and the second encounter history was based on the best available data. This was typically data from the iButton, but sometimes included data from in-person visits in instances where iButtons were not recovered. Encounter histories contained nests of only a single species and both real nest and simulation encounter histories were analyzed with Program MARK using

the RMark package (Laake 2013) in R to look for differences in estimated daily survival rate and the associated precision.

To further investigate our third objective, we conducted a statistical simulation study to more generally explore the impact of iButtons on sample size, estimation of daily survival rate, and associated precision. Nest data were generated in R and analyzed using package RMark. Data sets of nests were simulated using code modified from Gibson et al. (2016; Gibson 2016). Nest histories were modeled on the 12 day incubation stage of red-wing blackbirds with a constant daily survival rate of 0.91, which was the value we estimated using our dataset of 141 red-winged blackbird nests. We simulated data sets of 400, 100, and 40 nests with a random failure date that had a geometric distribution with a daily survival rate of 0.91.

A nest detection matrix was then created by assigning each day a nest was active a probability of 0.75 that it would be detected. A binomial trial was run for each nest starting on the first day it was active to determine if it was found on that day. Once a nest was first discovered (and assigned a value of 1), the rest of the days the nest was active in the detection history were also populated with 1 values. Completed nest detection matrices held fewer than the starting number of nests because some nests failed before discovery. A detection probability of 0.75 was chosen because the resulting distribution of age at first discovery approximated the distribution in our real data.

Two encounter histories were then created from each nest detection history. The first encounter history was created by determining the first day a nest was detected in the detection matrix and what its status was starting on the day discovered and at fixed interval of 2–7 days thereafter. A second encounter history was created by determining the first day a

nest was detected in the detection matrix and checking its status every day to simulate the data provided by an iButton. Each pair of encounter histories based on the same nest detection history were then analyzed using package RMark in Program R to compare sample size, estimated daily survival rate, and standard error of the estimated daily survival rate. We ran the simulation for 400, 100, and 40 nests at each visit interval of 2–7 days 5000 times to produce 10,000 paired encounter histories per nest number and visit interval combination (Appendix C).

RESULTS

In 2015, we located 18 dickcissel, 92 red-winged blackbird, and 23 vesper sparrow nests and assigned iButtons to all nests. In 2016, we located and randomly assigned iButtons to 235 passerine nests (Table 3.1). We were unable to retrieve 29 of 163 iButtons (17.8%) deployed in 2015 or 21 of 171 iButtons (12.3%) deployed in 2016 due to nest predation or flooding events. The loss rate for nest parasite egg-accepting species was 14.0% and the loss rate for egg-rejecting species was 21.4%, but the difference was not significant ($P = 0.66$). Nests treated with iButtons that were not recovered were still included in the analyses using the survival dates estimated from in-person visits. See Appendix B for a full list of nests found in 2015 and 2016.

To assess the impact of iButtons on hatching success, we used data from 239 nests of 10 species located and monitored during the summer of 2016 (Table 3.1). We found no evidence that insertion of an iButton affected hatching success ($OR_{iButton} = 0.813$, $CI_{iButton} = 0.477–1.377$).

We monitored nests of 218 nest parasite egg-accepting species and 21 nest parasite egg-rejecting species (Table 3.1) in 2016. Nest parasite egg-accepting and egg-rejecting

group hatching rates did not differ before accounting for iButton presence ($OR_{\text{Accepting}} = 0.601$, $CI_{\text{Accepting}} = 0.242\text{--}1.503$). An additive model incorporating effects for iButton presence and egg-accepting or egg-rejecting status with an interaction term did not show a significant effect for the interaction ($OR_{\text{iButton:Accepting}} = 0.594$, $CI_{\text{iButton:Accepting}} = 0.082\text{--}3.819$). We also found no evidence that nest parasite egg-accepting or rejecting status affected hatching success when added as a contrast to a model of iButton treatment plus species plus an interaction (intercept = 0.688, $CI = -2.353\text{--}0.345$).

TABLE 3.1 NESTS WITH RANDOMIZED ASSIGNMENT OF IBUTTONS

Nests fitted with iButton thermal data loggers or held as controls with nest parasite egg-accepting or egg-rejecting status. Nests were located on farms in central Iowa, USA in the summer of 2016.

Species	Nest parasite egg-accepting or egg-rejecting	iButton nests (hatch:fail)	Control nests (hatch:fail)
American goldfinch (<i>Spinus tristis</i>)	Accepting	2:0	1:2
Common yellowthroat (<i>Geothlypis trichas</i>)	Accepting	1:3	0:1
Dickcissel (<i>Spiza americana</i>)	Accepting	9:18	7:14
Grasshopper sparrow (<i>Ammodramus savannarum</i>)	Accepting	0:1	0:0
Red-winged blackbird (<i>Agelaius phoeniceus</i>)	Accepting	26:43	28:48
Song sparrow (<i>Melospiza melodia</i>)	Accepting	1:0	0:1
Vesper sparrow (<i>Pooecetes gramineus</i>)	Accepting	2:5	0:5
Subtotal: Egg-accepting nests		41:70	36:71
American robin (<i>Turdus migratorius</i>)	Rejecting	3:2	2:4
Brown thrasher (<i>Toxostoma rufum</i>)	Rejecting	1:2	0:0
Eastern/Western meadowlark (<i>Sturnella spp.</i>)	Rejecting	3:2	1:1
Subtotal: Egg-rejecting nests		7:6	3:5
Total nests		48:76	39:76

Predictions of hatch rate were estimated based on a fully interactive iButton:Accepting model. Predicted hatch rates were lower for nest parasite egg-rejecting species that received iButtons ($P[\text{hatch}] = 0.462$, $\text{SE} = 0.138$) than for egg-rejecting species without iButtons ($P[\text{hatch}] = 0.625$, $\text{SE} = 0.171$) or for egg-accepting species with and without iButtons ($P[\text{hatch}] = 0.624$, $\text{SE} = 0.046$ and $P[\text{hatch}] = 0.657$, $\text{SE} = 0.046$, respectively). However, a goodness of fit test indicated the data did not fit the model ($X_{235}^2 = 311.41$, $P < 0.001$).

A total of 141 red-winged blackbird nests, 61 dickcissel nests, and 35 vesper sparrow nests found in 2015 and 2016 were used for comparing in-person visits to iButton-derived nest histories. In-person visit intervals averaged 3.78 days ($\text{SD} = 1.64$ days). iButton visit intervals averaged 1.33 days ($\text{SD} = 0.997$ days) due to some iButtons not being retrieved and in-person visit intervals being used instead. iButton-derived encounter histories had later last

TABLE 3.2. COMPARISON OF ESTIMATES MADE WITH IN-PERSON VERSUS IBUTTON DATA

Number of nests, nest exposure-days, estimated daily survival rate (DSR), probability of a nest surviving 12 days until hatching ($P[\text{hatch}]$), and associated standard error (SE) for red-winged blackbird, dickcissels, and vesper sparrows calculated using visit-only information and combined visit and iButton data. Data collected in central Iowa, USA in the summers of 2015 and 2016.

	Exposure				
	Nests	days (<i>n</i>)	DSR	$P(\text{hatch})$	SE
Dickcissel visit-only	61	308	0.8927	0.2562	0.0164
Dickcissel visit and iButton	61	355	0.8955	0.2658	0.0161
% change	0.0%	15.3%	0.3%	3.8%	-2.0%
Vesper sparrow visit-only	34	216	0.9069	0.3094	0.0189
Vesper sparrow visit and iButton	35	244	0.9148	0.3433	0.0177
% change	2.9%	12.9%	0.9%	11.0%	-6.3%
Red-winged blackbird visit-only	139	869	0.9085	0.3161	0.0093
Red-winged blackbird visit and iButton	141	975	0.9120	0.3313	0.0090
% change	1.4%	12.2%	0.4%	4.8%	-3.5%

active dates than visit-derived encounter histories ($P < 0.001$, $\bar{x} = 0.726 \pm 0.189$) and had 0.3–0.9% higher estimates of daily survival rate with 2.0–6.3% smaller standard errors (Table 3.2).

To test the general case of these results, we simulated the differences between visiting nests on intervals of 2–7 days and using an iButton to check nest status every day for data sets starting with 400, 100, and 40 nests. Sample sizes (n = number of days nests were under observation) were consistently larger for data created using a one-day interval and standard errors were smaller (Fig. 3.3). The percent difference in standard errors between estimates made from fine and coarse scale visit intervals (Fig. 3.4) were small for smaller visit intervals (0.11–0.14%) and for larger data sets (0.11–1.4%), but increased as visit intervals increased (1.4–1.8%) and sample sizes decreased (0.14–1.8%).

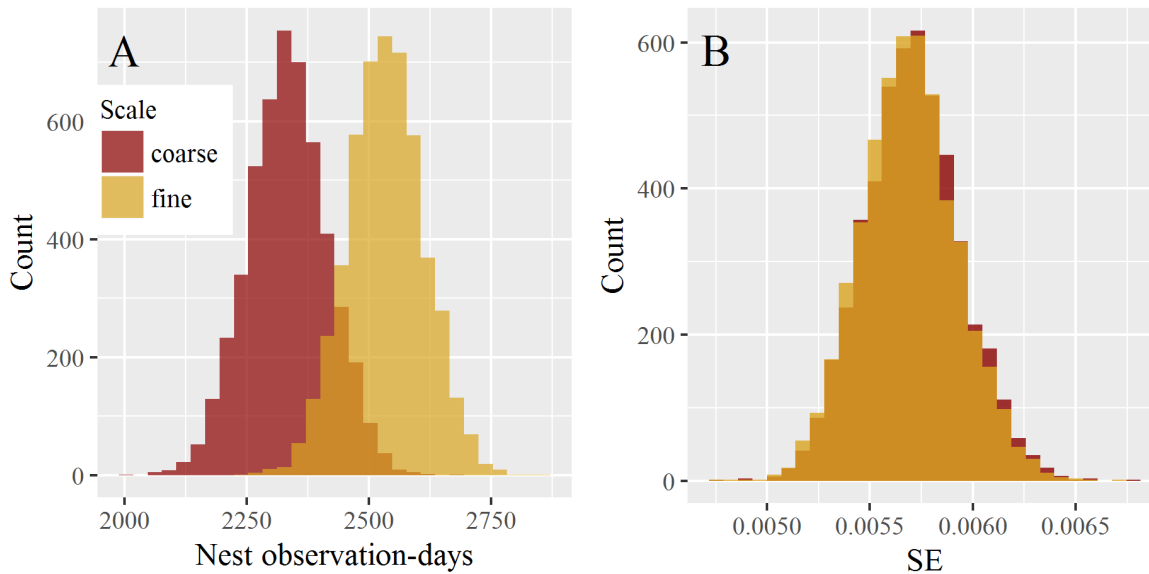


FIGURE 3.3. SIMULATED 3-DAY VISIT INTERVAL VERSUS DAILY IButton DATA

Comparison of simulated nest encounter histories based on a 3-day visit schedule (coarse) or an iButton-based daily visit schedule (fine). Each nest data set was started with 400 nests and the simulation was run 5000 times to produce 10,000 paired nest encounter histories. (A) Distributions of sample sizes (number of days nests were under observation) between coarse and fine scale encounter histories. (B) Distributions of standard errors for coarse and fine level visit data.

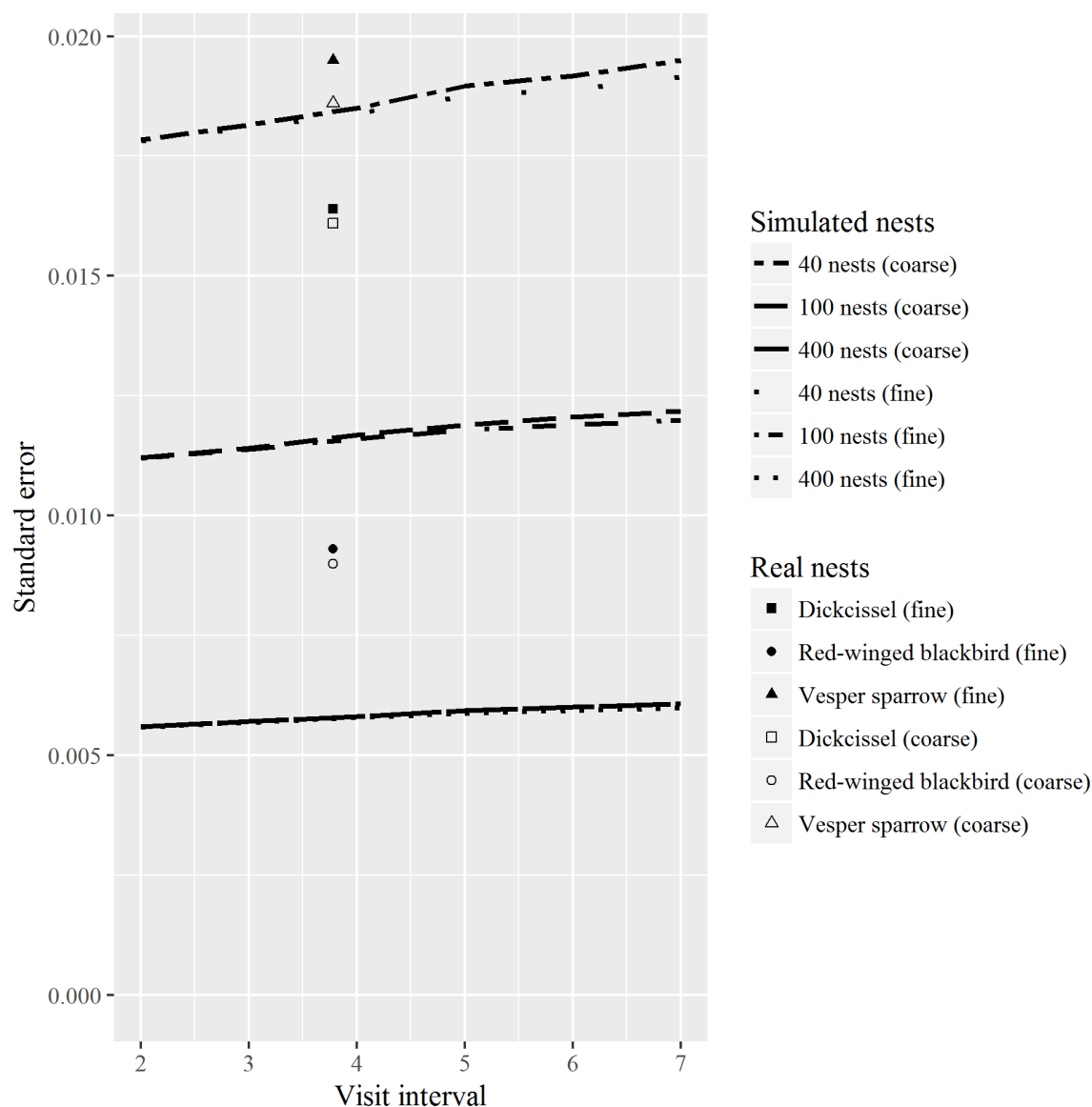


FIGURE 3.4. STANDARD ERRORS ON ESTIMATION OF DAILY SURVIVAL RATE AS A FUNCTION OF VISIT INTERVAL AND DATA SET SIZE

Standard errors of daily survival rates estimated from simulated data. Simulated data sets were started with 400, 100, and 40 nests and each run at visit intervals of 2–7 days. Simulated nest histories at each of 2–7 day (coarse) visit intervals (dashed lines) were paired with daily (fine) iButton intervals (dotted lines) for comparison. Each paired visit interval and iButton interval was simulated 5000 times. Standard errors from real nest data (Table 3.2) are also included for dickcissel, red-winged blackbird, and vesper sparrow for both coarse (mean visit interval 3.78 d) and fine (mean visit interval 1.33 d). Improvements in standard errors increased with smaller sample sizes and longer in-person visit intervals.

DISCUSSION

In monitoring nests of 10 passerine species with iButtons, we did not find evidence of a lower overall hatching success rate nor evidence of differences among nest parasite egg-accepting and egg-rejecting species. However, additional study of iButton impact on nest parasite egg-rejecting species' nests may be warranted. Use of iButtons to create nest encounter histories also resulted in larger nest survival sample sizes, higher estimated daily survival rates, and smaller standard errors compared to those created using visits by observers every 3–4 days. By simulating daily nest visits compared to visits at intervals ranging 2–7 days, we found that daily nest checks resulted in larger sample sizes and more precise estimates of daily survival rate, with increases in precision growing as the interval between in-person visits lengthened.

iButton effect on hatching success

When analyzing all species together, we did not find a difference in hatching rates between nests treated with an iButton and those that were not. We looked at hatching success and not fledging success in this study because fledging rates were low, which produced an unbalanced failure to success sample ratio and because insertion of a foreign object into the nest was hypothesized to have small or no effect on a nest already containing hatched young. Cowbird eggs laid in nests where host young have already hatched were rarely successful (Stephenson, pers. obs.) and may not have been viewed as a threat that warranted abandonment by either egg-accepting or egg-rejecting host birds.

When we added a grouping effect for nest parasite egg-accepting and egg-rejecting species, we did not find a difference in hatch rate. However, our sample was not well balanced between egg-accepting and egg-rejecting species, with almost 10 times fewer nests

of egg-rejecting species. Predictions based on the model of hatching rate as a function of iButton treatment and nest parasite response status for nests of egg-rejecting species treated with an iButton hatched only 72.6% as often as the other three groups. While this finding is interesting from a study planning perspective, the predictions were made from a model with over-dispersed data and a low level of statistical support, and care should be taken in interpreting it. Additional research should be focused on increasing sample sizes of egg-rejecting species' nests to confirm or refute our finding of no significant difference in hatching rates.

This support for the safety and utility of using iButtons to study nests of nest parasite egg-accepting passerine species gives researchers assurance that using iButtons to improve their nest monitoring studies does not adversely affect hatching success. Although our prediction of a lower hatching rate from nest parasite egg-rejecting species treated with an iButton was based on a model with poor statistical support, the trend present in the data should encourage researchers to be cautious with iButton use in nests of egg-rejecting species until further study with larger sample sizes can provide more insight.

iButton effect on daily survival rate

The daily survival rates of the nests we studied were in the general range of published estimates. Reported daily survival rates for dickcissels varied from 0.967 in CP33 (USDA Conservation Reserve Program upland bird habitat) buffers in northeast Mississippi, USA (Adams et al. 2013) to 0.940 in agricultural buffers in Mississippi (Conover et al. 2011) to 0.913 in CP33 buffers in southeast Iowa (Henningesen and Best 2005). Our observed estimate of 0.893–0.896 is somewhat lower, but similar to the numbers reported for similar habitat reported by Henningesen and Best (2005). Published daily survival rates for red-winged

blackbirds varied from 0.959–0.907 in CP33 buffers in northeast Mississippi (Adams et al. 2013) to 0.914–0.931 in CP33 buffers in southeast Iowa (Henningsen and Best 2005) to 0.903 in agricultural buffers in Mississippi (Conover et al. 2011). Our observed values of 0.909–0.912 fall within the reported range.

Using real nests from three species of grass-nesting songbirds, we compared estimates of daily survival rates derived from in-person visits and from iButton data. We found that compared to in-person visit data, iButton data resulted in sample sizes that were 12.2–15.3% larger with daily survival rates estimated 0.3–0.9% higher, or an estimated 3.8–11.0% increased probability of eggs surviving until hatching. Standard errors of the estimated daily survival rate decreased by 2.0–4.5%.

Sample sizes for estimating daily survival rate in Program MARK are measured in nest exposure-days, or the number of days a nest was under observation. Each exposure-day contributes one degree of freedom to the maximum likelihood estimation of daily survival rate, with an additional degree of freedom provided by the entire period between the last confirmed active nest date and the date of failure discovery. Sample sizes were larger for encounter histories created using iButton data because long uncertainty periods at the end of unsuccessful nests could be converted to multiple additional nest exposure-days with a shorter uncertainty period, thus increasing the total degrees of freedom. For example, the nest in Figure 3.2 was determined to be first active on 1 June, the last live check was 20 June, and the last check was 25 June. This yielded 19 degrees of freedom for being confirmed active 1–20 June, and one degree of freedom for the uncertainty period from 21–25 June. From the iButton data on this nest, we determined that incubation began 1 June, it remained active until 22 June, and it was assigned a last checked date of 23 June (the day after the iButton

recorded the failure). This gave us 21 degrees of freedom for being active from 1–22 June and one degree of freedom for the uncertainty period from 22–23 June. In this example, the iButton data allowed us 2 additional degrees of freedom in the maximum likelihood estimation of daily survival rate. This increased sample size lowered the standard error and contributed to a more precise estimate of daily survival rate, which allowed greater statistical power for testing covariates on daily survival rates.

Simulated nest histories based on daily nest checks with an iButton also resulted in an increase in sample size and small improvements in precision over nest histories simulated based on multi-day visit intervals. Improvements in precision increased with larger visit intervals and smaller nest data sets (Fig. 3.4). In the simulated data, the effect size of the increased precision was smaller than in the real nest data, with estimates using real data showing an improvement of 2.0–4.5% and simulated data showing between 0.1–1.8% for similar visit intervals. We hypothesize that this is likely due to the small amount of variation present in the simulated data. The simulated data was created from a model of constant daily survival rates and estimated in Program MARK using the same model. Daily survival rates of nests in real data sets are affected by many factors operating at multiple scales and are never estimated with a completely accurate model. We believe this helps to explain the magnitude in the differences in the improvement of the standard errors between the in-person visit and the iButton data. However, the simulated data does validate the general case that iButton-derived visit histories will generally increase sample sizes and decrease standard errors compared to in-person visit derived nest histories, and that the improvements are larger for longer visit intervals.

Improvements to precision due to simulated iButton use were much smaller than improvements made by increasing the number of nests in the data set (Fig. 3.4). Potential improvements to statistical power from iButtons thus comes mainly from increased logistical flexibility resulting from having to conduct fewer nest checks. When using an iButton, most nests only need to be re-visited shortly after predicted hatching or fledging dates so the researcher can accurately determine the fate of the nest. This allows researchers to spend more time searching for new nests, and less time re-checking previously found nests.

Conclusions

Our study design also allowed us to determine an error rate for assignment of nest status by in-person observation. By comparing iButton temperature data to in-person visit data, we found only 3.3% of nests were erroneously labeled active during a period when they had actually failed. In addition, iButton temperature data allowed the inclusion of 3 nests (1.3%) that became active and subsequently failed between observer visits. For example, the nest in Figure 3.2 had an iButton inserted during the egg-laying period before incubation began. If it had been predated between 1 June and 4 June, the next observer who visited on 4 June would have found a failed nest with no evidence it had ever been active and the nest would not have been included in the analysis. Nests with erroneous last active dates contributed 20 nest observation days (1.3% of the total) and nests with iButtons that became active and failed between observer visits contributed 7 observation days (0.4% of the total).

Our study experienced a low rate of iButton loss. Many iButtons that were removed from a nest by a predator could be located by manually searching the area under the nest, but on occasion we were unable to locate removed iButtons. We attribute this to predators carrying the iButtons some distance before discarding them. In 2016, the use of a small metal

detector (Garrett™ Super Scanner® Model 1165180, Garrett Metal Detectors, Garland, Texas, USA) improved our iButton recovery rate.

Finally, we did not find iButtons to be useful for determining the date of nest failures caused by brown-headed cowbird nest parasitism. We defined failure dates for these nests as the last observed date that viable host eggs or young were present in the nest. Depending on how nest failure dates for parasitized nests are defined for a particular study, this may be an important consideration.

In conclusion, we found that use of iButtons for monitoring nest status did not affect hatching success of shrub- and grass-nesting passerines generally, although further research is warranted to determine if nest parasite egg-rejecting species hatch rates are negatively affected. We also found that nest histories created using temperature data from iButtons increased estimated daily survival rates and sample sizes, and lowered standard errors, resulting in greater statistical power. This finding was generally confirmed using a simulation study, although the gains in precision offered by shortening uncertainty dates in individual nest histories are not as great as gains made by increasing the number of nests overall. Researchers conducting nest survival studies should consider using thermal data loggers to maximize the contribution to statistical power from each nest found and allow researchers to re-visit nests less often, resulting in more time to locate new nests. However, caution may be warranted when using iButtons in the nests of nest parasite egg-rejecting species.

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Any mention of trade, product, or firm names is for descriptive purposes only, and does not imply endorsement by the U.S. Government.

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CHAPTER 4: GENERAL CONCLUSIONS

Grassland birds in North America have declined by almost 40% between 1968–2011 (Sauer et al. 2013). This decline is being driven by loss or degradation of grassland habitat continent-wide, including replacement of grassland with agricultural land, fragmentation of remaining grasslands, degradation of rangelands in the western US, and re-forestation in the eastern US (Brennan and Kuvlesky 2005). Stopping and eventually reversing the loss of grassland habitat will be necessary to halt the decline of North American grassland birds.

Conversion of native grasslands to row-crop agriculture has had many impacts in Iowa, including loss of wildlife habitat, large-scale soil loss, and degradation of water quality. An innovative approach to conservation called prairie strips (Science-based Trials of Row-crops Integrated with Prairie Strips) is seeking to lessen these impacts. The prairie strips conservation practice converts 10–20% of a field-level watershed in a row-crop field to diverse native perennial contour buffer strips. Research began on prairie strips at Iowa State University in 2005 and has demonstrated that contour strips of dense, thick-stemmed native vegetation is effective at reducing nitrogen runoff by up to 84% (Zhou et al. 2014), phosphorus runoff by up to 90% (Zhou et al. 2014), and sediment runoff by up to 96% (Helmets et al. 2012). Early research efforts also showed that birds were 1.5–2.9 times more abundant in fields with prairie strips (Schulte et al. 2016), but more research on their usefulness to wildlife is needed, including whether prairie strips serve as quality nesting habitat or are functioning as ecological traps.

Studying the nest survival of birds that nest in grasslands presents many challenges, including difficulty locating very cryptic nests in large enough numbers to draw robust conclusions. My study came with the additional challenge of only having access to 14.8 ha of prairie strips, limiting the total number of nests within the focus land cover that was available for

research. For these reasons, my initial investigation of birds nesting in prairie strips has focused on investigating methods of improving nest detection using a thermal imager and obtaining more information from each nest using iButton thermal data loggers.

In Chapters 2 and 3, I presented findings on two methods for improving nest survival studies. In Chapter 2, I investigated the effectiveness of using a thermal-imaging camera for locating warm nests against a cool background. I found that having a thermal imager available for use under appropriate conditions did not improve nest detection rates, likely due to prevailing sunny conditions during most survey hours and dense vegetation obstructing the thermal signature from warm nests. It is possible that a study focusing on use of the thermal imager during optimal sunlight conditions might find a significant effect, but my study was a practical test of the imager's usefulness over the whole of a regular day of field work (approximately 0500–1300 hours). Because I have already invested in the thermal imager, I will continue to use it when conditions allow, but it will not be a significant part of my nest-searching strategy.

In Chapter 3, I presented a study regarding the use of iButton thermal data loggers for determining nest success or failure dates. I found that installing an iButton into grass- and shrub-nesting passerine nests did not affect egg hatching rates overall, or for nest parasite egg-accepting or egg-rejecting species analyzed as separate groups. Although I did not find statistically significant differences, a trend in the data from nest parasite egg-rejecting species was suggestive of higher failure rates that may become significant with larger sample sizes. I found that use of iButtons to determine nest failure dates increased sample sizes and resulted in higher estimates of daily survival rate with increased precision. The direction and trend of these findings were supported using a simulation study, although the magnitude of the effect was not as large and greater gains can be made by increasing the number of nests in the sample. In light

of these findings, in the future I will use iButtons to improve estimates of daily survival rate in the nests of all birds except for nest parasite egg-rejecting species to allow me more time to locate new nests. For nests of nest-parasite egg-rejecting species, I will continue to randomly assign treatments of iButtons or no iButtons to obtain a larger sample and clarify if iButtons are indeed reducing hatching rates.

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APPENDIX A:STUDY SITE SUMMARY

TABLE A.1. SUMMARY OF STUDY SITES.

Farm	County	Years searched	Crop rotation	Area searched (ha)	Conservation features	Feature area (ha)
GUTH	Story	2015-2016	Corn/soybean with cover crop	16.9	Grass waterways	2.2
					Prairie strips	1.2
KALD	Jasper	2015-2016	Soybean/corn	65-90	Contour strips	2.9
					Filter strip	4.5
					Grass waterways	5.2
					Prairie strips	1.3
					Terraces	0.4
MCCL	Jasper	2015-2016	Soybean/corn	65-80	Contour strips	4.8
					Filter strips	2.4
					Grass waterways	5.1
					Terraces	2.0
RHOD	Marshall	2016	Soybean/corn	33.3	Filter strip	0.8
					Grass waterways	1.0
					Prairie strips	0.8
SMIT	Wright	2015-2016	Corn/soybean with cover crop	149.7	Block grassland	5.9
					Filter strips	4.2
					Grass waterways	1.5
					Prairie strips	4.5
WORL	Story	2015-2016	Corn/corn/soybean	21.4	Block grassland	1.7
					Grass waterways	0.9
					Prairie strips	0.7
WTRK	Guthrie	2016	Corn/soybean with cover crop	128.0	Block grassland	50.2
					Contour strips	4.4
					Grass waterways	9.0
					Prairie strips	5.4
					Terraces	1.3

APPENDIX B: ALL NESTS BY LAND COVER

TABLE B.1. TOTAL NESTS FOUND IN 2015 AND 2016

Nests found in 2015 and 2016 by species and land cover type. Search effort was not even between land cover types, so nests found should not be interpreted as nest densities. See chapter 3 for descriptions of investigated land cover types.

Species	Block grassland	Contour strip	Ditch	Filter strip	Prairie strip	Row crop	Stream	Terrace	Water -way	Woody	Other	Total
American goldfinch (<i>Spinus tristis</i>)		1		1				2	3			7
American robin (<i>Turdus migratorius</i>)	4	1	3	3		3		1	7	15	1	38
Brown thrasher (<i>Toxostoma rufum</i>)			3					1	2	4		10
Chipping sparrow (<i>Spizella passerine</i>)	1								1			2
Common yellowthroat (<i>Geothlypis trichas</i>)	6			1				1	2			10
Dickcissel (<i>Spiza americana</i>)	8	29	3	3	17	3		10	23	1	1	98
Eastern bluebird (<i>Sialia sialis</i>)									1			1
Grasshopper sparrow (<i>Ammodramus savannarum</i>)					1				2			3
Gray catbird (<i>Dumetella carolinensis</i>)				1						4		5
Gray partridge (<i>Perdix perdix</i>)						1						1
Killdeer (<i>Charadrius vociferus</i>)				1		8						9
Lark sparrow (<i>Chondestes grammacus</i>)						1						1
Loggerhead shrike (<i>Lanius ludovicianus</i>)	1											1
Mallard (<i>Anas platyrhynchos</i>)								1				1
E./W. meadowlark (<i>Sturnella magna/neglecta</i>)		12							2	1		15
Mourning dove (<i>Zenaida macroura</i>)	3					2		1		4		10
Northern cardinal (<i>Cardinalis cardinalis</i>)								1				1
Ring-necked pheasant (<i>Phasianus colchicus</i>)	1	1							1			3

TABLE B.1 CONTINUED

Species	Block grassland	Contour strip	Ditch	Filter strip	Prairie strip	Row crop	Stream	Terrace	Water -way	Woody	Other	Total
Red-winged blackbird (<i>Agelaius phoeniceus</i>)	26	15	12	65	23		4	2	110		2	259
Song sparrow (<i>Melospiza melodia</i>)				2	2			1				5
Spotted sandpiper (<i>Actitis macularius</i>)					1							1
Upland sandpiper (<i>Bartramia longicauda</i>)					2	3						5
Vesper sparrow (<i>Pooecetes gramineus</i>)			1	1	16	22			8			48
Wild turkey (<i>Meleagris gallopavo</i>)				1								1
Yellow-billed cuckoo (<i>Coccyzus americanus</i>)				1								1
Total	50	59	22	80	62	43	4	22	162	29	4	536

APPENDIX C:SIMULATION CODE

```
#####
# Nest survival simulation
# Effect of monitoring interval on SE
# Last updated 04-17-2017
#####

#####
# Section 1: Describe simulation
#####
# Below is a modified version of the nest simulation modeling code published at http://dan-gibson.weebly.com/nest-survival-simulation.html
# a version of which was originally presented in Gibson et al. 2016. doi: 10.1002/ece3.2148
# The premise behind the simulation is that iButton thermal dataloggers allow a 1-day or less visit frequency,
# which allows for improved precision of the estimate of Daily Survival Rate in Program MARK
# This analysis was fit using Program MARK with the RMark package
# The original code that was provided on Dan Gibson's website was modified for this project by Matt
Stephenson and Dr. Robert Klaver
#####

require(RMark)
require(plyr)
require(reshape)
require(reshape2)
require(data.table)
require(dplyr)
library(ggplot2)
library(extrafont)

#####
# The simulation is currently set for an initial sample sizes of 100 nests
# Modify the mod.occ and n variables to adjust initial sample size

#####
#Changes to
#Using a similar number of nests to the real-world nest dataset seems appropriate

sim.nsurviv <- function() {
  #Specify number of occasions
  n.occasions<-80
  #Modify the number of occasions for other lengths
  mod.occ <- 60
  #Specify the nesting period
  nest.period<-12
  #Define nest initiation rates
  n = 5
  #Release the individuals
  n.marked<-c(rep(n,n.occasions-mod.occ), rep(0,n,n.occasions-mod.occ))
  n.indiv<-sum(n.marked)
  nest.init<-rep(1:10, each = n)
  logit<-function(p) log(p/(1-p))
  expit<-function(x) 1/(1+exp(-x))
}
```

```

#Define nest survival as a constant function (dot model)
S0 <- 0.91
#S0<-0.8
b0<-logit(S0)
p<-rep(1,n.occasions-1)
S<-expit(b0)

# Create the 'truth' scenario
simul.pos<-function(Phi,P,n.marked)
{
  Phi<-matrix(S,n.occasions,nrow=n.indiv,byrow=FALSE)
  n.occasions<-length(p)+1
  P<-matrix(p,n.occasions-1,nrow=n.indiv,byrow=T)
  CH<-matrix(0,ncol=n.occasions,nrow=sum(n.marked))
  #define a vector with marking occasion
  mark.occ<-rep(1:length(n.marked),n.marked[1:length(n.marked)])
  #fill in CH
  for (i in 1:sum(n.marked))
  {
    CH[i,mark.occ[i]]<-1
    if (mark.occ[i]==n.occasions) next
    for(t in (mark.occ[i]+1):n.occasions)
    {
      #survive?
      sur<-rbinom(1,1,Phi[i,t-1])
      if(sur==0) break #move to next
      #recaptured?
      rp<-rbinom(1,1,P[i,t-1])
      if(rp==1) CH[i,t]<-1
    } #t
  } #i
  return(CH)
}

####function to create capture history character strings (need for input to RMARK)
pasty<-function(x)
{
  k<-ncol(x)
  n<-nrow(x)
  out<-array(dim=n)
  for (i in 1:n)
  {
    out[i]<-paste(x[i,],collapse="")
  }
  return(out)
}

#Simulate a run
sim.nests<-simul.pos(Phi,P,n.marked)
n.ind <- sum(n.marked)
encounter.history<-matrix(ncol = n.occasions, nrow = n.ind)
nest.init<-rep(1:(n.occasions-mod.occ), each = n)
# allow nests to hatch
hatch <- nest.period
for(i in 1:n.ind){

```

```

for(j in 1:n.occasions){
  if(sum(sim.nests[i,1:j]) > hatch) {
    encounter.history[i,j] <- 0 } else {
      encounter.history[i,j] <- sim.nests[i,j]
    }
  }
}

# Define how often observers check nests, once at a coarse scale and once at a fine scale
#####
##### Coarse scale visitation #####
#####

#####
# 2 day schedule
# visit.history.c <- encounter.history
# for(i in 1:n.ind){
#   for(j in 1:(n.occasions-nest.period+1)){
#     if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+3]<-0
#       visit.history.c[i,j+5]<-0
#       visit.history.c[i,j+7]<-0
#       visit.history.c[i,j+8]<-0
#       visit.history.c[i,j+10]<-0
#     }
#     else
#       if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
#       visit.history.c[i,j+1]<-0
#     }
#   }
# }

#####
# 3 day schedule
# visit.history.c <- encounter.history
# for(i in 1:n.ind){
#   for(j in 1:(n.occasions-nest.period+1)){
#     if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+2]<-0
#       visit.history.c[i,j+4]<-0
#       visit.history.c[i,j+5]<-0
#       visit.history.c[i,j+7]<-0
#       visit.history.c[i,j+8]<-0
#       visit.history.c[i,j+10]<-0
#     }
#     else
#       if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+2]<-0
#     }
#   }
# }

```

```
#####
# 4 day schedule
visit.history.c <- encounter.history
for(i in 1:n.ind){
  for(j in 1:(n.occasions-nest.period+1)){
    if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
      visit.history.c[i,j+1]<-0
      visit.history.c[i,j+2]<-0
      visit.history.c[i,j+3]<-0
      visit.history.c[i,j+5]<-0
      visit.history.c[i,j+6]<-0
      visit.history.c[i,j+7]<-0
      visit.history.c[i,j+9]<-0
      visit.history.c[i,j+10]<-0
    }
    else
      if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
        visit.history.c[i,j+1]<-0
        visit.history.c[i,j+2]<-0
        visit.history.c[i,j+3]<-0
      }
    }
  }
}
#####
# 5 day schedule
# visit.history.c <- encounter.history
# for(i in 1:n.ind){
#   for(j in 1:(n.occasions-nest.period+1)){
#     if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+2]<-0
#       visit.history.c[i,j+3]<-0
#       visit.history.c[i,j+4]<-0
#       visit.history.c[i,j+6]<-0
#       visit.history.c[i,j+7]<-0
#       visit.history.c[i,j+8]<-0
#       visit.history.c[i,j+9]<-0
#       visit.history.c[i,j+10]<-0
#     }
#     else
#       if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
#         visit.history.c[i,j+1]<-0
#         visit.history.c[i,j+2]<-0
#         visit.history.c[i,j+3]<-0
#         visit.history.c[i,j+4]<-0
#       }
#     }
#   }
# }
#####
# 6 day schedule
# visit.history.c <- encounter.history
# for(i in 1:n.ind){
#   for(j in 1:(n.occasions-nest.period+1)){
```

```

#   if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
#     visit.history.c[i,j+1]<-0
#     visit.history.c[i,j+2]<-0
#     visit.history.c[i,j+3]<-0
#     visit.history.c[i,j+4]<-0
#     visit.history.c[i,j+5]<-0
#     visit.history.c[i,j+7]<-0
#     visit.history.c[i,j+8]<-0
#     visit.history.c[i,j+9]<-0
#     visit.history.c[i,j+10]<-0
#   }
#   else
#     if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+2]<-0
#       visit.history.c[i,j+3]<-0
#       visit.history.c[i,j+4]<-0
#       visit.history.c[i,j+5]<-0
#     }
#   }
# }
#####
# 7 day schedule
# visit.history.c <- encounter.history
# for(i in 1:n.ind){
#   for(j in 1:(n.occasions-nest.period+1)){
#     if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & visit.history.c[i,j+(nest.period-1)] == 1){
#       visit.history.c[i,j+1]<-0
#       visit.history.c[i,j+2]<-0
#       visit.history.c[i,j+3]<-0
#       visit.history.c[i,j+4]<-0
#       visit.history.c[i,j+5]<-0
#       visit.history.c[i,j+6]<-0
#       visit.history.c[i,j+8]<-0
#       visit.history.c[i,j+9]<-0
#       visit.history.c[i,j+10]<-0
#     }
#     else
#       if(encounter.history[i,j] == 1 & visit.history.c[i,j] == 1 & length(which(encounter.history[i,]==1)) !=
nest.period){
#         visit.history.c[i,j+1]<-0
#         visit.history.c[i,j+2]<-0
#         visit.history.c[i,j+3]<-0
#         visit.history.c[i,j+4]<-0
#         visit.history.c[i,j+5]<-0
#         visit.history.c[i,j+6]<-0
#       }
#     }
#   }
#####
#####
#Create a matrix of detection dates
det.prob <- 0.75
DH<-matrix(0,ncol=n.occasions,nrow=sum(n.marked))

```

```

for(i in 1:sum(n.marked)){
  for(j in 1:n.occasions){
    detected<-rbinom(1,1,det.prob)
    if(visit.history.c[i,j] == 1 & detected==1){
      DH[i,j] <- 1
    }
  }
}
#Incorporate detection probabilities
DayFound<-matrix(nrow = n.ind, ncol = 1)
for(i in 1:n.ind){
  if(rowSums(DH)[i] == 0){
    DayFound[i] <- 0
  }
  else{
    DayFound[i] <- which.max(DH[i,])
  }
}

#Need to ensure nests are discovered on a vist day so they don't get credit for being observed before being
discovered
FirstFound<-DayFound
#####
# 2 day schedule
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
# 3 day schedule
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 4){
#     FirstFound[i] <- 4
#   }
#   if(FirstFound[i] > 4 & FirstFound[i] < 7){
#     FirstFound[i] <- 7
#   }
#   if(FirstFound[i] > 7 & FirstFound[i] < 10){
#     FirstFound[i] <- 10
#   }
#   if(FirstFound[i] > 10 & FirstFound[i] < 13){
#     FirstFound[i] <- 12
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####

```



```

# 4 day schedule
for(i in 1:n.ind){
  FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
}
for(i in 1:n.ind){
  if(FirstFound[i] > 1 & FirstFound[i] < 5){
    FirstFound[i] <- 5
  }
  if(FirstFound[i] > 5 & FirstFound[i] < 9){
    FirstFound[i] <- 9
  }
  if(FirstFound[i] > 9 & FirstFound[i] < 12){
    FirstFound[i] <- 12
  }
  if(FirstFound[i] < 1 | FirstFound[i] >= 13){
    FirstFound[i] <- NA
  }
}
#####

# 5 day schedule
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 6){
#     FirstFound[i] <- 6
#   }
#   if(FirstFound[i] > 6 & FirstFound[i] < 11){
#     FirstFound[i] <- 11
#   }
#   if(FirstFound[i] > 11 & FirstFound[i] < 16){
#     FirstFound[i] <- 16
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####

# 6 day schedule
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 8){
#     FirstFound[i] <- 7
#   }
#   if(FirstFound[i] > 8 & FirstFound[i] < 13){
#     FirstFound[i] <- 13
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####

# 7 day schedule

```

```

# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 8){
#     FirstFound[i] <- 8
#   }
#   if(FirstFound[i] > 9 & FirstFound[i] < 13){
#     FirstFound[i] <- 15
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
row.sums <- apply(visit.history.c, 1, sum)
KnownAlive<-matrix(nrow = n.ind, ncol = 1)
for(i in 1:n.ind){
  if(row.sums[i] > 0){ #changed from 1 to 0
    KnownAlive[i]<- tail(which(visit.history.c[i,] == 1), n=1)
  } else{
    KnownAlive[i] <- NA
  }
}
LastAlive<-KnownAlive - nest.init + 1
#Hatched nests terminate at fate date, failed nests terminate after being
# detected, which is 1-6 days post-failure, depending on visit interval
LastCheck<-matrix(nrow = n.ind, ncol = 1)
daysactive <- max.col(visit.history.c, ties.method = "last") - max.col(visit.history.c, ties.method = "first") + 1
Fate<-matrix(nrow = n.ind, ncol = 1)
for(i in 1:n.ind){
  if(daysactive[i] == nest.period) {
    Fate[i] <-0}
  else{
    Fate[i] <-1}
}
#####
# 2 day schedule
# for(i in 1:n.ind){
#   if(Fate[i] == 0) {LastCheck[i] <- hatch}
#   else
#   if(Fate[i] == 1 & daysactive[i] == 11) {LastCheck[i] <- hatch}
#   else{LastCheck[i]<- daysactive[i] + 2}
# }
# 3 day schedule
# for(i in 1:n.ind){
#   if(Fate[i] == 0) {LastCheck[i] <- hatch}
#   else
#   if(Fate[i] == 1 & daysactive[i] == 10) {LastCheck[i] <- hatch}
#   else{LastCheck[i]<- daysactive[i] + 3}
# }
# 4 day schedule
for(i in 1:n.ind){
  if(Fate[i] == 0) {LastCheck[i] <- hatch}
  if(Fate[i] == 1 & daysactive[i] == 1) {LastCheck[i] <- 5}
  if(Fate[i] == 1 & daysactive[i] == 5) {LastCheck[i] <- 9}
}

```

```

    if(Fate[i] == 1 & daysactive[i] == 9) {LastCheck[i] <- 12}
  }
  # 5 day schedule
  # for(i in 1:n.ind){
  #   if(Fate[i] == 0) {LastCheck[i] <- hatch}
  #   if(Fate[i] == 1 & daysactive[i] == 1) {LastCheck[i] <- 6}
  #   if(Fate[i] == 1 & daysactive[i] == 6) {LastCheck[i] <- 11}
  #   if(Fate[i] == 1 & daysactive[i] == 11) {LastCheck[i] <- hatch}
  # }
  # 6 day schedule
  # for(i in 1:n.ind){
  #   if(Fate[i] == 0) {LastCheck[i] <- hatch}
  #   if(Fate[i] == 1 & daysactive[i] == 1) {LastCheck[i] <- 7}
  #   if(Fate[i] == 1 & daysactive[i] == 7) {LastCheck[i] <- hatch}
  # }
  # 7 day schedule
  # for(i in 1:n.ind){
  #   if(Fate[i] == 0) {LastCheck[i] <- hatch}
  #   if(Fate[i] == 1 & daysactive[i] == 1) {LastCheck[i] <- 8}
  #   if(Fate[i] == 1 & daysactive[i] == 8) {LastCheck[i] <- hatch}
  # }
#####
  for(i in 1:n.ind){
    if(LastCheck[i]>hatch) {LastCheck[i] <- hatch}
  }
  Freq<-matrix(1, nrow = n.ind, ncol = 1)

  sim.data.c<-as.data.frame(cbind(FirstFound, LastAlive,LastCheck,Fate,Freq))
  names(sim.data.c)<-c("FirstFound","LastPresent","LastChecked","Fate", "Freq")
  sim.data.c <- sim.data.c[sim.data.c$FirstFound <= sim.data.c$LastPresent,] #Removing nests that were not
  found prior to discovery
  sim.data.c <- sim.data.c[!is.na(sim.data.c$FirstFound),]

#####
##### Fine (1 day) visitation #####
#####

  observer.effort.f<-1
  visit.history.f <- encounter.history
  for(i in 1:n.ind){
    for(j in 1:n.occasions){
      if(encounter.history[i,j] == 1){visit.history.f[i,j]<-rbinom(visit.history.f[i,j], 1, observer.effort.f)}
    }
  }
  #Incorporate random aspect of nest detection
  DayFound<-matrix(nrow = n.ind, ncol = 1)
  for(i in 1:n.ind){
    if(rowSums(DH)[i] == 0){
      DayFound[i] <- 0
    }
    else{
      DayFound[i] <- which.max(DH[i,])
    }
  }
  #Need to ensure nests are discovered on a vist day so they don't get credit for being observed before being
  discovered

```

```
#####
# 2 day schedule
# FirstFound<-DayFound
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
# 3 day schedule
# FirstFound<-DayFound
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 4){
#     FirstFound[i] <- 4
#   }
#   if(FirstFound[i] > 4 & FirstFound[i] < 7){
#     FirstFound[i] <- 7
#   }
#   if(FirstFound[i] > 7 & FirstFound[i] < 10){
#     FirstFound[i] <- 10
#   }
#   if(FirstFound[i] > 10 & FirstFound[i] < 13){
#     FirstFound[i] <- 12
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
# 4 day schedule
FirstFound<-DayFound
for(i in 1:n.ind){
  FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
}
for(i in 1:n.ind){
  if(FirstFound[i] > 1 & FirstFound[i] < 5){
    FirstFound[i] <- 5
  }
  if(FirstFound[i] > 5 & FirstFound[i] < 9){
    FirstFound[i] <- 9
  }
  if(FirstFound[i] > 9 & FirstFound[i] < 12){
    FirstFound[i] <- 12
  }
  if(FirstFound[i] < 1 | FirstFound[i] >= 13){
    FirstFound[i] <- NA
  }
}
#####
```

```

# 5 day schedule
# FirstFound<-DayFound
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 6){
#     FirstFound[i] <- 6
#   }
#   if(FirstFound[i] > 6 & FirstFound[i] < 11){
#     FirstFound[i] <- 11
#   }
#   if(FirstFound[i] > 11 & FirstFound[i] < 16){
#     FirstFound[i] <- 16
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
# 6 day schedule
# FirstFound<-DayFound
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 8){
#     FirstFound[i] <- 7
#   }
#   if(FirstFound[i] > 8 & FirstFound[i] < 13){
#     FirstFound[i] <- 13
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
# 7 day schedule
# FirstFound<-DayFound
# for(i in 1:n.ind){
#   FirstFound[i] <- FirstFound[i] - nest.init[i] + 1
# }
# for(i in 1:n.ind){
#   if(FirstFound[i] > 1 & FirstFound[i] < 8){
#     FirstFound[i] <- 8
#   }
#   if(FirstFound[i] > 9 & FirstFound[i] < 13){
#     FirstFound[i] <- 13
#   }
#   if(FirstFound[i] < 1 | FirstFound[i] >= 13){
#     FirstFound[i] <- NA
#   }
# }
#####
row.sums <- apply(visit.history.f, 1, sum)

```

```

KnownAlive<-matrix(nrow = n.ind, ncol = 1)
for(i in 1:n.ind){
  if(row.sums[i] > 0){ #changed from 1 to 0
    KnownAlive[i]<- tail(which(visit.history.f[i,] == 1), n=1)
  } else{
    KnownAlive[i] <- NA
  }
}
LastAlive<-KnownAlive - nest.init + 1
#Hatched nests terminate at fate date, failed nests terminate after being
# detected, which at this resolution is always 1 day post-failure
LastCheck<-matrix(nrow = n.ind, ncol = 1)
ObserverEffort.f<-matrix(sample(1:1, size = nrow(encounter.history)*1, replace = TRUE), nrow =
nrow(encounter.history), ncol = 1) #Adjust sample frame
daysactive <- max.col(visit.history.f, ties.method = "last") - max.col(visit.history.f, ties.method = "first") + 1
Fate<-matrix(nrow = n.ind, ncol = 1)
for(i in 1:n.ind){
  if(daysactive[i] == nest.period) {
    Fate[i] <-0}
  else{
    Fate[i] <-1}
}
for(i in 1:n.ind){
  if(Fate[i] == 0) {LastCheck[i] <- hatch}
  else{
    LastCheck[i]<- daysactive[i] + ObserverEffort.f[i]}
}
for(i in 1:n.ind){
  if(LastCheck[i]>hatch) {LastCheck[i] <- hatch}
}
Freq<-matrix(1, nrow = n.ind, ncol = 1)

sim.data.f<-as.data.frame(cbind(FirstFound, LastAlive,LastCheck,Fate,Freq))
names(sim.data.f)<-c("FirstFound","LastPresent","LastChecked","Fate", "Freq")
sim.data.f <- sim.data.f[sim.data.f$FirstFound <= sim.data.f$LastPresent,] #Removing nests that were not
found prior to discovery
sim.data.f <- sim.data.f[!is.na(sim.data.f$FirstFound),]

#####
##### Run MARK #####
#####
DotCoarse=mark(sim.data.c, nocc=nest.period, model="Nest", output=FALSE,
               model.parameters=list(S=list(formula=~1)))

est.c <- DotCoarse$results$real[1]
se.c <- DotCoarse$results$real[2]
n <- DotCoarse$results$n
coarse <- cbind(est.c, se.c, n)
coarse$resolution <- "coarse"

DotFine=mark(sim.data.f, nocc=nest.period, model="Nest", output=FALSE,
             model.parameters=list(S=list(formula=~1)))

est.f <- DotFine$results$real[1]
se.f <- DotFine$results$real[2]
n <- DotFine$results$n

```

```

    fine <- cbind(est.f, se.f, n)
    fine$resolution <- "fine"

    result <- rbind(fine, coarse)

    return(result)
}

#Create outputs for fine and coarse visit schedules
output.f <- data.frame(sim=NA, estimate=NA, se=NA, n=NA)
output.c <- data.frame(sim=NA, estimate=NA, se=NA, n=NA)

start.time <- Sys.time()

for(i in 1:20) {
  mysim <- sim.nsurviv()
  output.f[i,"sim"] <- i          #simulation rep
  output.f[i,"estimate"] <- mysim[1,1] #DSR estimate (fine)
  output.f[i,"se"] <- mysim[1,2]    #SE (fine)
  output.f[i,"n"] <- mysim[1,3]     #n (fine)
  output.c[i,"sim"] <- i          #simulation rep
  output.c[i,"estimate"] <- mysim[2,1] #DSR estimate (coarse)
  output.c[i,"se"] <- mysim[2,2]    #SE estimate (coarse)
  output.c[i,"n"] <- mysim[2,3]     #n (coarse)
}

end.time <- Sys.time()
time.taken <- end.time - start.time
time.taken

output.f$scale <- 'fine'
output.c$scale <- 'coarse'
output.combined <- rbind(output.f, output.c)
output.combined$Err2 <- (output.combined$estimate - 0.91)^2
output.combined$MSE[output.combined$scale=="fine"] <-
mean(output.combined$Err2[output.combined$scale=="fine"])
output.combined$MSE[output.combined$scale=="coarse"] <-
mean(output.combined$Err2[output.combined$scale=="coarse"])
output.combined$var[output.combined$scale=="fine"] <-
var(output.combined$estimate[output.combined$scale=="fine"])
output.combined$var[output.combined$scale=="coarse"] <-
var(output.combined$estimate[output.combined$scale=="coarse"])
output.combined$se2 <- output.combined$se^2
output.combined$bias <- output.combined$estimate - 0.91

names(output.combined)[names(output.combined)=="scale"] <- "Scale"

#write.csv(output.combined, "sim output 100n dsr91 10000 nests 2 day.csv", row.names=F)
#write.csv(output.combined, "sim output 100n dsr91 10000 nests 3 day.csv", row.names=F)
#write.csv(output.combined, "sim output 100n dsr91 10000 nests 4 day.csv", row.names=F)
#write.csv(output.combined, "sim output 100n dsr91 10000 nests 5 day.csv", row.names=F)
#write.csv(output.combined, "sim output 100n dsr91 10000 nests 6 day.csv", row.names=F)
#write.csv(output.combined, "sim output 100n dsr91 10000 nests 7 day.csv", row.names=F)

```

```
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 2 day.csv", header=T)
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 3 day.csv", header=T)
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 4 day.csv", header=T)
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 5 day.csv", header=T)
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 6 day.csv", header=T)
#output.combined <- read.csv("sim output 100n dsr91 10000 nests 7 day.csv", header=T)
```

```
#####
#### Graphing the Results ####
#####
```

```
library(ggplot2)
library(extrafont)
#loadfonts(device="win")
```

```
library(ggplot2)
```

```
plot.dsr <- ggplot(output.combined, aes(estimate, fill = Scale)) +
  geom_histogram(alpha = 0.7, position = 'identity') +
  scale_fill_manual(values=c("darkred", "goldenrod")) +
  geom_vline(xintercept=0.91, linetype="dashed") +
  xlab("Daily survival rate") +
  ylab("Count") +
  ggtitle("Daily survival rate estimate") +
  theme(plot.title=element_text(hjust=0.5), text=element_text(size=18)) +
  theme(legend.position="none") +
  theme(legend.position = c(0.9, 0.9))
```

```
plot.dsr
```

```
plot.n <- ggplot(output.combined, aes(n, fill = Scale)) +
  geom_histogram(alpha = 0.7, position = 'identity') +
  scale_fill_manual(values=c("darkred", "goldenrod")) +
  ggtitle("Sample size") +
  labs(x="Nest observation-days", y="Count") +
  theme(text=element_text(family="Times New Roman", size=12))+
  theme(plot.title=element_text(hjust=0.5), text=element_text(size=12)) +
  theme(legend.position="none") +
  theme(legend.position = c(0.13, 0.69)) +
  theme(legend.title=element_text(size=10), legend.text=element_text(size=10)) +
  annotate("text", label="A", family="Times New Roman", x=2000, y=720, size=8)
```

```
plot.n
```

```
plot.se <- ggplot(output.combined, aes(se, fill = Scale)) +
  geom_histogram(alpha = 0.8, position = 'identity') +
  scale_fill_manual(values=c("darkred", "goldenrod")) +
  ggtitle("Standard error") +
  labs(x="SE", y="Count") +
  theme(text=element_text(family="Times New Roman", size=12))+
  theme(plot.title=element_text(hjust=0.5), text=element_text(size=12)) +
  annotate("text", label="B", family="Times New Roman", x=.00475, y=590, size=8)+
  guides(fill=FALSE)
```

```
plot.se
```

```
#####
```



```
#### Graphing SE by visit interval ####
#####
```

```
library(ggplot2)
library(extrafont)
#loadfonts(device="win")
```

```
ses <- read.csv("Sim Standard Errors.csv", header=T) #Results from different combinations of visit interval and
starting nest number are stored in a .csv file
ses$Nests <- as.factor(ses$Nests)
ses$Interval <- as.numeric(ses$Interval)
```

```
real <- read.csv("Real Nest SEs.csv", header=T) #Comparison to standard errors from real data set
```

```
ggplot() +
  geom_line(data=ses, aes(x=Interval, y=Standard.Error, group=interaction(Nests, Scale), color=Nests,
linetype=Scale), size=1) +
  scale_color_manual(name = "Starting nest number",
    labels = c("40 nests", "100 nests", "400 nests"),
    values = c("orangered3", "orange4", "orange", "blue", "red")) +
  scale_shape_manual(name = "Real nests",
    labels = c("Dickcissel fine", "Red-winged blackbird fine", "Vesper sparrow fine", "Dickcissel
coarse", "Red-winged blackbird coarse", "Vesper sparrow coarse"),
    values = c(15, 16, 17, 0, 1, 2)) +
  geom_point(data=real, aes(x=Interval, y=Standard.Error, group=interaction(Species, Scale),
shape=interaction(Species, Scale)))+
  scale_y_continuous(limits=c(0,NA)) +
  theme(text=element_text(family="Times New Roman", size=12))+
  xlab("Visit interval") +
  ylab("Standard error")
```