AnimalFinder: A semi-automated system for animal detection in time-lapse camera trap images

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ABSTRACT

Although the use of camera traps in wildlife management is well established, technologies to automate image processing have been much slower in development, despite their potential to drastically reduce personnel time and cost required to review photos. We developed AnimalFinder in MATLAB® to identify animal presence in time-lapse camera trap images by comparing individual photos to all images contained within the subset of images (i.e. photos from the same survey and site), with some manual processing required to remove false positives and collect other relevant data (species, sex, etc.). We tested AnimalFinder on a set of camera trap images and compared the presence/absence results with manual-only review with white-tailed deer (*Odocoileus virginianus*), wild pigs (*Sus scrofa*), and raccoons (*Procyon lotor*). We compared abundance estimates, model rankings, and coefficient estimates of detection and abundance for white-tailed deer using N-mixture models. AnimalFinder performance varied depending on a threshold value that affects program sensitivity to frequently occurring pixels in a series of images. Higher threshold values led to fewer false negatives (missed deer images) but increased manual processing time, but even at the highest threshold value, the program reduced the images requiring manual review by ~40% and correctly identified >90% of deer, raccoon, and wild pig images. Estimates of white-tailed deer were similar between AnimalFinder and the manual-only method (~1–2 deer difference, depending on the model), as were model rankings and coefficient estimates. Our results show that the program significantly reduced data processing time and may increase efficiency of camera trapping surveys.

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1. Introduction

Camera trap surveys have become increasingly popular for monitoring elusive wildlife in recent years and can provide a way to reduce the cost of monitoring programs relative to many traditionally invasive and labor-intensive methods. Rowcliffe and Carbone (2008) documented a 50% annual growth in publications using cameras or assessing camera survey methodologies between 1998 and 2008; a trend that has persisted (Burton et al., 2015; Rovero et al., 2013), and will likely to continue due to ever-improving camera technology and the popularity of camera traps for citizen science projects (Cohn, 2008). Monitoring with camera traps is potentially advantageous because surveys are non-invasive, capture data on elusive animals, reduce field hours, and provide high quality data. Among other applications, camera trap data, along with relevant quantitative methods, have been used by researchers to estimate demographic parameters and inventory species,

for both marked and unmarked populations (e. g. Giman et al., 2007; Karanth et al., 2006; Keever, 2014). However, there are issues associated with camera traps surveys, including equipment failures, data management requirements, observer errors when manually reviewing photos, and heterogeneity in the detection probability of individuals within a population (Meek et al., 2015; Newey et al., 2015; Rovero et al., 2013; Swann et al., 2011).

Another issue with camera traps is the variability in detection probability as a result of camera equipment. Most cameras use motion sensing (passive infrared) to detect animals and take photographs, or use time-lapse photography to take photos at a specified interval regardless of animal presence (Meek et al., 2015; Rovero et al., 2013; Swann et al., 2011). Motion sensing results in fewer empty photos (photos without an animal), but greater sampling variability due to variation in trigger sensitivity and detection probabilities of individuals and species (Hamel et al., 2013; Newey et al., 2015; O'Connell et al., 2010; Rovero et al., 2013). These differences are apparent between camera makes and models for detection between and among species (Hamel et al., 2013; Newey et al., 2015), and even within the same camera model (Damm et al., 2010; Newey et al., 2015). It is advised that practitioners

fully understand the factors that affect camera trap limitations: make and model quality and the resultant limitations they exhibit (Meek et al., 2015; Newey et al., 2015). Many different factors contribute to whether or not a picture is taken, including environmental conditions at the camera site, size of the object moving in the frame, and sensitivities of the triggers themselves (Damm, 2010; Meek et al., 2015; Swann et al., 2004). In contrast, the time-lapse setting takes photos at specified intervals; thus reducing sampling error. Newey et al. (2015) reported that motion detection cameras failed to detect 49–68% of animals captured at the same time by time-lapse data. Hamel et al. (2013) found that raw error rates in daily presence varied between 30 and 70% among seven artic/subarctic species (hooded crow, *Corvus cornix*, common raven, *Corvus corax*, white-tailed eagle, *Haliaeetus albicilla*, golden eagle, *Aquila chrysaetos*, arctic fox, *Vulpes lagopus*, red fox, *Vulpes vulpes*, and wolverine, *Gulo gulo*) using a motion-trigger survey design, while a 5-minute time-lapse setting varied between 5 and 30% among species. However, time-lapse camera surveys also possess drawbacks, and can generate a staggering number of uninformative images that must be manually processed to extract relevant data – adding time and overall cost to the monitoring program (Harris et al., 2010; Newey et al., 2015). Time-lapse surveys may also miss capturing events that occur during the time intervals between images, and potentially inappropriate for species occurring at low densities and when sites are not baited (Hamel et al., 2013; Newey et al., 2015). Ultimately, when designing a camera survey, researchers and managers must weigh tradeoffs between greater survey cost and greater sampling variability, considering both methods risk losing informative images (Hamel et al., 2013; Meek et al., 2015; Newey et al., 2015; Swann et al., 2011; Weingarth et al., 2012).

Significant strides have been made to streamline processing of camera trap images. Harris et al. (2010), Fegraus et al. (2011), Krishnappa and Turner (2014), He et al. (2016), Niedballa et al. (2016), and Bubnicki et al. (2016), among others, have developed software packages for managing large quantities of camera trap images. These programs offer a wide array of features, including standardization procedures for retrieval and storage of images, cataloguing options for tagging species and individuals, and methods for extracting data into a useable format for further analysis. Species-specific recognition software has also been developed to assist in identifying individuals of numerous species, including elephants (Ardovini et al., 2008), tigers (Raj et al., 2015), and marine mammals (Adams et al., 2006; Gope et al., 2005). These methods utilize unique individual characteristics and compare images to a catalogue of known individuals. Bolger et al. (2012) developed an open source software package for pattern extraction and matching in a variety of species, which performed very well on Masai giraffe (*Giraffa camelopardalis tippelskirchi*).

Despite these advancements, there are few automated tools available to identify animal presence/absence in photos. eMammal is a subscription-based service for camera trap image collection and analysis that employs a method that identifies animals and species from image sequences collected triggered by a motion sensor (He et al., 2016). However, this program analyses sequences of images with multiple pictures of the same animal within a short span of time and was not developed for time-lapse images, which frequently only contain a one or two images per animal encounter. Alternatively, methods to detect motion in videos captured by camera traps may also be applicable animal identification in images if sequences of image files converted into a video file (Swinnen et al., 2014; Weinstein, 2015). These approaches were not optimized for images and have not been tested for this application. Similar to eMammal, images captured using a time-lapse survey may not provide enough images per animal visit and/or changes between images may be too drastic relative to changes between video frames. To address this need, we developed AnimalFinder in MATLAB® (2012b, The MathWorks, Inc., Natick, Massachusetts, United States) to classify animal presence/absence in time-lapse photographs. The AnimalFinder source code is freely available for download (Appendix 1), and was

developed to analyze time-lapse photos by site and survey, producing a directory of photos likely to contain a medium- to large-bodied animal. Thereafter, some manual review is required to remove false positives and collect relevant data (number of animals, sex, etc.). In this paper we describe the program and test it on a set of camera trap photos obtained from a white-tailed deer (*Odocoileus virginianus*) survey. We estimate population abundance using results from our semi-automated program vs. manual-only image review and examine differences in resulting parameter estimates, coefficient estimates, and model rankings and weights. We also consider the potential of the program to detect wild pigs (*Sus scrofa*) and raccoons (*Procyon lotor*), two non-target mammals who frequently visited the baited sites, in addition to white-tailed deer.

2. Methods

2.1. How the program works

We developed AnimalFinder to identify animal presence/absence in time-lapse camera trap photos and tested it on white-tailed deer in Alabama; however, the system could be applied to other medium- or large-bodied species that are relatively monotone (we did not directly test the program on species with stripes or spots). First, the program takes a set of pictures from one survey location and separates day and night photos. Due to the different nature of daytime (full color and shadows) and nighttime (grayscale) pictures, the respective subsets are processed using different methods. These photos are first converted to grayscale, and an edge-detection algorithm, called a canny edge detector, is applied to identify lines in the images. Since deer are inherently smooth, AnimalFinder identifies large areas with low line density and applies a color saturation mask. The result is a single binary "blob" which is analyzed in size and shape. Nighttime pictures are first filtered with a median filter of pixel size 40, and then a canny edge detector is applied. The result is a binary image of lines.

From this point, the classification of deer presence is the same for day and night photos. Because the pictures may have common features that may trigger a false positive classification (i.e. large rocks, bushes, logs), we use a threshold value that will ignore pixels that appear in a given frequency throughout the data set (a threshold value of 0.5 will ignore pixels that are seen in half of images). Finally, the line pixels, excluding ignored pixels, are counted for each image and those with a count of line pixels greater than two standard deviations of the respective subsets are classified as positive animal presence.

2.2. Evaluation of program performance

We tested our program on a dataset of images obtained from a camera survey that was conducted by Keever (2014) at Fort Rucker, Alabama during February and March of 2012. Fort Rucker is a U.S. Army post located in southeastern Alabama in Dale and Coffee Counties and is predominantly comprised of pine (*Pinus* spp.) and mixed pine-hardwood forests (Keever, 2014). Twenty camera sites, spaced 2.42 km apart, were cleared and baited with 11 kg of whole corn for one week. Then cameras were deployed 4 m away from the bait pile and set to take an image every 4 min for 7 days. Bait was refreshed with up to 11 kg as necessary every 3–4 days for the duration of the survey. These images were reviewed manually by Keever (2014), who recorded raw counts of deer and non-target animals (i.e. pigs, raccoons) observed in each image. See Keever (2014) for further information regarding study design.

We ran AnimalFinder on the images collected from the 20 camera sites using a range of pixel frequency threshold values between 0.01 and 0.95. For each threshold value we compared AnimalFinder performance with results obtained from Keever (2014) by counting the number of images in which both methods classified an image as containing a deer (deer presence), both methods classified an image as not

containing a deer (deer absence), AnimalFinder flagged an image classified as deer absence by the manual method (type I error), and AnimalFinder missed an image classified as deer presence by the manual method (type II error).

We selected one frequency threshold value to further test AnimalFinder by assessing the tradeoff between type II errors and total number of images flagged. We calculated the change in the proportion of type II errors relative to deer images classified by manual review and the change in proportion of flagged images relative to the total number of images reviewed for each incremental increase in the threshold value, and used the threshold value at the equilibrium point between those two measurements to further test the performance of our semi-automated approach. We conducted a concordance analysis to estimate Cohen's kappa, which measures the normalized difference between the rate of agreement between the two methods that is observed and the rate of agreement that would be expected by chance (Cohen, 1960). We used the presence/absence data obtained from both methods to estimate Cohen's kappa, replacing AnimalFinder type I errors with zeros to simulate the final dataset (assuming further manual review would remove all false positive).

Using the selected threshold value, we constructed count histories for all deer counted from the manual review-only results and from the AnimalFinder semi-automated results. Following Keever (2014), we reduced the survey occasions to every 12 min and used only images between 15:36 to 8:12; two hours before mean sunset time until two hours after mean sunrise time [i.e., we eliminated "day time" photographs because white-tailed deer are inactive during day time hours (Keever, 2014)]. We used the count data from the manual-only method for all images flagged by AnimalFinder; this eliminated potential observer bias that could arise from another observer reviewing the images. Thus, all correctly classified images and false positives had the same count data recorded as the observer-only method. When AnimalFinder committed a Type II error (missed a deer image) the deer count was recorded as zero for that occasion.

We further tested the utility of AnimalFinder for use in time-lapse camera monitoring programs aimed at estimating demographic parameters and covariate effects, and to demonstrate a method for practitioners to conduct their own pilot study to assess the performance of AnimalFinder with their own images. We used the AnimalFinder results to estimate deer abundance, and compared the results to estimates using counts obtained by manual-only review. Some low levels of overlooked deer (Type II errors) might be acceptable if the goal is to estimate demographic parameters and those estimates are relatively unaffected by using AnimalFinder compared to the manual-only method. We estimated total deer abundance, covariate effects on abundance and detection, and ranked models with AnimalFinder-derived count histories and manual-only derived count histories from Keever (2014) using the maximum likelihood, single season N-mixture model developed by Royle (Royle, 2004) and implemented in function pCount of the 'unmarked' package (Fiske and Chandler, 2011) in R (R Core Team, 2015). Royle's (2004) N-mixture model is a hierarchical abundance estimate model that uses spatially or temporally replicated counts of unmarked individuals in which spatial replicates are achieved by deploying multiple cameras across space and temporal replicates are obtained using images captured at given time increments. The N-mixture model is comprised of a binomial model for detection probability (p) and a Poisson model for abundance (λ) and allows for covariates to be incorporated for both parameters.

Our study estimated mean abundance and detection probability of white-tailed deer on Fort Rucker using the combined counts of mature bucks, immature bucks, does, and fawns. We included covariate data from Keever (2014), including habitat covariates with our abundance parameter (% of habitat type), and time and precipitation for our detection parameter. We excluded wild pigs as a covariate because we did not have the original covariate data, and further, we did not want to confound performance of AnimalFinder for use on deer with its

performance with wild pigs. Our single-season analysis also necessitated the elimination of the covariate for season. We selected a subset of the models developed by Keever (2014), comprised of a null model and the highest-ranked abundance models with each combination of detection covariates excluding covariates relating to wild pig or season.

To assess the efficacy of using AnimalFinder for research applications, in which models with covariates are examined to address competing hypotheses about the ecological system, we compared model rankings and weights from 20 models using manual-only and AnimalFinder-derived count histories. We ranked an identical suite of models for each method using Akaike's information-theoretic criterion (AIC) and estimated coefficient estimates, model weights, and parameter estimates (Burnham and Anderson, 2002). We then estimated total abundance and 95% confidence intervals for each method using a parametric bootstrap analysis with 1000 iterations.

The original survey by Keever (2014) was intended for white-tailed deer; however, wild pigs and raccoons were also detected at camera sites. We examined the ability of the program to correctly identify images containing these species and considered potential utility to use AnimalFinder in an occupancy or abundance framework. We determined the type II error rates for AnimalFinder's detection of an animal over a range of threshold values when a pig or raccoon was manually identified. We also calculated the number of days that each species was correctly detected at each camera site at least once to determine potential utility of the program in an occupancy framework. Daily presence data would allow researchers to create occupancy capture histories with sampling occasions on each day of the survey, and estimate species occupancy probability in relation to environmental covariates and estimate detection probability.

Finally, we estimated the time savings achieved by using AnimalFinder relative to the traditional manual-only method. We estimated the rate of images reviewed per hour by recording the time required for an observer to classify animal presence/absence in a subset of images and extrapolated the review rate to estimate time required to review the full set of images and the images flagged by AnimalFinder. We also recorded the time it took to run the images through AnimalFinder, but did not include it in the time comparison between methods because it is inactive time for the observer.

3. Results

A total of 65,291 images were collected from 20 cameras, and Keever (2014) classified 1577 images as containing deer (deer presence), 590 as containing wild pigs, and 2108 as containing raccoons. Increasing the threshold value of AnimalFinder increased the total number of images flagged; which varied from 2174 images (3% of total) at a threshold
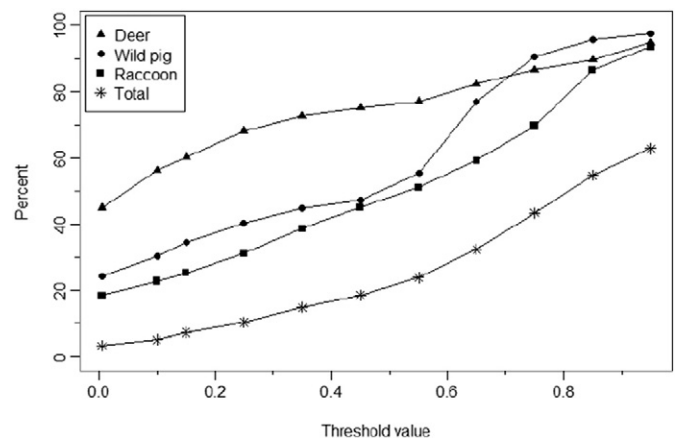

Fig. 1. Percent of deer, wild pig, and raccoon images identified by the semi-automated system compared to the manual-only review and the percent of total images flagged under a range of threshold values.
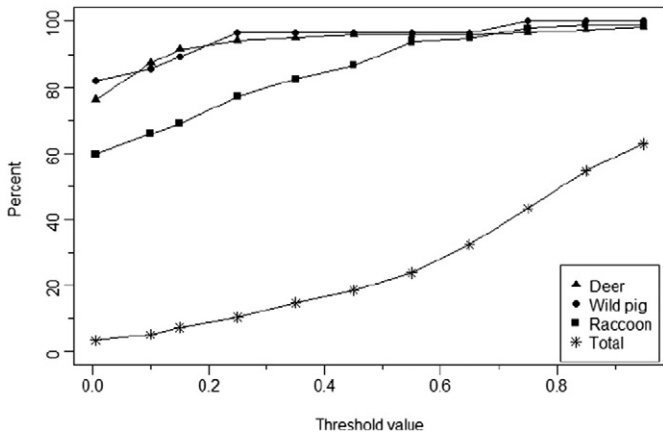
Fig. 2. Percent of site- days with at least one detection for deer, wild pigs, and raccoons by the automated system compared to the manual-only method and the percent of total images flagged under a range of threshold values.

Table 1
Concordance tables for white-tailed deer using the semi-automated system using a threshold value of 0.35 for a) night images, b) day images, and c) day and night images.

| | | Manual-only | | |
		Deer present	Deer absent	Total
	a) Night			
AnimalFinder	Deer present	1098	6144	7242
	Deer absent	367	28,937	29,304
	Total	1465	35,081	36,546
	b) Day			
AnimalFinder	Deer present	46	2382	2428
	Deer absent	66	26,250	26,316
	Total	112	28,632	28,744
	c) Night + day			
AnimalFinder	Deer present	1144	8526	9670
	Deer absent	433	55,187	55,620
	Total	1577	63,713	65,290

of 0.001, to 21,147 images (63%) when the threshold value was set to 0.95. At a threshold value of 0.005, AnimalFinder correctly classified 45% of deer images, 23% of wild pig images, and 18% of raccoon images, and these numbers increased to 95% of deer images, 97% of wild pig images, and 94% of raccoon images at a threshold of 0.95 (Fig. 1). If using the data to apply an occupancy analysis, AnimalFinder correctly detected at least one individual present on 95% of days with a threshold of ≥0.25 for deer and wild pigs and a threshold of ≥0.55 for raccoons (Fig. 2).

The threshold value that represented the best tradeoff between type II errors and total images flagged for deer was 0.35. At this threshold value and for night images, there were 1098 images correctly classified

as deer presence, 28,937 images correctly classified as deer absence, 6144 type I errors, and 367 type II errors (Table 1). At the same threshold for the day images, there were 46 images correctly classified as deer presence, 26,250 images correctly classified as deer absence, 2382 type I errors, and 66 type II errors. Cohen's kappa, estimating observer agreement, for the adjusted presence/absence dataset was 0.838.

The manual-only and AnimalFinder-derived count histories contained 756 observations per site (15,120 observations in total). For each image review method, deer were detected at 17 of the 20 sites. The manual-only count history contained 436 observations with one deer counted, 63 with two deer, 11 with three deer, and 1 with four deer. The AnimalFinder count history contained 317 observations with one deer counted, 48 with two deer, 11 with three deer, and 1 with four deer.
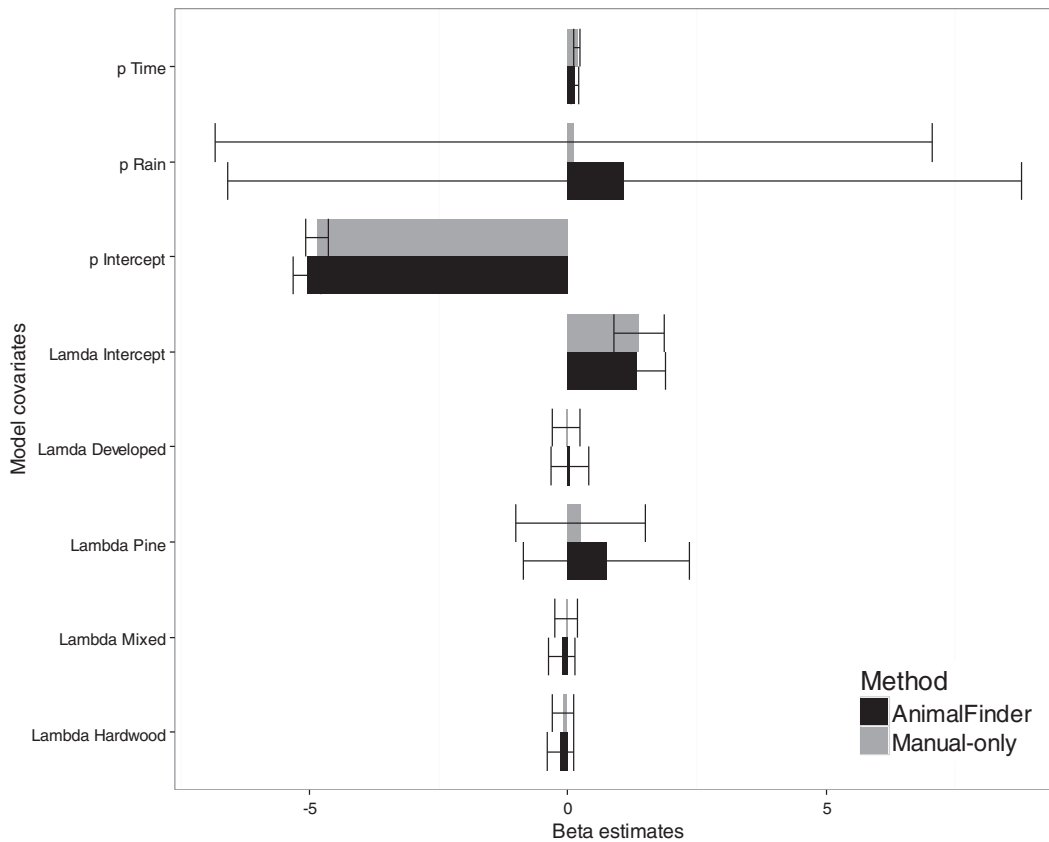

Fig. 3. Model-averaged abundance (lambda) and probability of detection (p) beta estimates and 95% confidence intervals using all models with AnimalFinder results in black and manual-only results in gray.

Table 2

The AIC table including estimates of total abundance and detection probability for AnimalFinder (AF) and the manual-only method (MO) for models with model weight ≥0.01. Total abundance was estimated by summing the site-specific abundance estimates and confidence intervals were estimated using parametric bootstrap analyses with 1000 simulations. Probability of detection (p) and standard errors were averaged across all sites for each model. *Standard errors were 0.0011 for all manual models and 0.0010 for all AnimalFinder models.

Model	Par.	AIC		Delta AIC		AIC model weight		Cumulative weight		Total abundance		Mean detection probability*	
	–	MO	AF	MO	AF	MO	AF	MO	AF	MO	AF	MO	AF
lam(.)p(time)	3	4639	3811	0.00	0.00	0.43	0.36	0.43	0.36	78 (47, 192)	76 (46, 185)	0.0101	0.0079
lam(Pine)p(time)	4	4641	3812	1.83	1.15	0.17	0.20	0.60	0.56	78 (47, 220)	77 (44, 228)	0.0101	0.0078
lam(.)p(rain + time)	4	4641	3813	2.00	1.90	0.16	0.14	0.76	0.69	78 (46, 190)	76 (44, 206)	0.0101	0.0079
lam(Dev + Pine)p(time)	5	4643	3813	3.83	2.80	0.06	0.09	0.83	0.78	78 (47, 234)	77 (48, 251)	0.0101	0.0077
lam(Pine)p(rain + time)	5	4643	3814	3.83	3.05	0.06	0.08	0.89	0.86	78 (46, 217)	76 (44, 206)	0.0101	0.0078
lam(Hrdwd + Mixed + Pine)p(time)	6	4644	3814	4.64	3.82	0.04	0.05	0.93	0.91	79 (49, 284)	78 (49, 284)	0.0100	0.0077
lam(Dev + Pine)p(rain + time)	6	4645	3815	5.80	4.70	0.02	0.03	0.96	0.95	78 (47, 239)	77 (46, 276)	0.0101	0.0077
lam(Dev + Hrdwd + Mixed + Pine)p(time)	7	4645	3816	6.24	5.52	0.02	0.02	0.98	0.97	79 (48, 314)	78 (48, 356)	0.0100	0.0077
lam(Hrdwd + Mixed + Pine)p(rain + time)	7	4646	3816	6.61	5.80	0.02	0.02	0.99	0.99	79 (48, 298)	78 (50, 288)	0.0100	0.0077
lam(Dev + Hrdwd + Mixed + Pine) p(rain + time)	8	4647	3818	8.21	7.42	0.01	0.01	1.00	1.00	79 (49, 305)	78 (49, 360)	0.0100	0.0077

The model-averaged deer abundance across all sites was estimated to be 78 deer (confidence interval (CI): 47, 211) using the manual-only method and 77 (CI: 46, 220) for the AnimalFinder method. The model-averaged detection was 0.0101 (SE = 0.0011) for manual-only review and 0.0078 (SE = 0.0010) for AnimalFinder. Model-averaged beta estimates and 95% confidence intervals were similar between both methods (Fig. 3).

Using the N-mixture modeling analysis for manual-only and AnimalFinder data, each method resulted in the same model rankings for all model weights of 0.01 or greater; however there were slight differences in model weights between equivalent models (Table 2). Results from both methods ranked three models as competitive based on delta 2 AIC. However the second and third-ranked models contained only one additional parameter relative to the highest-ranked model, indicating weak, if any, evidence that their addition improved model fit (Burnham and Anderson, 2002). The highest-ranked model included time of day as a detection covariate (manual-only model weight [w] = 0.43; AnimalFinder w = 0.36), followed by the model with % pine forest and time of day (manual-only w = 0.17; AnimalFinder w = 0.20), and the model with rain and time of day (manual-only w = 0.16; AnimalFinder w = 0.14). These models accounted for 0.76 of the cumulative model weight for the manual-only method and 0.70 for the AnimalFinder method.

The manual-only method required 16.84 h for four observers to classify animal presence/absence in 62,288 images with an average review rate of 4274 images per hour. AnimalFinder required <5 min of manual prep and 2.5 h of unassisted processing time to analyze the same set of images using three threshold values, exceeding 26,000 images reviewed per hour. We estimated that the average review rate for AnimalFinder saved between 99.5% and 45.3% of presence-absence manual review time for the same set of images, depending on the threshold value applied (Fig. 4). At a threshold value of 0.35, AnimalFinder saved 14.8 h (~1 h per 4400 images) of manual review time compared to the manual-only method.
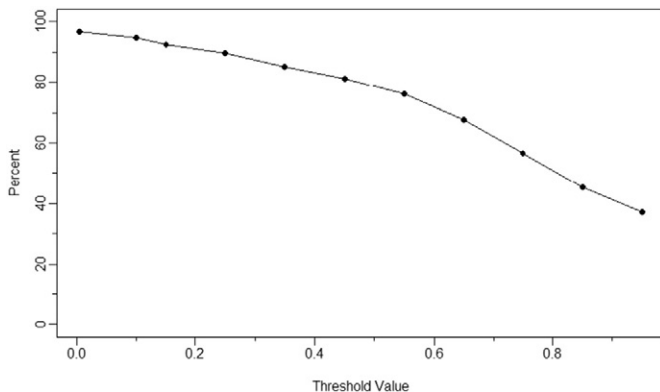

Fig. 4. Percent time savings for presence-absence review of camera trap images using AnimalFinder relative to manual-only review under a range of threshold values.

4. Discussion

We demonstrated that our semi-automated approach for processing time-lapse camera trap photos has the capacity to reduce effort and overall monitoring costs for deer and other animals by reducing the number of images from our data set requiring manual review. While our dataset was relatively small (one season and twenty cameras), we amassed over 60,000 images and realized a reduction of >70% of images that required manual review due to AnimalFinder. The benefits of this program could be significant for larger datasets that are the result of long-term and large-scale surveys. For example, Alabama's Department of Conservation and Natural Resources recently completed a 6-season time-lapse camera survey at 256 camera sites each season generating >3 million images (Price et al. unpublished data). Based on our results in this study, the application of AnimalFinder could save up to 600 h (15, 40-hour weeks) of presence/absence classification. This time savings may reduce lag time between data collection and project results, which could translate to increased speed with which managers can utilize results to inform decision-making. Financially, our program could save the agency $5400 compared to employing a technician at a rate pf $9 per hour to manually review images. These benefits may make large-scale surveys and monitoring programs more cost and time effective to implement.

There are tradeoffs between cost/time savings and program performance when using AnimalFinder which are important to consider with regards to survey objectives. Employing a greater threshold level decreased the number of photos with animals that are missed (type II errors), but also increased the number of photos with no animal present flagged for review. In our study, the low rate of type II errors in presence/absence image classification experienced when using our semi-automated approach produced a negligible effect on our analysis of a white-tailed deer population. Slight differences in estimated model weights, covariate effects, and total abundance did not change the ecological and demographic inference resulting from the study and is unlikely to impact management decisions pertaining to the population. We anticipate that, in most cases, a bias of a few individuals will be an acceptable tradeoff given the time and cost savings attributed to the new method. Still, it is important to consider the project objective and the precision and accuracy required to inform decision-making. In some cases, the decreased precision may affect management decisions. For example, decreased precision in estimates of demographic parameters for an endangered species may result in the selection of a different management action relative to the alternative that would have been selected using estimates obtained using manual-only image review and hurt species recovery. We suggest utilizing recent quantitative methods

to calculate the value of information for management such as the expected value of perfect information and expected value of sample information to determine whether or not the decreased precision resulting from using AnimalFinder is justifiable (Canessa et al., 2015; Williams and Johnson, 2015).

We observed differences between estimates of detection probability and related covariate effects between the manual-only method and AnimalFinder. Detection probability is a parameter that accounts for the probability of an animal being available for detection (i.e. in the camera frame) and the conditional capture probability that the animal is correctly detected given that it is available (O'Donnell et al., 2015; Pollock et al., 2004; Pollock et al., 2006). Both components of detection can affect parameter estimates (O'Donnell et al., 2015). AnimalFinder does not influence the availability of target organisms, but we anecdotally found that several environmental factors, including rain and time of day, have the potential to influence the conditional capture probability of AnimalFinder relative to the manual-only method. While there was little evidence for the influence of rain on detection probability (and any effect may also be attributed to its effect on animal availability), rain drops on the camera lens sometimes blur the images and have the potential to make animal bodies less likely to be detected. Similarly, the presence of shadows in daytime photos can lead to type II errors by obscuring an animal body. Utilizing methods aimed at sheltering cameras from rain or removing shadows from images prior to analysis (Finlayson et al., 2002; Prati et al., 2003), and/or applying more complex object detection algorithms, may further reduce false absences. However, in most cases, including this study, detection probability is not a focal parameter and differences in estimates or covariate relationships are only a concern if it affects abundance and other demographic estimates of interest to the extent that it alters a management decision (Williams et al., 2002). Future studies may include covariates on availability and conditional capture probabilities and model these components separately. Pollock et al. (2006) and O'Donnell et al. (2015) have developed such models which could lead to improved insights regarding the influence of bias in the conditional capture probability on estimates of parameter values of interest arising from semi-automated image review.

AnimalFinder committed more type II errors for wild pigs and raccoons than deer. A greater threshold value was required for pigs and raccoons to achieve the same low level of type II errors obtained with a deer when using a threshold value of 0.35. We believe that type II errors were produced when animals in a frame were directly in front of the corn pile. Because the corn pile was present in a high frequency of images, those pixels were ignored at low threshold values. Raccoons and pigs were often captured when their bodies were in front of the bait while they were feeding. This was less common with deer whose taller stature kept their bodies above the corn pile. Thus, if the pixels comprising the bait are ignored, animal bodies within that boundary will be missed. Ultimately, the program could be improved by finding a better way to filter out blobs that remain in a high frequency of the images while still allowing for the detection of new blobs within that same space. For example, an additional layer or image processing could be incorporated that would characterize regions within the image based on color, saturation, texture, or other image traits. Such methods could be utilized as a "bait pile detector" which could help the program determine the orientation of the camera with respect to the bait and our expectation of detecting animals in different regions of the images (i.e. we would not expect animals in sky or treetop portion of the image). In the meantime, studies targeting raccoons, pigs, or animals with similar characteristics (i.e. short-statured) may reduce false absences by positioning cameras lower to the ground to improve the angle of the animals with respect to the bait pile. However, repositioning of the camera in such a way could also negatively affect later manual review where animals in front of the camera block the view of other animals. We may have experienced additional false negatives as a result of the presence of some spotted pigs in our study because AnimalFinder was developed to detect non-patterned animals that create monotone

blobs in the image processing. Considering that >95% of images containing wild pigs were identified when applying a high threshold value, we feel that the program performed better than expected on patterned animals, however, further testing is needed to validate AnimalFinder for such animals. Although we did not estimate demographic parameters for wild pigs or raccoons, our results suggest that AnimalFinder may be used to reduce manual review efforts for count and occupancy based studies for many medium and large bodied animals.

Ultimately, a careful evaluation of AnimalFinder and a range of threshold values for potential target species using a subset of images will be essential to inform users of the tradeoffs between type I and type II errors and lead to the most efficient use of the program. Researchers may also examine the sensitivity of their decision models to anticipate the level of precision required by the intended analyses. We suggest conducting a pilot study by reviewing a subset of survey images manually and conducting an analysis similar to ours to 1) evaluate efficacy of using AnimalFinder to identify presence/absence and estimate demographic parameters of the target animal, and 2) determine what threshold value to employ given project needs. We also encourage users to consider camera placement to reduce sources of error and natural blobs that may interfere with the ability of the program to identify an animal occupying the same space in the images. For example, placing bait in several small piles instead of one large pile may reduce type II errors related to animals within the bait pile.

AnimalFinder can provide numerous benefits to animal monitoring. Using a semi-automated system to review camera trap images can reduce survey costs, lag time between data collection and data analysis, and potentially reduce observer errors. It can be used in conjunction with other programs and procedures developed in recent years to streamline and reduce costs of time-lapse camera trap surveys (e.g. Harris et al., 2010; He et al., 2016; Krishnappa and Turner, 2014). Increasing the efficiency of data management for such non-invasive survey techniques without significantly sacrificing analytical accuracy may enable researchers and managers to better monitor animal populations and inform natural resource decision-making.

Data accessibility

Data used for this research will be made available upon publication on the Auburn University server.

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecoinf.2016.11.003.

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