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Occupancy Rates of Eastern Wild Turkeys: Estimating effects of experimental harvest regulations and automating image analysis

by

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CHAPTER I: INTRODUCTION

It is difficult to make informed predictions about a population's response to effective management actions without knowledge of the dynamics of the population. There are a number of sampling methods that can be applied to gain information on population dynamics, including, but not limited to: transect sampling (Amstrup et al. 2004, Silveira et al. 2003), banding and radio-telemetry (Guetterman et al. 1991), and camera traps (Cobb et al. 1997). However, camera trap surveys are one of the most cost-effective options for sampling populations in remote locations and over large spatial scales (Mace et al. 1973, Damm et al. 2010). Camera traps are also repeatable across space and time, making them valuable tools for monitoring species for multiple years at large scales.

While camera trap surveys are increasing in popularity (Rowcliffe and Carbone 2008), the images produced require expert interpretation, which may come at a great cost. The number of images collected can be very large, with some surveys surpassing 1.2 million images (Swanson et al. 2015) depending on the objectives and scale of the survey. There are programs that automate image analysis, resulting in more economical image interpretation (Maydanchik 2007, Harris et al. 2010, Fegraus et al. 2011, Bubnicki et al. 2016, He et al. 2016); however, they are not applicable for all camera trap survey images due to customization for specific camera programming or focus on a species of interest.

Eastern wild turkeys (*Meleagris gallopavo silvestris*; hereafter turkey) are the most popular game bird species in Alabama, yet little research has been conducted on the population during the past 30 years. In addition to suspected declines in productivity across Alabama (S. Barnett, ADCNR, personal communication), the effect that hunting regulations have on turkey population demographics is unknown. It is important for managers to monitor the impacts of changes in hunting regulations on population dynamics to evaluate their effects (Williams 1997). Occupancy is a useful parameter to monitor because turkeys occur at low densities, and at large spatial scale (MacKenzie et al. 2002, MacKenzie and Nichols 2004). Managers are able estimate and quantify the parameters that influence occupancy including imperfect detection using camera trap surveys (Karanth et al. 2006, Damm et al. 2010). When sites are surveyed on more than one occasion and more than one season, it is possible to estimate occupancy dynamics, extinction, and colonization rates, which are related to population dynamics (MacKenzie et al. 2017).

Each chapter in this thesis contributes to the available knowledge about turkey populations in Alabama, the effects of management on those populations, and the ability to conduct cost-effective surveys for monitoring their dynamics. In Chapter 2, I present the results of using Machine Learning (ML) to automate image classification as a means of reducing the cost of camera trap surveys. I also compare occupancy estimates from ML classified images to those that were manually interpreted and suggest ways to improve estimates of occupancy based on ML classified images. In Chapter 3, I present an analysis of the effects of experimental changes in hunting regulations at several wildlife management areas across Alabama on turkey occupancy dynamics using camera trap surveys conducted during late summer. Together these chapters represent significant advances in methods to monitor the effects of management on turkey populations across their range.

Literature Cited

Amstrup, S.C., G. York, T.L. McDonald, R. Nielson, and K. Simac. 2004. Detecting denning polar bears with forward-looking infrared (FLIR) imagery. BioScience 54:337-344.

Bubnicki, J. W., M. Churski, D. P. J. Kuijper, and T. Poisot. 2016. Trapper: An open source web-based application to manage camera trapping projects. Methods in Ecology and Evolution 7:1209–1216.

Cobb, D. T., R. S. Fuller, D. L. Francis, and G. L. Sprandel. 1997. Research priorities for monitoring wild turkeys using cameras and infrared sensors. Proceedings of the Annual Conference Southeastern Association of Fish and Wildlife Agencies 51:362-372.

Damm, P. E., J. B. Grand, and S. W. Barnett. 2010. Variation in detection among passive infrared triggered-cameras used in wildlife research. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 64:125-130.

Fegraus, E. H., K. Lin, J. A. Ahumada, C. Baru, S. Chandra, and C. Youn. 2011. Data acquisition and management software for camera trap data: a case study from the TEAM Network. Ecological Informatics 6:345–353.

Guetterman, J.H., J.A. Burns, J.A. Reid, R.B. Horn, and C.C. Foster. 1991. Radio telemetry methods for studying spotted owls in the Pacific Northwest. Gen. Tech. Rep. PNW-GTR-

272. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Harris, G., R. Thompson, J. L. Childs, and J. Sanderson. 2010. Automatic storage and analysis of camera trap data. Bulletin of the Ecological Society of America 91:352–360.

He, Z., R. Kays, Z. Zhang, G. Ning, C. Huang, T. X. Han, J. Millspaugh, T. Forrester, and W. McShea. 2016. Visual informatics tools for supporting large-scale collaborative wildlife monitoring with citizen scientists. IEEE Circuits and Systems Magazine 16:73–86.

Karanth, K. U., J. D. Nichols, N. S. Kumar, and J. E. Hines. 2006. Assessing tiger population dynamics using photographic capture–recapture sampling. Ecology 87:2925–2937.

Mace, R. D., S. C. Minta, T. L. Manley, and K. E. Aune. 1973. Estimating grizzly bear population size using camera sightings. Wildlife Society Bulletin 22:74–83.

MacKenzie, D. I., & J. D. Nichols. 2004. Occupancy as a surrogate for abundance estimation. Animal Biodiversity and Conservation 27(1):461-467.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. A. Royle, and C. A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83(8):2248-2255.

MacKenzie, D.I., Nichols, J.D., Royle, J.A., Pollock, K.H., Bailey, L.A. and Hines, J.E., 2006. Occupancy modeling and estimation.

Maydanchik, A. 2007. Data quality assessment. Technics publications.

Rowcliffe, J.M., and C. Carbone. 2008. Surveys using camera traps: are we looking to a brighter future? Animal Conservation 11:185-186.

Silveira, L., A.T.A. Jacomo and J.A.F. Diniz-Filho. 2003. Camera trap, line transect census and track surveys: a comparative evaluation. Biological Conservation 114:351-355.

Soisalo, M.K., and S.M.C. Cavalcanti. 2006. Estimating the density of a jaguar population in the Brazilian Pantanal using camera-traps and capture–recapture sampling in combination with GPS radio-telemetry. Biological Conservation 129:487-496.

Swanson, A., M. Kosmala, C. Lintott, R. Simpson, A. Smith, and C. Packer. 2015. Snapshot Serengeti, high-frequency annotated camera trap images of 40 mammalian species in an African savanna. Scientific Data 2:150026. Nature Publishing Group.

Williams, B. K. 1997. Approaches to the management of waterfowl under uncertainty. Wildife Society Bulletin 25(3):714-720.

CHAPTER II: AUTOMATED TECHNIQUES FOR ANALYZING CAMERA IMAGES FROM EASTERN WILD TURKEY SURVEYS

Abstract

Estimating eastern wild turkey (*Meleagris gallopavo silvestris*; hereafter turkeys) population demographics precisely and accurately is essential for effective harvest and habitat management. Demographic estimates, which were once based on expert opinion or harvest data, are now being estimated from data collected during camera trap surveys that can be repeated across space and time. However, camera trap surveys usually result in large numbers of images that must be interpreted in a timely manner. Classifying these images based on expert review can be time-consuming, costly, and error prone. To address these issues, we developed models using supervised classification and Machine Learning (ML) to determine the presence or absence of turkeys in images. We conducted camera trap surveys on three study areas, which allowed a wide variety of backgrounds in images. We compared 23 classification algorithms and selected six for further investigation. To estimate how misclassification of images using ML would affect estimates of occupancy, we compared estimates of occupancy from images classified with trained models, manually interpreted images, and then a combination of both manual and ML classification of images. As a result, from commission errors, ML classification occupancy estimates were 1.0 (0.994-0.998, 95% CL), doubling estimates of occupancy from manual interpretation, 0.53 (0.39-0.67, 95% CL). When using ML in combination with manual interpretation, estimates of occupancy overlapped with the confident limits of manual interpretation alone. The manual interpretation image processing rate was estimated at ~2,000 images/hr, whereas the Machine Learning image interpretation rate was 15,120 images/hr. Manual interpretation in combination with ML required 80% less time than manual

interpretation-only. Our results suggest that ML shows great potential as a labor-saving tool for analyzing images from camera trapping surveys, and, when used in combination with expert review, can be used to derive population parameters from camera trap surveys that are comparable to estimates from manual image interpretation.

Introduction

Automated cameras (hereafter camera traps) have been used to photograph and monitor wildlife since the 1950s (Gysel and Davis 1956). Camera traps are valuable tools for sampling a large area in a short time period when physical capture is undesired or difficult to conduct (Mace et al. 1973). The number of published papers describing the use of camera traps as research tools in *Ecology* grew by 50% annually from 1998 to 2008 (Rowcliffe and Carbone 2008). One reason for this rapid growth is that camera traps make wildlife monitoring significantly easier (Mace et al. 1973, Karanth et al. 2006, Damm et al. 2010, Manzo et al. 2012), and additionally, enable researchers to discover new species (Rovero et al. 2008). The images resulting from camera trap surveys are commonly used to estimate demographic parameters and population dynamics of species (Martorello et al. 1973, Soisalo and Cavalcanti 2006, Varma et al. 2006, Giman et al. 2007). However, the use of camera traps requires a significant time investment interpreting images and entering data.

Camera traps generally capture images by two means: motion-sensor triggers and time-lapse programming. Motion-sensor captures an image when passive infrared sensors (PIR) are triggered by a change in the infrared light detected (Swann et al. 2011). Time-lapse settings capture an image on specified time intervals regardless of motion (Swann et al. 2011). While time-lapse settings increase the number of uninformative images, they reduce sampling error that occurs from environmental conditions at the camera site and variation among camera sensors, thereby increasing the precision in subsequent population estimates (Damm et al. 2010, Hamel et al. 2013). Variation in estimates of presence varied between 30 and 70% when using motion-triggered cameras and only 5 to 30% using a 5-minute time-lapse (Hamel et al. 2013). A study conducted in Alabama found that variation in PIR sensitivity in camera traps deployed together at the same site resulted in up to a 33% difference in the number of images that captured an animal (Damm et al. 2010).

Estimating eastern wild turkey (*Meleagris gallopavo silvestris*; hereafter turkeys) population demographics precisely and accurately is essential for effective harvest and habitat management (Vangilder and Kurzejeski 1995). The Alabama Department of Conservation and Natural Resources (ADCNR) chose camera traps to survey turkey populations across the state due to the uniformity of surveys across space and time and their relative cost-effectiveness for estimating turkey demographics (Damm et al. 2010). Using time-lapse triggers allowed researchers to estimate detection rates and occupancy of turkeys in the study areas, while reducing variation in estimates (Swann et al. 2004, Damm et al. 2010). However, Gonnerman (2017) found that, on average, only 2.6% of the images collected during the surveys contain turkeys. Due to the large number of camera traps required to accurately monitor populations at statewide or regional scales and the large number of images generated per camera from the time-lapse programming, manually processing these images is not economical.

As a result, software has been developed to efficiently process and analyze large quantities of images while reducing the time spent and bias introduced by manually analyzing images (Maydanchik 2007). These data management programs range from project-specific cyber-infrastructures (Fegraus et al. 2011), to open source web-based applications (Harris et al. 2010, Bubnicki et al. 2016, He et al. 2016). Image analysis programs using deep learning have been designed to process sequences of images that are captured with motion-sensor triggers (Norouzzadeh et al. 2018), but were not designed to handle time-lapse surveys, such as the surveys conducted for turkey. In contrast, the AnimalFinder program was designed to classify the presence/absence of large- and medium-bodied species in time-lapse images. However, this program was developed for relatively monotone species such as white-tailed deer (*Odocoileus virginianis)* and cannot be adapted to classify textured species, such as turkey (Price Tack et al. 2016). While no program currently exists for detecting turkey in time-lapse images, Price Tack (2016) demonstrated the value of having an automated image analysis program for a large scale survey: AnimalFinder classified images at a rate of 26,000 images per hour in comparison to the manual-only method that required four observers at a processing rate of 4,274 images per hour (Price Tack et al. 2016).

The overarching objective of this study was to examine the potential use of Machine Learning (ML) algorithms to classify the presence or absence of turkeys in camera trap images, thereby reducing the amount of manual effort necessary to estimate occupancy over a large-scale, long-term survey. The ML algorithms needed to be able to classify turkey presence at multiple sites because turkey camera trap surveys are conducted across the state in varying-sized openings, resulting in variation in the background. The specific objectives of this research were to 1) determine the repeatability of model development; 2) optimize algorithm training; 3) estimate the potential bias associated with the misclassification of images on estimates of turkey occupancy using automated image classification techniques.

Study Area

We conducted camera trap surveys on three study areas in Alabama that varied in wildlife opening sizes, resulting in differences in the distance of turkey from the camera and a variety of backgrounds in the images. James D. Martin-Skyline WMA (Skyline) was in Jackson County in northeast Alabama, bordering Tennessee and Georgia. Skyline WMA was managed and owned by Alabama Power Company and Alabama Department of Conservation and Natural Resources (ADCNR) and composed of 24,577 ha of the Southwestern Appalachian Mountains, in the Cumberland Plateau physiographic region. We surveyed 44 of the available 285 wildlife openings within the WMA boundaries, and most of them were located on the western and southeastern region of the WMA. Wildlife opening sizes varied between 0.05 ha and 10 ha. Landcover on plateaus and slopes consisted of hardwood forests that contained beech (*Fagus* spp.), yellow poplar (*Liriodendron tulipifera*), oak (*Quercus* spp.), sugar maple (*Acer saccharum*), basswood (*Tilia Americana*), ash (*Fraxinus* spp.), and buckeye (*Aesculus* spp.) (Griffith et al. 2001). Lower elevations consisted of hardwoods, predominantly mixed oaks (*Quercus* spp.) interspersed with large tracts of privately-owned agricultural fields.

Oakmulgee WMA was located within the Talladega National Forest in west-central Alabama. It was managed under a cooperative partnership between ADCNR and the U.S. Forest Service. Oakmulgee WMA included sections of Bibb, Hale, Perry, and Tuscaloosa Counties. Oakmulgee WMA was composed of 18,008 ha of the Southeastern Plains physiographic region, consisting of rolling hills topography. Landcover consisted of oak, hickory (*Carya* spp.), and pine (*Pinus* spp.) (Griffith et al. 2001). We surveyed 45 of the available 100 wildlife openings evenly distributed within the WMA boundaries. Wildlife opening sizes varied between 0.04 ha and 1.10 ha.

Barbour WMA was in Barbour and Bullock Counties in southwest Alabama. It was owned and managed by ADCNR, with a timber lease that is managed by Weyerhaeuser Company. Barbour WMA was composed of 11,418 ha of the Southern Hilly Gulf Coastal Plain physiographic region, consisting of rolling hills topography with irregular plains. Landcover consisted of oak, hickory, and pine, along with some croplands throughout the WMA (Griffith et al. 2001). We surveyed 45 of the available 210 wildlife openings distributed within the WMA boundaries. Most of them were located in the western region of the WMA. Wildlife opening sizes on this WMA varied between 0.03 ha and 14 ha.

Methods

Study Design

We conducted camera trap surveys on the three study sites during the 2016 brood-rearing season (13 July–9 August). During this time period, hens with poults had moved to brood rearing areas, such as wildlife openings, and were actively feeding (Godfrey and Norman 1999). We deployed camera trap surveys at a total of 134 wildlife openings across Skyline WMA (n = 44), Oakmulgee WMA (n = 45), and Barbour WMA (n = 45). We selected sites at random from all known and accessible managed wildlife openings. To avoid the potential of double counting individuals, we required a minimum distance of 500m between sites. Reconyx PC800, Reconyx PC 85 (Reconyx, Inc., Holmen, Wisc.), and Spartan SR1-IR (HCO Outdoor Products, Norcross, Georgia) **camera** traps were used for the surveys. We selected a sturdy tree to attach a camera trap on the south edge of wildlife openings so cameras could be pointed north to avoid glare from the sun. Five days prior to camera deployment, we cleared the area $\leq$10 m north of the tree of vegetation and debris >0.1 m in height. We placed approximately 7.5 liters of bait (chicken scratch) 3 m north of the tree in the cleared area. After five days, we attached the camera trap to the tree approximately one meter above the ground and the bait was replenished to increase the likelihood that turkeys would remain in front of the camera long enough to be captured by time-lapse. We programed camera traps to capture images every four minutes from 0600h – 1900h.

We removed cameras after a minimum of five days. Experts manually interpreted images that were collected into two categories: turkey presence and turkey absence.

Image classification

We utilized the Statistics and Machine Learning (v 9.2, The MathWorks, Inc 2017*a*) and Computer Vision Toolboxes (v 7.3, The MathWorks, Inc, 2017*a*) in MATLAB® (Mathworks, Inc., Natick, Mass.) to train the 23 algorithms available in the Image Processing Toolbox (v 10.0, The MathWorks Inc., 2017*a*). The 23 algorithms were grouped into six overarching classifier categories: Decision Trees, Discriminant Analysis, Logistic Regression, Support Vector Machines, Nearest Neighbor Classifiers, and Ensemble Classifiers. Decision tree types included simple, medium, or complex trees. Discriminant analysis included Linear and Quadratic algorithms. Support Vector Machines (SVM) included six algorithm types: Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, and Course Gaussian SVM. There are six algorithms types of nearest neighbor classifiers (KNNs): Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, and Weighted KNN. Nearest neighbor classifiers used *k*-Nearest Neighbors to categorize points based on their distance to other points in the training dataset. The number of points used was 1, 10, and 100. Fine KNN used one point, and Coarse KNN used 100 points. Ensemble classifiers consisted of six algorithm types: Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN, and RUSBoost Trees. Ensemble classifiers use a combination of weakly performing algorithms from the other classifier categories to build a more accurate algorithm.

We used images from Skyline and Oakmulgee WMAs for model development and cross-validation. We labeled camera trap locations from 1 – 45 at each WMA; images collected at even-numbered sites were used for model development, whereas images collected at oddnumbered sites were used for model cross-validation. Images were randomly drawn from the turkey presence and turkey absence classifications for every training set. We manipulated the number of training images and the number of features used for image classification by the image processing toolbox. The BoF function in the Machine Learning Toolbox was used to select features (i.e., visual vocabulary) by selecting clusters of pixels from images based on their attributes and relationship to other pixels using a proprietary algorithm. Thus, as the number of features used for image classification increased, the more in-depth the description of an image became. Increasing the number of features also increased the time required to describe and classify an image.

Model repeatability and accuracy

Initially, 500 randomly selected images and 500 features were used to train models using each of the 23 image classification algorithms in the Image Processing Toolbox. To protect against overfitting, accuracy of the trained models was determined in five-fold cross-validation by determining the number of images correctly classified as turkey absence and presence. Due to the amount of time necessary to train algorithms, only the top six performing algorithms were compared for model repeatability and optimization of model development. Optimization was examined as the tradeoff between the number of features and the number of interpreted images used to train each algorithm. We used 125, 250, or 500 features to train the algorithms. The number of training images used included 200, 800, 2,000, 2,400, and 3,000 images. Model repeatability was determined by comparing the variation in accuracy from trained models that used each combination of algorithm, BoF, and number of training images over 25 iterations. Each iteration used a different set of randomly selected images. We assessed model accuracy using cross-validation based on images from the two study areas used for training the model.

For the outgroup validation, the six best-performing trained models were used to classify images from camera traps on Barbour WMA. A confusion matrix was constructed for each model to categorize image misclassification into two different sources of errors: omission and commission. Omission occurred when a turkey was present in an image, but the image was classified as turkey absent. Commission occurred when a turkey was not present in an image, but the image was classified as turkey present.

Occupancy estimation

We estimated occupancy for Barbour WMA in Program Mark (v 9.0, White and Burnham 1999) for the six trained models and manual interpretation only, then compared results. Encounter histories were generated from the image classifications based on each of the Machine Learning models and manual interpretation of the same images. Each hour 0600h-1900h during the five-day camera deployment was considered an occasion. If a single image during an hour was classified as turkeys present, the encounter history indicated that a turkey was present on that occasion. Thus, each site had 70 possible encounter occasions, but hours during which no images were recorded were treated as missing values (MacKenzie and Nichols 2004).

To test an approach for reducing the bias from misclassification, we also estimated occupancy using a combined approach of automated image classification and expert image interpretation. We replaced machine classifications with expert interpretation for all images classified as turkeys present by ML algorithms and generated new encounter histories. We then used the modified encounter histories to estimate occupancy and detection probabilities. For all occupancy analyses, we did not include covariates so we could compare the bias that remained from omission errors.

Results

We surveyed 135 managed wildlife openings from 13 July – 9 August 2016. We collected approximately 90,304 images from Oakmulgee WMA and Skyline WMA. Of those images, we used 44,179 in model training and 46,125 for cross-validation. The model training image set had 3,345 images with turkeys present and 40,834 images with turkeys absent. The cross-validation image set had 2,231 images with turkeys present and 43,894 images with turkeys absent. Barbour WMA had 52,920 images available for the independent test of accuracy, with 2.25% of those images manually classified as turkeys present. We manually classified all images at a processing rate of 2,000 images/hr.

Initially, we trained the 23 algorithms with 2,000 images and cross-validated with 500 images and 500 BoF (Table 2.1). Cubic SVM achieved the greatest accuracy. Simple tree achieved the worst accuracy. Ensemble algorithms achieved high accuracy, but only Ensemble Subspace was used in additional analyses. Overall, 16 of the 23 algorithms achieved accuracy greater than 80% (Table 2.1). Omission error ranged from 3.55 – 19.1%, with commission errors ranging from 3.4 – 18.2% (Table 2.1).

We analyzed the six algorithms with the highest accuracy for model-building optimization included: Cubic SVM, Fine KNN, Medium Gaussian SVM, Quadratic SVM, Quadratic Discriminant, and Ensemble Subspace KNN. Accuracy was more affected by the number of training images than BoF. However, BoF had more of an impact on accuracy when fewer training images were used (Figure 2.1, Tables 2.2-2.7). Variation in model accuracy decreased in all algorithms as the number of training images and BoF increased (Figure 2.1, Tables 2.2-2.7). Variation in accuracy was reduced by over 75% when the minimum number of training images and BoF was increased to the maximum number of training images and BoF

(Tables 2.2-2.7). Mean model accuracy ranged from 72.60 – 89.18%, with a maximum SE = 3.97%. Cubic SVM (Table 2.2) and Fine KNN (Table 2.3) were the top two performing models with a difference in mean accuracy of only 0.16%. Quadratic SVM (Table 2.4) and Medium Gaussian SVM (Table 2.5) algorithms achieved the third and fourth greatest mean accuracy. Quadratic Discriminant (Table 2.6) achieved the smallest training accuracy, with some combinations of BoF and training images inestimable. Ensemble Subspace KNN was a top-performing model; however, we did not include it for the independent test of accuracy due to the lack of description of which models were used during model building (Table 2.7).

In the outgroup-validation, accuracy ranged from 57.14-84.22% (Table 2.8). Commission was greatest when classifying images with the Fine KNN model (Table 2.8). Commission was smallest when images were classified with the trained Medium Gaussian SVM model (Table 2.8). Omission was greatest when classifying images with the trained Quadratic Discriminant model (Table 2.8). Omission was smallest when images were classified with the trained Ensemble Subspace KNN model (Table 2.8). Due to the large rates of commission in the automated image analysis methods, an expert examined a random subset of images with commission errors for possible causes of misclassification. We did not detect either the presence of other wildlife nor shadows as causative agents for image misclassification.

On Barbour WMA, we conducted 45 camera trapping sites with 70 encounter occasions each, for a total of 3,150 occasions. When we used an encounter history constructed from manual interpretation of Barbour 2016 images, we estimated occupancy (ψ) 0.53 (0.39-0.67, 95% CL) and detection (p) 0.15 (0.13-0.17; 95% CL). When we used encounter histories from classification of images using the six algorithms, ψ was 1.0 (0.994-0.997, 95% CL) for Ensemble Subspace KNN, Quadratic SVM, Cubic SVM, and Fine KNN; 0.91 (0.79-0.97, 95% CL) for

Medium Gaussian SVM, and 0.95 (0.84-0.99, 95% CL) for Quadratic Discriminant. All six models overestimated turkey occupancy by approximately double than the analysis of manually classified images.

When we recast the encounter histories again by substituting the manual interpretation of images for the images classified as turkeys present by each algorithm, thus eliminating the errors of commission, estimates of ψ and p were smaller than the estimates from manual interpretation alone (Table 2.9). All algorithms had overlapping confidence limits with the manual interpretation estimates of occupancy (Table 2.9). Fine KNN required the largest number of images to be manually interpreted (n = 22,672); Medium Gaussian SVM required the least number of images to be manually reclassified (n = 7,748). Estimates of ψ were smallest with the Medium Gaussian SVM and the greatest using Quadratic Discriminant. Detection probability from the image classification data was smallest with the Medium Gaussian SVM and greatest with Fine KNN. Detection probabilities were always smaller than manual interpretation because the errors of omission were retained in the data.

The manual interpretation image processing rate was estimated at ~2,000 images/hr, whereas the Machine Learning image interpretation rate was 15,120 images/hr. Manual interpretation of Barbour WMAs camera survey required 26.46 hours (Table 2.10). Machine Learning classification of Barbour WMA required 3.5 hours for each trained model (Table 2.10). When manual interpretation was used in conjunction with ML interpretation for better estimates of occupancy, the time for classifying all 52,920 from Barbour WMAs camera survey images ranged from 7.37 – 14.84 hours, depending on which algorithm was used (Table 2.10).

Discussion

Based on our results, ML shows great potential as a tool for analyzing images from camera trapping surveys. ML models achieved a high degree of accuracy in photo classification, and the accuracy was reasonably high when the models were applied to photos from another location. However, accuracy of image classification was misleading when the classification results were applied to estimating occupancy. Commission errors below 15% inflated estimates of occupancy by double. That said, we found a way to attain accurate estimates of occupancy that utilized manual classification in conjunction with ML classified results.

We found that the number of training images and BoF used to train models affected accuracy. The performance of the six top ML trained models varied with the different combinations of BoF and training image sets. Across algorithms, the number of training images had a greater effect on accuracy than BoF. Additionally, accuracy was inversely related to the variance in accuracy among iterations. The reduction in variation of accuracy indicated more consistent model performance. The overall accuracy of the models increased as BoF and training set size increased. Accuracy increased drastically between smaller training set sizes but started to plateau once we advanced to larger training sets, never reaching an asymptote. Training set size was limited to a maximum of 3,000 images due to the small number of images from Oakmulgee WMA and Skyline WMA that contained turkeys. This limitation could be overcome, and the point of diminishing returns could be identified if images from other areas were incorporated in the training image set.

The rate of omission and commission errors varied for each of the trained models when applied to an outside image set. These affected estimates of occupancy and the time to remediate for them. Naïvely using the image classification results could result in large errors in the estimates of population parameters: commission error lends itself to biasing the population high, omission errors bias the population low (Miller et al. 2011). To reduce the errors, we utilized manual classification to reclassify images classified as turkeys present by ML models. This removed commission errors, resulting in estimates of occupancy that were like occupancy from manual classification. Manual reclassification of images increased the amount of time necessary to interpret an image set, but the ML algorithms we used only classified turkey presence and absence. Additionally, this process would allow managers to achieve measurements of abundance for different sex and age classes of turkey by counting and categorizing turkeys in the images (Royle and Nichols 2003). Even with the additional time associated with using manual interpretation in conjunction with ML, processing time was greatly reduced from manual interpretation method alone.

Estimators have been developed to estimate occupancy in the presence of false-positive detections (Miller et al. 2011, Clement 2016). One estimator sets two observation states: uncertain detections or certain detections (Miller et al. 2011). One assumption of this estimator is that detections classified as certain are never false positives (Ferguson et al. 2015). To achieve this, a subset of images classified as turkey presence by algorithms would need to be manually reinterpreted. Additionally, while these estimators allow covariates such as interpreter or algorithm, only interpreting a subset of the images would remove the ability to include abundance from manually reinterpreting the images classified as turkey presence.

While models achieved high accuracy during cross-validation, accuracy was greatly reduced when applied to an outside dataset. This may be due differences at the sites surveyed for the outgroup comparison such as types of vegetation, size of the openings, or the number of shadows cast in wildlife openings. The outgroup validation, Barbour WMA, had the largest opening size, 14 ha, which was 4 ha larger than the maximum opening size in the training sets. This decrease in accuracy may be corrected by including images from more sites into the training sets prior to training models or increasing the number of images used to train the models. Another option would be to have ML models trained with individual study area images that would result in models that are only applicable for the study area that is being surveyed.

Recommendations

There is great potential application for using ML to reduce the amount of work necessary to derive population estimates from camera trap surveys. However, there is much room for improvement. Future research should be conducted to find the point of diminishing returns in accuracy for combinations of BoF and training set sizes. Managers should opt to train models with the largest feasible BoF and training set size. Sources of misclassification error, not accuracy, should be used as the determining factor for the selection of automated image classification methods. Practitioners should plan to manually reinterpret some images to reduce bias in estimates of occupancy.

With the development of ML models, users will be able to generate accurate, timely, and cost-effective estimates of occupancy from camera trap surveys. These results will allow managers to generate and use estimates of occupancy in a more cost-effective manner when monitoring the response of turkey population to specific management actions. Moving forward, ML programs can be expanded to count and identify the presence of other species of interest using camera traps.

Literature Cited

Bubnicki, J. W., M. Churski, D. P. J. Kuijper, and T. Poisot. 2016. Trapper: an open source web-based application to manage camera trapping projects. Methods in Ecology and Evolution 7:1209–1216.

Clement, M. J. 2016. Designing occupancy studies when false-positive detections occur. Methods in Ecology and Evolution 7: 1538 – 1547.

Damm, P. E., J. B. Grand, and S. W. Barnett. 2010. Variation in detection among passive infrared triggered-cameras used in wildlife research. Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 64:125–130.

Fegraus, E. H., K. Lin, J. A. Ahumada, C. Baru, S. Chandra, and C. Youn. 2011. Data acquisition and management software for camera trap data: a case study from the TEAM Network. Ecological Informatics 6:345–353.

Ferguson, P.F.B., M.J. Conroy, and J. Hepinstall-Cymerman. 2015. Occupancy models for data with false positive and false negative errors and heterogeneity across sites and surveys. Methods in Ecology and Evolution 6:1395–1406.

Giman, B., R. Stuebing, N. Megum, W. J. Mcshea, and C. M. Stewart. 2007. A camera trapping inventory for mammals in a mixed use planted forest in Sarawak. The Raffles Bulletin in Zoology 55:209–215.

Godfrey, C. L., and G. W. Norman. 1999. Effect of habitat and movement on wild turkey poult survival. Proceedings of the Annual Conference Southeastern Association Fish and Wildlife Agencies 53:330-339.

Gonnerman, M. B. 2017. Estimating use, density, and productivity of eastern wild turkey in Alabama. Thesis. Auburn University, Auburn, Alabama, USA.

Griffith, G. E., J. M. Omernick, J. A. Comstock, S. Lawrence, G. Martin, A. Goddard, V. J. Hulcher, and T. Foster. 2001. Ecoregions of Alabama and Georgia. (2 sided color poster with map, descriptive text, summary tables, and photographs). Reston, VA.

Gysel, L. W., and E. M. Davis. 1956. A simple automatic photographic unit for wildlife research. The Journal of Wildlife Management 20:451–453.

Hamel, S., S. T. Killengreen, J. A. Henden, N. E. Eide, L. Roed-Eriksen, R. A. Ims, and N. G. Yoccoz. 2013. Towards good practice guidance in using camera-traps in ecology: Influence of sampling design on validity of ecological inferences. Methods in Ecology and Evolution 4:105–113.

Harris, G., R. Thompson, J. Childs, and J. Sanderson. 2010. Automatic storage and analysis of camera trap data. Bulletin Ecological Society of America 91:352–360.

He, Z., R. Kays, Z. Zhang, G. Ning, C. Huang, T. X. Han, J. Millspaugh, T. Forrester, and W. McShea. 2016. Visual informatics tools for supporting large-scale collaborative wildlife monitoring with citizen scientists. IEEE Circuits and Systems Magazine 16:73–86.

Karanth, K. U., J. D. Nichols, N. S. Kumar, and J. E. Hines. 2006. Assessing tiger population dynamics using photographic capture–recapture sampling. Ecology 87:2925–2937.

Mace, R. D., S. C. Minta, T. L. Manley, and K. E. Aune. 1973. Estimating grizzly bear population size using camera sightings. Wildlife Society Bulletin 22:74–83.

MacKenzie, D. I. and J. D. Nichols. 2004. Occupancy as a surrogate for abundance estimation. Animal Biodiversity and Conservation 27(1):461-467.

Manzo, E., P. Bartolommei, J. M. Rowcliffe, and R. Cozzolino. 2012. Estimation of population density of European pine marten in central Italy using camera trapping. Acta Theriologica 57:165–172.

Martorello, D. A., T. H. Eason, and M. R. Pelton. 1973. A sighting technique using cameras to estimate population size of black bears. Wildlife Society Bulletin 29:560–567.

Maydanchik, A. 2007. Data quality assessment. Technics publications.

Miller, D.A., J. D. Nichols, B.T McClintock, E.H.C Grant, L.L Bailey, and L.A. Weir. 2011. Improving occupancy estimation when two types of observational error occur: non-detection and species misidentification. Ecology 92:1422–1428.

Norouzzadeh, M.S., A. Nguyen, M. Kosmala, A. Swanson, M.S. Palmer, C. Packer, and J. Clune. 2018. Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. Proceedings of the National Academy of Sciences of the United States of America 115(25):E5716-E5725.

Price Tack, J. L., B. S. West, C. P. McGowan, S. S. Ditchkoff, S. J. Reeves, A. C. Keever, and J. B. Grand. 2016. AnimalFinder: a semi-automated system for animal detection in time-lapse camera trap images. Ecological Informatics 36:145–151.

Rovero, F., G. B. Rathbun, A. Perkin, T. Jones, D. O. Ribble, C. Leonard, R. R. Mwakisoma, and N. Doggart. 2008. A new species of giant sengi or elephant-shrew (genus Rhynchocyon) highlights the exceptional biodiversity of the Udzungwa Mountains of Tanzania. Journal of Zoology 274:126–133. Blackwell Publishing Ltd.

Rowcliffe, J.M., and C. Carbone. 2008. Surveys using camera traps: are we looking to a brighter future? Animal Conservation 11:185-186.

Royle, J. A. and J. D. Nichols. 2003. Estimating abundance from repeated presence-absence data or point counts. Ecology 84:777 – 790.

Soisalo, M. K., and S. M. C. Cavalcanti. 2006. Estimating the density of a jaguar population in the Brazilian Pantanal using camera-traps and capture–recapture sampling in combination with GPS radio-telemetry. Biological Conservation 129:487–496.

Swann, D. E., C. C. Hass, D. C. Dalton, and S. A. Wolf. 2004. Infrared-triggered cameras for detecting wildlife: an evaluation and review. Wildlife Society Bulletin 32:357–365.

Swann, D. E., K. Kawanishi, and J. Palmer. 2011. Evaluating types and features of camera traps in ecological studies: A guide for researchers. Pages 27–43 in Camera Traps in Animal Ecology. Springer Japan, Tokyo

The MathWorks Inc. 2017. Image Processing Toolbox. Natick, Massachusetts.

The MathWorks Inc. 2017a. Statistics and Machine Learning Toolbox. Natick, Massachusetts.

The MathWorks Inc. 2017b. Computer Vision Toolbox. Natick, Massachusetts.

Vangilder, L. D., and E. W. Kurzejeski. 1995. Population ecology of the eastern wild turkey in northern Missouri. Wildlife Monographs 130:3–50.

Varma, S., A. Pittet, and H. Jamadagni. 2006. Experimenting usage of camera-traps for population dynamics study of the Asian elephant Elephas maximus in southern India. Current Science 91(3):324-331.

White, G. C., and K. P. Burnham. 1999. Program MARK: Survival estimation from populations of marked animals. Bird Study 46:S120–S139.

Table 2.1. Cross-validation accuracy of 23 algorithms used for supervised image classification for Eastern wild turkey (*Meleagris gallopavo silvestris*) presence/ absence in the MATLAB Image Classification toolbox (Mathworks, Inc.). Each model was trained with 2,000 images and 500 BagofFeatures (BoF). We collected images at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016. Accuracy was estimated using 5-fold cross-validation on 500 images. Omission is the percent of images misclassified as turkey absence. Commission is the percent of images misclassified as turkey presence.

Algorithm	Accuracy (%)	Omission (%)	Commission (%)
Cubic SVM	89.0	4.7	6.3
Quadratic SVM	88.1	5.9	6.0
Subspace KNN	88.1	4.0	8.0
Fine KNN	87.4	4.4	8.2
Weighted KNN	86.2	3.6	10.3
Medium Gaussian SVM	85.5	6.8	7.7
Bagged Trees	85.0	7.6	7.5
Quadratic Discriminant	84.9	6.4	8.7
Cosine KNN	84.9	6.4	8.7
Medium KNN	84.5	6.5	9.1
Linear SVM	84.1	9.0	6.9
Cubic KNN	84.1	6.5	9.4
Boosted Trees	84.1	7.7	8.3
Subspace Discriminant	83.8	8.3	8.0
Fine Gaussian SVM	82.9	13.7	3.4
Linear Discriminant	80.8	9.9	9.4
Logistic Regression	78.0	10.5	11.6
Medium Tree	75.1	12.3	12.6
RUSBoosted Trees	75.1	12.3	12.7
Complex Tree	74.8	11.4	13.8
Coarse KNN	71.1	10.7	18.2
Coarse Gaussian SVM	70.8	13.9	15.3
Simple Tree	70.0	19.1	10.9

Bag of Features (BoF) - increment of visual vocabulary used to train models. Cross-Validation Accuracy – accuracy when tested on image set that differs from training set. SVM – Support Vector Machine. KNN – *k*-Nearest Neighbors.

Table 2.2. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Cubic SVM models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	72.94 (±3.07)	75.42 (±4.45)	76.00 (±3.22)
800	81.58 (±1.88)	83.60 (±1.41)	84.14 (±1.85)
2000	85.59 (±0.66)	87.03 (±0.69)	88.02 (±0.75)
2400	86.52 (±0.60)	87.08 (±0.75)	87.80 (±0.87)
3000	88.63 (±0.78)	88.45 (±0.82)	89.18 (±0.59)

Table 2.3. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Fine KNN models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	72.60 (±2.63)	73.98 (±4.00)	74.12 (±3.73)
800	81.43 (±1.57)	82.38 (±1.61)	82.11 (±1.70)
2000	86.44 (±0.81)	86.85 (±0.82)	87.31 (±0.75)
2400	87.47 (±0.77)	88.29 (±0.75)	87.66 (±0.95)
3000	88.88 (±0.58)	88.13 (±0.62)	89.02 (±0.59)

Table 2.4. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Quadratic SVM models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	72.94 (±3.31)	75.34 (±3.70)	76.68 (±2.59)
800	81.22 (±1.56)	83.10 (±1.64)	83.52 (±1.79)
2000	85.58 (±0.92)	86.43 (±0.79)	87.47 (±0.54)
2400	86.31 (±0.66)	87.03 (±0.78)	87.24 (±0.58)
3000	88.02 (±0.67)	87.61 (±0.89)	88.56 (±0.64)

Table 2.5. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Medium Gaussian SVM models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	69.26 (±2.58)	71.48 (±2.91)	72.94 (±3.28)
800	72.84 (±1.43)	76.99 (±1.17)	79.77 (±1.32)
2000	76.40 (±1.02)	80.59 (±0.77)	84.68 (±0.68)
2400	77.07 (±0.66)	77.70 (±0.78)	81.48 (±0.58)
3000	82.77 (±0.67)	85.04 (±0.89)	86.48 (±0.64)

Table 2.6. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Quadratic Discriminant models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	-	-	-
800	81.03 (±1.72)	78.47 (±1.65)	-
2000	82.93 (±0.91)	85.44 (±0.81)	83.64 (±0.96)
2400	83.06 (±0.71)	83.00 (±0.70)	85.78 (±0.77)
3000	86.25 (±0.79)	84.77 (±0.82)	86.32 (±0.60)

Table 2.7. Effect of number of features (BoF) and size of training set on mean cross-validation accuracy of Ensemble Subspace KNN models for determining turkey presence (*n* = 25 iterations). Images were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.

	Accuracy ($\bar{x} \pm$ SE)		
Training Images	125 BoF	250 BoF	500 BoF
200	72.86 (±3.46)	74.50 (±3.36)	74.50 (±2.88)
800	81.60 (±1.46)	82.51 (±1.76)	82.53 (±1.33)
2000	86.61 (±0.71)	86.99 (±1.01)	87.49 (±0.84)
2400	87.77 (±0.68)	88.34 (±0.65)	88.06 (±0.68)
3000	89.01 (±0.52)	88.35 (±0.72)	89.24 (±0.48)

Table 2.8. Comparison of accuracy of trained models applied to images from Barbour wildlife management area (WMA) from 5 July – 15 August 2016 as an independent test of accuracy. Barbour WMA image set contained 52,920 images, with 1,193 (2.25%) images containing turkeys, and the remaining 51,727 images with turkeys absent. Omission is the percent of images that were misclassified as turkey absence. Commission is the percentage of images misclassified as turkey presence.

	Correctly classified		Misclassified	
Model	Present (%)	Absent (%)	Omission (%)	Commission (%)
Cubic SVM	0.70	77.99	1.56	19.75
Fine KNN	1.12	56.02	1.13	41.72
Medium Gaussian SVM	0.56	83.66	1.70	14.08
Quadratic SVM	0.77	79.03	1.49	18.71
Quadratic Discriminant	0.38	82.74	1.88	15.01
Ensemble Subspace KNN	1.18	60.08	1.07	37.67

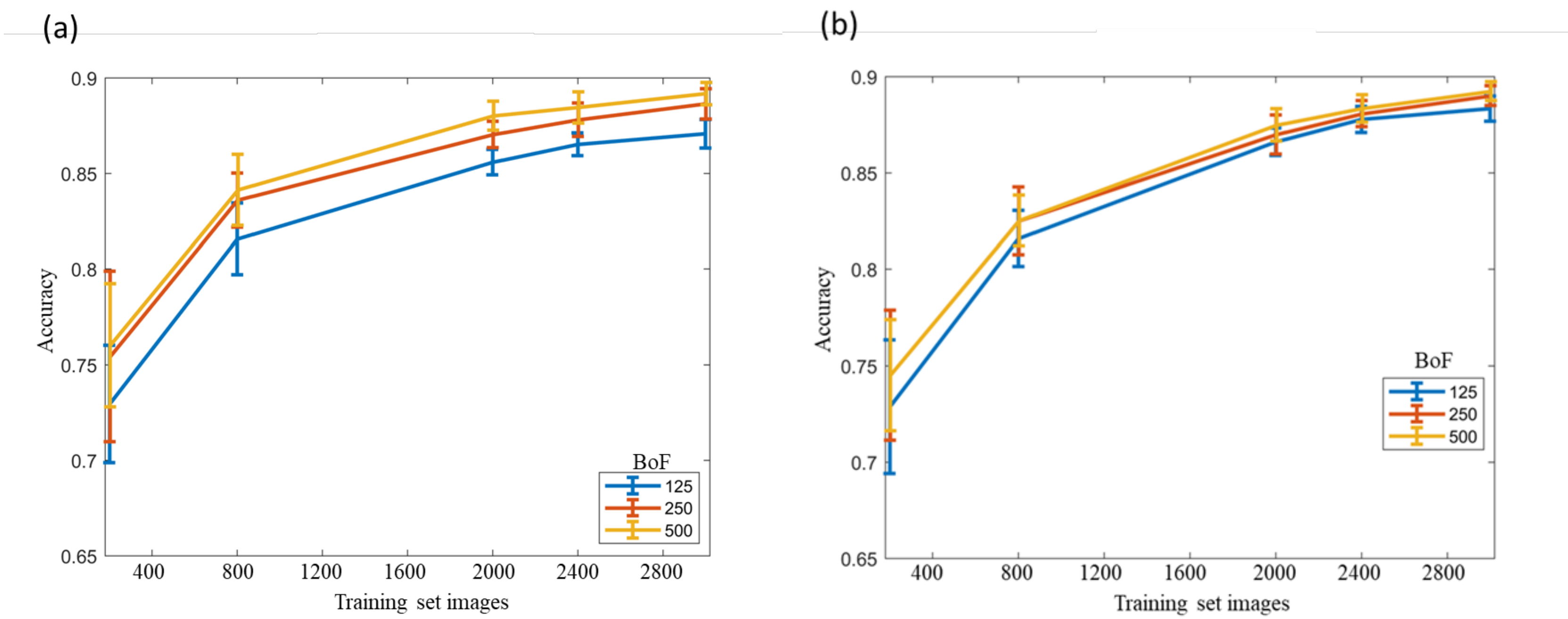
Table 2.9. Comparison of estimates of occupancy (ψ) and probability of detection (*p*) with 95% Confidence Limits of trained models after manual reclassification of images classified as turkey present from Barbour wildlife management area.

Method	ψ	*p*
Manual only	0.533 (0.389 – 0.672)	0.151 (0.134 – 0.169)
Cubic SVM	0.467 (0.328 – 0.611)	0.109 (0.095 – 0.127)
Fine KNN	0.511 (0.368 – 0.652)	0.143 (0.127 – 0.161)
Medium Gaussian SVM	0.423 (0.289 – 0.570)	0.082 (0.068 – 0.098)
Quadratic SVM	0.445 (0.308 – 0.590)	0.118 (0.102 – 0.136)
Quadratic Discriminant	0.512 (0.369 – 0.653)	0.091 (0.078 – 0.106)
Ensemble Subspace KNN	0.489 (0.348 – 0.632)	0.137 (0.121 – 0.155)

Table 2.10. Comparison of time to classify images from Barbour WMA camera trap survey with 52,920 images. We conducted surveys from 5 July – 15 August 2016. Manual classification (MC) image interpretation rate was ~2,000 images per hour. Machine learning (ML) algorithms classified 15,120 images in 3.50 hr. Machine learning was used in conjunction with manual classification to remove errors of commission.

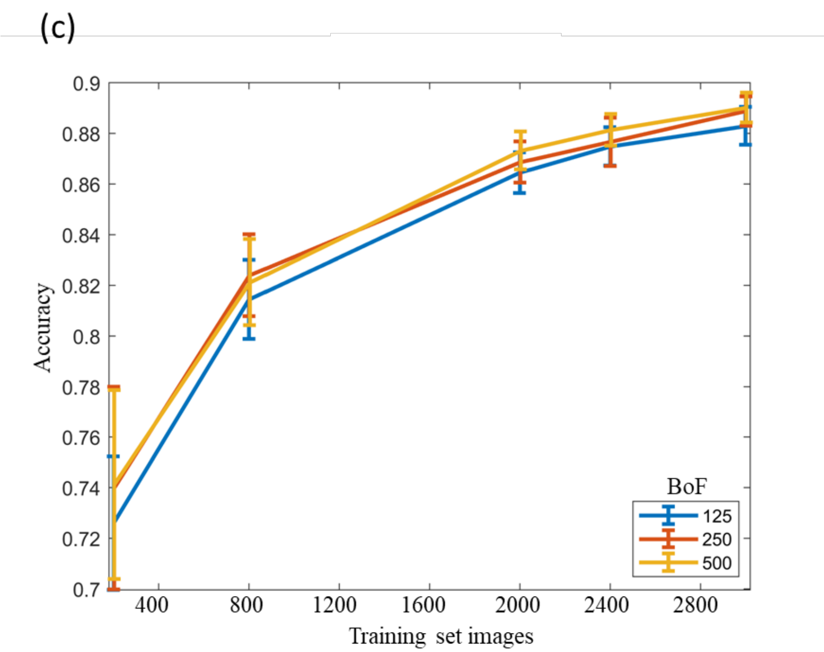
Method	MC (hr)	Total (hr)
Manual Classification (MC)	26.46	26.46
Cubic SVM + MC	5.41	8.91
Fine KNN + MC	11.34	14.84
Medium Gaussian SVM + MC	3.87	7.37
Quadratic SVM + MC	5.15	8.65
Quadratic Discriminant + MC	4.07	7.57
Ensemble Subspace KNN + MC	10.28	13.78

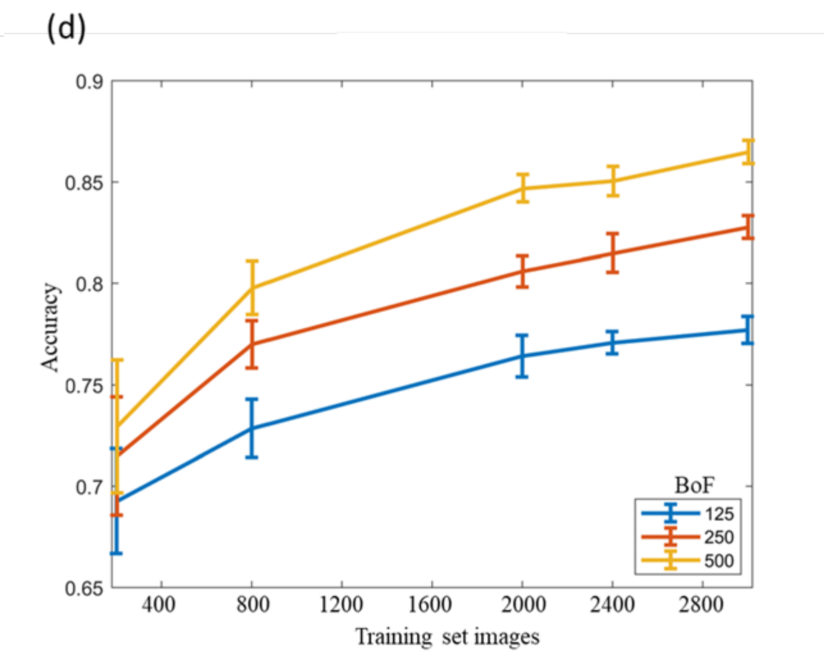
Figure 2.1. Changes in accuracy for determining turkey presence due to variation in the number of features (BoF) and size of training set used to train machine learning models developed using six algorithms (n = 25 iterations). Images of Eastern wild turkey (*Meleagris gallopavo silvestris*) presence/absence were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.



a - Cubic SVM. b – Ensemble Subspace KNN. c – Fine KNN. d – Medium Gaussian SVM. e – Quadratic Discriminant. f – Quadratic SVM.

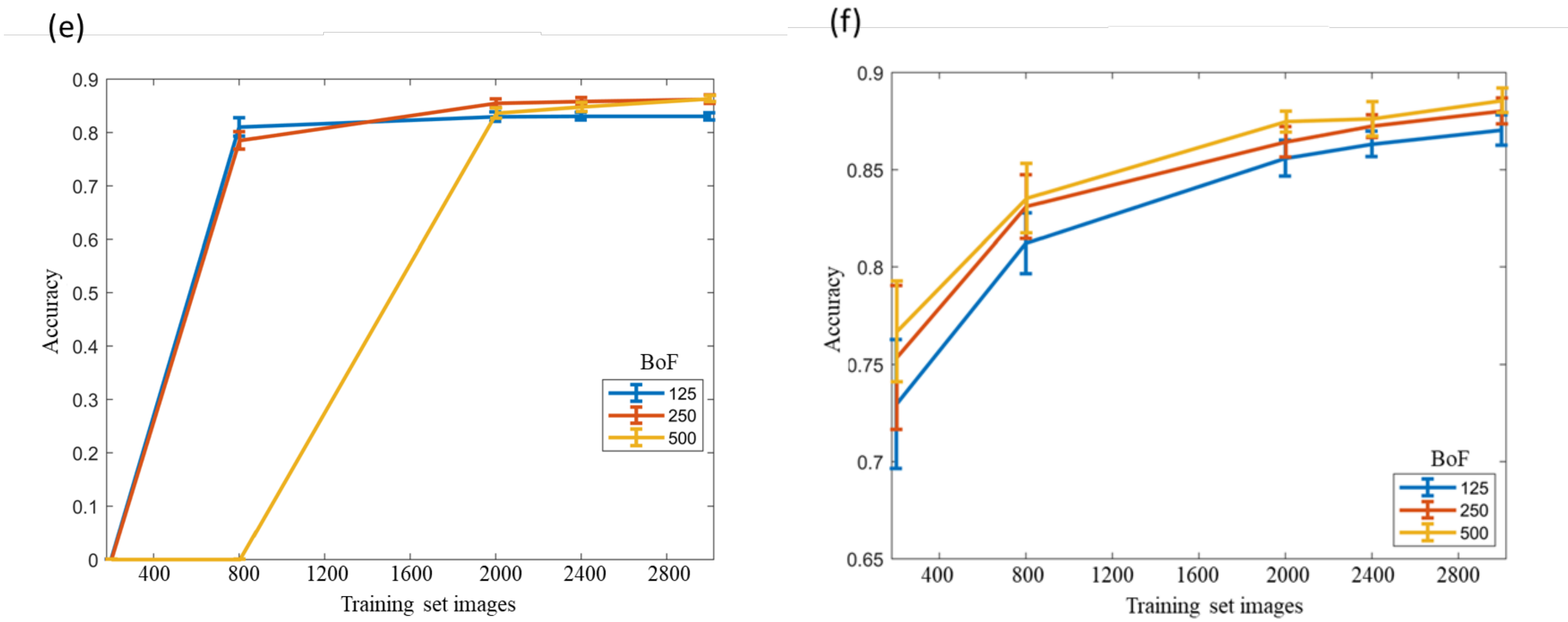
Figure 2.1. Changes in accuracy for determining turkey presence due to variation in the number of features (BoF) and size of training set used to train machine learning models developed using six algorithms (n = 25 iterations). Images of Eastern wild turkey (*Meleagris gallopavo silvestris*) presence/ absence were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.





a - Cubic SVM. b – Ensemble Subspace KNN. c – Fine KNN. d – Medium Gaussian SVM. e – Quadratic Discriminant. f – Quadratic SVM.

Figure 2.1. Changes in accuracy for determining turkey presence due to variation in the number of features (BoF) and size of training set used to train machine learning models developed using six algorithms (n = 25 iterations). Images of Eastern wild turkey (*Meleagris gallopavo silvestris*) presence/ absence were collected at Oakmulgee and Skyline wildlife management areas in Alabama, USA during 5 July – 15 August 2016.



a - Cubic SVM. b – Ensemble Subspace KNN. c – Fine KNN. d – Medium Gaussian SVM. e – Quadratic Discriminant. f – Quadratic SVM

CHAPTER III: EASTERN WILD TURKEY POPULATION RESPONSE TO A DELAY IN SPRING HARVEST

Abstract

Understanding how hunting regulations influence populations can provide insight into appropriate management actions. Eastern wild turkey (*Meleagris gallopavo silvestris*; hereafter turkey) breeding, nesting, and hunting occur simultaneously during the spring in the southeast United States. Some managers believe that the spring hunting season may decrease turkey productivity by reducing the number of males available for breeding, disturbing nests, and leading to illegal hen harvest. To improve understanding of how these factors influence turkey populations, we performed a manipulative experiment on seven wildlife management areas (WMA) in Alabama. The hunting season was from 15 March–30 April on all seven areas during 2016–2017. In 2018, the start of the hunting season was delayed by 9 days to 24 March on 3 WMAs, while the end date was held constant. Hunting seasons on the remaining four WMAs remained constant throughout the study period. We conducted annual camera trap surveys on each area during late summer to estimate occupancy of adult males and females, poults, and all turkeys entering the fall population. We classified turkeys in 625,722 images into categories of sex and age. We used robust design occupancy models to estimate detection, colonization, and extinction rates in each area. The best approximating models for detection and occupancy dynamics varied among sex and age classes. Detection rates were always greater during the morning hours, and the best models included quartic functions of time of day. There was only weak support (ΔAICc > 2.0) for the effect of season change among models of occupancy dynamics for all sex and age classes. Hunting effort, which was determined by expert opinion, had the greatest effect on male and poult occupancy. Robust, quantitative estimates of hunting

effort could strengthen inferences effects on population estimates. While a 9-day delay in hunting season was not detected as a factor affecting poult occupancy, season change should not be dismissed as a possible population driver because occupancy is not linearly related to abundance at all population sizes and our study was of relatively limited duration. Future research should be conducted to determine whether greater changes in season opening dates have a detectable effect on poult production and to improve estimates of the effect of hunting effort on male turkey abundance.

Introduction

It is difficult, if not impossible, to generate informed management actions for a game species without knowledge of how hunting seasons affect population dynamics. Eastern wild turkeys (*Meleagris gallopavo silvestris*; hereafter turkeys) are the most popular game bird species in Alabama; however, little research has been conducted in the past thirty years on the population. State agencies and wildlife managers have recently documented declines in turkey populations throughout the Southeast (Byrne et al. 2012, ADCNR 2015, Eriksen et al. 2016). Given the species' intrinsic and extrinsic value, coupled with the lack of recent information and apparent decline of the population, quantitative data regarding how the population responds to changes in hunting regulations is critical to effective management.

Changes in productivity are a major driver affecting population dynamics (Vangilder 1992). Turkey breeding, nesting, and hunting seasons occur simultaneously during spring. Some managers believe that starting the spring turkey hunting season after peak nest initiation may increase turkey productivity by reducing disturbance during this biologically-sensitive period (S. Barnette, personal communication). It has been hypothesized that hunter-induced biological effects may include the reduction in availability of males during the breeding season due to hunting, nest disturbance, and illegal hen harvest (Palmer et al. 1993, Norman et al. 2001, Isabelle et al. 2018), but there is currently no empirical data to support this hypothesis.

However, it is also important to consider hunter satisfaction and opportunity when determining season dates (Kurzejeski and Vangilder 1992, Isabelle et al. 2018), due to the economic and recreational importance of turkeys. Hunting season lengths in the Southeast vary from 11 days in Arkansas to 55 days in Mississippi, with opening dates as early as 25 February (Isabelle et al. 2018). Hunting season bag limits range from conservative (i.e., 1 male), to liberal (i.e., 5 males; Isabelle et al. 2018). For the majority of Alabama, spring turkey hunting season opens 11 March for youth hunting season, 15 March for the regular season, and spans 49 days with a bag limit of five males.

The timing and effect of male harvest in spring are well documented. Most male harvest is concentrated at the beginning of the hunting season (Miller et al. 1997). Spring harvest represents an additive source of mortality for male turkeys (Moore et al. 2008), and male survival increased 2-fold in Louisiana when the bag limit and season length were reduced (Chamberlain et al. 2012). Thus, a large harvest of males in one year would reduce the density of males across the landscape, affecting both the age structure and population density of males in subsequent years (Kurzejeski and Vangilder 1992). It is assumed that spring hunting of males does not influence population growth, since turkeys are polygamous and a single breeding encounter may be sufficient to fertilize eggs for an initial and a renest attempt (Grigg 1957, Kurzejeski and Vangilder 1992, Healy and Powell 2000). However, since more dominant turkeys engage in reproductive activities (e.g., gobbling) earlier than subdominant turkeys, hunting seasons that open prior to peak nest initiation may lead to removal of males with greater fitness before they make a reproductive contribution (Harris et al. 2002, Milner et al. 2007).

In contrast, spring hunting seasons may have little effect on nesting females. Hens lay an entire clutch (10-12 eggs) in two weeks, while only spending about one hour each day on the nest (Williams and Peoples 1974, Healy 1992). Once the clutch is complete, hens spend 26 days incubating, recess from the nest for about an hour three times every four days, and do not travel >100 m from the nest during the incubation period (Williams et al. 1971, Healy 1992, Martin et al. 2015). Since hens spend over one month in close proximity to their nest, it is hypothesized that opening hunting seasons during nest incubation may reduce the risk of illegal harvest of hens (Vangilder and Kurzejeski 1995, Isabelle et al. 2018). Studies of nesting chronology report median nest initiation dates ranging from late April to early May throughout the Southeast, with mean peak nest incubation occurring two weeks after. More specifically, mean nest initiation in Alabama, Georgia, and Mississippi occurs 20–30 April (Pylant 1977, Everett et al. 1980, Speake et al. 1985, Miller et al. 1997, Whitaker et al. 2005), and 1–7 May in Tennessee (Whitaker et al. 2005). In each of these states hunting season opens one month prior to peak nest initiation. Thus, the Wild Turkey Working Group of the Wildlife Resources Committee recently recommended delaying the opening of the spring hunting season in the southeastern United States to coincide with peak nest initiation to reduce the potential negative effects of the hunting season on population growth (SEAFWA 2016).

Due to the lack of understanding of the mechanisms that may influence turkey populations during reproductive periods, research was needed to better understand whether spring harvest seasons and hunting effort influence the population. The overarching objective of this research was to examine the effects of delaying the opening date of spring turkey season from 15–24 March on turkey populations. The specific objectives of this research were to 1) estimate population occupancy, detection probability, and spring production of eastern wild turkeys on seven Alabama Wildlife Management Areas (WMAs); 2) estimate the effects of hunting effort on occupancy; 3) estimate the effects of a 9-day delay in the opening date and a reduction in season length on occupancy. After two years of pretreatment monitoring on the WMAs, we experimentally changed the hunting season on a subset of these WMAs. We hypothesized that the occupancy rate of males and poults would increase following implementation of the later opening date due to decreased harvest and increased production. We also hypothesized that the occupancy of females would be unaffected at that time since they are not a hunted sex class. We also hypothesized that the effects of hunting effort on each WMA could be more important than season change on occupancy rates of turkeys.

Study areas

We selected seven wildlife management areas (WMAs) in Alabama for a manipulative experiment to estimate the effects of spring hunting season on turkey populations. We selected the areas based on their variation in landscapes and locations, along with the level of hunting effort. We conducted camera trap surveys on wildlife openings during the summer for three years on seven Wildlife Management Areas (WMAs) in Alabama. We selected wildlife openings during the summer because hens with poults move to brood-rearing areas (wildlife openings) and actively feed during this time (Godfrey and Norman 1999). James D. Martin-Skyline WMA (Skyline) was in Jackson County in northeast Alabama, bordering both Tennessee and Georgia. Skyline WMA was managed and owned by the Alabama Department of Conservation and Natural Resources (ADCNR) and was composed of 24,577 ha of the Southwestern Appalachian Mountains, in the Cumberland Plateau physiographic region. There were 285 wildlife openings within the WMA boundaries, and most of them were located on the western and southeastern region of the WMA. Wildlife opening sizes varied between 0.05 ha and 10 ha. Landcover on the plateaus and slopes consisted of hardwood forests that contained Beech (*Fagus* spp.), yellow poplar (*Liriodendron tulipifera*), sugar maple (*Acer saccharum*), oak (*Quercus* spp.), basswood (*Tilia Americana*), ash (*Fraxinus* spp.), and buckeye (*Aesculus* spp.) (Griffith et al. 2001). Lower elevations consisted of hardwoods, predominantly mixed oaks and chestnut oak (*Q. montana*), interspersed with large tracts of privately-owned agricultural fields.

Oakmulgee WMA was located within the Talladega National Forest in west-central Alabama. It was managed under a cooperative partnership between ADCNR and the U.S. Forest Service. Oakmulgee WMA included sections of Bibb, Hale, Perry, and Tuscaloosa Counties. Oakmulgee WMA was composed of 18,008 ha of the Southeastern Plains physiographic region, consisting of rolling hills topography. Landcover consisted of oak, hickory (*Carya* spp.), and pine (*Pinus* spp.) (Griffith et al. 2001). There were 100 wildlife openings evenly distributed within the WMA boundaries. Wildlife opening sizes varied between 0.04 ha and 1.1 ha.

Coosa WMA was located within Coosa County in central Alabama. It was managed under partnerships between the Forever Wild Program, ADCNR, Alabama Power Company, Kaul Lumber Company, Cahaba Timber, International Paper, and F. Perkins. Coosa WMA was composed of 9,302 ha of the Southern Inner Piedmont physiographic region, consisting of rolling hills topography. Landcover consisted of oak, hickory, and pine forests (Griffith et al. 2001). There were 46 wildlife openings distributed throughout the WMA. Wildlife opening sizes varied between 0.04 ha and 0.81 ha.

Blue Spring WMA was located in Covington County, inside the Conecuh National Forest in southeastern Alabama. It was managed under a cooperative partnership between ADCNR and the U.S. Forest Service. Blue Spring WMA was composed of 10,029 ha of the Dougherty and Southern Pine Plains in the Southeastern Plains physiographic region, consisting of low rolling hills topography. Landcover consisted of southern mixed forest and southern floodplain forests, including oak, hickory, and pine (Griffith et al. 2001). There were 57 wildlife openings evenly distributed within the WMA boundaries. Wildlife opening sizes varied between 0.20 ha and 2.85 ha.

Little River WMA was located in DeKalb and Cherokee Counties in northeast Alabama. Little River was managed under partnerships between the Alabama Division of State Parks, National Parks Service, Forever Wild Land Trust, and ADCNR. Little River WMA was composed of 5,261 ha of Southwestern Appalachians and the Ridge and Valley physiographic regions, consisting of rolling tablelands topography. Landcover of tablelands consisted of oak and hickory. Landcover of the ravines and gorges consisted of oak, elm (*Ulmus* spp.), hickory, ash, maple, blackgum (*Nyssa sylvatica*), pine, sweetgum (*Liquidambar styraciflua*), basswood, and beech (Griffith et al. 2001). There were 30 wildlife openings within the WMA boundaries, and most of them were located on the southern region of the WMA. Wildlife opening sizes varied between 0.04 ha and 1.22 ha.

Mulberry Fork WMA was located in Walker and Tuscaloosa Counties in west-central Alabama. It was managed in a partnership between ADCNR and Molpus Timberlands. Mulberry Fork WMA was composed of 13,468 ha of Southwestern Appalachians physiographic region, consisting of plateaus and strong sloping topography. Landcover consisted of oak, hickory, and pine, along with loblolly pine (*P. taeda*) stands managed for industrial timber production (Griffith et al. 2001). There were 45 wildlife openings within the WMA boundaries, with most of them were located in the northeastern region of the WMA. Wildlife opening sizes varied between 0.10 ha and 0.81 ha.

Perdido River WMA was located in Baldwin County in southwest Alabama, bordering the state of Florida. It was managed and owned by ADCNR and was composed of 7,016 ha of Southeastern Plains physiographic region, consisting of low rolling hills topography. Landcover consisted of southern mixed forest and southern floodplain forests, including oak, hickory, and pine (Griffith et al. 2001). There were 40 wildlife openings within the WMA boundaries, with most of them located in the central and eastern regions of the WMA. Wildlife opening sizes varied between 0.20 ha and 1.22 ha.

Methods

We monitored the 7 WMAs for 3 years: four of the WMAs served as pseudo-controls, while the remaining three served as experimental areas that experienced a change in season length and opening date. Specifically, the season remained constant (i.e., March 15 – 30 April) for the duration of the study period at Blue Spring, Coosa, Little River, and Mulberry Fork WMAs (Table 3.2). In contrast, the opening date of the hunting season was delayed 9 days and the end date was not changed (24 March – 30 April), resulting in a reduction of season length during 2018 on Perdido River, Oakmulgee, and Skyline WMAs (Table 3.2).

We conducted camera trap surveys on wildlife openings at the seven study sites during late summer of each year. We selected sites at random from all known and accessible managed wildlife openings. To avoid the potential of double counting individuals, we required a minimum distance of 500m between sites. We selected a sturdy tree to attach a camera trap on the south edge of wildlife openings so cameras could be pointed north to avoid glare from the sun. Five days prior to camera deployment, we cleared the area $\leq$10-m north of the tree of vegetation and debris >0.1 m high. We placed approximately 7.5 l of bait (chicken scratch) 3-m north of the tree in the cleared area. After five days, we attached the camera trap to the tree approximately 1 m above the ground and the bait was replenished. We programmed camera traps to capture images every 4 minutes from 0600h – 1900h, and bait was used to increase the likelihood that turkeys would remain in front of the camera long enough to be captured by time-lapse. We removed cameras after a minimum of five days.

We manually interpreted images that were collected into three categories of sex and age classes: adult males (>0.5 years old), adult females (>0.5 years old), and poults (1 day to 0.5 years; Pelham and Dickson 1992). We included an unknown classification category for turkeys that the expert interpreter was unable to categorize into a sex or age class confidently. All unknown classifications were reviewed by a second expert.

We calculated hunting effort estimates by expert opinion of the number of man-days per WMA during the spring turkey hunting season divided by the size of the WMA (Table 3.1). We categorized hunting effort into high, medium, and low levels.

We cast models of detection and use using robust design occupancy estimation in Program MARK (White and Burnham 1999, Version 9.0). We generated encounter histories for individual categories of sex and age classes and all turkeys (including unknowns) for every WMA for all three years. We considered each hour during the five-day camera deployment an occasion, resulting in 14 encounters per day. If we classified a single image during an hour as turkeys present, the encounter history indicated that a turkey was present on that occasion for that sex and age class, and for the total turkey category. Thus, each camera trap site had 70 possible encounter occasions per year, and hours during which no images were recorded were treated as missing values (MacKenzie and Nichols 2004). We included camera trap survey sites that were not surveyed every year in the encounter history with the missing year recorded as 70 missing occasions. We concatenated the three years of encounter histories for each of the 171 camera trap sites, resulting in 210 encounter occasions per camera trap site for the robust design (multi-season) analysis. We used a multi-season occupancy estimator to estimate detection probability (p), probability of use in 2016 (ψ), probability of use if not occupied during the previous season (i.e., local colonization, γ), and probability non-use if the site was occupied in the previous season (i.e., local extinction, ε). We performed each analysis for males, females, poults, and for all turkeys.

We hypothesized that detection would vary among study areas and years in an interactive or additive fashion, by time of day in quadratic and quartic forms, and by day of year. We hypothesized that ψ would vary by study area or hunting effort. We also hypothesized that γ and ε would be affected by study area, hunting effort, year, and season change in an interactive or additive fashion. *A priori* models of p, ψ, γ, and ε were compared using Akaike Information Criterion (AICc), corrected for small sample size. To reduce the number of models in the final analysis, we compared models of p using a model where (i.e., occupancy dynamics) were different for each study area in each year. We combined the best models of p with the *a priori* models of occupancy dynamics for the final analysis. We compared models using AICc, difference in AICc from the best model (ΔAIC), model probability (w), model likelihood (Lik), and deviance residuals (White and Burnham 1999, MacKenzie et al. 2006).

Results

We deployed a total of 419 camera traps over the three years: 156 in 2016, 126 in 2017, and 137 in 2018 (Appendix A). We deployed and removed camera traps within an 8-week period between 29 June and 26 August. We captured and interpreted a total of 625,722 images. These images resulted in 29,330 encounter occasions that we then used in the occupancy analysis. We detected turkeys in 3,085 (9.51%) of those encounter occasions. Females were the most frequently observed class of turkey and appeared in 2,343 (75.95%) of encounter occasions that contained turkeys. Males were observed in 958 (31.05%) encounter occasions and poults in 497 (16.11%) encounter occasions that contained turkeys. Additionally, 386 (12.51%) encounter occasions that contained a turkey were classified as an unidentifiable sex or age class. We detected turkeys at 60.25% of the camera traps in 2016, 63.5% in 2017, and 57.67% during 2018.

Detection model selection

The best approximating models for detection varied between sex and age classes. The best model for the detection for the turkey population, males, and females included the effect of study area and a quartic relationship with time of day that varied among years (Table 3.3-3.5). The best model of variation for poults included the effect of study area, effect of day of year, and the quartic relationship with the time of day (Table 3.6). We did not include models for poults at Perdido River WMA in the analysis because poults were not detected during 2016 and 2017 camera trap surveys.

Detection rates were always greater during the morning hours. Turkey detection was greatest for the Coosa WMA camera trap survey conducted in 2016 (Figure 3.1). Detection varied between years but peaked between 0900h - 1000h and again around 1700h - 1800h at all study areas (Figure 3.1). Male detection was greatest at the Blue Springs WMA survey conducted in 2018 (Figure 3.2). Males were not detected during the 2016 survey at Blue Springs or Little River WMAs, or at Perdido River during the 2017 survey (Figure 3.2). Male detection was greatest between 0800h - 0900h (Figure 3.2). Female detection was greatest for the Coosa WMA survey during 2018 (Figure 3.3). Female detection peaked between 1000h – 1200h (Figure 3.3). Poult detection was greatest at Coosa WMA (Figure 3.4). Poult detection peaked between 1200h - 1400h for all study areas (Figure 3.4).

Occupancy model selection

The best approximating models for occupancy dynamics varied among sex and age classes. Due to the nature of the multi-season models, estimates of annual occupancy derived from ψ, γ and ε were different each year on each study area. The best model for all turkey occupancy included estimates for ψ, γ, and ε that were different for each study area, but γ and ε did not differ between years (Table 3.7, 3.8). The best model for males and poults included ψ, γ, and ε that were similar for study areas with similar categories of hunting effort, but γ and ε were not different between years (Table 3.9, Table 3.10). All categories of turkey had unequivocal best models (i.e., next best models with ΔAIC>2.0). The unequivocal best model for males includes the effect of HE and had more than 40 times the support as the model without hunting effort and 4 times as much support as the next best model (Table 3.9).

Estimates of annual occupancy for turkeys were greatest for Little River WMA during the 2016 camera trap survey and least for Perdido River during the 2018 camera trap survey (Table 3.11). Estimates of annual occupancy for males varied throughout the survey (Table 3.12). Estimates of annual occupancy were greatest for females in comparison to other classes of turkeys (Table 3.13). Neither hunting effort nor season change described the changes in estimates of hen occupancy (ΔAICc > 2.0). Estimates of annual occupancy were smallest for poults in comparison to other classes of turkey (Table 3.14). Perdido River was excluded from the analysis of poults due to the lack of detections during 2016-2017. Uncertainty in lambda was always greater in 2016-2017 than 2017-2018 for all sex and age classes (Figures 3.5-3.8).

Discussion

We hypothesized that occupancy rate of males and poults would increase in response to implementation of the later opening date on select areas due to decreased harvest and increased production. However, this hypothesis was not supported. Our hypothesis that females would not be influenced by season change or hunting effort was supported by this study. Lastly, we hypothesized that hunting effort would have more of an influence than season change on occupancy rates. Our hypothesis was supported in that the changes in estimates of occupancy for both males and poults was best described by the hunting effort model, not the season change model.

There was no support (ΔAICc > 2.0) for the effects of season change in models of occupancy dynamics for all sex and age classes. The lack of support could be explained in a multitude of ways. First, the effect may be too small to detect in a single year. Surveys conducted for multiple years after the delay in season may be needed to detect the compounding effect of poult production on wild turkey occupancy or abundance. Poult detection was very low compared to other classes of turkey. If there is a net effect on poult production, it may be detectable as an increase in recruitment to the adult population in subsequent years. Second, occupancy may not be sensitive enough to detect a change in poult production. Third, any effect of season change may be concealed by environmental variables such as weather. Poult survival (Healy and Nenno 1985) and male harvest (Norman et al. 2001) are highly dependent on annual spring weather conditions. Fourth, the 9-day reduction in season change may not be sufficient to affect poult production. The season opened on 24 March, which is still 22 days prior to peak nest initiation date of 20 April in Alabama (Everett et al. 1980, Speake et al. 1985, Whitaker et al. 2005). Finally, it is also possible that delaying the start of the turkey season does not increase poult production according to mechanisms outlined by some biologists.

The hypothesis that the effects of hunting effort on each WMA are more important than season change on occupancy rates of turkeys was not supported for all sex-age classes. Females cannot legally be hunted during spring in Alabama and neither hunting effort nor season change influenced female occupancy. Only male turkeys are hunted in Alabama, thus we expected hunting effort to affect male occupancy the most.

The model including hunting effort was the unequivocal best for estimating male turkey occupancy, but confidence intervals on lambda included 1.0 for all levels of hunting effort. Even with this large amount of uncertainty, we detected trends in changes in occupancy that may be biologically significant. Hunting effort can be influenced in several ways; reducing season length, only allowing hunting on certain days throughout the season, and quota hunts. This information, coupled with quantitative measurements of hunting effort, could be used to inform decisions intended to increase the number of males in areas of high hunting effort by reducing the amount of hunting effort.

Hunting effort had inconsistent effects on annual occupancy of poults. This could be due to the very low detection rates of poults or inconsistent camera trap deployment dates. For example, Coosa WMA experienced the greatest increase in annual poult production following a change in camera deployment dates from 29 June in 2016 to 19 July in 2018. In contrast, Little River WMA experienced a sharp decline in annual poult production following the change in camera trap surveys from 26 July in 2016 to July 3 in 2018. Peak hatch for poults in Alabama occurs during late May (Everett et al. 1980). Animal matter makes up over 50% of a poults diet during the first 14 days of life (Hurst 1992). By 38 days old, poult diets consist of 75% plant matter and 25% animal matter (Hurst 1992). This dietary shift from animal to plant matter could be the cause in the increase of poult detection at baited sites during July. We suggest future surveys adhere strictly to camera deployments in July and to ensure poult detection and reduce turkey misclassification errors.

Annual estimates of occupancy for females were always greater than poults. This is expected because some females do not nest, and others lose their entire broods. The ratio of female occupancy to poult occupancy could be a good indicator of the productivity of females (Vangilder and Kurzejeski 1995). For example, occupancy by females was six times greater than occupancy by poults on Coosa WMA in 2016. This could indicate that female success was very low that year.

Understanding sources of variation in detection on camera trap surveys is important for obtaining accurate estimates of occupancy (MacKenzie et al. 2006). In this study, time of day, study area, and year were important sources of variation in detection probability. Time of day was related to detection probabilities for every class of turkeys indicating that there were specific times that turkeys were present on wildlife openings. Males demonstrated two distinct peaks of detection during the day, once in the morning and once in the afternoon. This pattern was observed in other wild turkey camera trap surveys (Damm et al. 2010, Gonnerman 2017), and has been observed in other avian species (Hutto 1981). Female detection peaked before 1200h, and there was a similar trend for poults. We expect such similarities since poults remain with the hen until five months of age, and some female poults remain in brood groups until the start of the next breeding season (Healy 1992). The quartic relationship coupled with low detection during midday can be used to shorten the length of future surveys, hence reducing the number of images requiring manual interpretation. Detection probability also varied among study areas. This could be attributable to differences in landcover; or differences in the management of wildlife openings, including the height and type of vegetation.

Poult detection did not appear to vary between the three years of this study, most likely due to the low encounter rate. This could be attributable to the small size of young poults

(Pelham and Dickson 1992) or the diet of poults, which predominantly consists of insect matter (Hurst 1992) for the first few weeks after hatching. Thus, poults may not be as attracted to bait at camera traps. Restricting surveys to the month of July could increase the detection of poults due to their dietary shift from insect matter to mast, and their increase in body size.

The timing of camera surveys can influence estimates of detection and occupancy (Burton et al. 2015). Camera trap deployment dates at sites varied from one-day to three weeks among years (Appendix A). Male and female detection rates varied each year for each study area, which could be the result of variation in deployment date of the camera trap in each year. Moreover, some trap sites were eliminated, and others added between years. Restricting the deployment dates of cameras at each site would minimize this source of variation by design, and also would reduce the potential for misclassification of poults as adults in images collected in mid- to late-August. Peak hatch in Alabama occurs in late May (Everett et al. 1980) and by August most poults are three months old and hard to distinguish from adults in camera trap images. Poults have adult-colored plumage by three months of age (Pelham and Dickson 1992) and are indistinguishable from adults by 6 months of age. Restricting surveys to the month of July could reduce the misclassification of poults as adults, resulting in more accurate estimates of annual occupancy for individual sex and age classes.

Additionally, uncertainty in lambda was greatly reduced from 2016-2017 to 2017-2018 for all sex and age classes (Figures 3.5-3.8). Further reduced levels of uncertainty would allow for more inferences to be made about the population trends. Decreasing the number of survey sites did not increase uncertainty in estimates of lambda. The uncertainty in lambda was similar when the number of survey sites increased or remained constant. Therefore, increasing the number of annual surveys may be more important than increasing the number of camera trap sites surveyed annually at the WMAs.

Recommendations

Camera traps are useful tools that when combined with occupancy analysis, can be used to monitor changes in population and assist managers in determining the influence of hunting on game populations. However, it is important for surveys to be conducted using a standardized method. The number of seasons that surveys are conducted pre- and post- management changes should also be considered. To further reduce uncertainty, the analysis should include robust, quantitative covariates.

High levels of uncertainty are likely related to the use of categorical covariates. It is necessary for managers to be able to quantify variables such as hunting effort with empirical data to help strengthen inferences pertaining to changes in population estimates. While season change was not detected as a factor affecting poult production, it should not be dismissed as a possible population driver. Future research should be conducted to determine whether a greater delay in season opening dates has a detectable effect on poult production.

Additionally, camera trap surveys should be conducted when detection is more likely to occur for targeted sex and age classes. Managers can reduce the length of time that surveys are conducted each day to 0600h-1400h since it would capture the peaks in detection for males, females, and poults increasing detection rates overall and thereby increasing the precision of estimates of occupancy (MacKenzie et al. 2006). Surveys should be conducted during a consistent time frame each year to avoid introducing bias related to poult misclassification and availability. For wild turkeys in Alabama, poult detection increased in late July. More research should be conducted to validate this observation, and surveys should be adjusted accordingly. To reduce uncertainty from factors influencing detection at the camera trap site level, surveys that include land cover and management covariates that may influence detection should be included in future surveys.

Lastly, the number of seasons a survey is conducted for a population may be important for robust design occupancy. On a restricted budget, managers may opt for more seasons of surveys to be conducted over an increase of sites surveyed per season. Future research should be conducted to determine if uncertainty in lambda continues to decrease as the number of seasons surveyed increases.

Literature Cited

Alabama Department of Conservation and Natural Resources. 2015. Full Fans & Sharp Spurs: Wild Turkey Report 2015. Alabama Department of Conservation and Natural Resources. Montgomery, Alabama, USA.

Burton, A. C., E. Neilson, D. Moreira, A. Ladle, R. Steenweg, J. T. Fisher, E. Bayne, and S. Boutin. 2015. Review: Wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. Journal of Applied Ecology 52(3):675–685.

Byrne, M. E., M. J. Chamberlain, and B. A. Collier. 2012. Southeast Regional Wild Turkey Reproductive Decline Study. Athens, GA.

Byrne, M. E., M. J. Chamberlain, and B. A. Collier. 2015. Potential density dependence in wild turkey productivity in the southeastern United States. Proceedings of the National Wild Turkey Symposium 11:329-351.

Damm, P. E., J. B. Grand, and S. W. Barnett. 2010. Variation in detection among passive infrared triggered-cameras used in wildlife research Proceedings of the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 64:125–130.

Eriksen, R. E., T. W. Hughes, T. A. Brown, M. D. Akridge, K. B. Scott, and C. S. Penner. 2016. Status and distribution of wild turkeys in the United States: 2014 Status. Proceedings of the National Wild Turkey Symposium 11:7-18.

Everett, D., D. Speake, and W. Maddox. 1980. Natality and mortality of a north Alabama wild turkey population. Proceedings of the National Wild Turkey Symposium 4:117–126.

Godfrey, C. L., and G. W. Norman. 1999. Effect of habitat and movement on wild turkey poult survival. Proceedings of the Annual Conference Southeastern Association Fish and Wildlife Agencies 53:330-339.

Gonnerman, M. B. 2017. Estimating use, density, and productivity of eastern wild turkey in Alabama. Thesis. Auburn University, Auburn, Alabama, USA.

Griffith, G. E., J. M. Omernick, J. A. Comstock, S. Lawrence, G. Martin, A. Goddard, V. J. Hulcher, and T. Foster. 2001. Ecoregions of Alabama and Georgia. (2 sided color poster with map, descriptive text, summary tables, and photographs). Reston, VA.

Grigg, G. W. 1957. The structure of stored sperm in the hen and the nature of the release mechanism. Poultry Science 36:450–451.

Harris, R. B., W. A. Wall, and F. W. Allendorf. 2002. Genetic consequences of hunting: What do we know and what should we do? Wildlife Society Bulletin 30(2): 634-643.

Healy, W. M. 1992. Behavior. Pages 46–65 in J. G. Dickson, editor. Wild turkey biology and management. Stackpole Books, Harrisburg, Pennsylvania.

Healy, W. M., and E. S. Nenno. 1985. Effect of weather on wild turkey poult survival. Proceedings of the National Wild Turkey Symposium 5:91-101.

Healy, W. M., and S. M. Powell. 2000. Wild turkey harvest management: biology, strategies, and techniques. US Department of the Interior, US Fish and Wildlife Service.

Hurst, G. A. 1992. Foods and Feeding. Pages 66–83 in. The Wild Turkey: biology and management. Stackpole Books, Harrisburg, Pennsylvania, USA.

Hutto, R. L. 1981. Temporal patterns of foraging activity in some wood warblers in relation to the availability of insect prey. Behavioral Ecology and Sociobiology 9:195–198.

Isabelle, J. L., A. B. Butler, C. Ruth, and D. K. Lowrey. 2018. Considerations for timing of spring wild turkey hunting seasons in the southeastern United States. Journal of the Southeastern Association of Fish and Wildlife Agencies 5: 106-113.

Kurzejeski, E. W., and L. D. Vangilder. 1992. Population management. Pages 165–185 in J. G. Dickson, editor. Wild turkey biology and management. Stackpole Books, Harrisburg, Pennsylvania, USA.

MacKenzie, D. I and J. D. Nichols. 2004. Occupancy as a surrogate for abundance estimation. Animal Biodiversity and Conservation 27: 461-467.

MacKenzie, D. I., J. D. Nichols, J. A. Royle, K. H. Pollock, L. L. Bailey, and J. E. Hines. 2006. Occupancy estimation and modeling: inferring patterns and dynamics of species occurrence. Elsevier.

Martin, J. A., W. E. Palmer, S. M. Juhan, and J. P. Carroll. 2015. Incubation and predation ecology of wild turkey nests: a cautionary case study regarding video camera surveillance. Proceedings of the National Wild Turkey 11:295–301.

Miller, D. A., G. A. Hurst, and B. D. Leopold. 1997. Chronology of wild turkey nesting, gobbling, and hunting in Mississippi. The Journal of Wildlife Management 61(3):840-845.

Milner, J. M., E. B. Nilsen, and H. Andreassen. 2007. Demographic side effects of selective hunting in ungulates and carnivores. Conservation Biology 21:36–47.

Norman, G. W., J. C. Pack, C. I. Taylor, D. E. Steffen, and K. H. Pollock. 2001. Reproduction of Eastern Wild Turkeys in Virginia and West Virginia. The Journal of Wildlife Management 65:1-9.

Palmer, W. E., S. R. Priest, R. S. Seiss, P. S. Phalen, and G. A. Hurst. 1993. Reproductive effort and success in a declining wild turkey population. Proceedings the Annual Conference of the Southeastern Association of Fish and Wildlife Agencies 47:138–147.

Pelham, P. H., and J. G. Dickson. 1992. Physical characteristics. Pages 32–45 in. The Wild Turkey: biology and management. Stackpole Books, Mechanicsburg, PA.

Pylant, D. B. 1977. A study of mortality and nest desertion in eastern wild turkeys. Dissertation. Auburn University, Auburn, Alabama, USA.

Southeastern Association of Fisheries and Wildlife Agencies. 2016. Establishing opening dates for spring wild turkey hunting seasons. White Paper. SEAFWA Board of Directors Oct. 18.

Speake, D. W., R. Metzler, and J. McGlincy. 1985. Mortality of wild turkey poults in northern Alabama. The Journal of Wildlife Management 49(2):472-474.

Vangilder, L.D. 1992. Population dynamics. Pages 165-184 in J. G. Dickson, editor. Wild turkey biology and management. Stackpole Books, Harrisburg, Pennsylvania, USA.

Vangilder, L. D., and E. W. Kurzejeski. 1995. Population ecology of the eastern wild turkey in northern Missouri. Wildlife Monographs 130:3–50.

Whitaker, D. M., J. C. Pack, G. W. Norman, D. F. Stauffer, and S. D. Klopfer. 2005. A range-wide meta-analysis of wild turkey nesting phenology and spring season opening dates. National Wild Turkey Symposium 9:351–360.

White, G. C., and K. P. Burnham. 1999. Program MARK: survival estimation from populations of marked animals. Bird Study 46:S120–S139.

Williams, L. E., D. H. Austin, T. E. Peoples, and R. W. Phillips. 1971. Laying data and nesting behavior of wild turkeys. Proceedings of the Annual Conference of the Southeastern Association of Game and Fish Commissioners 25:90-107.

Williams, L. E., and T. E. Peoples. 1974. Movement of wild turkey hens in relation to their nests. Proceedings of the Annual Conference of the Southeastern Association of Game and Fish Commissioners 28:602–622.

Table 3.1. Hunting effort categorization and size of seven wildlife management areas in Alabama chosen for a manipulative study of the effect of season change.

Site	Hunting effort	Area (ha)
Coosa WMA	High	9,302
Blue Spring WMA	Medium	10,029
Little River WMA	Low	5,261
Mulberry Fork WMA	Low	13,468
Skyline WMA	High	24,577
Oakmulgee WMA	Medium	18,008
Perdido River WMA	Low	7,016

Table 3.2. Spring hunting season dates of seven wildlife management areas in Alabama. Seasons that received no change in season are pseudo-controls. Experimental WMAs received a nine-day delay in the opening date and a reduction of the season length in 2018.

		Spring hunting season dates		
Site	Site type	2015-2016	2016-2017	2017-2018
Coosa WMA	Control	15 Mar – 30 April	15 Mar – 30 April	15 Mar – 30 April
Blue Spring WMA	Control	15 Mar – 30 April	15 Mar – 30 April	15 Mar – 30 April
Little River WMA	Control	15 Mar – 30 April	15 Mar – 30 April	15 Mar – 30 April
Mulberry Fork WMA	Control	15 Mar – 30 April	15 Mar – 30 April	15 Mar – 30 April
Skyline WMA	Experimental	15 Mar – 30 April	15 Mar – 30 April	24 Mar – 30 April
Oakmulgee WMA	Experimental	15 Mar – 30 April	15 Mar – 30 April	24 Mar – 30 April
Perdido River WMA	Experimental	15 Mar – 30 April	15 Mar – 30 April	24 Mar – 30 April

Table 3.3. Comparison of detection (p) models for wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (w), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Model	AICc	ΔAICc	w	Lik	K	Dev
p (G*Y+HR^4) ψ(G) γ(G) ε(G)	15834.55	0.00	1.000	1.000	46	15730.93
p (G+Y+HR^4) ψ(G) γ(G) ε(G)	15867.97	33.42	0.000	0.000	34	15793.78
p (G+Y+HR^2) ψ(G) γ(G) ε(G)	15902.50	67.94	0.000	0.000	32	15833.03
p (G+HR^4) ψ(G) γ(G) ε(G)	15918.87	84.32	0.000	0.000	32	15849.40
p (G+Y+HR) ψ(G) γ(G) ε(G)	15950.59	116.04	0.000	0.000	31	15883.47
p (G+Y) ψ(G) γ(G) ε(G)	15951.57	117.01	0.000	0.000	30	15886.77
p (G+HR) ψ(G) γ(G) ε(G)	15999.27	164.72	0.000	0.000	29	15936.80
p (G) ψ(G) γ(G) ε(G)	16000.09	165.54	0.000	0.000	28	15939.93

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in.

Table 3.4. Comparison of detection (*p*) models for male wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Model	AICc	ΔAICc	*w*	Lik	K	Dev
p (G*Y+HR^4) ψ(G) γ(G) ε(G)	6023.50	0.00	1.000	1.000	46	5919.88
p (G+Y+HR^4) ψ(G) γ(G) ε(G)	6069.49	45.99	0.000	0.000	34	5995.29
p (G+HR^4) ψ(G) γ(G) ε(G)	6086.63	63.12	0.000	0.000	32	6017.15
p (G+Y+HR^2) ψ(G) γ(G) ε(G)	6136.97	113.47	0.000	0.000	32	6067.50
p (G+Y) ψ(G) γ(G) ε(G)	6159.43	135.93	0.000	0.000	30	6094.64
p (G+Y+HR) ψ(G) γ(G) ε(G)	6160.13	136.63	0.000	0.000	31	6093.01
p (G) ψ(G) γ(G) ε(G)	6175.01	151.51	0.000	0.000	28	6114.85
p (G+HR) ψ(G) γ(G) ε(G)	6175.75	152.25	0.000	0.000	29	6113.28

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in.

Table 3.5. Comparison of detection (*p*) models for female wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Model	AICc	ΔAICc	*w*	Lik	K	Dev
p (G*Y +HR^4) ψ(G) γ(G) ε(G)	12617.55	0.00	1.000	1.000	46	12513.93
p (G+Y+HR^4) ψ(G) γ(G) ε(G)	12676.50	58.95	0.000	0.000	34	12602.30
p (G+Y+HR^2) ψ(G) γ(G) ε(G)	12677.42	59.87	0.000	0.000	32	12607.95
p (G+Y) ψ(G) γ(G) ε(G)	12708.55	91.00	0.000	0.000	30	12643.75
p (G+HR^4) ψ(G) γ(G) ε(G)	12709.13	91.59	0.000	0.000	32	12639.66
p (G+Y+HR) ψ(G) γ(G) ε(G)	12710.34	92.80	0.000	0.000	31	12643.22
p (G) ψ(G) γ(G) ε(G)	12740.02	122.48	0.000	0.000	28	12679.86
p (G+HR) ψ(G) γ(G) ε(G)	12741.86	124.31	0.000	0.000	29	12679.39

1 G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in.

Table 3.6. Comparison of detection (p) models for poult wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (w), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Model	AICc	ΔAICc	w	Lik	K	Dev
p (G+HR^4+DOY) ψ(G) γ(G) ε(G)	3202.44	0.00	0.749	1.000	29	3139.429
p (G+HR^4+DOY^2) ψ(G) γ(G) ε(G)	3204.67	2.23	0.246	0.328	30	3139.298
p (G+HR^4) ψ(G) γ(G) ε(G)	3212.84	10.40	0.004	0.006	28	3152.176
p (G+HR^2) ψ(G) γ(G) ε(G)	3215.53	13.09	0.001	0.001	26	3159.523
p (G) ψ(G) γ(G) ε(G)	3225.38	22.94	0.000	0.000	24	3173.974
p (G*Y) ψ(G) γ(G) ε(G)	3227.29	24.85	0.000	0.000	36	3147.460
p (G+Y) ψ(G) γ(G) ε(G)	3228.01	25.56	0.000	0.000	26	3171.996

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in. DOY – day of year that survey began on.

Table 3.7. Comparison of use (ψ), gamma (γ), epsilon (ε), and detection (*p*) models for wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Models	AICc	ΔAICc	*w*	Lik	K	Dev
ψ(G) γ(G) ε(G) *p* (G*Y+HR^4)	15834.55	0.00	0.827	1.000	46	15730.93
ψ(G)γ(G*SC) ε(G*SC) *p* (G*Y+HR^4)	15839.18	4.63	0.082	0.099	52	15720.12
ψ(G) γ(G+SC) ε(G +SC) *p* (G*Y+HR^4)	15839.51	4.95	0.070	0.084	48	15730.79
ψ(HE) γ(HE*SC) ε(HE*SC) *p* (G*Y+HR^4)	15842.33	7.77	0.017	0.021	40	15753.65
ψ(HE) γ(HE) ε(HE) *p* (G*Y+HR^4)	15845.62	11.07	0.003	0.004	34	15771.42
ψ(HE) γ(HE+SC) ε(HE+SC) *p* (G*Y+HR^4)	15847.51	12.96	0.001	0.002	36	15768.54

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in. SC - season change implemented in 2018. HE – categorical levels of hunting effort: high, medium, low.

Table 3.8. Comparison of use (ψ), gamma (γ), epsilon (ε), and detection (*p*) models for female wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Models	AICc	ΔAICc	*w*	Lik	K	Dev
ψ(G) γ(G) ε(G) *p* (G*Y+HR^4)	12617.52	0.00	0.795	1.000	46	12513.90
ψ(G)γ(G+SC) ε(G+SC) *p* (G*Y+HR^4)	12620.38	2.86	0.190	0.239	48	12511.67
ψ(G) γ(G*SC) ε(G*SC) *p* (G*Y+HR^4)	12625.94	8.42	0.012	0.015	52	12506.88
ψ(HE) γ(HE) ε(HE) *p* (G*Y+HR^4)	12630.88	13.36	0.001	0.001	34	12556.69
ψ(G) γ(G*Y) ε(G*Y) *p* (G*Y+HR^4)	12631.69	14.17	0.001	0.001	60	12491.25
ψ(HE) γ(HE*SC) ε(HE*SC) *p* (G*Y+HR^4)	12633.03	15.51	0.000	0.000	40	12544.36
ψ(HE) γ(HE+SC) ε(HE+SC) *p* (G*Y+HR^4)	12633.46	15.94	0.000	0.000	36	12554.49

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in. HE – categorical levels of hunting effort: high, medium, low. SC - season change implemented in 2018.

Table 3.9. Comparison of use (ψ), gamma (γ), epsilon (ε), and detection (*p*) models for male wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Models	AICc	ΔAICc	w	Lik	K	Dev
ψ(HE) γ(HE) ε(HE) *p* (G*Y+HR^4)	6013.76	0.00	0.733	1.000	34	5939.56
ψ(HE) γ(HE*SC) ε(HE*SC) *p* (G*Y+HR^4)	6016.73	2.98	0.166	0.226	40	5928.06
ψ(HE) γ(HE+SC) ε(HE+SC) *p* (G*Y+HR^4)	6017.84	4.08	0.095	0.130	36	5938.87
ψ(G) γ(G) ε(G) *p* (G*Y+HR^4)	6023.50	9.74	0.006	0.008	46	5919.88
ψ(G) γ(G +SC) ε(G +SC) *p* (G*Y+HR^4)	6027.75	13.99	0.001	0.001	48	5919.04
ψ(G) γ(G*SC) ε(G*SC) *p* (G*Y+HR^4)	6035.70	21.95	0.000	0.000	52	5916.64
ψ(G) γ(G*HE*Y) ε(G*HE*Y) *p* (G*Y+HR^4)	6041.25	27.49	0.000	0.000	60	5900.80

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in. SC - season change implemented in 2018. HE – categorical levels of hunting effort: high, medium, low.

Table 3.10. Comparison of use (ψ), gamma (γ), epsilon (ε), and detection (*p*) models for poult wild turkey using Multi-Season Occupancy estimator and camera trap surveys in Alabama for three years, 2016-2018. For each model, values for AICc, relative difference in AICc (ΔAICc), model probability (*w*), model likelihood (Lik), number of parameters (K), and deviance (Dev) are shown[1].

Models	AICc	ΔAICc	*w*	Lik	K	Dev
ψ(HE) γ(HE) ε(HE) *p* (G+HR^4+DOY)	2865.81	0.00	0.660	1.000	19	2824.83
ψ(HE) γ(HE+SC) ε(HE+SC) *p* (G+HR^4+DOY)	2868.79	2.98	0.149	0.226	21	2823.13
ψ(HE) γ(HE*Y) ε(HE*Y) *p* (G+HR^4+DOY)	2869.78	3.97	0.091	0.137	31	2799.62
ψ(HE) γ(HE*SC) ε(HE*SC) *p* (G+HR^4+DOY)	2871.75	5.94	0.034	0.051	31	2801.58
ψ(G) γ(G) ε(G) *p* (G+HR^4+DOY)	2873.27	7.46	0.016	0.024	28	2810.66

[1] G - study area that camera trap survey was performed on. HR - hour of day the image was captured in. Y - year that survey was performed in. DOY – day of year that survey began on. SC - season change implemented in 2018. HE – categorical levels of hunting effort: high, medium, low.

Table 3.11. Estimates of annual occupancy (ψ) and 95% upper and lower confidence limits (UCL, LCL) for wild turkey on managed wildlife openings during the years of 2016, 2017, and 2018.

	2016			2017			2018		
Study Area	ψ	LCL	UCL	ψ	LCL	UCL	ψ	LCL	UCL
Blue Spring WMA[MC]	0.375	0.108	0.642	0.519	0.322	0.716	0.569	0.339	0.799
Coosa WMA[HC]	0.853	0.662	1.043	0.851	0.692	1.010	0.850	0.674	1.026
Little River WMA[LC]	0.865	0.611	1.119	0.737	0.552	0.922	0.676	0.422	0.930
Mulberry Fork WMA[LC]	0.550	0.332	0.768	0.732	0.584	0.880	0.708	0.581	0.836
Perdido River WMA[LE]	0.429	0.169	0.688	0.350	0.160	0.541	0.335	0.123	0.546
Oakmulgee WMA[ME]	0.667	0.529	0.805	0.751	0.641	0.861	0.750	0.641	0.858
Skyline WMA[HE]	0.542	0.395	0.690	0.424	0.292	0.556	0.387	0.229	0.544

[H] – High hunting effort site. [M] – Medium hunting effort site. [L] – Low hunting effort area. [C] – Control season change site (15 Mar – April 15). [E] – Experimental season change site (24 Mar – 30 April).

Table 3.12. Estimates of annual occupancy (ψ) and 95% upper and lower confidence limits (UCL, LCL) for male wild turkey on managed wildlife openings during the years of 2016, 2017, and 2018. Managed wildlife openings are grouped into categorical levels of hunting effort: high, medium, and low. High hunting effort sites include Coosa WMA and Skyline WMA. Medium hunting effort sites include Blue Spring WMA and Oakmulgee WMA. Low hunting effort sites include Little River WMA, Mulberry Fork WMA, and Perdido River WMA.

	2016			2017			2018		
Hunting effort	ψ	LCL	UCL	ψ	LCL	UCL	ψ	LCL	UCL
High	0.305	0.184	0.426	0.249	0.135	0.362	0.229	0.099	0.360
Medium	0.445	0.300	0.591	0.442	0.327	0.556	0.441	0.321	0.562
Low	0.141	0.010	0.272	0.275	0.171	0.379	0.302	0.186	0.418

Table 3.13. Estimates of annual occupancy (ψ) and 95% upper and lower confidence limits (UCL, LCL) for female wild turkey on managed wildlife openings during the years of 2016, 2017, and 2018.

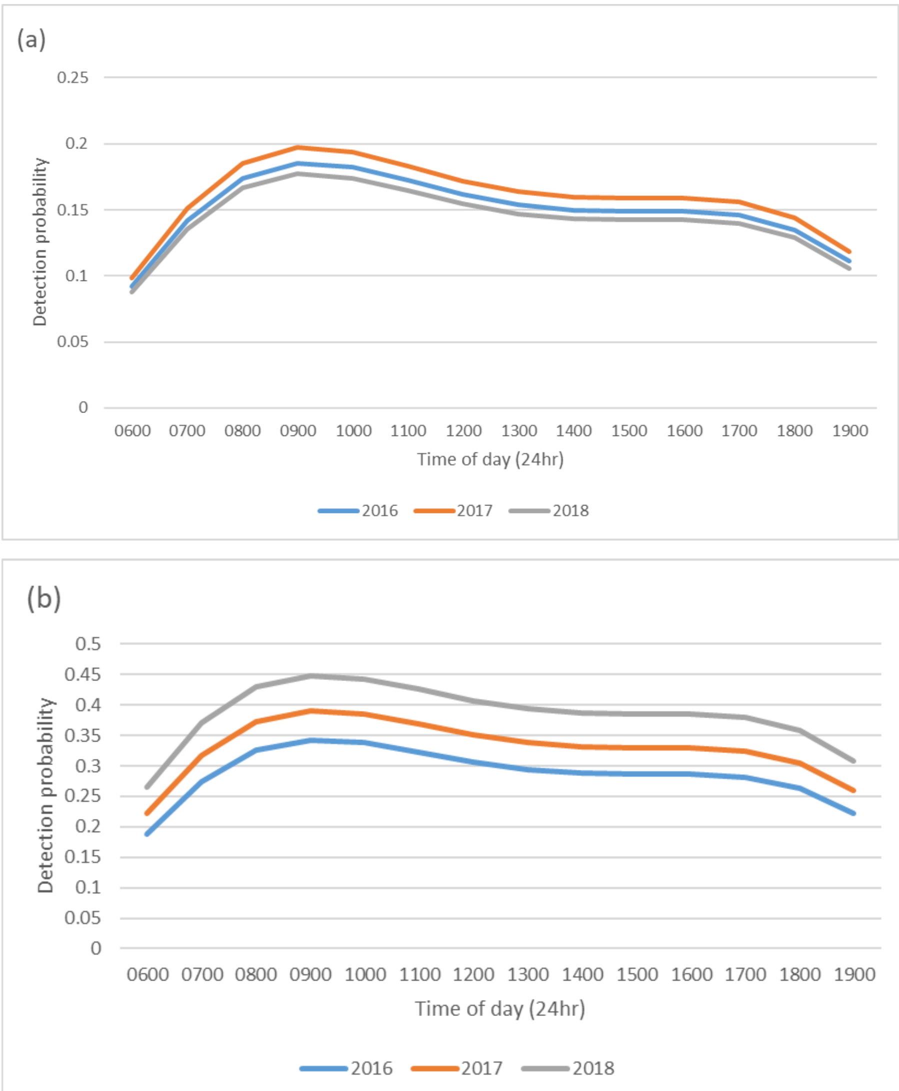
	2016			2017			2018		
Study Area	ψ	LCL	UCL	ψ	LCL	UCL	ψ	LCL	UCL
Blue Spring WMA^{MC}	0.312	0.053	0.571	0.492	0.299	0.685	0.528	0.314	0.743
Coosa WMA^{HC}	0.853	0.662	1.043	0.851	0.692	1.010	0.850	0.674	1.026
Little River WMA^{LC}	0.856	0.593	1.118	0.722	0.531	0.914	0.645	0.399	0.892
Mulberry Fork WMA^{LC}	0.500	0.281	0.719	0.740	0.592	0.888	0.702	0.575	0.829
Perdido River WMA^{LE}	0.358	0.106	0.609	0.315	0.127	0.504	0.302	0.080	0.523
Oakmulgee WMA^{ME}	0.424	0.279	0.569	0.452	0.325	0.579	0.459	0.307	0.610
Skyline WMA^{HE}	0.475	0.328	0.623	0.359	0.228	0.490	0.330	0.181	0.478

^{H} – High hunting effort site. ^{M} – Medium hunting effort site. ^{L} – Low hunting effort area. ^{C} – Control season change site (15 Mar – April 15). ^{E} – Experimental season change site (24 Mar – 30 April).

Table 3.14. Estimates of annual occupancy (ψ) and 95% upper and lower confidence limits (UCL, LCL) for wild turkey poults on managed wildlife openings during the years of 2016, 2017, and 2018. Managed wildlife openings are grouped into categorical levels of hunting effort: high, medium, and low. High hunting effort sites include Coosa WMA and Skyline WMA. Medium hunting effort sites include Blue Spring WMA and Oakmulgee WMA. Low hunting effort sites include Little River WMA, Mulberry Fork WMA, and Perdido River WMA.

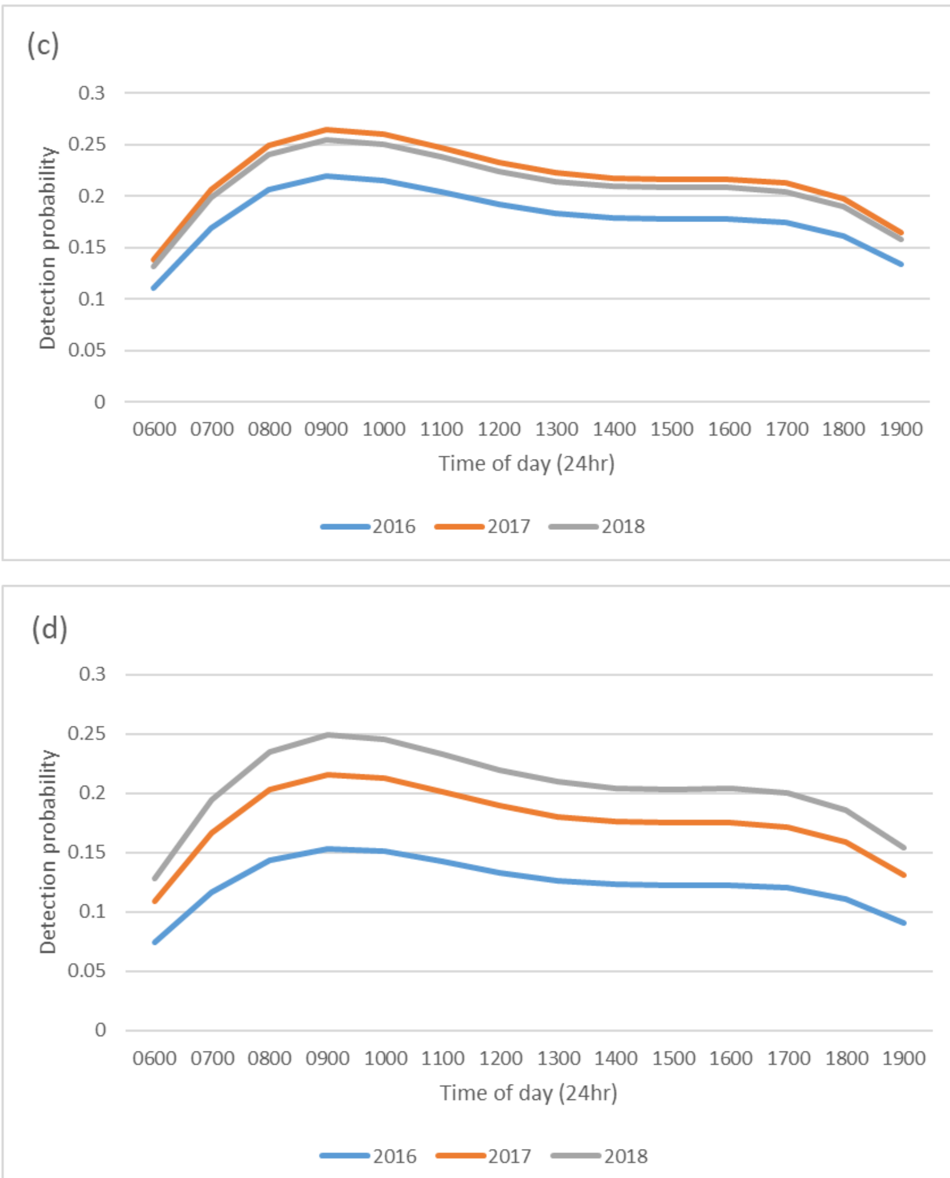
	2016			2017			2018		
Hunting effort	ψ	LCL	UCL	ψ	LCL	UCL	ψ	LCL	UCL
High	0.142	0.051	0.233	0.154	0.077	0.232	0.156	0.070	0.242
Medium	0.153	-0.045	0.351	0.130	-0.015	0.275	0.122	-0.049	0.293
Low	0.426	0.242	0.610	0.264	0.153	0.374	0.250	0.128	0.371

Figure 3.1. Variation in probability of detection (p) for wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera survey traps were programmed to start at 0600 h and end at 1900 h.



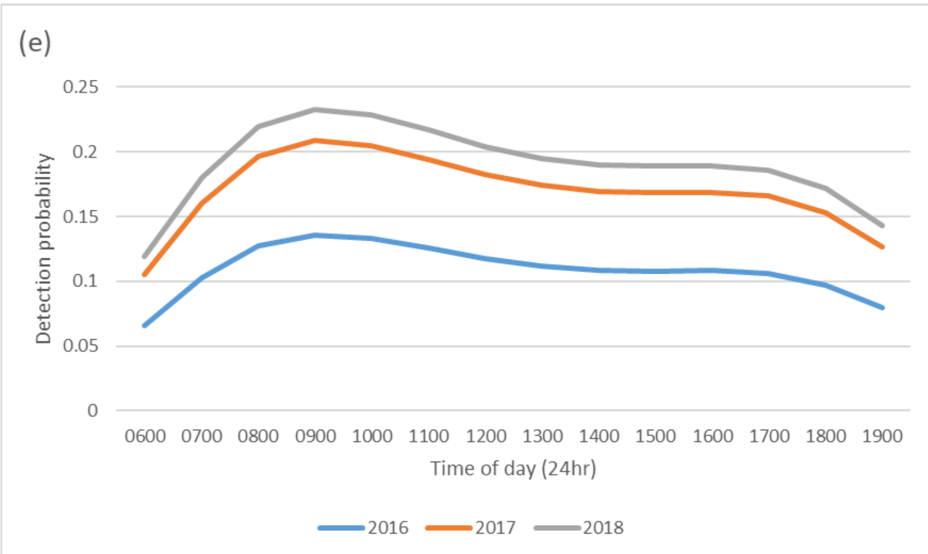
a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

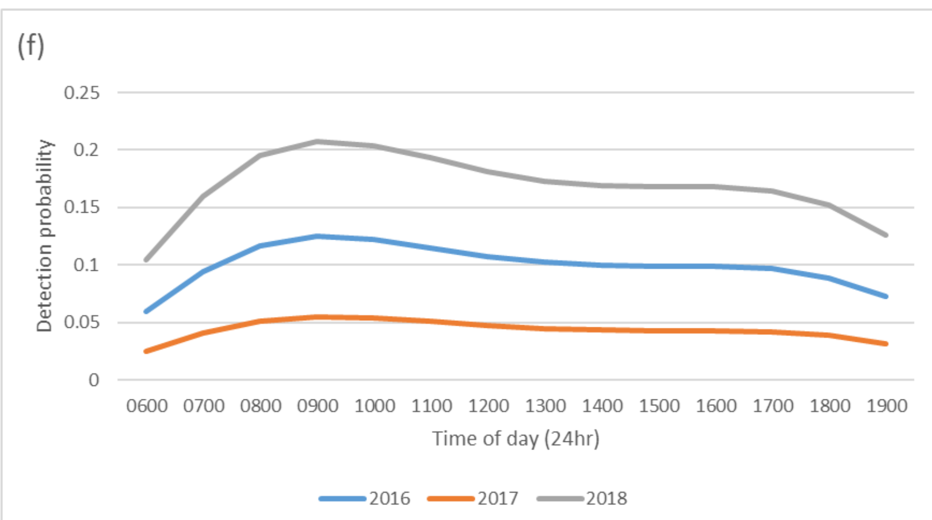
Figure 3.1. Variation in probability of detection (*p*) for wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera survey traps were programmed to start at 0600 h and end at 1900 h.



a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

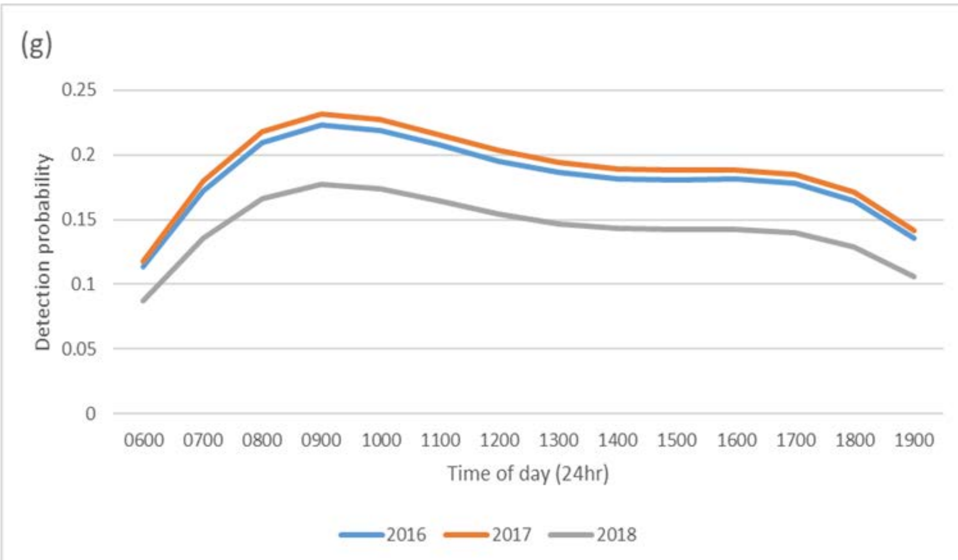
Figure 3.1. Variation in probability of detection (p) for wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera survey traps were programmed to start at 0600 h and end at 1900 h.





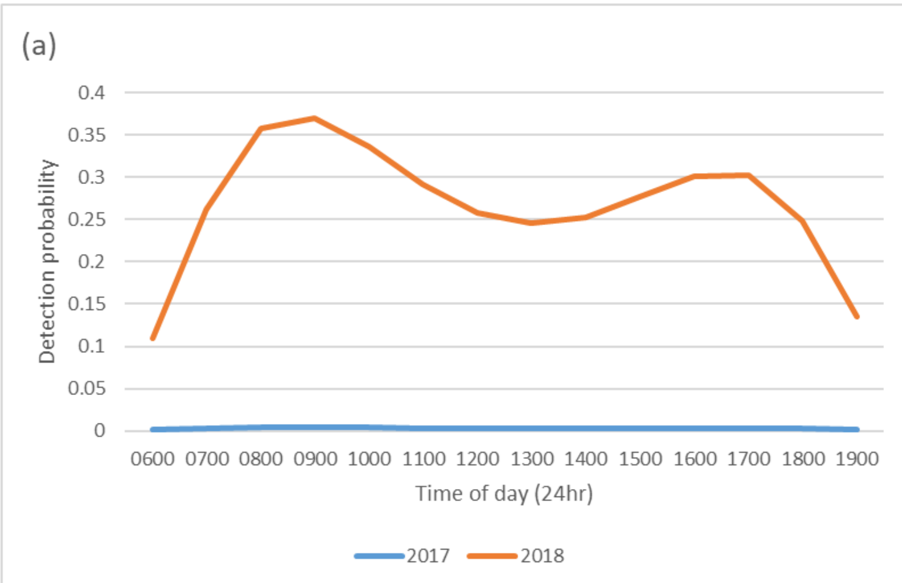
a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

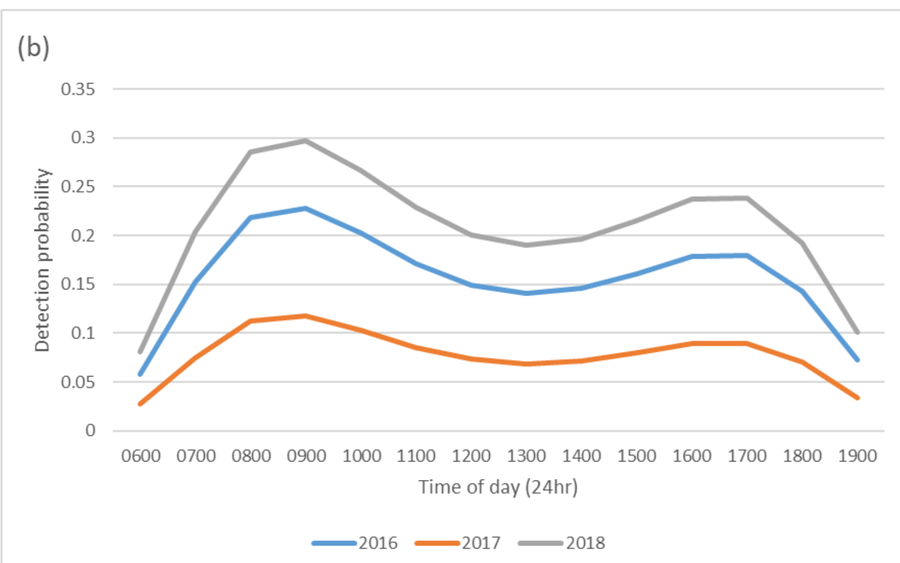
Figure 3.1. Variation in probability of detection (*p*) for wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera survey traps were programmed to start at 0600 h and end at 1900 h.



a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

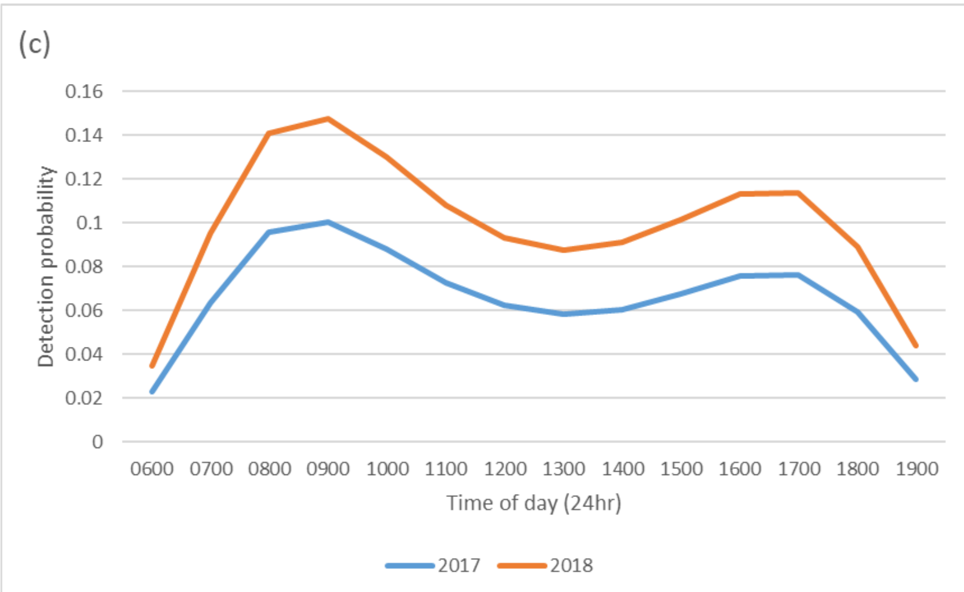
Figure 3.2. Variation in probability of detection (p) for male wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h. Years that had no male detections were omitted.

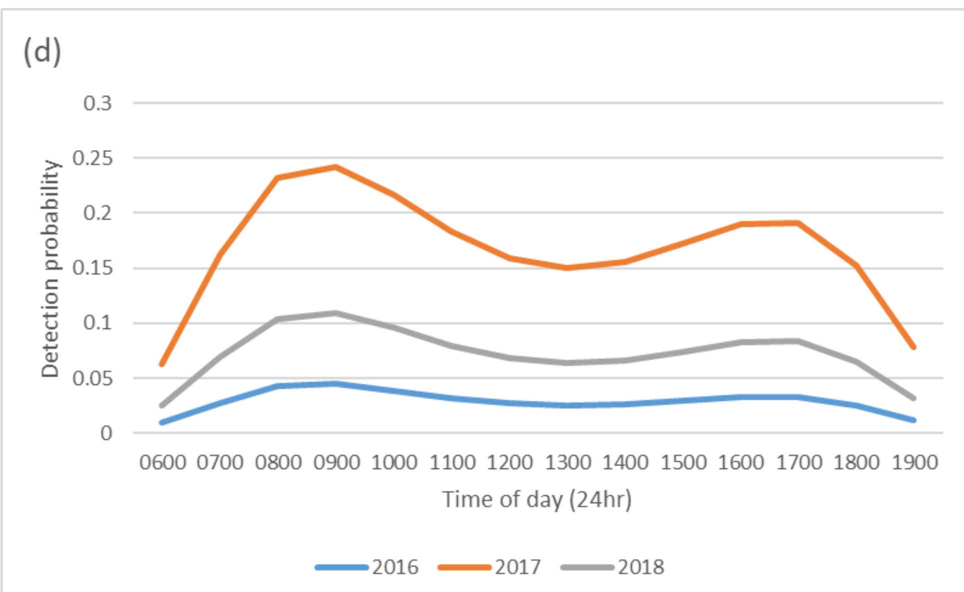




a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

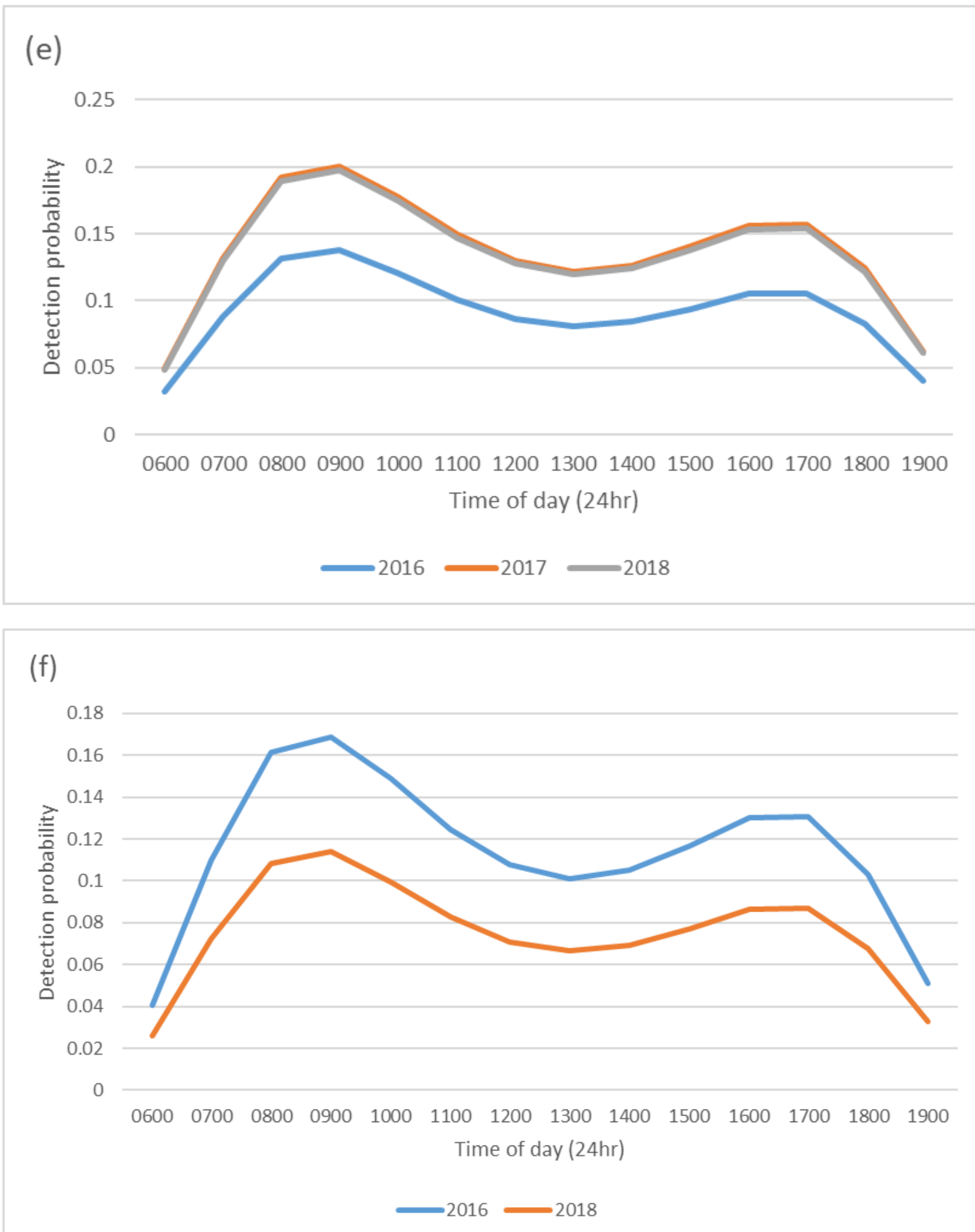
Figure 3.2. Variation in probability of detection (p) for male wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h. Years that had no male detections were omitted.





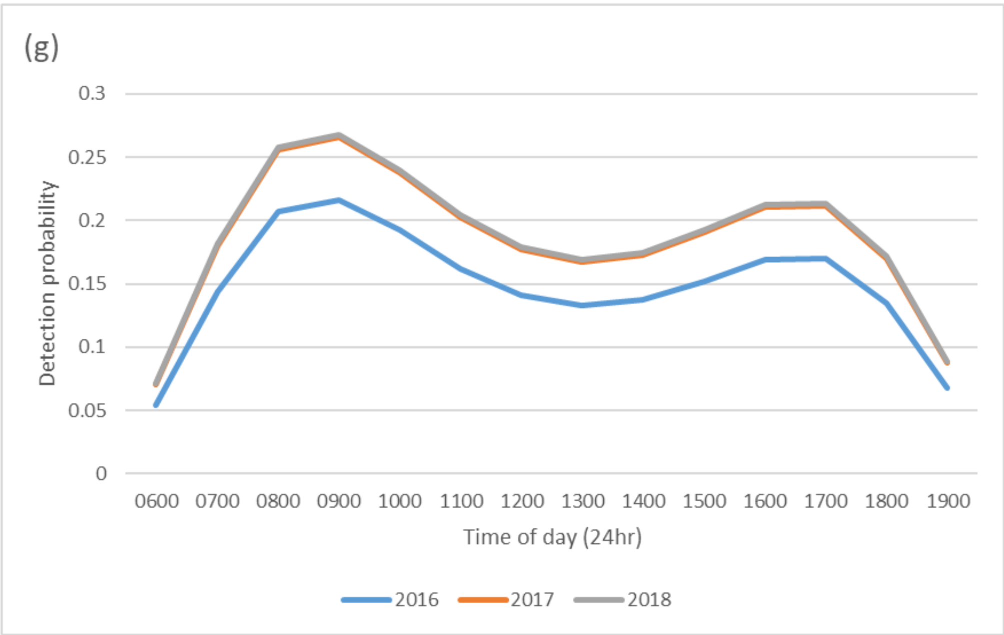
a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

Figure 3.2. Variation in probability of detection (p) for male wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h. Years that had no male detections were omitted.



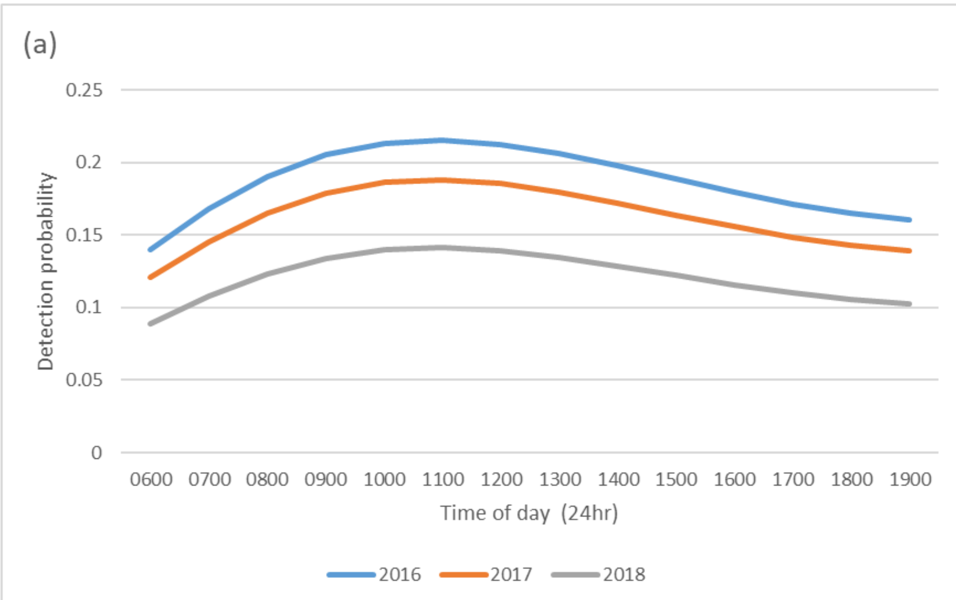
a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

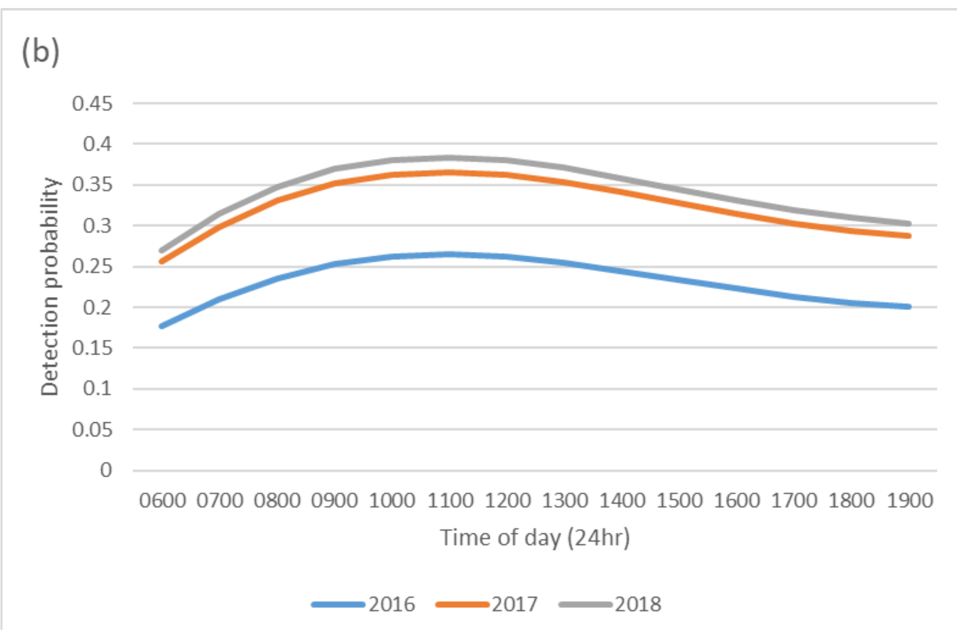
Figure 3.2. Variation in probability of detection (p) for male wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h. Years that had no male detections were omitted.



a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

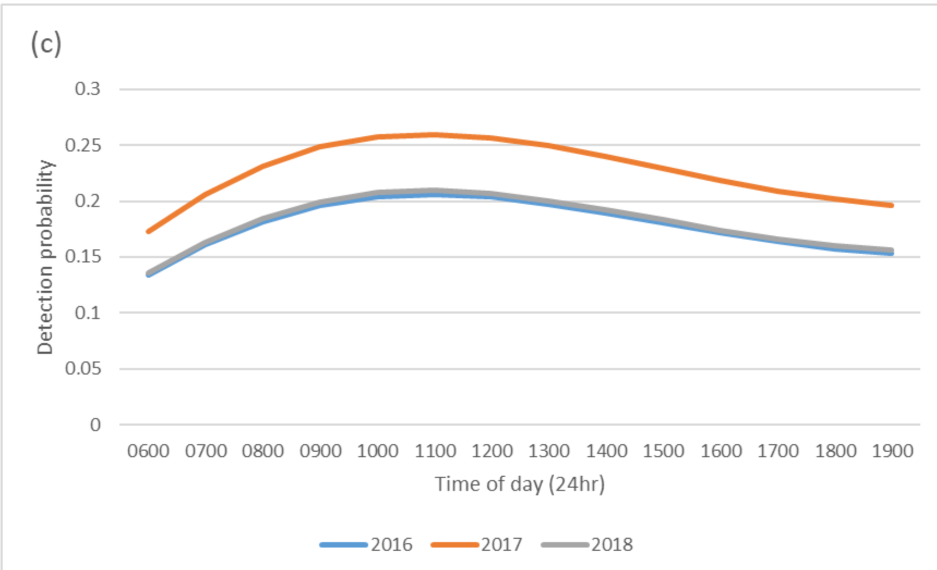
Figure 3.3. Variation in probability of detection (p) for female wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h.

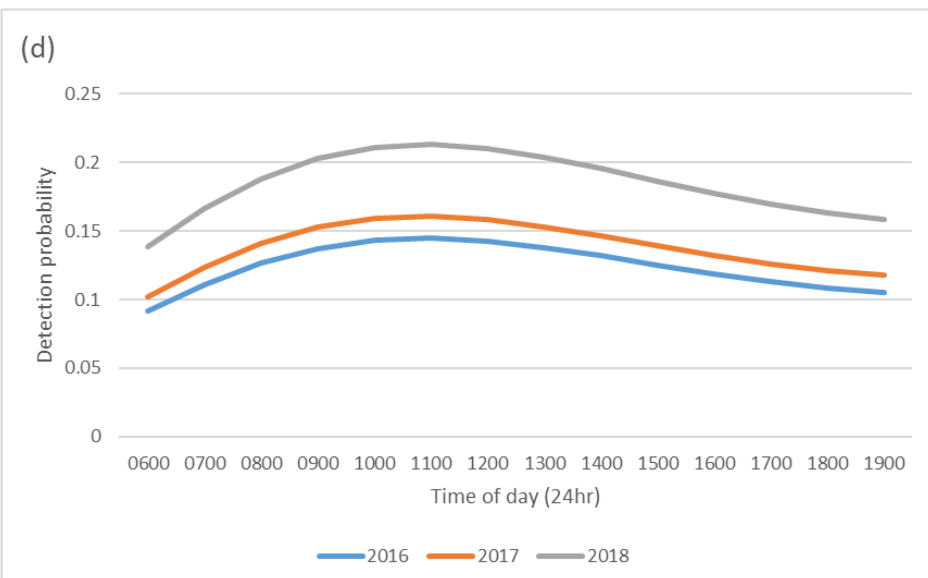




a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

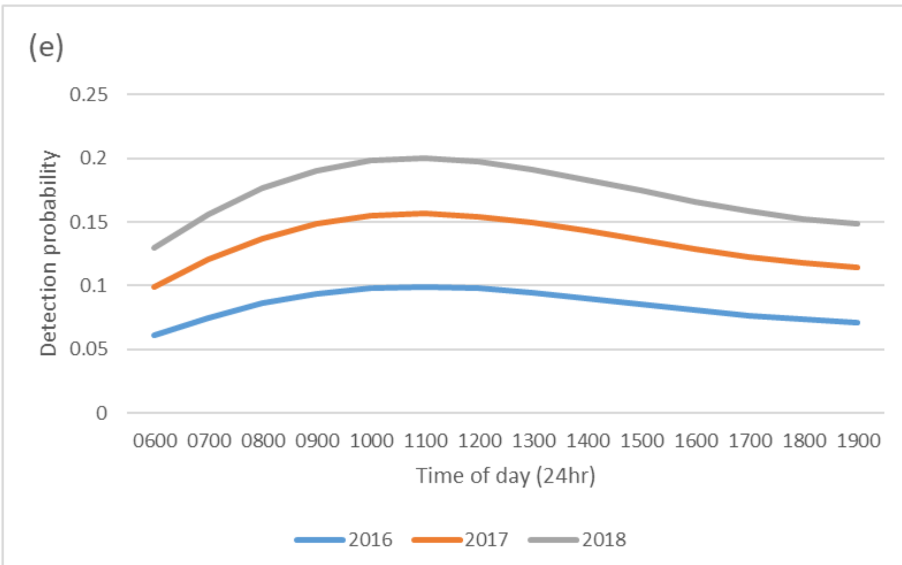
Figure 3.3. Variation in probability of detection (p) for female wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h.

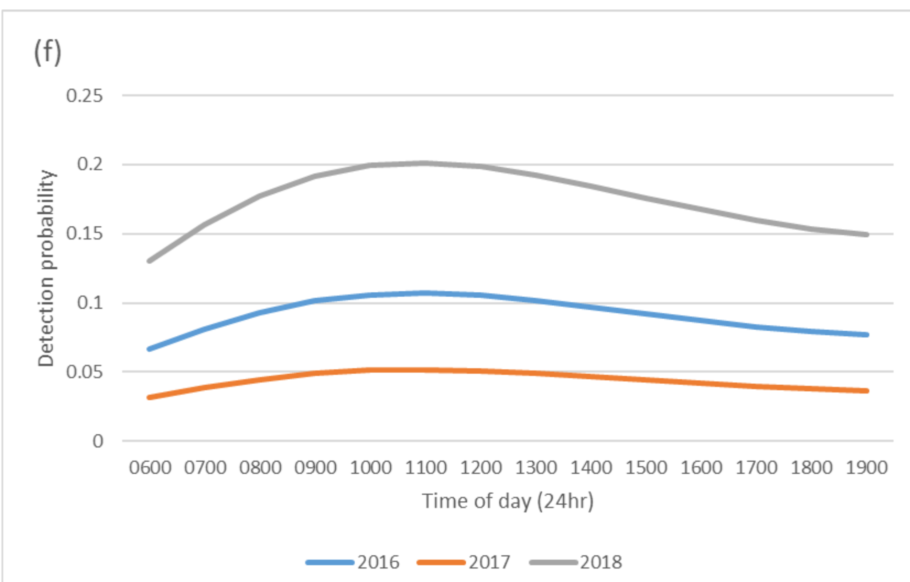




a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

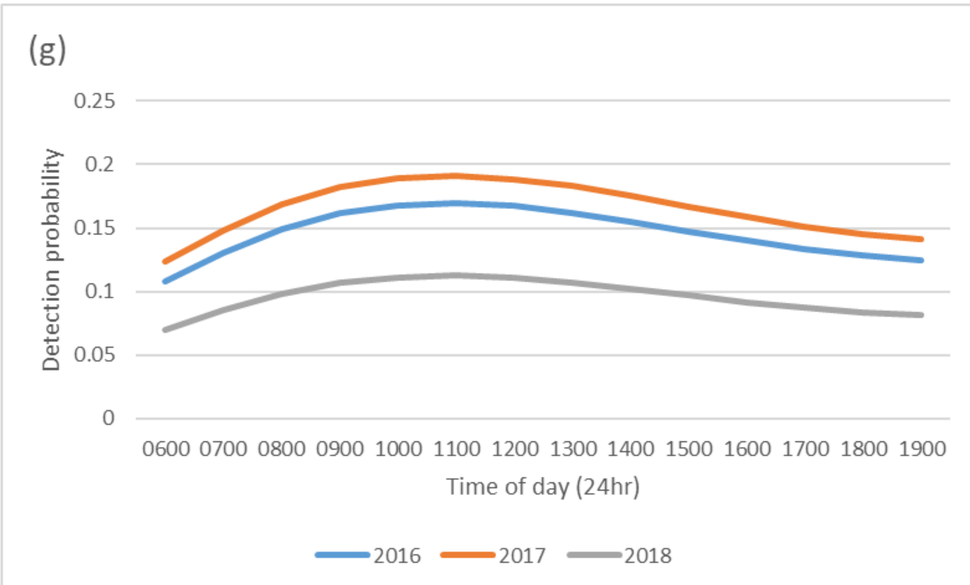
Figure 3.3. Variation in probability of detection (*p*) for female wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h.





a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

Figure 3.3. Variation in probability of detection (p) for female wild turkey on managed wildlife openings across the years of 2016, 2017, and 2018. Camera trap surveys were conducted from 0600h – 1900h.



a – Blue Spring WMA. b – Coosa WMA. c – Little River WMA. d – Mulberry Fork WMA. e – Oakmulgee WMA. f – Perdido River WMA. g – Skyline WMA.

Figure 3.4. Variation in probability of detection (p) for poult wild turkey on managed wildlife openings. Camera survey traps were programmed to start at 0600 h and end at 1900 h

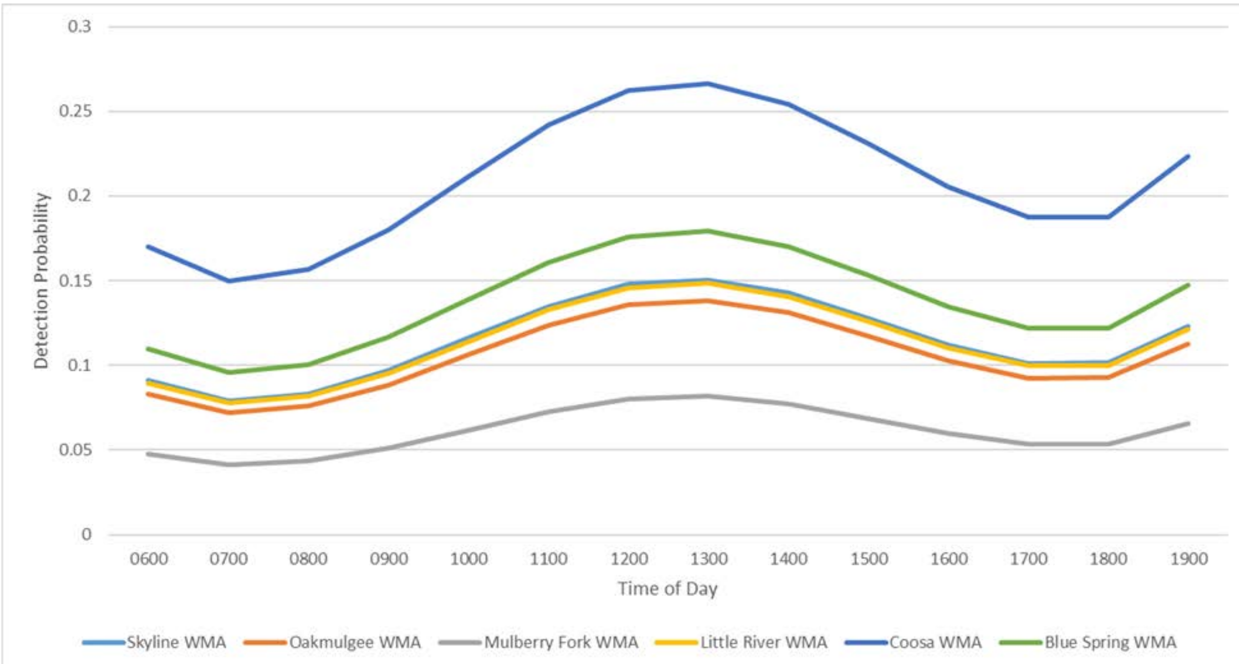
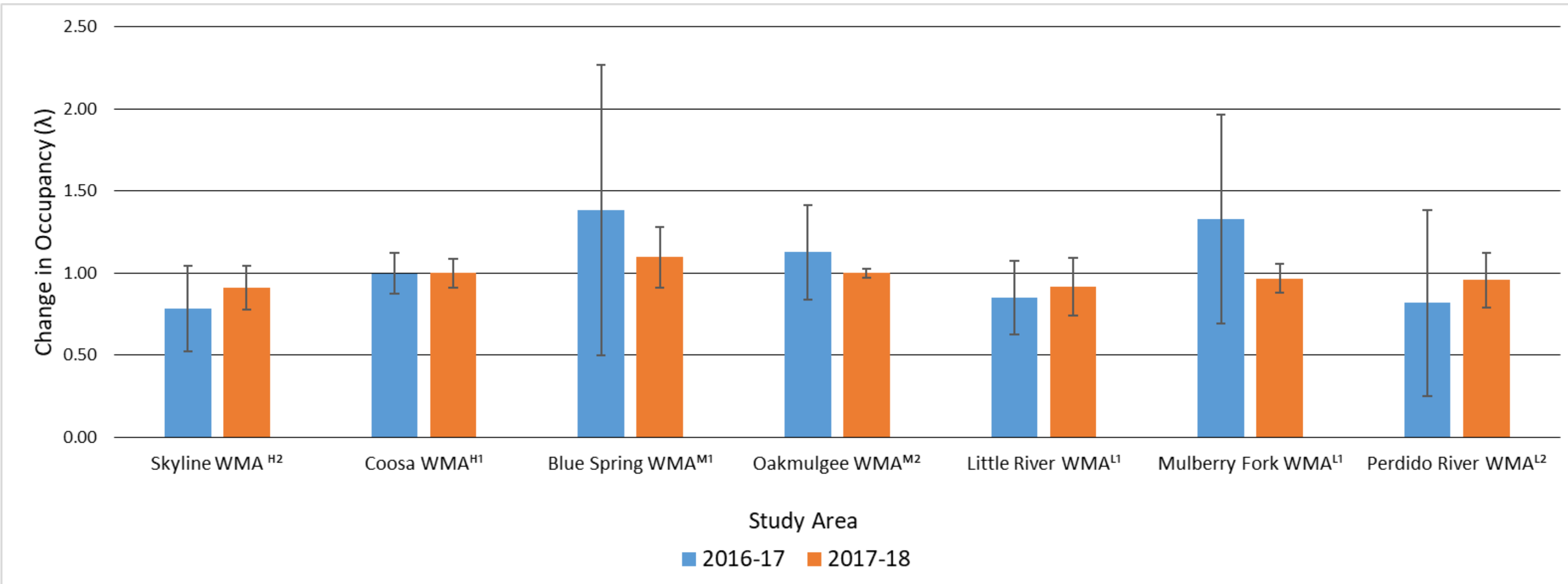
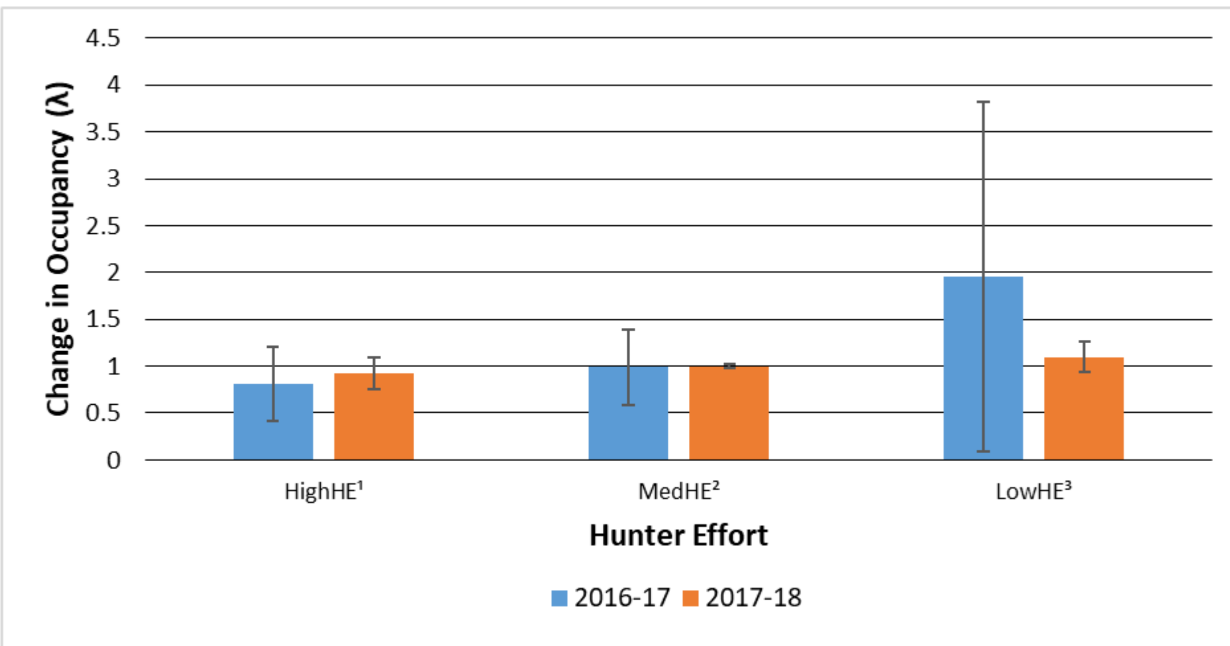


Figure 3.5. Annual change in occupancy (λ) for wild turkey populations on wildlife openings on seven wildlife management areas in Alabama, 2016-2018. (λ =1.0 indicates no change in occupancy, λ <1.0 indicates a decline in occupancy, and λ >1.0 indicates an increase in occupancy.



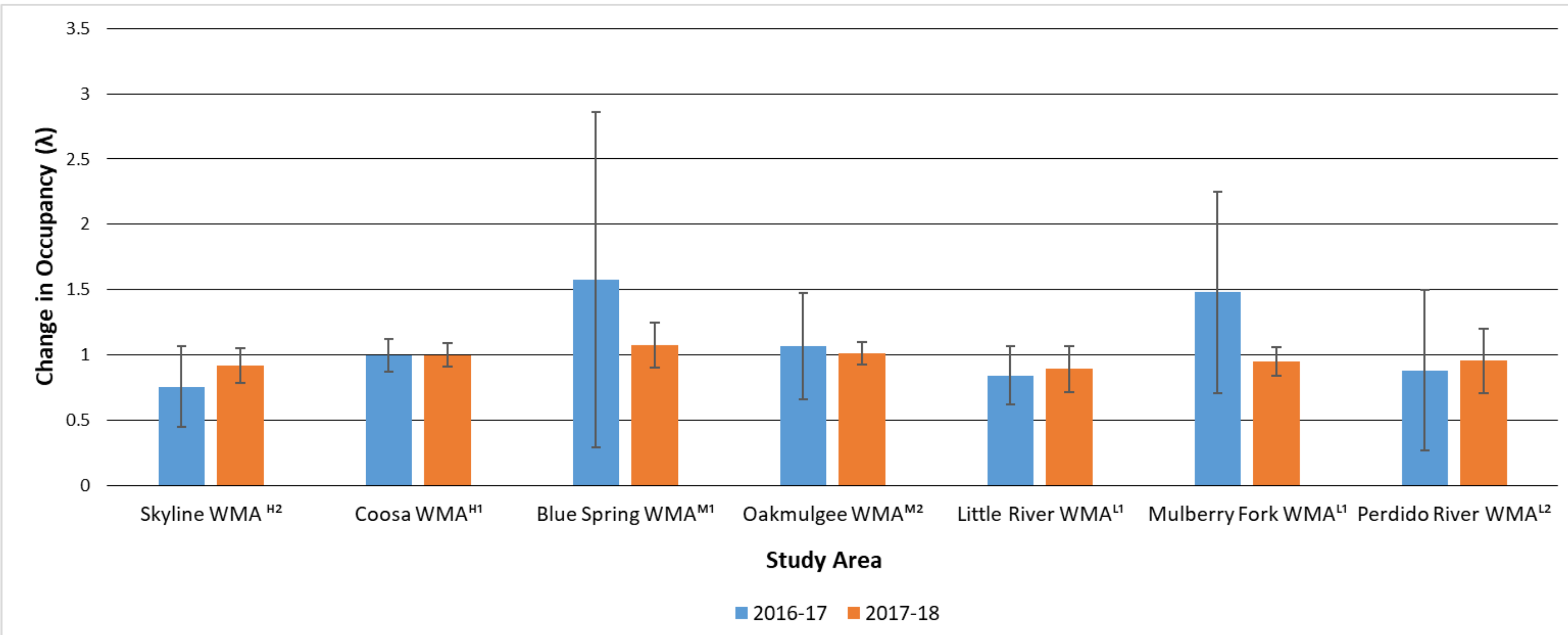
L - Low hunting effort. M - Medium hunting effort. H - High hunting effort. 1 - Control Study Area. 2 - Experimental Season Change Study Area.

Figure 3.6. Annual change in occupancy (λ) for male wild turkey populations on wildlife openings on size wildlife management areas in Alabama, 2016-2018. (λ =1.0 indicates no change in occupancy, λ <1.0 indicates a decline in occupancy, and λ >1.0 indicates an increase in occupancy.



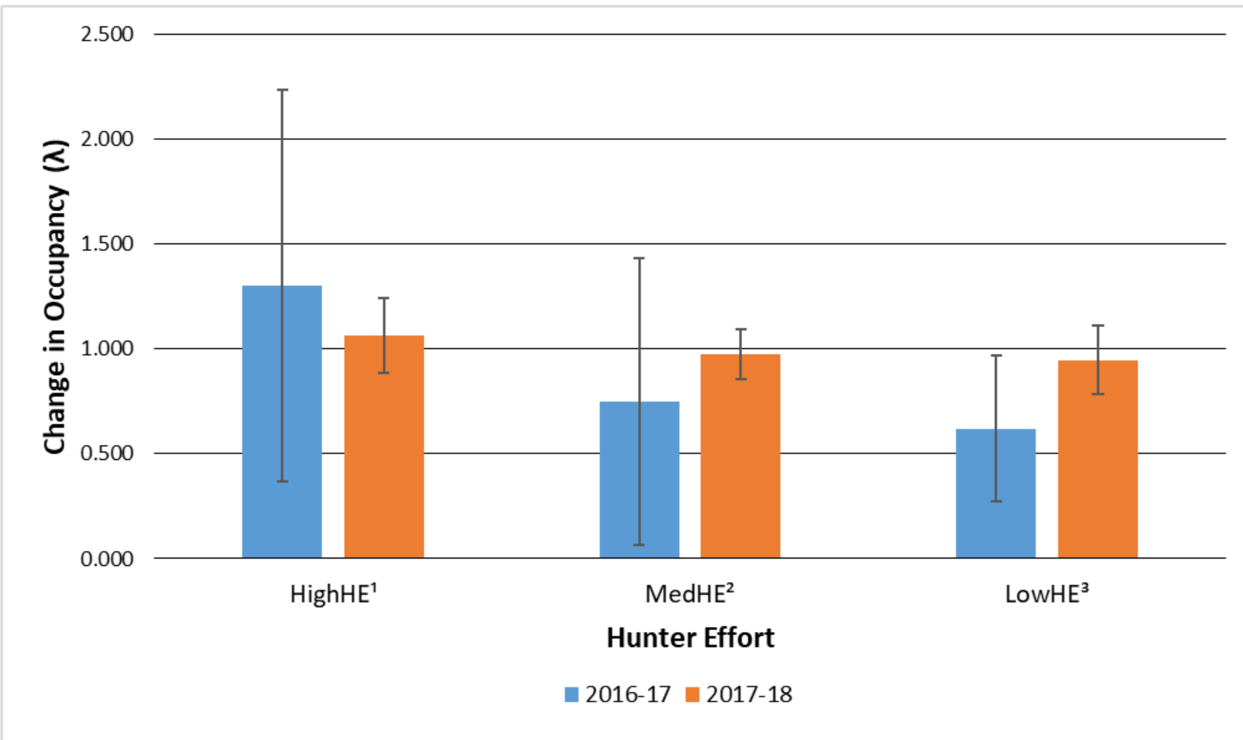
[1] - Skyline WMA, Coosa WMA. [2] - Oakmulgee WMA, Blue Spring WMA. [3] - Little River WMA, Mulberry Fork WMA, Perdido River WMA.

Figure 3.7. Annual change in occupancy (λ) for female wild turkey populations on wildlife openings on size wildlife management areas in Alabama, 2016-2018. (λ =1.0 indicates no change in occupancy, λ <1.0 indicates a decline in occupancy, and λ >1.0 indicates an increase in occupancy.



L - Low hunting effort. M - Medium hunting effort. H - High hunting effort. 1 - Control Study Area. 2 - Experimental Season Change Study Area.

Figure 3.8. Annual change in occupancy (λ) for poult wild turkey populations on wildlife openings on size wildlife management areas in Alabama, 2016-2018. (λ =1.0 indicates no change in occupancy, λ <1.0 indicates a decline in occupancy, and λ >1.0 indicates an increase in occupancy.



[1] - Skyline WMA, Coosa WMA. [2] - Oakmulgee WMA, Blue Spring WMA. [3] - Little River WMA, Mulberry Fork WMA

Appendix A. Camera trap deployment dates over three years at seven wildlife management areas. Missing values indicate no camera trap was deployed at that site during that year.

		Camera trap deployment date		
Study Area	Site	2016	2017	2018
Blue Springs WMA	1	16-Aug	11-Aug	2-Aug
Blue Springs WMA	2	16-Aug	11-Aug	
Blue Springs WMA	3	16-Aug	11-Aug	21-Aug
Blue Springs WMA	4	16-Aug	11-Aug	2-Aug
Blue Springs WMA	5	16-Aug	11-Aug	2-Aug
Blue Springs WMA	6	16-Aug	11-Aug	2-Aug
Blue Springs WMA	7		11-Aug	2-Aug
Blue Springs WMA	8	16-Aug	11-Aug	2-Aug
Blue Springs WMA	9		11-Aug	2-Aug
Blue Springs WMA	10	16-Aug	11-Aug	2-Aug
Blue Springs WMA	11	16-Aug	11-Aug	2-Aug
Blue Springs WMA	12	16-Aug	11-Aug	2-Aug
Blue Springs WMA	13		11-Aug	21-Aug
Blue Springs WMA	14	16-Aug	11-Aug	2-Aug
Blue Springs WMA	15	16-Aug	11-Aug	2-Aug
Coosa WMA	1			19-Jul
Coosa WMA	2	29-Jun	17-Jul	19-Jul
Coosa WMA	3	29-Jun	17-Jul	19-Jul
Coosa WMA	4	29-Jun	17-Jul	19-Jul
Coosa WMA	5	29-Jun	17-Jul	19-Jul
Coosa WMA	6	29-Jun	17-Jul	19-Jul
Coosa WMA	7	29-Jun	17-Jul	19-Jul
Coosa WMA	8	29-Jun	17-Jul	19-Jul
Coosa WMA	9	29-Jun	17-Jul	19-Jul
Coosa WMA	10	29-Jun	17-Jul	19-Jul
Coosa WMA	11	29-Jun		19-Jul
Coosa WMA	12	29-Jun	17-Jul	19-Jul
Coosa WMA	13	29-Jun	17-Jul	19-Jul
Coosa WMA	14			19-Jul
Coosa WMA	15			19-Jul
Little River WMA	1	26-Jul	25-Jul	3-Jul
Little River WMA	2	26-Jul	25-Jul	3-Jul
Little River WMA	3	26-Jul	25-Jul	3-Jul
Little River WMA	4	26-Jul	25-Jul	3-Jul

Appendix A. Camera trap deployment dates over three years at seven wildlife management areas. Missing values indicate no camera trap was deployed at that site during that year.

		Camera trap deployment date		
Study Area	Site	2016	2017	2018
Little River WMA	5	26-Jul	25-Jul	3-Jul
Little River WMA	6	26-Jul	25-Jul	3-Jul
Little River WMA	7	26-Jul		3-Jul
Little River WMA	8	26-Jul	25-Jul	3-Jul
Little River WMA	9	26-Jul	25-Jul	3-Jul
Little River WMA	10		25-Jul	3-Jul
Little River WMA	11			3-Jul
Little River WMA	12			3-Jul
Little River WMA	13			3-Jul
Little River WMA	14			3-Jul
Little River WMA	15			3-Jul
Mulberry Fork WMA	1	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	2	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	3	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	4	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	5	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	6	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	7	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	8	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	9	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	10	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	11	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	12	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	13	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	14	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	15	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	16	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	17	2-Aug		13-Aug
Mulberry Fork WMA	18	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	19	2-Aug	25-Jul	13-Aug
Mulberry Fork WMA	20	2-Aug		13-Aug
Perdido River WMA	1	14-Jul	10-Jul	12-Jul
Perdido River WMA	2	14-Jul	10-Jul	12-Jul
Perdido River WMA	3	14-Jul	10-Jul	12-Jul
Perdido River WMA	4	14-Jul	10-Jul	12-Jul
Perdido River WMA	5	14-Jul	10-Jul	12-Jul

Appendix A. Camera trap deployment dates over three years at seven wildlife management areas. Missing values indicate no camera trap was deployed at that site during that year.

		Camera trap deployment date		
Study Area	Site	2016	2017	2018
Perdido River WMA	6	14-Jul	10-Jul	12-Jul
Perdido River WMA	7	14-Jul	10-Jul	12-Jul
Perdido River WMA	8	14-Jul	10-Jul	12-Jul
Perdido River WMA	9	14-Jul	10-Jul	12-Jul
Perdido River WMA	10	14-Jul	10-Jul	12-Jul
Perdido River WMA	11	14-Jul	10-Jul	12-Jul
Perdido River WMA	12	14-Jul	10-Jul	12-Jul
Perdido River WMA	13	14-Jul	10-Jul	12-Jul
Perdido River WMA	14	14-Jul	10-Jul	12-Jul
Oakmulgee WMA	2	20-Jul	20-Jul	19-Jul
Oakmulgee WMA	4	20-Jul	3-Aug	2-Aug
Oakmulgee WMA	9		10-Aug	9-Aug
Oakmulgee WMA	10	20-Jul		
Oakmulgee WMA	12	21-Jul	20-Jul	19-Jul
Oakmulgee WMA	13	20-Jul	10-Aug	9-Aug
Oakmulgee WMA	15	20-Jul	3-Aug	2-Aug
Oakmulgee WMA	20	20-Jul	10-Aug	8-Aug
Oakmulgee WMA	21	20-Jul	10-Aug	8-Aug
Oakmulgee WMA	22	13-Jul	20-Jul	9-Aug
Oakmulgee WMA	23	13-Jul	3-Aug	2-Aug
Oakmulgee WMA	25	13-Jul	20-Jul	19-Jul
Oakmulgee WMA	27	13-Jul		
Oakmulgee WMA	29	13-Jul		
Oakmulgee WMA	31	13-Jul		
Oakmulgee WMA	32	13-Jul	3-Aug	2-Aug
Oakmulgee WMA	33	13-Jul		
Oakmulgee WMA	34	21-Jul		
Oakmulgee WMA	35	4-Aug		
Oakmulgee WMA	37	4-Aug	20-Jul	19-Jul
Oakmulgee WMA	40	4-Aug		
Oakmulgee WMA	41	21-Jul	10-Aug	8-Aug
Oakmulgee WMA	42	4-Aug		
Oakmulgee WMA	44	21-Jul	3-Aug	2-Aug
Oakmulgee WMA	46	21-Jul	3-Aug	2-Aug
Oakmulgee WMA	48	29-Jul	20-Jul	19-Jul
Oakmulgee WMA	50	21-Jul	20-Jul	19-Jul

Appendix A. Camera trap deployment dates over three years at seven wildlife management areas. Missing values indicate no camera trap was deployed at that site during that year.

		Camera trap deployment date		
Study Area	Site	2016	2017	2018
Oakmulgee WMA	52	21-Jul		
Oakmulgee WMA	53	4-Aug	10-Aug	9-Aug
Oakmulgee WMA	61	21-Jul	20-Jul	19-Jul
Oakmulgee WMA	62	21-Jul		
Oakmulgee WMA	64	4-Aug		
Oakmulgee WMA	65	29-Jul	3-Aug	2-Aug
Oakmulgee WMA	68	4-Aug		
Oakmulgee WMA	69		20-Jul	19-Jul
Oakmulgee WMA	71	29-Jul	10-Aug	9-Aug
Oakmulgee WMA	72	29-Jul		
Oakmulgee WMA	73	29-Jul	10-Aug	9-Aug
Oakmulgee WMA	75	29-Jul	20-Jul	19-Jul
Oakmulgee WMA	83	29-Jul		
Oakmulgee WMA	84	29-Jul		
Oakmulgee WMA	85	29-Jul	3-Aug	2-Aug
Oakmulgee WMA	88	4-Aug	10-Aug	8-Aug
Oakmulgee WMA	90	29-Jul	3-Aug	2-Aug
Oakmulgee WMA	91	29-Jul	10-Aug	8-Aug
Oakmulgee WMA	92	29-Jul		
Oakmulgee WMA	93	4-Aug	3-Aug	2-Aug
Skyline WMA	1	18-Jul	19-Jul	18-Jul
Skyline WMA	2	18-Jul		
Skyline WMA	3	18-Jul	9-Aug	9-Aug
Skyline WMA	4	24-Jul		
Skyline WMA	5	24-Jul	9-Aug	8-Aug
Skyline WMA	6	18-Jul	19-Jul	19-Jul
Skyline WMA	7	24-Jul		
Skyline WMA	8	11-Jul		
Skyline WMA	9	11-Jul	25-Jul	18-Jul
Skyline WMA	10	18-Jul	9-Aug	9-Aug
Skyline WMA	11	11-Jul		
Skyline WMA	12	18-Jul	20-Jul	18-Jul
Skyline WMA	13	11-Jul	19-Jul	19-Jul
Skyline WMA	14	11-Jul	10-Aug	8-Aug
Skyline WMA	15	18-Jul	15-Aug	13-Aug
Skyline WMA	17	11-Jul	10-Aug	8-Aug

Appendix A. Camera trap deployment dates over three years at seven wildlife management areas. Missing values indicate no camera trap was deployed at that site during that year.

		Camera trap deployment date		
Study Area	Site	2016	2017	2018
Skyline WMA	19	24-Jul	3-Aug	1-Aug
Skyline WMA	20	24-Jul		
Skyline WMA	21	18-Jul	20-Jul	18-Jul
Skyline WMA	22	18-Jul	15-Aug	13-Aug
Skyline WMA	24	11-Jul	10-Aug	8-Aug
Skyline WMA	25	18-Jul		
Skyline WMA	26	18-Jul		
Skyline WMA	27	24-Jul		
Skyline WMA	28	24-Jul	20-Jul	19-Jul
Skyline WMA	29	24-Jul		
Skyline WMA	30	18-Jul	19-Jul	19-Jul
Skyline WMA	31	18-Jul	3-Aug	1-Aug
Skyline WMA	32	18-Jul		
Skyline WMA	33	24-Jul		
Skyline WMA	35	18-Jul	2-Aug	2-Aug
Skyline WMA	36	24-Jul	3-Aug	1-Aug
Skyline WMA	37	24-Jul	19-Jul	19-Jul
Skyline WMA	38	11-Jul		
Skyline WMA	39	18-Jul	2-Aug	2-Aug
Skyline WMA	40	18-Jul	3-Aug	1-Aug
Skyline WMA	41	11-Jul		
Skyline WMA	43	18-Jul	3-Aug	1-Aug
Skyline WMA	44	18-Jul	9-Aug	9-Aug
Skyline WMA	46	24-Jul	9-Aug	8-Aug
Skyline WMA	47	18-Jul		
Skyline WMA	48	24-Jul		
Skyline WMA	49	11-Jul	2-Aug	2-Aug
Skyline WMA	50		9-Aug	9-Aug
Skyline WMA	53	24-Jul	19-Jul	18-Jul

Appendix B. Beta estimates from unequivocal model for wild turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.[1]

Parameter	Estimate	SE	LCI	UCI
Psi Intercept	0.170	0.303	-0.423	0.763
Psi MedHE	0.524	0.438	-0.334	1.382
Psi LowHE	-0.457	0.619	-1.670	0.757
Psi MedHE*g1	-1.206	0.662	-2.504	0.093
Psi LowHE*g3	2.145	1.233	-0.273	4.562
Psi LowHE*g4	0.488	0.703	-0.889	1.866
Psi HighHE*g2	1.586	0.831	-0.043	3.215
Epsilon Intercept	-0.274	0.395	-1.049	0.501
Epsilon MedHE	-0.804	0.528	-1.839	0.230
Epsilon LowHE	0.426	0.798	-1.138	1.990
Epsilon MedHE*g1	0.062	0.741	-1.390	1.515
Epsilon LowHE*g3	-1.549	0.913	-3.339	0.242
Epsilon LowHE*g4	-0.875	0.804	-2.451	0.701
Epsilon HighHE*g2	-2.848	1.099	-5.003	-0.694
Gamma Intercept	-1.082	0.410	-1.884	-0.279
Gamma MedHE	2.234	0.707	0.848	3.620
Gamma LowHE	0.067	0.671	-1.249	1.383
Gamma MedHE*g1	-1.599	0.783	-3.134	-0.065
Gamma LowHE*g3	0.276	1.572	-2.805	3.356
Gamma LowHE*g4	2.420	0.926	0.605	4.235
Gamma HighHE*g3	-0.105	1.167	-2.393	2.184
p intercept 2016	-2.059	0.106	-2.266	-1.852
p Y*g1	-0.231	0.178	-0.580	0.117
p Y*g2	0.598	0.108	0.387	0.809
p Y*g3	-0.023	0.130	-0.277	0.230

Appendix B. Beta estimates from unequivocal model for wild turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.[1]

Parameter	Estimate	SE	LCI	UCI
p Y*g4	-0.457	0.137	-0.726	-0.189
p Y*g5	-0.698	0.177	-1.044	-0.352
p Y*g6	-0.601	0.098	-0.794	-0.408
p intercept 2017	-2.010	0.118	-2.242	-1.779
p Y*g1	-0.205	0.156	-0.511	0.101
p Y*g2	0.753	0.125	0.509	0.998
p Y*g3	0.175	0.130	-0.079	0.429
p Y*g4	-0.089	0.118	-0.320	0.143
p Y*g5	-1.636	0.387	-2.395	-0.877
p Y*g6	-0.133	0.111	-0.351	0.085
p intercept 2018	-2.346	0.145	-2.629	-2.062
p Y*g1	0.001	0.185	-0.360	0.363
p Y*g2	1.327	0.138	1.057	1.598
p Y*g3	0.460	0.156	0.154	0.765
p Y*g4	0.432	0.153	0.133	0.732
p Y*g5	0.196	0.177	-0.151	0.543
p Y*g6	0.342	0.137	0.074	0.609
ToD	64.412	8.962	46.847	81.978
ToD^2	-1704.755	287.910	-2269.058	-1140.451
ToD^3	17017.557	3376.320	10399.970	23635.145
ToD^4	-58614.073	12943.517	-83983.367	-33244.778

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE – Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.

Appendix C. Beta estimates from unequivocal model for male turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown. Years that had no male detections were omitted from detection probabilities.

Parameter	Estimate	SE	LCI	UCI
Psi Intercept	-0.823	0.290	-1.392	-0.254
Psi MedHE	0.603	0.418	-0.216	1.422
Psi LowHE	-0.986	0.623	-2.207	0.236
Epsilon Intercept	0.063	0.648	-1.206	1.333
Epsilon MedHE	0.063	0.717	-1.341	1.468
Epsilon LowHE	0.149	0.842	-1.502	1.800
Gamma Intercept	-1.774	0.364	-2.486	-1.061
Gamma MedHE	1.451	0.520	0.431	2.471
Gamma LowHE	0.659	0.503	-0.328	1.646
p Intercept 2016	-2.854	0.209	-3.264	-2.445
p Y*g2	0.067	0.193	-0.310	0.445
p Y*g4	-1.774	0.485	-2.724	-0.823
p Y*g5	-0.307	0.391	-1.073	0.460
p Y*g6	-0.547	0.137	-0.815	-0.279
p Intercept 2017	-2.581	0.235	-3.043	-2.120
p Y*g1	-4.350	1.068	-6.443	-2.257
p Y*g2	-1.001	0.270	-1.530	-0.472
p Y*g3	-1.178	0.254	-1.675	-0.680
p Y*g4	-0.126	0.219	-0.556	0.304
p Y*g6	-0.369	0.173	-0.708	-0.030
p Intercept 2018	-2.571	0.261	-3.083	-2.060
p Y*g1	0.471	0.352	-0.219	1.161
p Y*g2	0.143	0.223	-0.294	0.579
p Y*g3	-0.750	0.275	-1.288	-0.211
p Y*g4	-1.091	0.281	-1.643	-0.540

Appendix C. Beta estimates from unequivocal model for male turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown. Years that had no male detections were omitted from detection probabilities.

Parameter	Estimate	SE	LCI	UCI
p Y*g5	-1.048	0.325	-1.685	-0.411
p Y*g6	-0.397	0.209	-0.807	0.013
ToD	146.592	20.313	106.778	186.405
ToD^2	-4467.186	649.820	-5740.833	-3193.538
ToD^3	49523.408	7578.475	34669.596	64377.220
ToD^4	-182507.590	28936.841	-239223.800	-125791.380

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE – Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.

Appendix D. Beta estimates from unequivocal model for female turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.

Parameter	Estimate	SE	LCI	UCI
Psi Intercept	-0.100	0.302	-0.691	0.492
Psi g1	-0.691	0.686	-2.035	0.653
Psi g2	1.856	0.831	0.228	3.484
Psi g3	1.881	1.127	-0.327	4.089
Psi g4	0.101	0.540	-0.957	1.159
Psi g5	-0.486	0.634	-1.730	0.757
Psi g6	-0.207	0.427	-1.044	0.630
Epsilon Intercept	0.035	0.446	-0.839	0.909
Epsilon g1	-0.572	0.755	-2.053	0.908
Epsilon g2	-3.157	1.118	-5.350	-0.965
Epsilon g3	-1.452	0.765	-2.952	0.047
Epsilon g4	-0.704	0.607	-1.893	0.485
Epsilon g5	-0.134	0.876	-1.850	1.582
Epsilon g6	-0.379	0.607	-1.568	0.810
Gamma Intercept	-1.156	0.383	-1.906	-0.406
Gamma g1	0.870	0.636	-0.377	2.117
Gamma g2	-0.030	1.158	-2.300	2.240
Gamma g3	-0.047	1.306	-2.606	2.513
Gamma g4	2.667	0.846	1.010	4.324
Gamma g5	-0.238	0.692	-1.594	1.119
Gamma g6	0.555	0.523	-0.469	1.580

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE – Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.

Appendix D. Beta estimates from unequivocal model for female turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.

Parameter	Estimate	SE	LCI	UCI
p intercept 2016	-2.107	0.118	-2.339	-1.876
p Y*g1	0.294	0.187	-0.073	0.662
p Y*g2	0.567	0.120	0.333	0.801
p Y*g3	0.240	0.136	-0.026	0.506
p Y*g4	-0.189	0.148	-0.480	0.102
p Y*g5	-0.533	0.202	-0.930	-0.137
p Y*g6	-0.619	0.129	-0.871	-0.366
p intercept 2017	-1.962	0.135	-2.226	-1.698
p Y*g1	-0.022	0.166	-0.346	0.303
p Y*g2	0.893	0.137	0.625	1.160
p Y*g3	0.395	0.144	0.113	0.677
p Y*g4	-0.212	0.136	-0.478	0.055
p Y*g5	-1.466	0.389	-2.229	-0.702
p Y*g6	-0.242	0.150	-0.535	0.052
p intercept 2018	-2.585	0.175	-2.928	-2.242
p Y*g1	0.259	0.223	-0.178	0.697
p Y*g2	1.592	0.167	1.264	1.919
p Y*g3	0.736	0.184	0.375	1.098
p Y*g4	0.759	0.181	0.404	1.114
p Y*g5	0.688	0.207	0.282	1.094
p Y*g6	0.678	0.172	0.341	1.015

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE - Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.

Appendix D. Beta estimates from unequivocal model for female turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.

Parameter	Estimate	SE	LCI	UCI
ToD	25.006	9.879	5.644	44.369
ToD^2	-373.918	319.281	-999.708	251.872
ToD^3	1738.354	3751.017	-5613.639	9090.346
ToD^4	-2070.837	14382.324	-30260.193	26118.520

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE – Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.

Appendix E. Beta estimates from unequivocal model for poult turkeys. Values of beta estimate, standard error (SE), lower confidence interval (LCI) and upper confidence interval (UCI) are shown.

Parameter	Estimate	SE	LCI	UCI
Psi Intercept	-1.900	0.407	-2.698	-1.102
Psi Med HE	-0.057	0.573	-1.180	1.067
Psi LowHE	1.599	0.559	0.502	2.695
Epsilon Intercept	0.366	0.647	-0.903	1.634
Epsilon MedHE	1.308	1.243	-1.129	3.745
Epsilon Low HE	0.413	0.782	-1.119	1.945
Gamma Intercept	-1.870	0.349	-2.553	-1.186
Gamma MedHE	-0.526	0.536	-1.576	0.524
Gamma LowHE	0.641	0.542	-0.421	1.703
p Intercept	-7.706	1.375	-10.402	-5.010
p g1	0.675	0.266	0.153	1.196
p g2	1.793	0.225	1.351	2.235
p g3	0.844	0.211	0.430	1.258
p g4	-0.046	0.242	-0.521	0.428
p g5	0.707	0.221	0.274	1.141
ToD	-32.792	21.771	-75.463	9.879
ToD^2	1701.638	708.249	313.470	3089.805
ToD^3	-21916.379	8283.698	-38152.428	-5680.330
ToD^4	83507.194	31543.873	21681.201	145333.190
DOY	2.235	0.639	0.982	3.489

[1]g1 - Blue Spring WMA. g2 - Coosa WMA. g3 - Little River WMA. g4 - Mulberry Fork WMA. g5 - Perdido River WMA. g6 - Oakmulgee WMA. g7 - Skyline WMA. Skyline WMA was the reference study area. LowHE - Low hunting effort. MedHE – Medium hunting effort. HighHE – High hunting effort. High hunting effort was the reference condition. ToD- Time of Day. Y – year: 2016, 2017, 2018.