

MODELING DETECTION AND DENSITY USING DISTANCE SAMPLING FOR
THREE PRIORITY GRASSLAND BIRD SPECIES IN TEXAS – NORTHERN
BOBWHITE (*COLINUS VIRGINIANUS*), EASTERN MEADOWLARK
(*STURNELLA MAGNA*), AND PAINTED BUNTING
(*PASSERINA CIRIS*)

by

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LIST OF ABBREVIATIONS

| Abbreviation | Description |
|--------------|---|
| AIC | Akaike Information Criterion |
| Δ AIC | Difference in AIC units between the top model and specified model that is used in model selection |
| Crop | Cropland |
| CRP | Conservation Reserve Program |
| Date | Julian date |
| EMS | Texas Ecological Mapping Systems |
| K | Number of parameters in a model |
| NatGrass | Native grassland |
| NNGrass | Non-native grassland |
| Noise | Ambient noise |
| PDSI | Palmer Drought Severity Index |
| Poor | Poor quality vegetative cover |
| SE | Standard error |
| Shrub | Shrubland |
| Time | Time of morning |

ABSTRACT

In Texas, three priority grassland species have experienced declines due to the loss of native grasslands. These species are the Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*). Due to this, accurate density and abundance estimates are critical for management of these species. This 5-year study identified covariates that influence detection, availability for detection, and density for these species using data collected from 986 points across 11 Texas counties. Points were visited once per year from 2013 to 2017 in May and June, and 5-minute point counts were performed using distance sampling protocols. Models were fit using `gdistsamp` from the package “unmarked” in R. Covariates that influenced detection for Northern Bobwhite were observer, ambient noise, time of day, and Julian date. Detection was higher later in the season, earlier in the morning, and at lower ambient noise levels. Julian date and observer influenced Eastern Meadowlark detection, with detection declining later in the season. Painted Bunting detection was influenced by ambient noise and observer. The proportion of individuals available for detection was influenced by year, showing trends that are likely influenced by precipitation from the preceding year. However, despite this, availability for all species was not influenced by the Palmer Drought Severity Index. Vegetative cover was selected in the top density model for all three species. Native grasslands positively influenced density of Northern Bobwhite and Eastern Meadowlarks, shrubland positively influenced Northern Bobwhite and Painted Bunting, and cropland positively influenced Northern Bobwhite. Overall, there was high variability across the three species in the effect of the type of vegetative cover on density, indicating that management for one species may ignore vegetative cover needs of other grassland species. Finally, for all species, monitoring should emphasize observer training and attempt to survey only under low ambient noise conditions.

I. DETECTION MODELING FOR THREE PRIORITY GRASSLAND BIRD SPECIES IN TEXAS – NORTHERN BOBWHITE (*COLINUS VIRGINIANUS*), EASTERN MEADOWLARK (*STURNELLA MAGNA*), AND PAINTED BUNTING (*PASSERINA CIRIS*)

Before European settlement, tallgrass, mixed-grass, and shortgrass prairies were found from the northern Midwest to southern Texas (Steinauer and Collins 1996). After settlement, it is estimated that there has been a decline of 80 to 90 percent of tallgrass prairies, 30 to 90 percent of mixed-grass prairies, and 20 to 85 percent of shortgrass prairies in the Great Plains region (Samson and Knopf 1994). Within Texas, the prairies once extended from the Texas panhandle to the coast (Steinauer and Collins 1996). However, it has been estimated that the tallgrass prairie in Texas has declined by about 90% (Steinauer and Collins 1996). Additionally, there are two varieties of the mixed-grass prairie found in the state – the bluestem-grama (*Schizachyrium scoparium*, *Andropogon gerardii*, *Bouteloua spp.*) and mesquite-buffalograss (*Prosopis glandulosa*, *Buchloe dactyloides*) associations of the southern mixed-grass prairie (Bragg and Steuter 1996; Shiflet 1994). The Earth Resources Observation System estimated in 1995 that only about eight percent of the bluestem-grama and about 58 percent of the mesquite-buffalo grass associations remained (Bragg and Steuter 1996). Unlike tallgrass and mixed-grass prairies, some estimates suggest that there is still about 60 percent of the shortgrass prairie remaining in Texas; however, these remnants are noted to be of low quality (Weaver et al. 1996). The main sources of these grassland declines across North America and within Texas are the conversion of native grasslands to agricultural lands – both farmland and pastureland – and the suppression of the driving forces of natural

disturbance in grassland ecosystems – fire, drought, and native grazers (Askins et al. 2007; Knopf and Samson 1997). These declines in grassland habitat also have implications for species on these landscapes.

The overall decline of grasslands has heavily impacted grassland birds through loss of habitat and habitat fragmentation. Additionally, the resulting uniformity that the suppression of grassland ecological drivers has created across negatively affects the endemic avian assemblages, which evolved in the context of landscapes with heterogeneity in their percentage of shortgrasses, mixed-grasses, tallgrasses, and shrublands (Knopf and Samson 1997). Because of these many factors, declines in multiple bird species have been recorded, such as the Grasshopper Sparrow (*Ammodramus savannarum*), Greater Prairie-Chicken (*Tympanuchus cupido*), Lark Sparrow (*Chondestes grammacus*), Field Sparrow (*Spizella pusilla*), Northern Bobwhite (*Colinus virginianus*), and Eastern Meadowlark (*Sturnella magna*) (Herkert 1994). In addition, from 1969 to 1991 there was a recorded decline in grassland birds that increased from a loss of about 24 percent of grassland populations to a loss of about 91 percent of grassland populations in Illinois, Minnesota, Missouri, Nebraska, and Wyoming (Samson and Knopf 1994). Within Colorado, Kansas, New Mexico, North Dakota, Texas, and South Dakota, the decline of grassland populations increased from a loss of 17 percent to a loss of 48 percent (Samson and Knopf 1994). In Texas alone, from 1969 to 2013, there was a 55 to 93 percent decline in several priority grassland bird species (Samson & Knopf 1994; Sauer et al. 2014).

Monitoring of grassland bird species is essential for managers to be able to estimate rates of species' decline, as well as to be able to assess the viability and success

of different conservation actions. Additionally, it is important that these efforts produce reliable estimates of abundance. One common method in avian monitoring used to estimate abundance is the point count survey, in which one or more observers record detections of birds within a set period of time (Ralph et al. 1995). This is the most widely used method to estimate bird abundance, and one of the most notable examples of the use of point count surveys is the Breeding Bird Survey, which has used point counts to evaluate trends since 1966 (Sauer et al. 2013).

However, one aspect of point count surveys that must be considered in order to obtain accurate abundances is the probability of the detection of a bird. Probability of detection can be influenced by a variety of factors, including the behavior and physical attributes of the bird, environmental-based variables, and observer-based variables (Rosenstock et al. 2002). For example, there may be seasonal variation in detection of some species due to their timing in establishing and defending territories (Best 1981; Rollfinke and Yahner 1990; Selmi and Boulinier 2003). In addition, time of day may also affect detection due to variation in singing rate throughout the morning (Farnsworth et al. 2002; Lynch 1995; Rollfinke and Yahner 1990). Environmental-based variables that can influence detection include ambient noise, wind, precipitation, temperature, light intensity, and vegetation (Anderson 2001; Pacifici et al. 2008; Simons et al. 2007). All of these have the potential to impede an observer's ability to detect an individual either visually or aurally, as well affect the behavior of the individual bird itself. Finally, observer ability can influence detection due to variation in training, differences in hearing and vision acuity, and other variables that can impact a human's ability to hear, see, or identify individuals. Previous studies have noted that detection of grassland species is

especially variable by observer (Sauer et al. 1994; Diefenbach et al. 2003). While training and careful selection of observers as described by Kepler and Scott (1981) are ideal and would eliminate some of these differences, it is impossible for all observers to have equal survey abilities, and therefore we must attempt to account for observer variability.

One method by which detection probability can be estimated is through distance sampling estimators. Distance sampling involves measuring the distance from the observer to the individual detected with the assumption that detection of individuals will decrease as distance from the observer increases (Buckland et al. 2001). For point counts, it is expected that a certain proportion of individuals within a specific radius (w) will be detected. This is otherwise known as detection probability (\hat{P}_a). Therefore, if there are n distance measurements for k point counts, then density (\hat{D}) can be calculated using the following formula:

$$\hat{D} = \frac{n}{k\pi w^2 \hat{P}_a}$$

From this, we can then obtain total abundance in a specific area (A) for a closed population using the formula:

$$\hat{N} = \frac{\hat{D}}{A}$$

However, distance sampling has several assumptions that must be met for abundance estimates to be accurate. The assumptions include: all birds at the point itself are detected, the observer does not cause the bird to move prior to detection, and the distances to each bird are recorded accurately (Buckland et al. 2001). Violation of these assumptions can lead to inaccurate estimations of detection and abundance, so surveys must be designed to minimize assumption violations.

The goal of this study was to identify covariates that affect detection for three priority grassland bird species in Texas and to fit detection functions for these species to estimate density. These priority species are Northern Bobwhite, Painted Bunting (*Passerina ciris*), and Eastern Meadowlark. All three of these species are noted to be declining in Texas. The Partners in Flight Plan from 2016 estimated that the half-life for Northern Bobwhite and Eastern Meadowlarks within the Oaks and Prairies Joint Venture region were six and ten years respectively (Rosenberg et al. 2016). A half-life indicates how long it would take for 50 percent of the current population to disappear if no management actions were taken to change the current population trend. In other words, half of the Northern Bobwhite population as of 2016 in the Oaks and Prairies Joint Venture region would be lost within 6 years if no management actions were taken. The short half-lives for Northern Bobwhite and Eastern Meadowlark indicate that these populations are experiencing rapid declines in this region. On the other hand, the half-life for Painted Buntings across their North American range is greater than fifty years (Rosenberg et al. 2016). However, they are listed under the U.S. Fish and Wildlife Services' Birds of Management Concern (2011), which highlights species that need increased resource investment for conservation and management issues. Additionally, BirdLife International lists the Painted Bunting as a near threatened species due to its long-term decline, which has been documented by the Breeding Bird Survey (Sauer et al. 2017). Due to this, there is an immediate need to employ conservation actions for these three species in the most efficient manner possible. Therefore, these species were selected for analysis due to their conservation need. Modeling detection for these species will allow future monitoring efforts to design surveys that maximize detection probability,

increasing efficiency and accuracy of monitoring efforts by conservation and management organizations. Additionally, detection models will allow for correction of counts to account for imperfect detection, yielding more accurate abundance estimates. Since accurate abundance estimates are essential for successful abundance and density modeling, modeling detection will assist in future attempts to estimate abundance and to assess the covariates that affect it for these priority species. Finally, due to the immediate need for data about these species because of their predicted declines, accurate abundance and density estimates are also essential for assessing population trends, status, and viability.

Methods

Research Sites

Twenty Texas counties were selected for surveys, ranging from the border of Texas and Oklahoma to the northern edge of the coastal plain. These counties include: Archer, Austin, Baylor, Callahan, Clay, Colorado, Coryell, DeWitt, Ellis, Fayette, Gonzales, Karnes, Lavaca, Montague, Navarro, Shackelford, Stephens, Throckmorton, Washington, and Wilson (Figure 1). However, only counties that included data from all five years of the study were included in analyses, which excluded Archer, Callahan, Clay, Coryell, DeWitt, Gonzales, Karnes, Stephens, and Wilson county, reducing the number of counties to 11. The counties were selected based on their geographic locations within different ecoregions of grasslands within the state (Figure 1). These regions include the Central Great Plains, the Texas Blackland Prairies, the Cross Timbers, the East Central Texas Plains, the Southwestern Tablelands, and the Western Gulf Coastal Plain. By

surveying across many regions, more species can be surveyed and varying responses to different cover types, climatological variables, and other landscape characteristics can be assessed.

Species Surveyed

Surveys targeted 16 species that are found currently or historically within the range of the study areas (i.e. counties) as part of the Oaks and Prairies Joint Venture grassland bird monitoring program. These species were the: Wild Turkey (*Meleagris gallopavo*), Northern Bobwhite, Dickcissel (*Spiza americana*), Eastern Meadowlark, Grasshopper Sparrow, Painted Bunting, Lark Sparrow, Yellow-billed Cuckoo (*Coccyzus americanus*), Loggerhead Shrike (*Lanius ludovicianus*), Scissor-tailed Flycatcher (*Tyrannus forficatus*), Bell's Vireo (*Vireo bellii*), Black-capped Vireo (*Vireo atricapilla*), Bewick's Wren (*Thryomanes bewickii*), Cassin's Sparrow (*Peucaea cassinii*), Rufous-crowned Sparrow (*Aimophila ruficeps*), and Field Sparrow. Of these species, Northern Bobwhite, Eastern Meadowlark, and Painted Bunting were selected for detection modeling. These species were selected because of their conservation need.

Survey Design

Ninety-five 24.5 mile routes were randomly selected on tertiary roads, which were typically represented by county highways and routes, in the 20 Texas counties. Five routes were created per county, with at least 30 point count stations per route separated by ≥ 0.8 kilometers. In some cases, counties may only have had four routes if there were not enough public roads available to randomly create five routes that do not overlap.

Additionally, as mentioned previously, the number of routes was reduced to 52 due to the exclusion of locations that had less than five years of data. It should be noted that some routes experienced increased development over time, especially in counties neighboring large population centers such as Houston and Dallas. As such, some roads advanced into secondary and primary roads within a few years of the beginning of monitoring.

Surveys were performed in May and June from 2013 to 2017. At each point, a five-minute point count was performed. Surveys started at thirty minutes before sunrise and ended by 1105. As conditions grew hotter, surveys were ended earlier than 1105 as birds grew quieter due to increased heat. Only individuals seen or heard of the sixteen focal species were recorded. Distance from observer, type of observation (visual or auditory), time of detection during the survey, and direction from observer were estimated and recorded in a data sheet for each point. Distances to detections were measured using range finders. Ambient noise level was scaled from 0 to 3, with 0 representing silence, 1 as distant noise, 2 as noise levels that occasionally make it difficult to hear, and 3 as constant noise. For analysis, ambient noise, Julian date, and time (in minutes since 0000) were scaled and centered around zero.

Detection Modeling for Priority Species

Detection was modeled for all three priority species using methods similar to those described by Chandler (2017). Detections were sorted into 25-meter distance bins, ranging from 0 to 250 meters from the observer. Detections beyond 250 meters were discarded due to the unreliability of observations beyond this distance. Twenty-five meter

bins were selected to allow for inaccuracies in distance estimation by observers, especially due to the nature of birds often being detected only by sound rather than sight.

Detection was modeled as a function of $g(y)$ where $y = r$, which is the radial distance between the observer and a detected individual (Buckland et al. 2015). Specifically, the function utilized in this analysis was the half-normal key function:

$$g(y) = \exp\left[\frac{-y^2}{2\sigma^2}\right] \quad 0 \leq y \leq w$$

where σ is the scale parameter and w is the maximum radial distance selected for the point count survey. The scale parameter can be adjusted to account for covariates that influence detection. This can be evaluated using the following formula:

$$\sigma(z_i) = \exp\left(\alpha + \sum_{q=1}^Q \beta_q z_{iq}\right)$$

where z_i is a vector of covariate values (z_{i1}, \dots, z_{iQ}) recorded for the i^{th} detected individual, α is a coefficient for the intercept covariate, and β_1, \dots, β_Q are coefficients for detection covariates. Based on this, the original half-normal function can be rewritten as:

$$g(y_i, z_i) = \exp\left[\frac{-y_i^2}{2\sigma^2(z_i)}\right] \quad 0 \leq y_i \leq w$$

Detection models were fit in this manner for each species using the “unmarked” package in R (Fiske and Chandler 2011; R Core Team 2016). The `gdistsamp` function in “unmarked” was used to fit and evaluate detection models using distance sampling data (Fiske and Chandler 2011). For detection models, data from each year for each individual point was combined, and a variable representing the replicate, in this case the year, was associated with each point. This was to be used as an “availability” parameter, which can estimate the proportion of individuals available each year from the overall population at

each survey point across five years (Chandler et al. 2011). Therefore, it allows data from open populations, which are populations that are affected by births, deaths, immigrations, and emigrations, to be modeled. Further description of this term is discussed in the second chapter.

The inclusion of the covariate for availability was selected using Akaike's Information Criterion (AIC) to compare against the null half-normal model. This covariate was year, which was categorized as a factor variable. Models that included the year covariate were only selected if $\Delta AIC \leq 2$. The selected model was then used as the base for all future model building for that species.

Covariates used for detection model fitting were selected based on their effect in single covariate models. This was evaluated by fitting one half-normal model per covariate, and covariates that had a z-score of $|1.85|$ or higher were selected for model fitting. This score was selected instead of 1.96 since it is less discerning and allows the inclusion of covariates that influence the slope of the regression by more than 1.85 standard deviations. Therefore, it is less likely to exclude covariates that may have reduced effects in single-covariate models. Covariates included ambient noise level, Julian date, time (represented by minutes since 0000), and observer. For Northern Bobwhite, observer was reclassified due to large disparities between the number of detections by observers. Number of detections ranged from 0 to 497. Therefore, for this species, observers were reclassified into experience levels based on performing point counts for this study. Experience from field work for other organizations and studies was not included. Observers that had performed 150 or fewer points counts were reclassified as "few," observers that performed more than 400 point counts were reclassified as

“many,” and the remaining observers with 151 to 400 point counts were reclassified as “intermediate.” This modification of the covariate is referred to as “observer-level.” This covariate would indicate whether observers with more experience performing point counts have a better probability of detection of Northern Bobwhite.

Once the detection covariates were selected for each species, all possible half-normal models using the selected covariates were constructed for each species. This included a global model that included ambient noise, time, Julian date, and observer, and a null model that included no covariates. Detection models were selected using AIC, and models with the lowest AIC were selected when there were no competing models. Competing models were models with $\Delta AIC \leq 2$. When multiple models were competing, the most parsimonious model was selected.

Results

There were 4,780 point counts performed from 2013 to 2017, with 956 performed each year. There were 2,355 Northern Bobwhite detected across all five years, with 214 occurring in 2013, 174 in 2014, 418 in 2015, 793 in 2016, and 756 in 2017. A total of 1,475 Eastern Meadowlarks were detected, with 339, 171, 277, 345, and 343 in years 2013 through 2017 respectively. Finally, 2,971 Painted Buntings were detected, in which 567 were detected in 2013, 431 in 2014, 640 in 2015, 633 in 2016, and 700 in 2017. On average, 7.1 birds (only Northern Bobwhite, Eastern Meadowlark, and Painted Bunting out of the 16 focal species) were detected per point. Specifically, 1.5 Eastern Meadowlarks were detected per point, 3.1 Painted Buntings were detected per point, and 2.5 Northern Bobwhite were detected per point. There were 19 observers, with the

number of points performed ranging from as few as 33 to as many as 613. The most common ambient noise ranking was 1, which was selected by observers for 35% of the point counts, followed by rank 2 at 28%, rank 0 at 26%, and rank 3 at 11%. Point counts started as early as May 16th and ended as late as June 30th. Starts times for point counts ranged from 0545 to 1105. Probability of detection for the sampled points was 0.55 for Northern Bobwhite, 0.44 for Eastern Meadowlarks, and 0.20 for Painted Buntings.

Selection of the base model was performed first, with comparison between a null model with no covariates selected for the detection parameter p , the availability parameter ϕ , or the abundance parameter λ and a model that only contained the predictor of year on ϕ . Using AIC, the model with year as a covariate on ϕ was selected for Northern Bobwhite ($\Delta\text{AIC}=1005.71$), Eastern Meadowlark ($\Delta\text{AIC}=105.52$), and Painted Bunting ($\Delta\text{AIC}=68.12$) due to their lower AIC scores (Appendix A).

Covariates selected for detection model fitting varied greatly between species. For Northern Bobwhite, z-scores greater than or equal to $|1.85|$ were ambient noise, Julian date, observer-level, and time (Appendix B). For Painted Bunting, noise and observer were selected. Lastly, covariates selected for Eastern Meadowlark included date and observer.

The selected covariates were then assembled into combinations to create all possible detection models for each species. Models were ranked using AIC, and competing models were identified to be those with differences of less than or equal to 2 ΔAIC . For Northern Bobwhite, the top model selected was the full model, which included observer-level, noise, date, and time as detection covariates ($\Delta\text{AIC}= 20.36$; Table 1). Increases in ambient noise decreased detection probability ($\beta = -0.1079$; SE =

0.0172; $p < 0.01$), and detection increased later in the season ($\beta = 0.2574$; $SE = 0.0185$; $p < 0.01$) with detection at its highest in late June (Figure 2a; 2b). Concerning time of day, detection was highest early in the morning ($\beta = -0.0880$; $SE = 0.0175$; $p < 0.01$) (Figure 2d). Additionally, the observer category with the highest detection probability at farther distances was the intermediate group ($\beta = -0.0758$; $SE = 0.0323$; $p = 0.019$), followed by the group that performed few point counts ($\beta = 0.3316$; $SE = 0.1110$; $p < 0.01$) and the group that performed many point counts (Figure 2c). Detection of Northern Bobwhites by observers began to drop below 50% at about 175 meters.

The model selected for Eastern Meadowlark included the covariates of Julian date and observer ($\Delta AIC=38.67$; Table 2). Detection decreased as the date increased, with detection at its highest in mid-May ($\beta = -0.13142$; $SE = 0.0204$; $p < 0.01$) (Figure 3a). The influence of observer varied, but for most observers, detection dropped to about 50% between 125 and 175 meters from the observer (Table 3; Figure 3b).

For Painted Buntings, the model that included noise and observer as detection covariates was selected ($\Delta AIC=16.00$; Table 4). As ambient noise increased, there was a small decrease in detection ($\beta = -0.03658$; $SE = 0.00861$; $p < 0.01$) (Figure 4a). The effect of observer was highly variable, although, for most observers, detection dropped to about 50% at about 100 meters (Table 3; Figure 4b).

Discussion

Detection model results indicate that, while certain covariates such as observer, Julian date, and noise influence detection of multiple species, they affect detection of each species in different ways. The effects of observer were highly variable within

species and across species. Interestingly, for Northern Bobwhite, observers that had more experience performing point counts had lower detection probabilities at greater distances than observers that had performed a small or intermediate number of point counts. This could be due to experienced observers being more conservative with their estimates of distance. It is possible that observers with less experience over-estimate distances or have greater variability in their distance estimates. This could lead to the appearance that less experienced observers have a greater probability of detection at farther distances than experienced observers. Related to this, one study found that when the radius of the point count is not fixed or is very large, as is present within this study, observers typically underestimate the number of birds (Savard and Hooper 1995; Simons et al. 2007). This could be attributed to observers having increasing difficulty distinguishing neighboring individuals as distance increases or the inability to distinguish between individuals that are in the same direction but at different distances (Wolf et al. 1995). However, the results of the detection model for Northern Bobwhite indicate overestimation of individuals at increased distances for less experienced observers. This suggests that inability to distinguish individuals is likely not the source. Instead, it is likely the inability to accurately estimate the distance of individuals detected from the observer. There are several potential sources of this. One may be from the tendency of Northern Bobwhite to “whisper” when a bird detects more dominant males nearby, which could make localization of the sound difficult for an observer (Stokes 1967). Additionally, Alldredge et al. (2007) found that observers were not able to differentiate distances of auditory detections beyond 65 meters, and that, if the orientation of the vocalizing individual is away from the observer, distance estimates could be almost double the true distance of

the vocalizing individual. Both of these situations, especially for unexperienced observers who may not be familiar with the ability of Northern Bobwhite to extensively control the volume of their calls, could significantly influence distance estimations. Finally, a lack of rangefinder use or excessive rounding to the nearest 5 or 10-meter distance could lead to inaccurate distance estimation. Experienced point count observers are probably less likely to experience these kinds of issues due to repeated training, frequent opportunities to detect individuals, and increased knowledge of species patterns in vocalizations. As such, it is likely a combination of the factors mentioned previously, inadequate training for some observers, and potentially the failure of some observers to use range finders for all detections which led to these higher detection probabilities at increased distances for less experienced observers.

For Eastern Meadowlarks and Painted Buntings, there was high variability in detection by observers as well, although this variable was not broken into categories by experience and was rather categorized by individual observers. Despite this, the same problems with the ability of observers to estimate distances likely affect these species as well. The two outlying observers for Eastern Meadowlark are most likely subject to the aforementioned factors, inadequate training, and failure to use range finders. Eastern Meadowlark calls carry very far over open grasslands, and therefore these observers likely under-estimated distances to Eastern Meadowlarks that were outside of the 250-meter survey radius.

In addition to variability in observer ability, the observer covariates also reveal differences between the ability to detect each species at long distances. Detection of Eastern Meadowlarks began to drop below 50% around 125 to 175 meters away from the

observer, and detection for Northern Bobwhite began to drop below 50% at about 175 meters. These are much greater distances than for Painted Bunting, which drops below 50% at about 100 meters. This is likely due to Painted Bunting songs being relatively soft, making them difficult to hear across long distances and through dense vegetative cover as compared to Northern Bobwhite and Eastern Meadowlarks.

For Northern Bobwhite, detection increased later in the survey season, with detection being greatest in late June. This is in line with previous studies, which have found similar patterns in detection and calling rates for Northern Bobwhite. Two studies from Oklahoma also found that detection increased as Julian date increased from May to July (Hansen and Guthery 2001; Crosby and Elmore 2012). Studies have also identified varying peaks across years in calls, ranging from mid-June to some as late as mid-August (Hansen and Guthery 2001; Robel et al. 1969). Additionally, anecdotal evidence from observers in the Washington County to the Karnes County area has suggested that call frequency increases later in the season (Giocomo, pers. obs). If this is accurate across the survey study range, this could be a possible source of this increase in detection later in the breeding season. However, unlike Northern Bobwhite, detection decreased for Eastern Meadowlarks later in the survey season, with detection being highest in mid-May. In Eastern Meadowlarks, the timing of peak song intensity varies throughout the season. Song intensity is high after male arrival, and it peaks during female arrival and courtship with subsequent peaks again occurring during re-nesting (Jaster et al. 2012). This may be why detection is highest early in the survey season, as those surveys occur more recently after male and female arrival to the breeding grounds.

Ambient noise had a negative influence on Northern Bobwhite and Painted Bunting detection. It was expected that detection should decrease as ambient noise increases due to the observer's inability to make auditory detections when ambient noise masks bird vocalizations (Simons et al. 2007). This is supported by the Northern Bobwhite and the Painted Bunting detection models. For Northern Bobwhite, detection probability declined with increased ambient noise, falling from about 55% to about 40% as ambient noise increased from no noise (represented by 0) to constant noise (represented by 3). Additionally, Painted Bunting detection fell from around 20% to around 15% as ambient noise increased.

Finally, time of morning had a negative effect on Northern Bobwhite, with detection probability nearly being halved as it fell from about 60% to about 30% by the late morning. Previous research has found that covey calling and whistle intensity are highest before dawn and decline around 20 to 30 minutes after sunrise both during breeding season and the fall (Wellendorf et al. 2004; Robel et al. 1969). Therefore, this model likely reflects this decrease in call and whistle rate after dawn.

Overall, detection modeling results suggest that, regardless of species, observers influence detection. Increasing Julian date has a positive influence on detection of Northern Bobwhite and a negative influence on Eastern Meadowlark. Additionally, increasing ambient noise negatively influences Northern Bobwhite and Painted Bunting detection. Finally, detection decreases for Northern Bobwhite later in the morning.

Management Implications

Point count surveys are the most used avian survey technique for abundance estimation and have a key role in monitoring programs used to evaluate population trends and the effects of management actions. While point count survey protocol is well documented and easily employed, it is important to account for detection probability, especially in species such as the Northern Bobwhite, Painted Bunting, and Eastern Meadowlark, where abundance estimates are crucial to conservation and management decisions. The results of this study indicate that detection probability will be highest for Northern Bobwhite and Painted Buntings when levels of ambient noise are low. Detection is poor when in the presence of constant noise, such as high traffic roads, heavy machinery, or urban noise. Therefore, surveys that are designed to avoid areas of high ambient noise levels will likely maximize detection of individuals or have no negative influence on detection for these three species. Detection appears to be highest for Northern Bobwhite in Texas later in the breeding season, but earlier in the breeding season for Eastern Meadowlark. Depending on the target species, careful selection of survey dates can maximize detection. However, if multiple species need to be surveyed, it may be beneficial to perform detection modeling to account for variation in detection throughout the survey season. To maximize detection of Northern Bobwhite, surveys should be performed between 30 minutes before and after sunrise. Performance of surveys outside of this time period should consider correcting abundance estimates for this species due to the large change in detection throughout the morning. Finally, these results further provide evidence that training of observers is essential. Observers should be trained carefully and in a consistent manner to maintain consistent detection

probability across multiple observers. Kepler and Scott (1981) describe an excellent method in observer selection and training that can be used to accomplish this. In summary, surveys should avoid areas of high ambient noise, observers must be trained, and decisions about seasonal timing and daily timing of surveys should be determined based on species behavior and phenology. Overall, careful consideration of the variables that could affect detection and subsequent careful survey design can help to maximize detection probability, increase abundance estimate accuracy, and improve the efficiency of monitoring in general.

**II. DENSITY MODELING FOR THREE PRIORITY GRASSLAND BIRD
SPECIES IN TEXAS – NORTHERN BOBWHITE (*COLINUS VIRGINIANUS*),
EASTERN MEADOWLARK (*STURNELLA MAGNA*), AND PAINTED BUNTING
(*PASSERINA CIRIS*)**

Grassland bird decline has been attributed to the loss of grassland habitat, habitat fragmentation, and increasing uniformity of habitats and habitat structures across landscapes (Knopf and Samson 1997). It is estimated that there has been a decline of 80 to 90 percent of tallgrass prairies, 30 to 90 percent of mixed-grass prairies, and 20 to 85 percent of shortgrass prairies in the Great Plains region, all of which are critical habitat for many grassland species (Samson and Knopf 1994). Because of the loss of grassland habitats, declines in multiple bird species have been recorded, such as the Grasshopper Sparrow (*Ammodramus savannarum*), Greater Prairie-Chicken (*Tympanuchus cupido*), Lark Sparrow (*Chondestes grammacus*), Field Sparrow (*Spizella pusilla*), Northern Bobwhite (*Colinus virginianus*), and Eastern Meadowlark (*Sturnella magna*) (Herkert 1994). In addition, from 1969 to 1991 there was a significant decline in grassland birds that accelerated from a loss of about 24 percent of grassland populations to a loss of about 91 percent of grassland populations in Illinois, Minnesota, Missouri, Nebraska, and Wyoming (Samson and Knopf 1994). Within Colorado, Kansas, New Mexico, North Dakota, Texas, and South Dakota, the decline of grassland populations increased from a loss of 17 percent to a loss of 48 percent (Samson and Knopf 1994). In Texas alone, from 1969 to 2013, there was a 55 to 93 percent decline in several priority grassland bird species (Samson & Knopf 1994; Sauer et al. 2014).

For some species, these declines are slow, while for others declines may be very rapid. According to the Partner's in Flight Landbird Conservation Plan, ubiquitous species such as the Eastern Meadowlark, Grasshopper Sparrow, and Loggerhead Shrike (*Lanius ludovicianus*) have declined by over 65% in the past forty years, and an additional 50% of their current populations across North America will be lost within 23, 24 and 50 years respectively (Rosenberg et al. 2016). Additionally, within the Oaks and Prairies Joint Venture, which covers the Edwards Plateau, Oaks and Prairies region, and a portion of the Eastern Tallgrass Prairie in Texas and Oklahoma, there are multiple grassland species with half-lives of less than 20 years. A half-life indicates how long it would take for 50 percent of the current population to disappear if no management actions were taken to change the current population trend. Northern Bobwhite populations in Texas were estimated to be halved within six years of the plan's publication in 2016, Eastern Meadowlarks within ten years, Loggerhead Shrikes within seven years, and Grasshopper Sparrows within fifteen years (Rosenberg et al. 2016). Therefore, information about key habitat components and factors that affect abundance and density from studies in this region can play a key role in efforts to manage these grassland species.

This study will focus on factors that affect the abundance and density of Northern Bobwhite, Eastern Meadowlark, and Painted Bunting (*Passerina ciris*). All three of these species are noted to be declining in Texas as indicated by the Partners in Flight Plan and are priority species for the Oaks and Prairies Joint Venture (Rosenberg et al. 2016). Unlike the Northern Bobwhite and Eastern Meadowlark, the half-life for Painted Buntings across their North American range is greater than fifty years (Rosenberg et al.

2016). However, they are listed under the U.S. Fish and Wildlife Services' Birds of Management Concern (2011), which highlights species that need increased resource investment for conservation and management issues. Additionally, BirdLife International lists it as a near threatened species due to its long-term decline, which has been documented by the Breeding Bird Survey (Sauer et al. 2017). Due to this, there is an immediate need to employ conservation actions for these species in order to mitigate decline and improve population restoration efforts. Therefore, these three species were selected due to their conservation need and their representation of multiple kinds of grassland habitat.

Habitat use varies for these three species despite all of them utilizing grassland landscapes. Northern Bobwhite typically occupy early successional stage grasslands and open woodland habitats (Brennan et al. 2014; Spears et al. 1993). Additionally, Northern Bobwhite are typically found in landscapes that contain a mosaic of patches of open grasslands, shrublands, and forests, although selection for specific proportions is highly variable (Arredondo et al. 2006; Kopp et al. 1998; Rader et al. 2006). On the other hand, Painted Buntings occupy shrublands and early successional woodlands (Parmelee 1959). Specifically, within Texas, Painted Buntings are associated with small, uneven-aged stands of trees within the edge of open and wooded habitat such as fence-rows (Kopachena and Crist 2000). Finally, Eastern Meadowlarks strictly occupy grasslands and can be considered a grassland obligate species (Jaster et al. 2012; Roseberry and Klimstra 1970). Their abundance was recorded to be highest in grasslands that have a grass height between 10.2 to 30.4 cm (Skinner 1975). Additionally, Eastern Meadowlark abundance decreases when the grassland area is dominated by forbs, and density

increases in fields with lower cover percentages (Skinner 1975; Bollinger 1995). They also display higher densities in fields with less vegetative heterogeneity, indicating that, unlike Northern Bobwhite and Painted Buntings, Eastern Meadowlarks utilize large grassland landscapes that are uninterrupted by small shrubland and forest patches (Wiens 1974). While these three species all can be classified as grassland birds, they utilize grassland landscapes in very different ways. As such, it is important to identify which vegetative cover categories are most influential on abundance and density for each species. This information is needed to evaluate the effectiveness of management practices and restoration efforts for multiple species.

In addition to vegetative cover, these grassland species can also be affected by precipitation and drought, which can indirectly affect vegetative cover and structure. Survival, reproductive effort, and productivity of Northern Bobwhite decrease during dry seasons, and the prior year's rainfall has also been found to influence Northern Bobwhite abundance (Hernández et al. 2005; Giuliano and Lutz 1993). Additionally, Bridges et al. (2001) found that abundance of Northern Bobwhite increased in southern Texas as the modified Palmer Drought Severity Index (PDSI) increased (with higher numbers representing wetter conditions), indicating that Northern Bobwhite populations increased during wet seasons. Specific studies about the effects of precipitation on Eastern Meadowlarks and Painted Buntings are lacking, although a study from western North Dakota showed that densities of several grassland bird species declined during a severe drought while the density of Western Meadowlarks did not (George et al. 1992).

Due to the importance of vegetative cover, drought, and dry/wet seasons, the goal of this study was to identify key vegetative cover categories and estimate the effects of

drought via PDSI for Northern Bobwhites, Eastern Meadowlarks, and Painted Buntings using density modeling. Density modeling can help to identify conditions that have negative influences on these populations, and it can track changes in abundance and density over time in response to variation in these factors. This information would allow managers to target areas with habitat utilized by multiple species, as well as to understand how future climatological changes may affect abundance and density over time.

Methods

Research Sites

Twenty Texas counties were selected for surveys, ranging from the border of Texas and Oklahoma to the northern edge of the coastal plain. These counties include: Archer, Austin, Baylor, Callahan, Clay, Colorado, Coryell, DeWitt, Ellis, Fayette, Gonzales, Karnes, Lavaca, Montague, Navarro, Shackelford, Stephens, Throckmorton, Washington, and Wilson (Figure 1). However, only counties that included data from all five years of the study were included in analyses, which excluded Archer, Callahan, Clay, Coryell, DeWitt, Gonzales, Karnes, Stephens, and Wilson county, reducing the number of counties to 11. The counties were selected based on their geographic locations within different ecoregions of grasslands within the state (Figure 1). These regions include the Central Great Plains, the Texas Blackland Prairies, the Cross Timbers, the East Central Texas Plains, the Southwestern Tablelands, and the Western Gulf Coastal Plain. By surveying across many regions, more species can be surveyed and varying responses to different cover types, climatological variables, and other landscape characteristics can be assessed.

Species Surveyed

Surveys targeted 16 species that are found currently or historically within the range of the study areas (i.e. counties) as part of the Oaks and Prairies Joint Venture grassland bird monitoring program. These species were the: Wild Turkey (*Meleagris gallopavo*), Northern Bobwhite, Dickcissel (*Spiza americana*), Eastern Meadowlark, Grasshopper Sparrow, Painted Bunting, Lark Sparrow, Yellow-billed Cuckoo (*Coccyzus americanus*), Loggerhead Shrike (*Lanius ludovicianus*), Scissor-tailed Flycatcher (*Tyrannus forficatus*), Bell's Vireo (*Vireo bellii*), Black-capped Vireo (*Vireo atricapilla*), Bewick's Wren (*Thryomanes bewickii*), Cassin's Sparrow (*Peucaea cassinii*), Rufous-crowned Sparrow (*Aimophila ruficeps*), and Field Sparrow. Of these species, Northern Bobwhite, Eastern Meadowlark, and Painted Bunting were selected for density modeling. These species were selected because of their conservation need. Additionally, they cover a range of associations with grasslands. The Eastern Meadowlark represents grassland obligates, Northern Bobwhite represent species that utilize a mix of open grassland and shrubland, and Painted Bunting represent species that occupy shrubland and early successional woodlands (Jaster et al. 2012; Brennan et al. 2014; Parmelee 1959).

Survey Design

Ninety-five 24.5 mile routes were randomly selected on tertiary roads, which were typically represented by county highways and routes, in the 20 Texas counties. Five routes were created per county, with at least 30 point count stations per route separated by ≥ 0.8 kilometers. In some cases, counties may only have had four routes if there were not enough public roads available to randomly create five routes that do not overlap.

Additionally, as mentioned previously, the number of routes was reduced to 52 due to the exclusion of locations that had less than five years of data. It should be noted that some routes experienced increased development over time, especially in counties neighboring large population centers such as Houston and Dallas. As such, some roads advanced into secondary and primary roads within a few years of the beginning of monitoring.

Surveys were performed in May and June from 2013 to 2017. At each point, a five-minute point count was performed. Surveys started at thirty minutes before sunrise and ended by 1105. As conditions grew hotter, surveys were ended earlier than 1105 as birds grew quieter due to increased heat. Only individuals seen or heard of the sixteen focal species were recorded. Distance from observer, type of observation (visual or auditory), time of detection during the survey, and direction from observer were estimated and recorded in a data sheet for each point. Distances to detections were measured using range finders. Ambient noise level was scaled from 0 to 3, with 0 representing silence, 1 as distant noise, 2 as noise levels that occasionally make it difficult to hear, and 3 as constant noise. For analysis, ambient noise, Julian date, and time (in minutes since 0000) were scaled and centered around zero.

Vegetative Cover and Palmer Drought Severity Index Associations

The Ecological Mapping Systems (EMS) vegetative cover data, produced by the Texas Parks and Wildlife Department, was used to identify categorical vegetative cover variables associated with each point at which point counts took place (Elliot et al. 2014). The EMS contains 398 vegetative cover variables defined at a 10-meter resolution for the state of Texas, so these variables were reclassified into broader categories that are more

suited for the species included in this study. These categories were based on the “New Wildlife Habitat” categorization of these variables in the master list of the cover variables provided by the Texas Parks and Wildlife Department. The categories include: riparian/bottomland, crop/food plots, forests/timberlands, native grassland/savannah, native rangeland/brush, non-native pasture, wetlands, and “other,” which includes cover types such as cliffs, bluffs, dunes, urban/developed, and glades. The categories were further reclassified for analysis by combining riparian/bottomland and wetlands into “poor quality cover” since it is expected that these vegetative cover types will not be occupied by grassland species. The remaining categories were renamed into “forests,” “croplands,” “native grasslands,” “non-native grasslands,” and “shrublands,” but remained largely the same as was originally identified by the EMS meta data. The cover types within the “other” class were sorted into the selected categories by identifying the major species present within each cover type. If the cover type was predominantly cliffs, barren, urban, or riparian, then it was sorted into the poor quality vegetative cover category. Cover types dominated by trees were sorted into the forests category, while cover types dominated by shrubs or grasslands were sorted into the shrubland and native or non-native grassland categories respectively.

To determine the majority cover type at each point count location, each point was buffered to 250 meters, which was the farthest extent to which detections were made during point count surveys. Using ArcMap’s “Zonal Statistics” function, the cover type which made up the majority cover within each buffer was identified and assigned to the associated point (ESRI 2017).

Palmer Drought Severity Index 4-km resolution raster data was collected from the West Wide Drought Tracker, which obtains precipitation and temperature data from the PRISM Climate Mapping Program to estimate drought indices for the United States (Abatzoglou et al., in press). This index ranges from -10 to +10, in which more extreme negatives reflect more severe drought conditions and positives reflect wet conditions (Palmer 1965). The Palmer Drought Severity Index was chosen as a predictor over precipitation due to its successful prediction of Northern Bobwhite abundance in southern Texas (Bridges et al. 2001). Additionally, the PDSI takes into account not only precipitation, but also evapotranspiration, soil moisture recharge, runoff, soil moisture loss, and the conditions of the previous month (Palmer 1965). Therefore, PDSI can be used to identify long-term droughts or wet periods, which is likely to provide better predictions of habitat quality and densities of grassland birds. Additionally, precipitation from the preceding twelve months was removed from analysis because it was highly correlated with PDSI ($r > 0.80$).

Palmer Drought Severity Index map data from May 2012 to May 2017 was obtained and clipped to fit the region of interest for this study. PDSI from the 12 months prior to each survey (May to April) was summed using ArcMap's "Cell Statistics" tool to create five PDSI raster layers that reflected the drought or wet conditions of the year preceding data collection (ESRI 2017). This method was also used by the Bridges et al. (2001) study. The "Zonal Statistics" tool was then used to obtain the PDSI value associated with each point for each year (ESRI 2017). PDSI values were then scaled and centered around zero.

Density Modeling for Priority Species

Density was modeled using the `gdistsamp` function within the “unmarked” R package (Fiske and Chandler 2011; R Core Team 2016). This function allows abundance to vary temporally via the implementation of an “availability” term (ϕ) that accounts for how many individuals are available to be detected at a specific point within a specific time period (Fiske and Chandler 2011). Another interpretation of this variable can be the number of individuals “alive” and available to be detected at each point within each time period (A. Royle, personal communication). Therefore, if N is the abundance at point s at sampling occasion k , then the abundance of a point can be modeled with

$$N_{s,k} \sim \text{Binomial}(M_s, \phi)$$

where M , the abundance over all sampling periods, is estimated using

$$M_s \sim \text{Binomial}(\lambda_s)$$

and λ represents the expected overall population size present at s across all sampling periods. Under this definition, availability can be used to examine changes in abundance or density over time when availability includes a covariate for the survey replicate, which for this study would be year. This will identify the proportion of M that is available at point s for each year, which can then be used to track changes in density over time.

Covariates were modeled for both λ and ϕ . The vegetative cover covariate was tested for its influence on λ , and PDSI and year were tested for their influence on ϕ . PDSI was modeled with the availability parameter because PDSI should influence vegetative cover quality. Therefore, PDSI should affect the proportion of the overall population that will be present at each point over time.

The first stage of density model selection was to select between models that included no predictors (the null model) and year as a covariate for φ . If the addition of year improved the fit of the model by lowering the Akaike's Information Criteria (AIC) with a $\Delta\text{AIC} \leq 2$, then year was included as a covariate for φ for all future model fitting. If models were competing, then the most parsimonious model was selected for future model fitting for density. This was performed as part of the detection analysis, and these models were further fitted for detection before applying density and additional availability covariates. The selected detection models were then used as a base for further availability and density modeling. For further discussion of the detection modeling process, see chapter 1.

The second stage of model selection was to select either the negative-binomial or Poisson distribution to model density for each species. These distributions were selected due to the response variable, density, being based on count data. One model was created for each distribution using the detection models previously selected. The two models were then compared using AIC. The model with the lower AIC was selected for each species, and the selected distributions were then used for future density modeling for each species.

The third stage of model fitting was to fit all possible models with the remaining covariates of vegetative cover and PDSI. There were four possible models, including a model with λ set to the null and the full model, which included vegetative cover on λ and PDSI and year on φ . Models were selected using AIC, and models with $\Delta\text{AIC} \leq 2$ were considered competing. When models were competing, the most parsimonious model was selected.

Results

There were 4,780 point counts performed from 2013 to 2017, with 956 performed each year. There were 2,355 Northern Bobwhite detected across all five years, with 214 occurring in 2013, 174 in 2014, 418 in 2015, 793 in 2016, and 756 in 2017. A total of 1,475 Eastern Meadowlarks were detected, with 339, 171, 277, 345, and 343 in years 2013 to 2017 respectively. Finally, 2,971 Painted Buntings were detected, in which 567 were detected in 2013, 431 in 2014, 640 in 2015, 633 in 2016, and 700 in 2017.

The most common vegetative cover variable was native grassland, which was the majority cover type at 35% of point count locations. Non-native grasslands, cropland, and shrubland followed at 24%, 13%, and 13% respectively. Finally, forest and poor quality cover were the least common cover types at 9% and 7% respectively.

The PDSI sums for the 12 months preceding each survey period ranged from -6.09 to 11.05, showing a wide range of drought and wet conditions across the five-year data set. In 2013 and 2014, it ranged from -5.46 to -0.27 and from -6.09 to -0.77 respectively, indicating that the preceding twelve months were major drought years ($\bar{x}_{2013} = -3.6$; $\bar{x}_{2014} = -3.3$). In 2015, it ranged from -0.06 to 7.12, indicating that the drought of the previous years ended between May of 2014 to April of 2015 ($\bar{x}_{2015} = 3.7$). Finally, in 2016 and 2017, it ranged from 1.75 to 11.05 and from 1.40 to 9.15, showing that the last two years of the study were wetter than the preceding years ($\bar{x}_{2016} = 7.8$; $\bar{x}_{2017} = 5.4$).

For all three species, the negative-binomial distribution was selected over the Poisson distribution for density modeling due to ΔAIC being greater than 100 AIC points (Appendix C). The negative-binomial distribution was then used for all future density and availability modeling.

All possible models for the covariates of vegetative cover on λ and PDSI on φ were compared for each species using AIC. Year had already been permanently included from the detection model analysis to account for replication. For Northern Bobwhite, the model that contained vegetative cover and PDSI and the model that contained vegetative cover only were competing ($\Delta\text{AIC} = 1.68$; Table 5). The most parsimonious model, which was the model that contained vegetative cover only, was selected. With poor quality cover set as the reference category, forest cover and non-native grassland negatively influenced density, while native grassland, shrubland, and cropland positively influenced density ($\beta_{\text{forest}} = -1.282$; $\text{SE}_{\text{forest}} = 0.381$; $p_{\text{forest}} < 0.01$; $\beta_{\text{natgrass}} = 1.309$; $\text{SE}_{\text{natgrass}} = 0.243$; $p_{\text{natgrass}} < 0.01$; $\beta_{\text{nngrass}} = -0.798$; $\text{SE}_{\text{nngrass}} = 0.243$; $p_{\text{nngrass}} < 0.01$; $\beta_{\text{shrub}} = 2.437$; $\text{SE}_{\text{shrub}} = 0.262$; $p_{\text{shrub}} < 0.01$; $\beta_{\text{crop}} = 1.966$; $\text{SE}_{\text{crop}} = 0.262$; $p_{\text{crop}} < 0.01$). Density, in birds/ha, was highest in shrubland cover, followed by cropland, native grassland, poor quality cover, non-native grassland, and forest ($\text{density}_{\text{shrub}} = 2.010$; $\text{SE}_{\text{shrub}} = 0.311$; $\text{density}_{\text{crop}} = 1.256$; $\text{SE}_{\text{crop}} = 0.197$; $\text{density}_{\text{natgrass}} = 0.651$; $\text{SE}_{\text{natgrass}} = 0.082$; $\text{density}_{\text{poor}} = 0.176$; $\text{SE}_{\text{poor}} = 0.044$; $\text{density}_{\text{nngrass}} = 0.079$; $\text{SE}_{\text{nngrass}} = 0.015$; $\text{density}_{\text{forest}} = 0.176$; $\text{SE}_{\text{forest}} = 0.044$; Figure 5a). Additionally, availability, or the proportion of the number of birds that occur over five years that are present at each point at a specific time, varied across years. Availability was highest in 2016, followed by 2017, 2015, 2013, and 2014 ($\varphi_{2013} = 0.158$; $\text{SE}_{2013} = 0.014$; $p_{2013} < 0.01$; $\varphi_{2014} = 0.124$; $\text{SE}_{2014} = 0.012$; $p_{2014} < 0.01$; $\varphi_{2015} = 0.269$; $\text{SE}_{2015} = 0.021$; $p_{2015} < 0.01$; $\varphi_{2016} = 0.615$; $\text{SE}_{2016} = 0.041$; $p_{2016} = 0.41$; $\varphi_{2017} = 0.546$; $\text{SE}_{2017} = 0.036$; $p_{2017} = 0.43$; Figure 5b).

For Eastern Meadowlark, the vegetative cover only model and the model that included PDSI and vegetative cover were again competing ($\Delta\text{AIC} = 0.94$; Table 6).

Again, the vegetative cover only model was selected due to parsimony. The influences of the forest, shrubland, and cropland categories on density were negative, while the native grassland and non-native grassland category were positive ($\beta_{\text{forest}} = -1.372$; $\text{SE}_{\text{forest}} = 0.354$; $p_{\text{forest}} < 0.01$; $\beta_{\text{natgrass}} = 0.759$; $\text{SE}_{\text{natgrass}} = 0.238$; $p_{\text{natgrass}} < 0.01$; $\beta_{\text{nnggrass}} = 0.709$; $\text{SE}_{\text{nnggrass}} = 0.246$; $p_{\text{nnggrass}} < 0.01$; $\beta_{\text{shrub}} = -1.368$; $\text{SE}_{\text{shrub}} = 0.331$; $p_{\text{shrub}} < 0.01$; $\beta_{\text{crop}} = -0.009$; $\text{SE}_{\text{crop}} = 0.276$; $p_{\text{crop}} = 0.97$). The grassland categories had the highest densities (birds/ha), followed by cropland, poor quality cover, shrubland, and forest ($\text{density}_{\text{natgrass}} = 0.541$; $\text{SE}_{\text{natgrass}} = 0.131$; $\text{density}_{\text{nnggrass}} = 0.516$; $\text{SE}_{\text{nnggrass}} = 0.126$; $\text{density}_{\text{crop}} = 0.251$; $\text{SE}_{\text{crop}} = 0.070$; $\text{density}_{\text{poor}} = 0.254$; $\text{SE}_{\text{poor}} = 0.080$; $\text{density}_{\text{shrub}} = 0.065$; $\text{SE}_{\text{shrub}} = 0.022$; $\text{density}_{\text{forest}} = 0.065$; $\text{SE}_{\text{forest}} = 0.023$; Figure 6a). Meadowlark availability did not greatly vary over time (Figure 6b). Availabilities in 2013, 2015, 2016, and 2017 were similar, but availability was notably low in 2014 in comparison ($\phi_{2013} = 0.094$; $\text{SE}_{2013} = 0.023$; $p_{2013} < 0.01$; $\phi_{2014} = 0.067$; $\text{SE}_{2014} = 0.017$; $p_{2014} < 0.01$; $\phi_{2015} = 0.087$; $\text{SE}_{2015} = 0.021$; $p_{2015} < 0.01$; $\phi_{2016} = 0.099$; $\text{SE}_{2016} = 0.023$; $p_{2016} < 0.01$; $\phi_{2017} = 0.109$; $\text{SE}_{2017} = 0.026$; $p_{2017} < 0.01$).

Finally, the vegetative cover model was also selected for Painted Buntings ($\Delta\text{AIC} = 79.29$; Table 7). Forest, native grassland, non-native grassland, and shrubland all positively influenced density, while cropland negatively influenced density ($\beta_{\text{forest}} = 0.518$; $\text{SE}_{\text{forest}} = 0.133$; $p_{\text{forest}} < 0.01$; $\beta_{\text{natgrass}} = 0.134$; $\text{SE}_{\text{natgrass}} = 0.116$; $p_{\text{natgrass}} = 0.25$; $\beta_{\text{nnggrass}} = 0.029$; $\text{SE}_{\text{nnggrass}} = 0.120$; $p_{\text{nnggrass}} = 0.81$; $\beta_{\text{shrub}} = 0.807$; $\text{SE}_{\text{shrub}} = 0.122$; $p_{\text{shrub}} < 0.01$; $\beta_{\text{crop}} = -0.628$; $\text{SE}_{\text{crop}} = 0.148$; $p_{\text{crop}} < 0.01$). Density was highest in shrublands, followed by forest cover, native and non-native grasslands, poor quality cover, and cropland ($\text{density}_{\text{shrub}} = 0.382$; $\text{SE}_{\text{shrub}} = 0.028$; $\text{density}_{\text{forest}} = 0.286$; $\text{SE}_{\text{forest}} = 0.026$;

$\text{density}_{\text{natgrass}} = 0.195$; $\text{SE}_{\text{natgrass}} = 0.012$; $\text{density}_{\text{nngrass}} = 0.176$; $\text{SE}_{\text{nngrass}} = 0.012$;

$\text{density}_{\text{poor}} = 0.170$; $\text{SE}_{\text{poor}} = 0.019$; $\text{density}_{\text{crop}} = 0.091$; $\text{SE}_{\text{crop}} = 0.010$; Figure 7a).

Availability was relatively similar in 2013, 2014, and 2015, but it increased dramatically in 2016 and 2017 ($\phi_{2013} = 0.614$; $\text{SE}_{2013} = 0.045$; $p_{2013} = 0.02$; $\phi_{2014} = 0.565$; $\text{SE}_{2014} = 0.042$; $p_{2014} = 0.12$; $\phi_{2015} = 0.704$; $\text{SE}_{2015} = 0.046$; $p_{2015} < 0.01$; $\phi_{2016} = 0.924$; $\text{SE}_{2016} = 0.055$; $p_{2016} < 0.01$; $\phi_{2017} = 0.999$; $\text{SE}_{2017} = 0.006$; $p_{2017} = 0.55$; Figure 7b).

Discussion

Density modeling indicated that shrubland, cropland, and native grassland yield the highest densities for Northern Bobwhite. The high densities associated with shrublands and native grasslands and low densities associated with forest and poor quality cover, which contains cover such as urban and riparian, are not surprising as bobwhite are known to occupy mosaics of grasslands, shrublands, and forests (Arredondo et al. 2006; Kopp et al. 1998; Rader et al. 2006). However, it is notable that density is much lower in non-native grasslands as compared to native grasslands. Previous research from southwestern Texas rangelands has also documented that native grasslands supported almost twice as many Northern Bobwhite as non-native grasslands (Flanders et al. 2006). Additionally, Northern Bobwhite may avoid using locations with large patches of exotic grasses, which may also lead to reduced abundance in non-native grasslands (Sands et al. 2012). However, as documented by Kuvlesky et al. (2002), there is little research about the effect of non-native grasses on Northern Bobwhite. In addition to the difference between native and non-native grasslands, the high density associated with croplands was somewhat surprising as well. Previous studies have shown that Northern

Bobwhite are associated with landscapes with patches of row crops, grasslands, and woody edges (Janke and Gates 2013; Roseberry and Sudkamp 1998). It is important to note, however, that these studies have indicated that cropland is merely one aspect of optimum Northern Bobwhite habitat. In addition, Riddle et al. (2008) found that the presence of field borders in agricultural landscapes can dramatically increase the abundance of Northern Bobwhite. This is important to note, as the methodology used for the categorization of vegetative cover type associated the majority cover type with each point count location. Therefore, it ignored the presence of field borders due to cropland representing the majority of the 250-meter radius circle around the point count location. As such, it is possible that Northern Bobwhite abundance appears to be high in cropland, when, in actuality, it may be high due to the presence of field borders. It would be remiss to assume that large areas of cropland alone could support a density of 1.2 birds/ha. Future analyses should use percentage cover of the vegetative cover types identified as important predictors of density within this study and patch size covariates to further explore Northern Bobwhite habitat needs.

Eastern Meadowlarks displayed similar densities in both native and non-native grasslands. Coppedge et al. (2001) found that abundance of Eastern Meadowlarks increased in one study area with the creation of non-native grasslands. However, as the authors point out, this was in the presence of woody encroachment and few remaining patches of native grassland. It is possible that non-native grasslands show high densities due to the lack of native grasslands in the face of habitat conversion, woody encroachment, and overall loss of native grasslands, all of which are concerns within Texas (Steinauer and Collins 1996; Asner et al. 2003; Archer 1994). Although not as high

as the grassland densities, the density of Eastern Meadowlarks found in poor quality cover was unexpected. This category contains riparian cover, shrublands, and forests, as well as cover types that include swamps, open water, urban, and barren land. As such, it is not immediately clear why density was higher in what would be expected to be very poor quality vegetative cover than it is in shrubland or forest cover. It is possible that due to the decline of native grasslands, Eastern Meadowlarks may occupy areas that are not ideal habitat, such as parklands, suburban edges, or non-native grasslands as observed previously. Further exploration into this and ground-truthing of some of the cover types included in this category may provide some insight into why this pattern occurred.

Finally, density was intermediate in cropland for Eastern Meadowlarks. Studies about the effects of cropland, specifically row crops, on Eastern Meadowlarks are rare. One study showed that Eastern Meadowlarks have had reduced numbers in the presence of intense agriculture (Best et al. 2001), while another indicated that Eastern Meadowlarks did not avoid grassland-cropland edges (Walk et al. 2010). Studies examining the effects of conversion from cropland to land enrolled in the Conservation Reserve Program (CRP) have shown that Eastern Meadowlark abundances increase with increasing CRP lands (McCoy et al. 1999; Haroldson et al. 2004). Overall though, it is unexpected that Eastern Meadowlarks would be at high densities in cropland areas, especially in comparison to grasslands. Additionally, it is possible that the density within croplands is somewhat inflated due to Eastern Meadowlarks utilizing grassland-cropland edges. Like the cropland effect in Northern Bobwhite, it is likely that the edge effects discovered by Walk et al. (2010) were lost when the majority cover category was selected for each

point. Again, future analyses should focus on specific percentages of these cover types to better understand what drives Eastern Meadowlark density in Texas.

Painted Bunting density was highest in shrubland and forest cover categories, which was expected as Painted Buntings are known to utilize mosaics of grasslands and forests/shrublands (Parmelee 1959; Kopachena and Crist 2000). However, densities in grasslands were similar to densities in poor quality cover, which is unexpected due to their utilization of these mosaics that include grasslands. The inclusion of cover types such as riparian forests in the poor cover type category may be one of the drivers for this pattern. In southern Texas and arid regions of western North America, Painted Buntings are considered an obligate riparian species (Hunter et al. 1988; Rich 2002). Additionally, one study found that 82% of locations in which Painted Buntings were observed were associated with some kind of aquatic habitat (Kopachena and Crist 2000). Therefore, the inclusion of riparian cover types in the poor cover type category may be the reason why its associated density is higher than expected. Future analyses should also include riparian cover types. Additionally, as was likely with Northern Bobwhite and Eastern Meadowlarks, it is possible that some of the underrepresentation of grasslands in comparison to shrubland and forests is due to the use of majority cover types rather than percentages. Observers noted that Painted Buntings were typically detected in areas that could be classified as forest-grassland edge, often with small stands of trees or shrubs within the grassland. Therefore, it is likely that most locations where detections of Painted Buntings were high were classified as forest or shrubland cover types, causing those cover types to be over-represented and grasslands to be under-represented. Overall, caution should be used if future analyses attempt to use majority cover types to predict

abundance and density for these species, as it appears that in some cases the importance of cover types can be over- or under-emphasized.

It was somewhat surprising that PDSI was not selected as a predictor for any of the three species of interest, especially considering its previous success with Northern Bobwhite in south Texas (Bridges et al. 2001). However, because Bridges et al. (2001) found that PDSI was only a predictor for a southern population of Northern Bobwhite, it is possible that PDSI may only be able to predict density for a specific portion of the Northern Bobwhite surveyed for this study. Droege and Sauer (1990) attempted to use state-level PDSI values to explain population changes demonstrated by Breeding Bird Survey data, but found no relationship. However, the scale was likely too coarse to be able to detect these patterns. Another study found that PDSI from the survey month (May) and the previous year's survey month had little to no effect on the density of multiple grassland species in North Dakota (Niemuth et al. 2008). While this study utilized a smaller resolution (4 km) and broader temporal scale than the studies previously mentioned, more experimentation will be needed to identify whether the influence of drought on these species can be captured using PDSI. Future analyses should examine other temporal scales, such as the preceding winter months or the PDSI during the survey period.

Finally, patterns in availability over the five years of the study can be interpreted as changes in abundance over time. All three species show similar patterns in availability over time – availability is comparatively low in 2013, followed by a decline in 2014, and, excluding Northern Bobwhite in 2017, succeeded by increases from 2015 to 2017. Although PDSI failed to be selected as a covariate in the three species of interest, it is

likely that these availability patterns are influenced by precipitation and drought conditions. The mean PDSI values from each year of this study indicated that the 12 months leading up to surveys in 2013 were subjected to drought conditions, with the drought becoming somewhat reduced in the 12 months leading up to the 2014 surveys. The time periods leading up to the 2015 and 2016 surveys were increasingly wet, with a small decline in wet conditions leading up to 2017. Excluding rare exceptions, the availability measures follow this pattern with a one year delay. It is likely that precipitation and drought caused these variations over time in conjunction with other variables such as habitat loss and fragmentation. This study was unable to capture this change using PDSI from the preceding 12 months, but future analyses should still consider climatological and weather variables when attempting to decipher what causes temporal and spatial patterns in abundance and density.

Management Implications

Vegetative covariates that positively influence density of Northern Bobwhite, Eastern Meadowlark, and Painted Bunting vary amongst these species despite all three being listed as grassland species. This highlights the need for managers to consider the habitat needs of multiple species when developing comprehensive management plans. Northern Bobwhite may sometimes be considered an umbrella species for grassland birds due to the ability of their habitat requirements to be fulfilled by a broad range of vegetation types (Crosby et al. 2015; Howell et al. 2009). However, this study highlights that densities of these three species do not follow similar patterns across the different cover types. Therefore, managers should carefully consider the creation of landscapes

that include mosaics, including large and small patches, of shrubland, forest, and native grassland. Focus on restoration of shrubland alone or native grassland alone could negatively affect species such as Eastern Meadowlarks or Painted Buntings respectively. Additionally, although PDSI was not selected as an availability covariate, it is important to consider the effects of climate and weather on density of grassland species, as is indicated by the change in availability over the five years of the study. However, increases and declines in density should not be attributed to climate and weather alone, and long-term changes in grassland bird densities are more likely attributable to changes in vegetative cover, habitat structure, connectivity, and patch size.

TABLES

Table 1. Detection model selection for Northern Bobwhite (*Colinus virginianus*). All possible models were fit for each year using pre-selected detection covariates, which included ambient noise (Noise), Julian date (Date), and observer-level. Observer-level was sorted into categories that reflected the number of point counts performed. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|---|----|----------|--------------|
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Date} + \text{Time} + \text{Observer-level})$ | 12 | 16216.47 | 0 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Date} + \text{Time})$ | 10 | 16236.82 | 20.36 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Date} + \text{Observer-level})$ | 11 | 16239.80 | 23.33 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Time} + \text{Observer-level})$ | 11 | 16257.21 | 40.74 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Date})$ | 9 | 16259.91 | 43.44 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Observer-level})$ | 10 | 16279.24 | 62.77 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Time})$ | 9 | 16286.16 | 69.69 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date})$ | 8 | 16307.14 | 90.67 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Time} + \text{Observer-level})$ | 11 | 16429.68 | 213.21 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Time})$ | 9 | 16454.76 | 238.29 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Observer-level})$ | 10 | 16460.63 | 244.16 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Time} + \text{Observer-level})$ | 10 | 16462.66 | 246.19 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise})$ | 8 | 16487.76 | 271.29 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Time})$ | 8 | 16492.82 | 276.35 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Observer-level})$ | 9 | 16501.32 | 284.85 |
| $\lambda(.) \varphi(\text{Year}) p(.)$ | 7 | 16533.63 | 317.16 |

Table 2. Detection model selection for Eastern Meadowlark (*Sturnella magna*). All possible models were fit for each year using pre-selected detection covariates, which included ambient noise (Noise), Julian date (Date), and observer. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|--|----|----------|--------------|
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Observer})$ | 26 | 11713.64 | 0 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Observer})$ | 25 | 11752.30 | 38.67 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date})$ | 8 | 11772.16 | 58.52 |
| $\lambda(.) \varphi(\text{Year}) p(.)$ | 7 | 11811.97 | 98.33 |

Table 3. Estimates for the observer covariate for Eastern Meadowlark (*Sturnella magna*) and Painted Bunting (*Passerina ciris*) from covariate selection for detection modeling. Covariates that had $|z| \geq 1.85$ were selected as covariates to use in detection model selection, and therefore observer was included for both species. SE: Standard Error

| Observer | Eastern Meadowlark | | | | Painted Bunting | | | |
|----------|--------------------|--------|---------|----------|-----------------|---------|---------|----------|
| | Estimate | SE | z | P(> z) | Estimate | SE | z | P(> z) |
| A | -0.1083 | 0.0793 | -1.3653 | 1.72e-01 | -0.0027 | 0.03766 | -0.0716 | 9.43e-01 |
| B | -0.2987 | 0.0970 | -3.0786 | 2.08e-03 | -0.0546 | 0.04517 | -1.2077 | 2.27e-01 |
| C | -0.2987 | 0.0799 | -3.7359 | 1.87e-04 | 0.1202 | 0.03494 | 3.4401 | 5.81e-04 |
| D | 0.0191 | 0.0686 | 0.2787 | 7.80e-01 | 0.0225 | 0.02979 | 0.7551 | 4.50e-01 |
| E | -0.1261 | 0.0905 | -1.3931 | 1.64e-01 | 0.2212 | 0.04159 | 5.3182 | 1.05e-07 |
| F | 0.0077 | 0.0913 | 0.0846 | 9.33e-01 | -0.0699 | 0.03848 | -1.8164 | 6.93e-02 |
| G | -0.0683 | 0.0876 | -0.7803 | 4.35e-01 | 0.0218 | 0.03810 | 0.5733 | 5.66e-01 |
| H | -0.2489 | 0.1200 | -2.0748 | 3.80e-02 | 0.2881 | 0.04768 | 6.0423 | 1.52e-09 |
| I | -0.2912 | 0.0900 | -3.2341 | 1.22e-03 | 0.0461 | 0.04154 | 1.1094 | 2.67e-01 |
| J | -0.3437 | 0.1027 | -3.3478 | 8.15e-04 | -0.1236 | 0.06265 | -1.9721 | 4.86e-02 |
| K | -0.1107 | 0.0971 | -1.1401 | 2.54e-01 | -0.0359 | 0.04622 | -0.7756 | 4.38e-01 |
| L | 0.2418 | 0.1189 | 2.0326 | 4.21e-02 | 0.2225 | 0.04652 | 4.7827 | 1.73e-06 |
| M | 0.6980 | 0.3776 | 1.8483 | 6.46e-02 | 0.3969 | 0.06463 | 6.1409 | 8.20e-10 |
| N | -0.2125 | 0.1048 | -2.0269 | 4.27e-02 | -0.3221 | 0.05751 | -5.6002 | 2.14e-08 |
| O | -0.3178 | 0.2253 | -1.4103 | 1.58e-01 | -0.13980 | 0.09841 | -1.4206 | 1.55e-01 |
| P | -0.1721 | 0.0874 | -1.9694 | 4.89e-02 | 0.0950 | 0.03888 | 2.443 | 1.45e-02 |
| Q | -0.0867 | 0.1240 | -0.6989 | 4.85e-01 | 0.0025 | 0.05654 | 0.0448 | 9.64e-01 |
| R | -0.1684 | 0.0890 | -1.8920 | 5.85e-02 | 0.1034 | 0.04286 | 2.4124 | 1.58e-02 |

Table 4. Detection model selection for Painted Bunting (*Passerina ciris*). All possible models were fit for each year using pre-selected detection covariates, which included ambient noise (Noise), Julian date (Date), and observer. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|---|----|----------|--------------|
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Observer})$ | 26 | 20623.02 | 0 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Observer})$ | 25 | 20639.03 | 16.00 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise})$ | 8 | 20851.06 | 228.03 |
| $\lambda(.) \varphi(\text{Year}) p(.)$ | 7 | 20880.78 | 257.75 |

Table 5. Density and availability model selection for Northern Bobwhite (*Colinus virginianus*). All possible models were fit for each year using pre-selected availability and abundance covariates, which included Palmer Drought Severity Index (PDSI) and vegetative cover type. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|---|----|----------|--------------|
| $\lambda(\text{Vegetation}) \varphi(\text{PDSI} + \text{Year}) p(\text{Noise} + \text{Date} + \text{Time} + \text{Observer-level})$ | 19 | 14615.13 | 0 |
| $\lambda(\text{Vegetation}) \varphi(\text{Year}) p(\text{Noise} + \text{Date} + \text{Time} + \text{Observer-level})$ | 18 | 14616.82 | 1.68 |
| $\lambda(.) \varphi(\text{PDSI} + \text{Year}) p(\text{Noise} + \text{Date} + \text{Time} + \text{Observer-level})$ | 14 | 14939.38 | 324.25 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Noise} + \text{Date} + \text{Time} + \text{Observer-level})$ | 13 | 14943.22 | 328.09 |

Table 6. Density and availability model selection for Eastern Meadowlark (*Sturnella magna*). All possible models were fit for each year using pre-selected availability and abundance covariates, which included Palmer Drought Severity Index (PDSI) and vegetative cover type. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|--|----|----------|--------------|
| $\lambda(\text{Vegetation}) \varphi(\text{PDSI} + \text{Year}) p(\text{Date} + \text{Observer})$ | 33 | 11103.59 | 0 |
| $\lambda(\text{Vegetation}) \varphi(\text{Year}) p(\text{Date} + \text{Observer})$ | 32 | 11104.53 | 0.94 |
| $\lambda(.) \varphi(\text{PDSI} + \text{Year}) p(\text{Date} + \text{Observer})$ | 28 | 11216.43 | 112.84 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Observer})$ | 27 | 11218.53 | 114.94 |

Table 7. Density and availability model selection for Painted Bunting (*Passerina ciris*). All possible models were fit for each year using pre-selected availability and abundance covariates, which included Palmer Drought Severity Index (PDSI) and vegetative cover type. The table includes the model statements, number of parameters (K), AIC, and Δ AIC. Models were identified as competing when they were within 2 Δ AIC. When models were competing, the most parsimonious model was selected.

| Model | K | AIC | Δ AIC |
|--|----|----------|--------------|
| $\lambda(\text{Vegetation}) \varphi(\text{Year}) p(\text{Date} + \text{Observer})$ | 32 | 20353.50 | 0 |
| $\lambda(\text{Vegetation}) \varphi(\text{PDSI} + \text{Year}) p(\text{Date} + \text{Observer})$ | 33 | 20432.80 | 79.29 |
| $\lambda(.) \varphi(\text{PDSI} + \text{Year}) p(\text{Date} + \text{Observer})$ | 28 | 20521.75 | 168.25 |
| $\lambda(.) \varphi(\text{Year}) p(\text{Date} + \text{Observer})$ | 27 | 20522.42 | 168.91 |

FIGURES

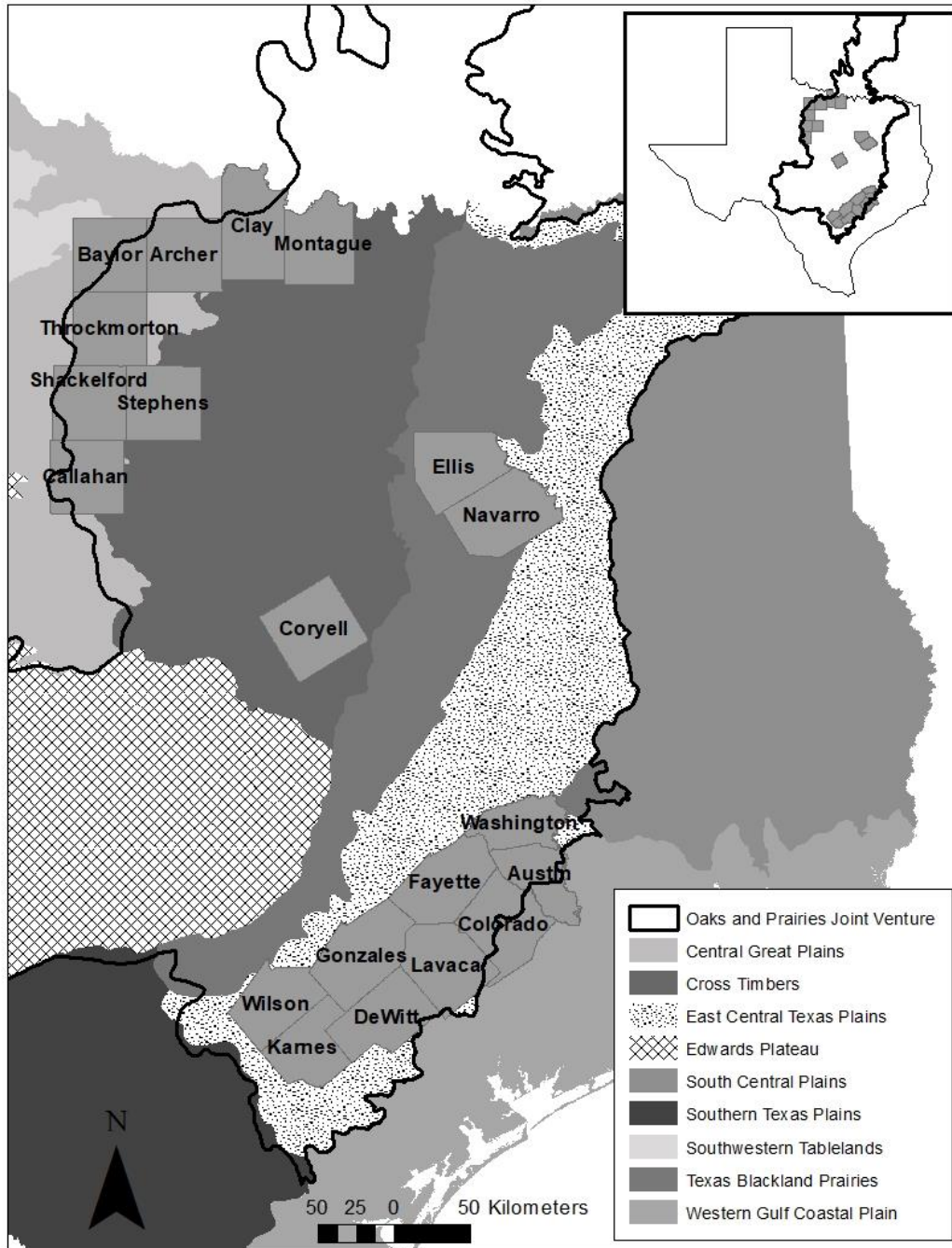


Figure 1. Texas counties surveyed within the Oaks and Prairies Joint Venture. Road-side points counts were performed in each county during the months of May and June from 2013 to 2017. Each county had 4 or 5 routes along secondary and tertiary roads, and 30 points were surveyed per route. Counties were selected to represent multiple Texas ecoregions.

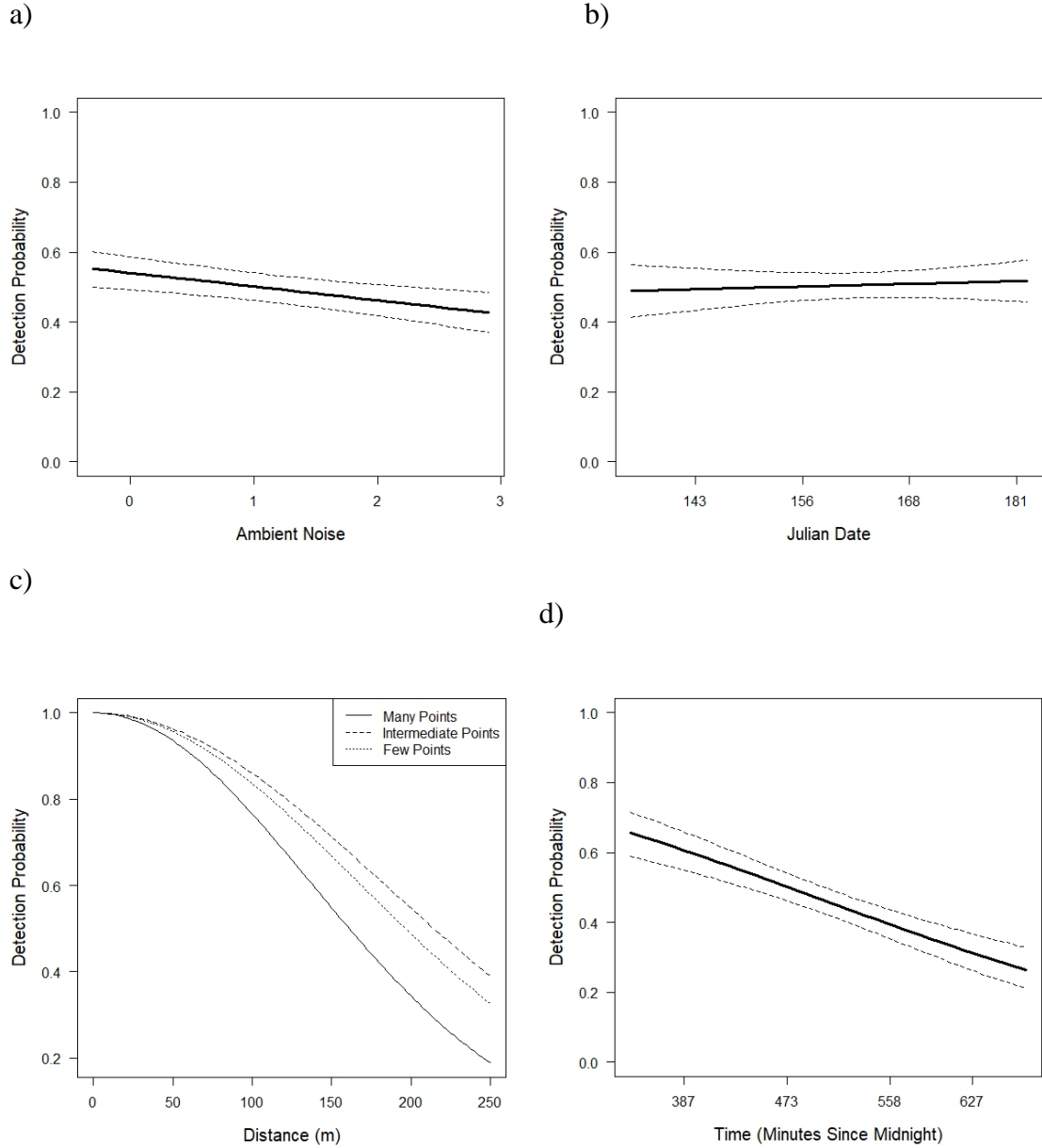
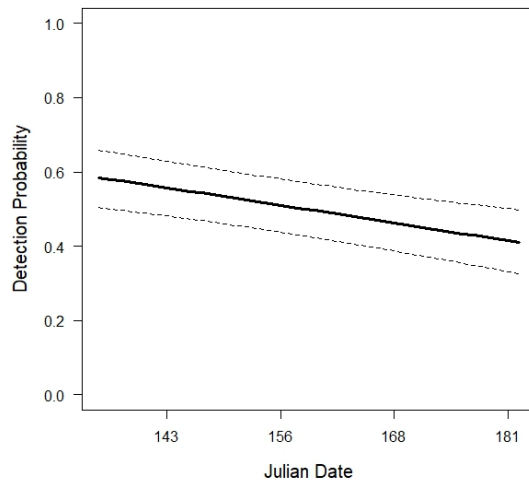


Figure 2. Effects of covariates on detection probability for Northern Bobwhite (*Colinus virginianus*). Figures show the estimated relationships of covariates that influence detection in 11 Texas counties across 5 years. For a), b), and d), solid lines indicate the estimated relationship, and dotted lines indicate the 95% confidence interval. Covariates included ambient noise (a), ranging from no noise (0) to constant noise (3); Julian date (b), ranging from mid-May to late June; observer-level (c), which was categorized by the number of point counts performed; and time (d), which ranged from thirty minutes before sunrise to 1100.

a)



b)

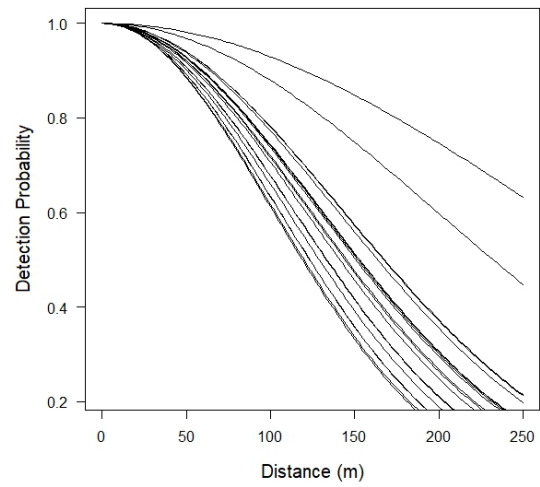
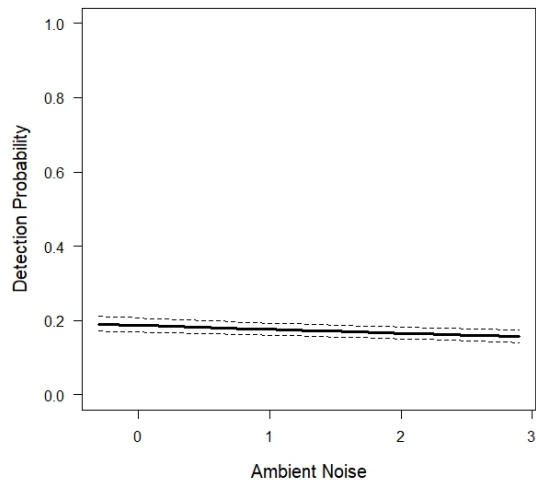


Figure 3. Effects of covariates on detection probability for Eastern Meadowlark (*Sturnella magna*). Figures show the estimated relationships of covariates that influence detection in 11 Texas counties across 5 years. Solid lines indicate the estimated relationship, and dotted lines indicate the 95% confidence interval. Covariates included Julian date (a), ranging from mid-May to late June, and observer (b), where each line represents a separate observer.

a)



b)

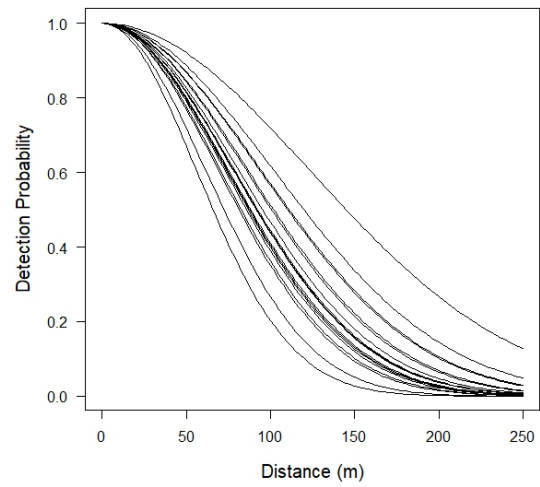
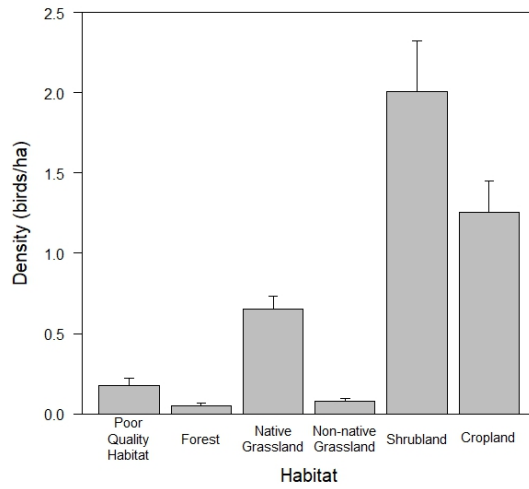


Figure 4. Effects of covariates on detection probability for Painted Bunting (*Passerina ciris*). Figures show the estimated relationships of covariates that influence detection in 11 Texas counties across 5 years. Solid lines indicate the estimated relationship, and dotted lines indicate the 95% confidence interval. Covariates included ambient noise (a), which ranges from no noise (0) to constant noise (3), and observer (b), where each line represents a separate observer.

a)



b)

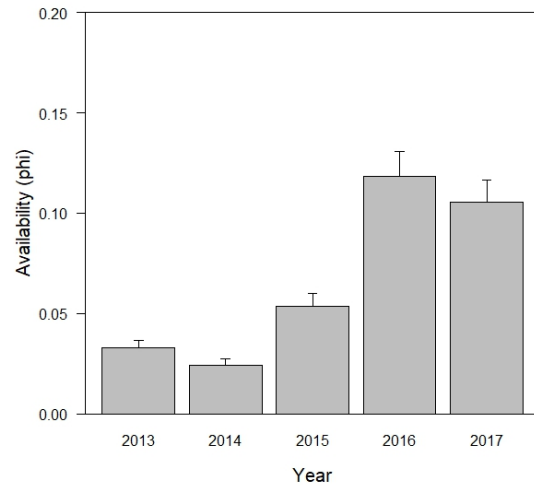
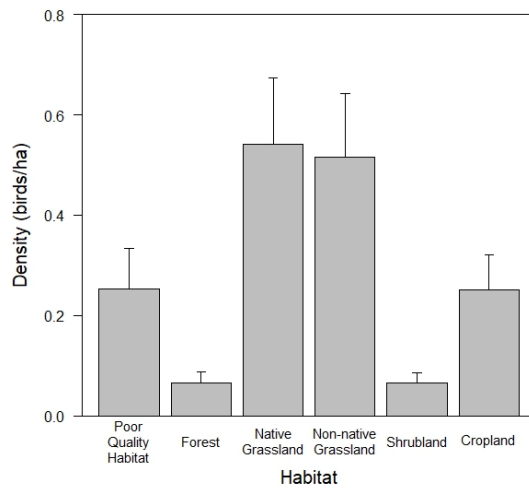


Figure 5. Effects of covariates on availability probability and density for Northern Bobwhite (*Colinus virginianus*). Figures show the estimated relationships of covariates that influence availability and detection in 11 Texas counties across 5 years. Error bars represent standard error. Covariates included year and vegetative cover type.

a)



b)

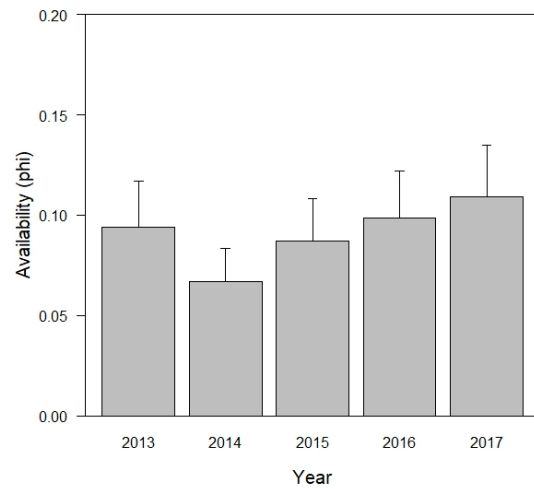
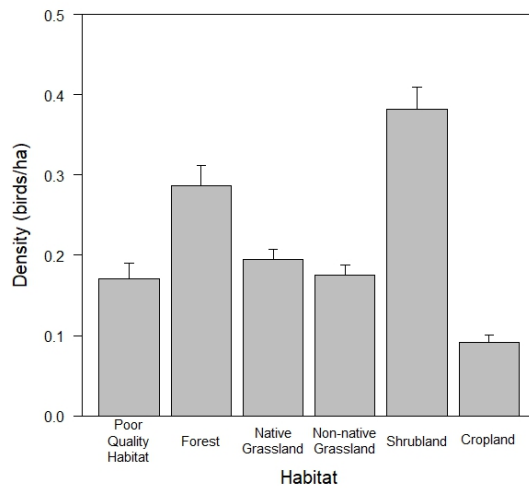


Figure 6. Effects of covariates on availability probability and density for Eastern Meadowlark (*Sturnella magna*). Figures show the estimated relationships of covariates that influence availability and detection in 11 Texas counties across 5 years. Error bars represent standard error. Covariates included year and vegetative cover type.

a)



b)

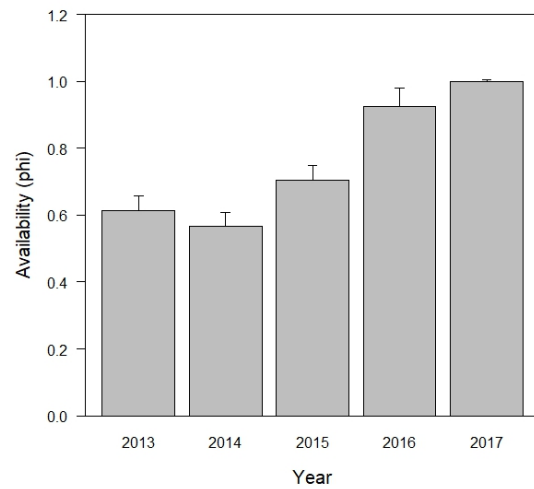


Figure 7. Effects of covariates on availability probability and density for Painted Bunting (*Passerina ciris*). Figures show the estimated relationships of covariates that influence availability and detection in 11 Texas counties across 5 years. Error bars represent standard error. Covariates included year and vegetative cover type.

APPENDIX SECTION

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APPENDIX A

Below are the results of null model selection for Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*) for detection model building. The complete null model for all three parameters (detection, availability, and abundance) was compared against a null model that contained one covariate for availability – year – while the remaining parameters remained at the null state. The analysis was performed on data from 956 points surveyed once per year from 2013 to 2017 in 11 Texas counties.

Table A1. Null model selection for detection and abundance modeling for Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*). p represents detection covariates, ϕ represents availability covariates, and λ represents abundance covariates. K is representative of the number of parameters estimated within the model.

| Species | Model | K | AIC | Δ AIC |
|--------------------|-------------------------------------|---|----------|--------------|
| Northern Bobwhite | $\lambda(.) \phi(\text{Year}) p(.)$ | 7 | 16533.63 | 0 |
| | $\lambda(.) \phi(.) p(.)$ | 3 | 17539.34 | 1005.71 |
| Eastern Meadowlark | $\lambda(.) \phi(\text{Year}) p(.)$ | 7 | 11811.97 | 0 |
| | $\lambda(.) \phi(.) p(.)$ | 3 | 11917.49 | 105.52 |
| Painted Bunting | $\lambda(.) \phi(\text{Year}) p(.)$ | 7 | 20880.78 | 0 |
| | $\lambda(.) \phi(.) p(.)$ | 3 | 20948.90 | 68.12 |

APPENDIX B

Below are the results of detection covariate selection for Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*) for detection model building. Single covariate models were built for the detection parameter and covariates were selected for future detection model building based on z-scores. The analysis was performed on data from 956 points surveyed once per year from 2013 to 2017 in 11 Texas counties.

Table B1. Detection covariate selection for detection modeling of Northern Bobwhite (*Colinus virginianus*). The covariate observer-level was classified into categories that reflected number of point counts performed during field work. Covariates were selected for detection modeling if the covariate had a z-score of $|1.85|$ or higher. p represents detection covariates, ϕ represents availability covariates, and λ represents density covariates. SE: standard error.

| Model | Predictor | Estimate | SE | z | P(> z) |
|---|--------------|----------|--------|--------|----------|
| $\lambda(.) \phi(\text{Year}) p(\text{Date})$ | Date | 0.26 | 0.0181 | 14.4 | 7.71e-47 |
| $\lambda(.) \phi(\text{Year}) p(\text{Noise})$ | Noise | -0.121 | 0.0186 | -6.51 | 7.53e-11 |
| $\lambda(.) \phi(\text{Year}) p(\text{Observer-level})$ | Intermediate | -0.2011 | 0.0359 | -5.599 | 2.16e-08 |
| | Few | -0.0484 | 0.0907 | -0.534 | 5.94e-01 |
| $\lambda(.) \phi(\text{Year}) p(\text{Time})$ | Time | -0.119 | 0.0188 | -6.3 | 3.02e-10 |

Table B2. Detection covariate selection for detection modeling of Eastern Meadowlark (*Sturnella magna*). Covariates were selected for detection modeling if the covariate had a z-score of $|1.85|$ or higher. p represents detection covariates, ϕ represents availability covariates, and λ represents density covariates. SE: standard error.

| Model | Predictor | Estimate | SE | Z | P(> z) |
|---|-----------|----------|--------|---------|----------|
| $\lambda(.) \phi(\text{Year}) p(\text{Date})$ | Date | -0.125 | 0.0196 | -6.39 | 1.71e-10 |
| $\lambda(.) \phi(\text{Year}) p(\text{Observer})$ | I | -0.3266 | 0.0881 | -3.709 | 0.000208 |
| | B | -0.3478 | 0.0940 | -3.699 | 0.000217 |
| | C | -0.2718 | 0.0784 | -3.466 | 0.000528 |
| | J | -0.2611 | 0.0969 | -2.695 | 0.007042 |
| | L | 0.4576 | 0.1802 | 2.539 | 0.011109 |
| | A | -0.1585 | 0.0766 | -2.068 | 0.038600 |
| | N | -0.2070 | 0.1044 | -1.982 | 0.047434 |
| | O | -0.4654 | 0.2387 | -1.950 | 0.051169 |
| | H | -0.2177 | 0.1184 | -1.838 | 0.066080 |
| | M | 0.6125 | 0.3478 | 1.761 | 0.078267 |
| | R | -0.1158 | 0.0978 | -1.184 | 0.236606 |
| | G | -0.0978 | 0.0857 | -1.142 | 0.253609 |
| | P | -0.0945 | 0.0854 | -1.106 | 0.268517 |
| | D | -0.0540 | 0.0649 | -0.833 | 0.404999 |
| | Q | -0.0645 | 0.1202 | -0.537 | 0.591388 |
| | E | -0.0490 | 0.0978 | -0.501 | 0.616248 |
| | K | -0.225 | 0.1117 | -0.202 | 0.840070 |
| | F | 0.0136 | 0.0874 | 0.155 | 0.876459 |
| $\lambda(.) \phi(\text{Year}) p(\text{Time})$ | Time | 0.0156 | 0.0167 | 0.933 | 0.351 |
| $\lambda(.) \phi(\text{Year}) p(\text{Noise})$ | Noise | -0.00118 | 0.0174 | -0.0679 | 0.946 |

Table B3. Detection covariate selection for detection modeling of Painted Bunting (*Passerina ciris*). Covariates were selected for detection modeling if the covariate had a z-score of $|1.85|$ or higher. p represents detection covariates, ϕ represents availability covariates, and λ represents density covariates. SE: standard error.

| Model | Predictor | Estimate | SE | Z | P(> z) |
|---|-----------|----------|---------|--------|----------|
| $\lambda(.) \phi(\text{Year}) p(\text{Observer})$ | M | 0.43477 | 0.0639 | 6.804 | 1.02e-11 |
| | H | 0.29246 | 0.0476 | 6.146 | 7.94e-10 |
| | E | 0.24373 | 0.0411 | 5.931 | 3.01e-09 |
| | N | -0.29524 | 0.0568 | -5.200 | 1.99e-07 |
| | L | 0.22470 | 0.0465 | 4.828 | 1.38e-06 |
| | C | 0.14721 | 0.0343 | 4.295 | 1.75e-05 |
| | R | 0.12646 | 0.0425 | 2.978 | 2.90e-03 |
| | F | -0.07474 | 0.0384 | -1.944 | 5.19e-02 |
| | P | 0.07140 | 0.0386 | 1.852 | 6.41e-02 |
| | D | 0.04709 | 0.0292 | 1.612 | 1.07e-01 |
| | J | -0.09719 | 0.0618 | -1.573 | 1.16e-01 |
| | O | -0.15342 | 0.0983 | -1.560 | 1.19e-01 |
| | B | -0.05745 | 0.0450 | -1.276 | 2.02e-01 |
| | G | 0.04233 | 0.0378 | 1.121 | 2.62e-01 |
| | I | 0.04469 | 0.0416 | 1.073 | 2.83e-01 |
| | K | -0.02252 | 0.0460 | -0.489 | 6.25e-01 |
| | Q | 0.01109 | 0.0565 | 0.196 | 8.44e-01 |
| | A | 0.00382 | 0.0377 | 0.101 | 9.19e-01 |
| $\lambda(.) \phi(\text{Year}) p(\text{Noise})$ | Noise | -0.0432 | 0.00767 | -5.63 | 1.77e-08 |
| $\lambda(.) \phi(\text{Year}) p(\text{Date})$ | Date | -0.00245 | 0.00796 | -0.308 | 0.758 |
| $\lambda(.) \phi(\text{Year}) p(\text{Time})$ | Time | 0.00237 | 0.00784 | 0.302 | 0.763 |

APPENDIX C

Below are the results of distribution selection for density modeling of Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*). The Poisson and negative-binomial distributions were compared on models that contained no covariates for density. Covariates for availability and detection were included based on prior model selection. The analysis was performed on data from 956 points surveyed once per year from 2013 to 2017 in 11 Texas counties.

Table C1. Selection of distribution for density model selection for Northern Bobwhite (*Colinus virginianus*), Eastern Meadowlark (*Sturnella magna*), and Painted Bunting (*Passerina ciris*). p represents detection covariates, ϕ represents availability covariates, and λ represents density covariates. The two distributions tested are negative-binomial (NB) and Poisson (P). K is representative of the number of parameters estimated within the model.

| Species | Distribution | Model | K | AIC | Δ AIC |
|--------------------|--------------|--|----|----------|--------------|
| Northern Bobwhite | NB | $\lambda(.) \phi(\text{Year}) p \left(\begin{matrix} \text{Noise} + \text{Date} + \\ \text{Time} + \text{Observerlevel} \end{matrix} \right)$ | 13 | 14943.22 | 0 |
| | P | $\lambda(.) \phi(\text{Year}) p \left(\begin{matrix} \text{Noise} + \text{Date} + \\ \text{Time} + \text{Observerlevel} \end{matrix} \right)$ | 12 | 16216.47 | 1273.25 |
| Eastern Meadowlark | NB | $\lambda(.) \phi(\text{Year}) p(\text{Date} + \text{Observer})$ | 27 | 11218.53 | 0 |
| | P | $\lambda(.) \phi(\text{Year}) p(\text{Date} + \text{Observer})$ | 26 | 11713.64 | 495.10 |
| Painted Bunting | NB | $\lambda(.) \phi(\text{Year}) p(\text{Noise} + \text{Observer})$ | 27 | 20522.42 | 0 |
| | P | $\lambda(.) \phi(\text{Year}) p(\text{Noise} + \text{Observer})$ | 26 | 20623.02 | 100.61 |

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