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RESEARCH ARTICLE

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Testing the detection of large, secretive snakes using camera traps

Danielle K. Walkup[1] | Wade A. Ryberg[1] | Josh B. Pierce[2] | Emlyn Smith[3] | James Childress[4] | Forrest East[1] | Brian L. Pierce[1] | Price Brown[1] | Corey M. Fielder[1] | Toby J. Hibbitts[5,6]

[1]Texas A&M University Natural Resources Institute, AgriLife Water and Natural Resources Building, 1001 Holleman Dr. E., College Station, TX 77840, USA

[2]United States Department of Agriculture-Forest Service, Southern Research Station, 506 Hayter Street, Nacogdoches, TX 75965, USA

[3]United States Department of Agriculture-Forest Service, Catahoula Ranger District, 5325 Highway 8, Bentley, LA 71407, USA

[4]100 Renfro Drive, Lufkin, TX 75901, USA

[5]Texas A&M University Natural Resources Institute, Biodiversity, Research and Teaching Collection, Department of Ecology and Conservation Biology, College Station, TX 77843, USA

[6]Texas A&M University, Wildlife, Fisheries and Ecological Sciences Building, 2258 TAMU, College Station, TX 77843, USA

Correspondence

Danielle K. Walkup, Texas A&M University Natural Resources Institute, 1001 Holleman Drive East, College Station, TX 77840, USA.
Email: dkwalkup@tamu.edu

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Abstract

Novel technologies, such as camera traps, have expanded the opportunities for species detection, especially for rare species. Corresponding changes in data processing must occur to handle the large volume of data gathered from technology like camera traps. Automated image data processing, usually by running images through different types of computer algorithms, is an overarching goal to reduce the number of images that researchers must manually review. However, differences in camera trap setups and species characteristics can make automatic processing a challenge. Here, we evaluated the detection accuracy and efficiency of a time-lapse triggered camera trapping technique combined with a pixel change detection algorithm as part of a monitoring program for a translocated population of the rare and federally threatened Louisiana Pinesnake (*Pituophis ruthveni*). We paired 5 cameras with automated pit tag readers to collect observations of *P. ruthveni*. We evaluated an image dataset of 1,500,187 images, collected over 7 months, both manually (i.e., researchers looking at each individual picture to determine snake presence) and automatically using a change detection algorithm. There were 18 *P. ruthveni* observations recorded by the tag readers, 7 of which occurred while a paired camera was not operational. Ten of the tag reader *P. ruthveni* observations were captured by the paired camera trap, with an additional *P. ruthveni* observation from a paired camera trap not recorded by the tag reader. There were 132 snake observations of 13 additional species and 18 observations of unknown snakes from the camera traps. The algorithm reduced the number of images reviewers evaluated by an average of 78.5% per camera (range = 37.3–98.7%) but had a 54.5% success rate at detecting observations of *P. ruthveni* (47.1% for individual images), and a slightly lower 48.9% success rate detecting other large snakes. Large snakes were 4 times more likely to be flagged by the algorithm than small snakes. Our time-lapse triggered camera trapping technique performed well with respect to *P. ruthveni* detection accuracy, compared to the tag readers. However, further research is needed to improve quality assurances of camera trap image filtering and object recognition algorithms across different sites or environments.

KEYWORDS

camera trap, change detection algorithm, conservation monitoring, detection, Louisiana Pinesnake, *Pituophis ruthveni*

Wildlife monitoring is evolving quickly as novel technologies (e.g., automated acoustic recorders, DNA barcoding, camera trapping) expand the possibilities for species detection (Pimm et al. 2015, Sugai et al. 2019). For rare species, updated technologies are improving detection and refining inferences of absence (Glover-Kapfer et al. 2019, Crawford et al. 2020, Meek et al. 2020), which are both critical to effective population monitoring, management, and conservation (Nichols and Williams 2006). Failing to detect a species when present, a false-negative, is a common problem for rare species comprised of small and often declining populations with limited sampling resources available (Tyre et al. 2003). In such circumstances, separating robust inferences of absence from inadequate sampling requires knowledge of detection probabilities, which may be prohibitively expensive to estimate in rare species, especially when such species are cryptic, occupy complex habitats, and exhibit secretive behaviors (McDonald 2004, Steen 2010, Durso and Seigel 2015, Crawford et al. 2020).

To address species detection problems, several camera trapping techniques have been incorporated into drift-fence sampling arrays to help increase detection and reduce costs of monitoring snakes and other reptiles. Reptiles provide challenges for camera traps as they are ectothermic and often match the background surface temperature which may not trigger passive infrared sensors (PIR) and are often small and may not trigger active infrared sensors (AIR; Welbourne 2013). Nevertheless, some studies have tried to enhance the PIR, which detects differences in surface temperatures between objects (Welbourne et al. 2017), by creating trapping stations designed to increase the likelihood of detecting reptiles (e.g., cork board ground cover under cameras, Welbourne 2013, Welbourne et al. 2020; bucket trap holes aligned with camera PIR, Martin et al. 2017). Related approaches have applied external near infrared beams at crossing stations that trigger the camera when broken by moving reptiles (Hobbs and Brehme 2017). Other techniques have applied time-lapse settings on camera traps mounted facing the ground at drift-fence intersections to increase detections (Neuharth et al. 2020) and reduce resource demands of long-term or distribution-wide monitoring for rare and secretive snake species (Adams et al. 2017, Anderson et al. 2020).

A common goal of both PIR and time-lapse triggered camera trapping techniques is to maximize the number of true positive detections and minimize the number of false negative detections (i.e., misses) for the target species. A criticism of PIR techniques is that success is dependent on camera sensor performance, which has been shown to be impacted by a variety of factors, including vegetation density, background surface temperature, their combination (i.e., dappled shade/sun), relative humidity, target animal body size, and temperature and distance from camera (Glover-Kapfer et al. 2019). In addition, research has shown the heat-in-motion functions used to trigger detections in PIR techniques can be as variable within camera trap brands or models as between them (Meek et al. 2014, 2015, 2020; Falzon et al. 2019). Product variation is thought to be market driven as camera trap manufacturers typically focus on satisfying needs of the hunting community, which typically involve animals with large heat signatures that can be detected with cheaper, lower quality components and thus reduce product costs for consumers (Meek et al. 2020). Wildlife research markets will likely never be as large as the hunter market, so manufacturers may not be incentivized to address the PIR factors described above that increase uncertainty in estimates of rare species detection, and by extension, inferences of absence.

For time-lapse triggered camera trapping techniques, the goal of maximizing the number of target species detections and minimizing the number of empty images (i.e., images without target species) can be accomplished without physical camera alteration by decreasing the time-lapse interval, thus taking pictures more frequently, assuming the target species is present. Decreasing the time-lapse interval to increase detections exacerbates a major criticism of the time-lapse technique, which is that thousands to millions of images are generated in the dataset and must be evaluated for target species, a time-consuming manual task in the absence of automation. Though accurate, this criticism is not unique to time-lapse techniques, as PIR techniques can generate empty images via factors contributing to poor sensor performance described above. Thus, regardless of the camera trapping technique employed, computational solutions working first on reducing the number of images to be evaluated and second on target species identification will be a huge benefit to practitioners globally (Meek et al. 2020).

Recently, there have been a variety of developments in automated image processing, and each has specific limitations depending on target species and image capture technique (Young et al. 2018, Meek et al. 2020). For example, several convolutional neural networking algorithms (CNN) have been designed to process images, but many of them are based on large mammals surveyed with PIR techniques to reduce the number of false positives prior to analysis (Tack et al. 2016, Villa et al. 2017, Norouzzadeh et al. 2018, Tabak et al. 2018, Yousif et al. 2019). Fundamental to the neural networking approach was the availability of hundreds to thousands of *in situ* target species images from a wide variety of habitats or backgrounds used to train the algorithms (Young et al. 2018, Meek et al. 2020). The minimum number of training images required to ensure optimal model accuracy across all datasets varies depending on species and habitat characteristics (Shahinfar et al. 2020), and the minimum number of training images available for rare species, especially rare snake species, typically do not meet training image number requirements.

An alternative to CNN algorithms is pixel change detection algorithms, which compare images on a pixel-by-pixel basis to detect changes (İlsever and Ünsalan 2012, Hussain et al. 2013). Paired with time-lapse triggered camera trapping techniques, pixel change detection algorithms may provide an opportunity to increase detections of rare snake species and reduce the number of false positive detections. Given that pictures taken closer together in time are more similar, camera traps set with short time-lapse intervals will take more similar pictures thus increasing detections of target species when present and increasing the probability that an arrival of the target species will provide a large enough change in subsequent images to be detected with pixel change algorithms. Here, we evaluate the detection accuracy and efficiency of a time-lapse triggered camera trapping technique paired with a pixel change detection algorithm in an on-going monitoring program for a translocated population of the federally threatened Louisiana Pinesnake (*Pituophis ruthveni*; U.S. Fish and Wildlife Service 2016, 2018). Specifically, we evaluate (1) the number of snakes captured on camera vs. by automated pit tag readers, (2) the number of snake images captured by the change detection algorithm vs. manual researcher review, and (3) characteristics of the images that may make detection by the change detection algorithm more or less likely.

STUDY AREA

Due to concerns about perceived population declines, various zoos established captive populations of *P. ruthveni* in 1988, and subsequently, a reintroduction effort was initiated in 2010 on the Catahoula Ranger District of the Kisatchie National Forest, Louisiana (~4,000 ha). The Catahoula Ranger District is within the South Central Plains ecoregion characterized by upland forest containing mixed pines, predominately longleaf pine (*Pinus palustris*), and sandy soils (Daigle et al. 2006). Forest management on the site includes sporadic thinning operations (every 20 years) and frequent prescribed burning (every 4 years) which helps maintain a generally open canopy, low midstory density, and a well-developed herbaceous understory. The climate is considered humid subtropical, consisting of long, hot summers and short, mild winters. Total precipitation during the period of our study (28 March–15 October 2019) was 101 cm. The average minimum and maximum temperatures during the spring (March–May) were 13.1 and 25.1°C respectively, summer (June–August) were 22.2 and 32.9°C respectively, and fall (September–October) were 19.4 and 31.9°C respectively.

METHODS

Study design

Between 2010 and 2019, 123 uniquely pit-tagged *P. ruthveni* individuals were released into the translocation area and monitored using automated pit tag readers buried at the intersection of cross-shaped drift fences made of 6.4 mm mesh hardware cloth (15 m long x 61 cm tall). By design, the tag reader monitoring system recorded the true number of pit-tagged *P. ruthveni* drift fence crossings and the individual pit-tag number, therefore it provided the opportunity to evaluate *P. ruthveni* detection accuracy and efficiency using both the time-lapse triggered camera trapping technique and pixel change detection algorithm. We mounted a camera trap 2 m above 5 different tag readers (pairwise distances between tag readers averaged 831 ± 398 m [SD], range = 284–1,630 m). Due to the size of the site and the home range size of *P. ruthveni*, the traps and cameras are not considered independent, meaning individual *P. ruthveni* could encounter multiple traps in the course of their normal movements.

Following the procedures of Neuharth et al. (2020), we mounted cameras facing the ground at the drift fence intersection, and we programmed them to take an image every 30 seconds with a time-lapse trigger. Since *P. ruthveni* are primarily diurnal snakes (Himes et al. 2006), we ran cameras from 0530 to 2115 hours daily. We deployed them on 28 March 2019 and removed them for the winter between 28 September and 15 October 2019, a typical monitoring season for *P. ruthveni*. We replaced memory cards and batteries approximately every 3 weeks and we backed up images from memory cards onto external hard drives prior to analysis.

Data collection

We evaluated the full image dataset both manually (i.e., researchers looking at each individual picture to determine if a snake was present) and using a pixel change detection algorithm. First, we evaluated all images manually from the 5 cameras using multiple reviewers, but only a single reviewer per image in a blind design. We reviewed the images using RECONYX MapView Professional Software v.3.7.2.2 (https://www.reconyx.com/software/mapview) which plays images as a slideshow at changeable speeds. For images containing snakes, we recorded the species, date, and time, along with qualitative information to help us evaluate the accuracy and efficiency of the algorithm in detecting snakes, including *P. ruthveni*. Specific information included relative snake size (estimated categories: small < 33 cm, 33 < medium < 66 cm, and large > 66 cm), approximate amount of snake showing in the image (little = less than 1/3; some = 1/3 to 2/3, most = more than 2/3), and whether half or more of the showing length of the snake was covered by vegetation or the drift fences. We also included an unknown snake category for images where species identification was not possible, often due to only part of the snake being captured on camera or low-light images where identifying characteristics were not visible. When the same snake stayed in the frame for multiple consecutive images, we considered those a single observation of an individual snake. One subject matter expert verified all observations of the snake species in each image, along with the relative snake size. Finally, we also examined the camera images encompassing the times a pit-tagged *P. ruthveni* was detected by the tag reader to ensure that all detections of the target species were included in the snake detection database.

Change detection algorithm

To reduce the number of empty images a researcher needed to review, we used a pixel-based change detection algorithm (Appendix A) to evaluate the difference between consecutive images and retain only images where the change met a specified threshold. The cameras used automatically adjusted ISO and shutter speed to approximate the image to that perceived by the human eye. As such, and because of the variability of lighting in the environment, the images were not adjusted to account for ISO and shutter speed, meaning the images used were normalized for visibility and not absolute measures of color and light.

For each of the 5 cameras, we compared reference images of *P. ruthveni* (Figure 1A), identified before image review from the tag reader records, from that camera to a set of snake-free images adjacent in time to create

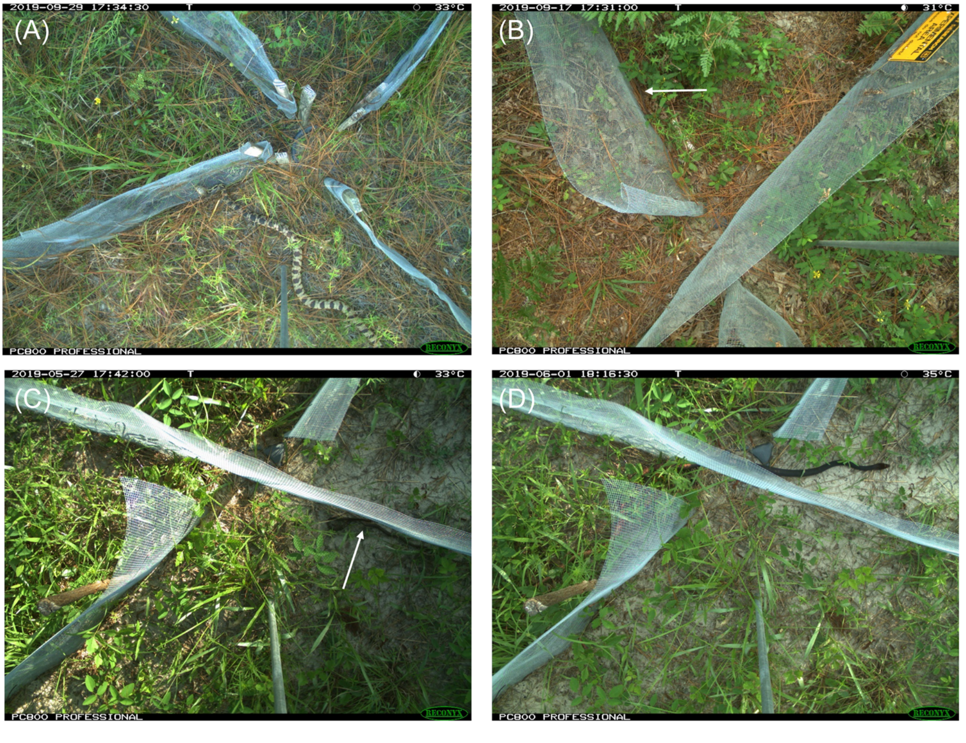

FIGURE 1 (A) Reference image of Louisiana Pinesnake (*Pituophis ruthveni*), used to determine the threshold of pixel numbers used in the change detection algorithm. Example images of (B) small, (C) medium, and (D) large coachwhip (*Masticophis flagellum*). These are also examples of snakes where most of the snake is shown in the picture, and where snakes are at least half covered (B & D) or not (A & C). All images were collected from the Kisatchie National Forest in Louisiana, USA during 28 March–15 October 2019.

difference thresholds in the extent (i.e., number of contiguous changed pixels) and brightness (i.e., per-pixel mathematical difference in grey-scale value from one image to the next) of pixel change between the snake and snake-free images.

First, to reduce processing time we converted each image to grayscale by averaging the pixel values between the RGB (Red, Green, Blue) layers for each pixel. Then, we created difference images by taking the absolute value of the difference of 2 images adjacent in time for both the snake reference images (i.e., 2 consecutive images, the reference image and the one immediately preceding it) and for random consecutive empty images for each camera. To determine the optimal brightness band (i.e., the band of grayscale brightness that may provide the optimal indicator of movement by the target organism), we partitioned the pixel values into 11 categories: true zero and by 0.1 intervals (i.e., 0.0 to 0.1, 0.1 to 0.2, etc.). Then we calculated the number of pixels in each category and compared the snake reference difference image with the random empty difference images to determine which category had the greatest difference in pixels between the 2 types of difference images. From the sample of reference images, we determined brightness values in the 0.1–0.2 range were optimal for the detection of *P. ruthveni* (i.e., had the largest difference compared to the empty images). We used the sum of the changes of pixels falling within the optimal brightness band as thresholds to determine which difference images were retained as part of the algorithm image set. Thresholds were specific to the individual cameras, based on the reference images retained from each camera. Finally, we ran the folders of images through the change detection algorithm and any image that met or exceeded the threshold for change was copied to a new folder for manual image review. All image processing was done in R v. 3.6.1 (R Core Team 2019) using package jpeg (Urbanek 2019).

Data analysis

We manually evaluated all images flagged by the algorithm. We confirmed each image was evaluated by a reviewer who had not previously seen that batch of images (i.e., providing 2 independent reviews of the images). We then coded each snake image as being found by the first reviewer only (in the full image set), by the second reviewer only (in the algorithm-reduced image set), or by both researchers (in both image sets). Using this coding system, we verified whether all the snake images found by the first reviewers were present or not present in the algorithm-reduced image set, classifying each image as true positive (i.e., there was a snake in the image flagged by the algorithm) or false negative (i.e., there was a snake in an image and the algorithm did not flag that image). We then calculated the number of algorithm false positive detections (i.e., an image flagged by the algorithm not containing any snake) and true negative detections (i.e., an image with no snake not flagged by the algorithm) by comparing images flagged by the algorithm with snake images found by the second reviewers.

Using logistic regression, we tested for the effects of relative snake size, the amount of snake showing, or whether there was cover (i.e., vegetation or fencing) obscuring the snake on the number of true positive snake detections by the algorithm (i.e., successes) compared to snake detections manually detected only, or false negatives (i.e., algorithm misses). We evaluated a global additive model (containing all 3 variables) and 5 additional models with different variable combinations determined a priori. We ranked the models and selected the best model using corrected Akaike's Information Criteria (AIC_c), where $\Delta AIC_c < 2.0$ indicates the best model (Burnham and Anderson 2002). We set statistical significance at $\alpha = 0.05$.

RESULTS

Over the 7 month period the cameras were deployed, the 5 camera traps ran for 764 trap days in total ($\bar{x} = 152.8$, SD = 12.3, range = 134–171 trap days per camera). We had a malfunction in 1 of the 5 cameras (C7), so it was not active from mid-May to early July 2019. Reviewers evaluated a total of 1,500,187 images and we detected 2,425 images of 161 individual snake observations comprising 14 identifiable species (Figure 1, Table 1, S1, available in Supporting Information). Individual snake observations consisted of between 1 and 1,779 consecutive images of the individual snake ($\bar{x}$ = 15, SD = 140, median = 2). Almost 75% of the images captured were from a single *Agkistrodon contortrix* (Eastern Copperhead) present under the camera for approximately a full day (1,779 images), which we considered an outlier and removed from our regression analysis, leaving us with 646 images of 160 snake observations ($\bar{x}$ = 4, SD = 7, median = 2, range = 1–68 images per individual observation).

Of those 160 snake observations, we detected 11 (17 images) *P. ruthveni* observations (Table 1, Figure 2). We detected 18 *P. ruthveni* observations with the 5 tag readers from 28 March 2019 to 15 October 2019. Seven of the 18 observations were not captured on camera because of the malfunctioning camera (C7) during the middle of the study, but the 11 remaining tag reader *P. ruthveni* observations were captured when all 5 cameras were functional. However, one of the tag reader *P. ruthveni* observations also captured by the cameras was missed in the manual review of the images, because the image captured only a small fraction of the snake's tail. As a result, that image was not counted as a successful camera trap observation. Only one camera trap observation (2 images) was not also detected by the tag reader. In those 2 images, the individual *P. ruthveni* reached the drift fence and then turned towards the distal end of the drift fence rather than the center where the tag reader was located. Thus, both camera traps and tag readers captured the same 10 *P. ruthveni* observations and a single unique observation each.

For the 10 overlapping observations, the tag readers identified 4 unique individuals. Two of the individual *P. ruthveni* were detected once each at one camera (C12). The other 2 individuals were detected at 2 cameras each, with no overlap between the camera pairs: C7 (twice) and C9 (once) for one individual and C11 and C12 for the

TABLE 1 Number of observations and number of images (in parentheses) for each relative size category (small ≈ <33 cm, medium ≈ 33–66 cm, and large ≈ >66 cm) and total, for the 14 snake species identified, along with an unknown snake group that contained observations of snakes where the images were not identifiable. Images captured by camera traps in the Kisatchie National Forest, Louisiana, USA, during 28 March–15 October 2019.

Scientific name	Common name	Small	Medium	Large	Total
Agkistrodon contortrix	Eastern Copperhead	-	12 (1889)[a]	-	12 (1889)[a]
Cemophora coccinea	Scarletsnake	3 (12)	-	-	3 (12)
Coluber constrictor	North American Racer	1 (1)	5 (16)	12 (16)	18 (33)
Crotalus horridus	Timber Rattlesnake	-	-	1 (14)	1 (14)
Lampropeltis getula	Eastern Kingsnake	-	-	2 (10)	2 (10)
Masticophis flagellum	Coachwhip	2 (4)	2 (16)	26 (36)	30 (56)
Micrurus tener	Texas Coralsnake	-	5 (15)	1 (1)	6 (16)
Opheodrys aestivus	Rough Greensnake	1 (16)	2 (7)	-	3 (23)
Pantherophis obsoletus	Western Ratsnake	-	1 (10)	2 (2)	3 (12)
Pantherophis slowinskii	Slowinski's Cornsnake	-	2 (9)	3 (5)	5 (14)
Pituophis ruthveni	Louisiana Pinesnake	-	-	11 (17)	11 (17)
Sistrurus miliarius	Pygmy Rattlesnake	1 (1)	-	-	1 (1)
Storeria dekayi	Dekay's Brownsnake	1 (6)		-	1 (6)
Thamnophis proximus	Western Ribbonsnake	11 (79)	36 (195)	-	47 (274)
Unknown snake	-	9 (17)	7 (28)	2 (3)	18 (48)

[a]Includes 1 observation (1779 images) of an eastern copperhead (*Agkistrodon contortrix*) where the snake coiled under the camera for a day. This observation and images were removed as an outlier in the binomial logistic models.

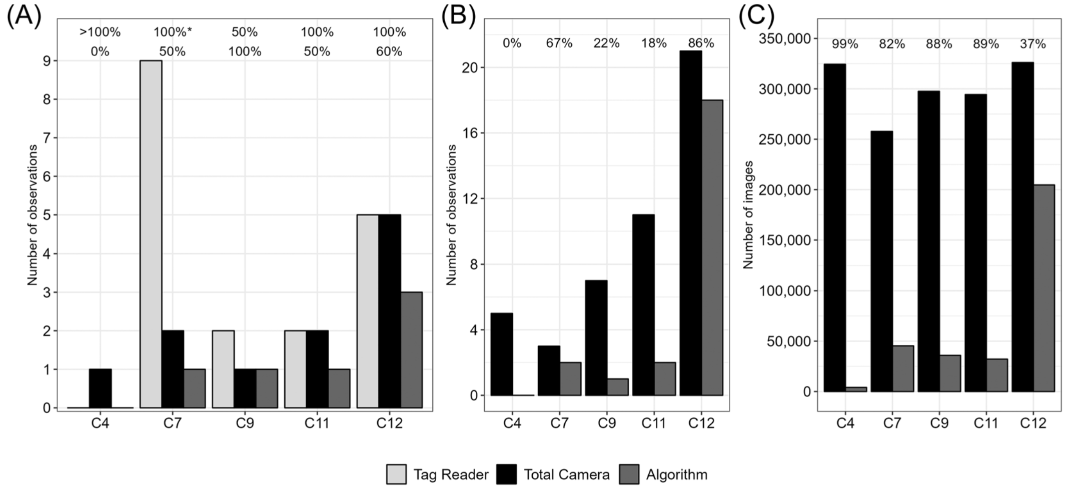

FIGURE 2 Algorithm success at locating snakes and reducing effort for each camera. (A) The number of observations collected by each tag reader and camera (i.e., C4, C7, C9, C11, and C12, along the x-axis) and flagged by the algorithm for Louisiana Pinesnakes (*Pituophis ruthveni*). The percentages in the top row are the number of *P. ruthveni* observations collected by the tag reader divided by the number of observations collected by the camera and in the bottom row are the number of observations returned by the algorithm divided by the number of observations collected by the camera. *Camera 7 was not functioning during 7 of the 9 *P. ruthveni* tag reader observations but captured both observations for which it was available. (B) The number of observations of other large snakes collected by each camera and flagged by the algorithm. The percentages are the number of observations returned by the algorithm divided by the number of observations collected by the camera. (C) Algorithm success in effort reductions (i.e., reducing the number of images reviewers evaluate manually). The percentages are the number of images returned by the algorithm divided by the total number of images collected by the camera. All images were collected from the Kisatchie National Forest in Louisiana, USA during 28 March–15 October 2019.

other individual (twice at C11, and thrice at C12; Figure 3). All individual *P. ruthveni* detected by the cameras were large adults and distributed almost evenly in the amount of snake showing in the images (Table S2, available in Supporting Information), while 11 of the 17 images (64.7%) had the *P. ruthveni* at least half covered by vegetation or fencing.

Over the 764 trap days, we recorded one *P. ruthveni* observation per 69.5 camera trap days at the release site. For individual cameras, *P. ruthveni* detections per trap day averaged one observation per 100.4 ± 54.5 (SD) camera trap days (range = 29.2–171 camera trap days). At the site, there were zero days to first detection; the initial *P. ruthveni* detection occurred on the first day the camera traps were deployed. However, by camera, the trap days to first *P. ruthveni* detection ranged 0 to 153 ($\bar{x}$ = 79.2, SD = 58.8 camera trap days).

We were also interested in determining how generalizable reference images were to detect other similarly sized snakes, i.e., the large snakes from the relative snake size category. We made 47 observations of 7 species of large snakes (mean = 1.8, SD = 2.1, n = 84 images, range = 1–14 images per observation), excluding *P. ruthveni*, along with 2 unidentified large snake observations (3 images; Tables 1, S1 and S2). Some of the common snake species (e.g., North American Racers [*Coluber constrictor*] and Coachwhips [*Masticophis flagellum*]) had representative individuals for each of the 3 size classes. For the large snakes, there were fewer images with little of the snake showing in the images (19.5%), but the rest were almost evenly distributed between some of the snake showing (36.8%) and most of the snake showing (43.7%; Figure 1B–D, Table S3, available in Supporting Information). Of the 84 large snake observations, 63 (75%) had snakes at least half covered by vegetation or fencing.

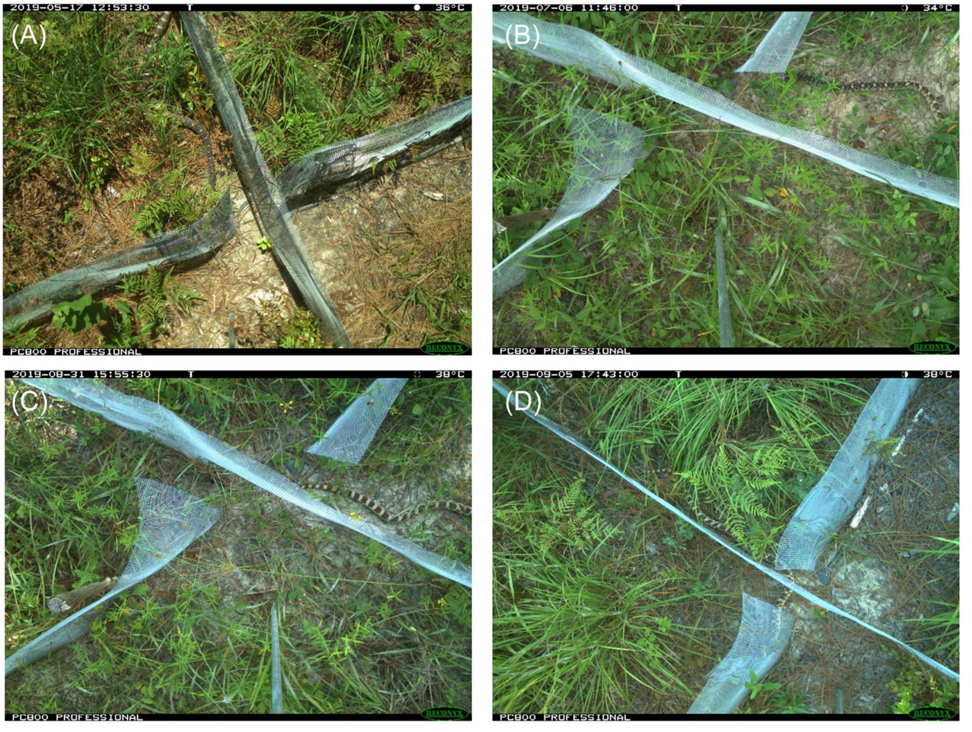

FIGURE 3 Louisiana Pinesnake (*Pituophis ruthveni*) No. 21801 captured at multiple cameras: (A) C11 on 17 May 2019, (B) C12 on 6 July 2019, (C) C12 on 31 August 2019, and (D) C11 on 5 September 2019. All images were collected from the Kisatchie National Forest in Louisiana, USA during 28 March–15 October 2019.

Change detection algorithm

The pixel changes between consecutive empty and reference *P. ruthveni* images varied greatly between the different cameras. The threshold for the difference images ranged between 26,383 and 2,800,000 pixels ($\bar{x}$ = 644,112, SD = 1,211,218 pixels) among the 5 cameras. The pixel counts are the total number of pixels within the (0.1–0.2] brightness band in the whole difference image that was used as the threshold to retain images for manual review. The algorithm did not retain any images falling under the thresholds as they were determined to not have a significant change based on the reference image for each camera.

The algorithm reduced the number of images reviewers evaluated by an average of 78.5% per camera (range = 37.3–98.7%) but had a 54.5% success rate at detecting observations of *P. ruthveni* (47.1% for individual images), and a slightly lower 48.9% success rate detecting other large snake observations and images (Figure 2, Table S1). The number of false positives averaged 64,384 images per camera (without the *A. contortrix*: $\bar{x}$ = 64,387 false positive images per camera), however, false positive average was skewed high by the very low percent reduction in algorithm images for tag reader and camera C12 (i.e., only 37.3% reduction; Figure 4, Table S1). The number of false negatives averaged 453 images per camera, but again the false negative average was skewed by a single *A. contortrix* present for an entire day (1,779 images) on camera C7 (without the *A. contortrix*: $\bar{x}$ = 101 false negative images per camera, Figure 4). For *P. ruthveni*, 8 images (6 observations) were classified as true positives (flagged by the algorithm), while 9 images (5 observations) were false negatives (missed by the algorithm) (Figure 4, Table S1). One of those false negatives included one of the reference images used by the change detection algorithm to determine the pixel change threshold for flagging images.

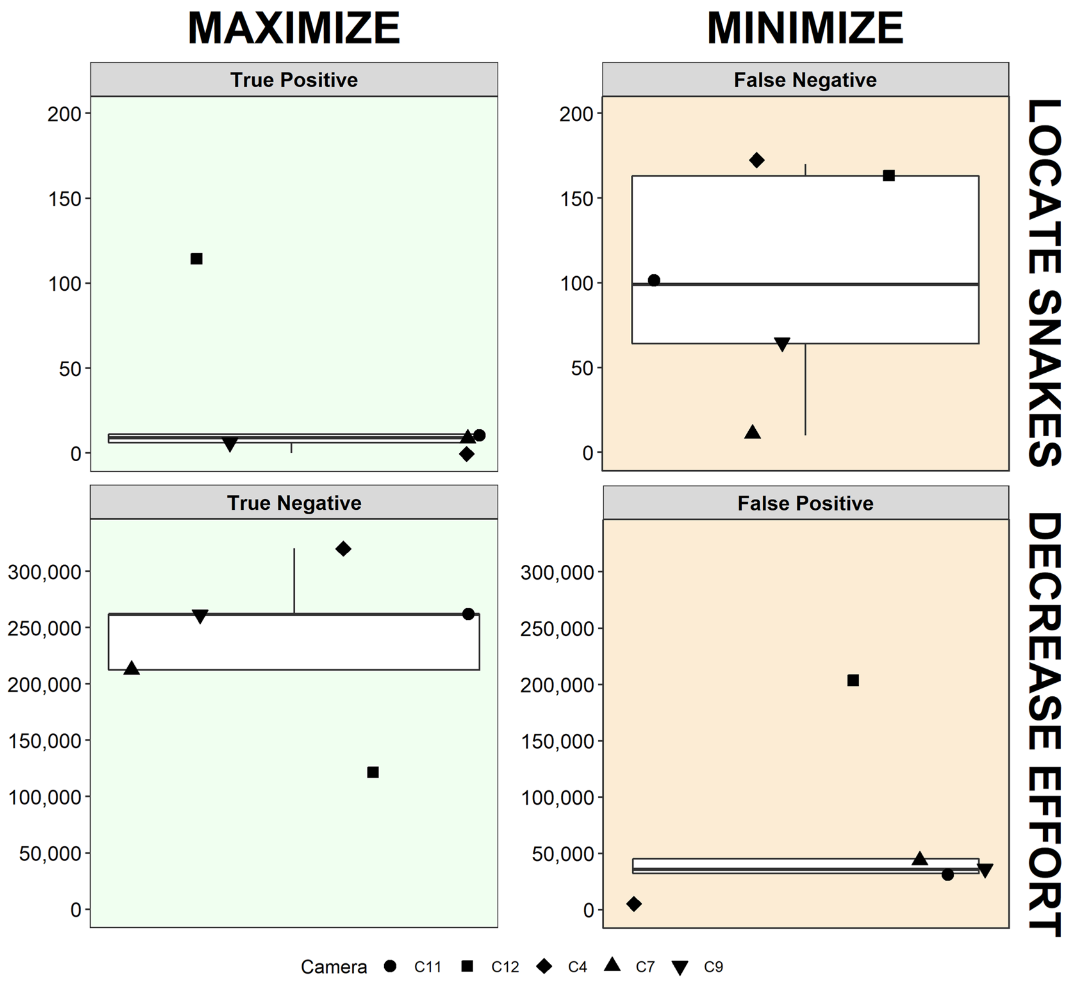

FIGURE 4 The number of images in each picture category for each camera (not including the Eastern Copperhead [*Agkistrodon contortix*] at C7). Our goals were to maximize true positives (algorithm flagged an image containing a snake) and true negatives (algorithm did not flag the image and there was no snake in it), while minimizing false negatives (algorithm did not flag the image containing a snake) and false positives (algorithm flagged an image and there was no snake in it). The true positives and false negatives (top row) reflect snake presence in images, while true negatives and false positives (bottom row) reflect effort reduction by the algorithm for manual review. All images were collected from the Kisatchie National Forest in Louisiana, USA during 28 March–15 October 2019.

The single top logistic model ($\Delta AIC_c < 2$) was the full additive model, comparing the effects of relative size, amount of snake showing, and at least half covered (no or yes), accounting for 0.81 of the AIC_c weight (Table 2). The odds ratio for relative size of the snake indicated large snakes were approximately 4 times more likely to be flagged by the algorithm than small snakes (Table 3). Additionally, snakes with approximately some, or most of their body length showing in the images were 2 and 1.3 times, respectively, more likely to be flagged by the algorithm than snakes with little of their body length showing (Table 3). Finally, counterintuitively, snakes at least half covered by vegetation or fencing in the images were 1.8 times more likely to be flagged by the algorithm (Table 3).

TABLE 2 Model selection results for all binomial logistic regression models. We used the difference in Akaike's Information Criterion adjusted for small sample sizes ($\Delta AIC_c < 2$) to identify the model that best predicts whether the algorithm would flag the snake image captured by camera traps in the Kisatchie National Forest in Louisiana, USA during 28 March to 15 October 2019. K = number of parameters, AIC_c = Akaike's Information Criterion, ΔAIC_c = change in AIC_c, w_i = model weight.

Model description	K	AIC_c	ΔAIC_c	w_i	Model likelihood	Log likelihood
Relative size + Snake amount + Covered	6	618.933	0.000	0.812	1.000	−303.401
Relative size	3	622.875	3.942	0.113	0.139	−308.419
Relative size + Snake amount	5	624.023	5.090	0.064	0.078	−306.965
Relative size * Snake amount * Covered	18	627.447	8.514	0.011	0.014	−295.178
Covered	2	669.733	50.800	0.000	0.000	−332.857
Snake amount	3	672.214	53.281	0.000	0.000	−333.088

TABLE 3 Parameter values (β) and odds ratios for each of the parameters in the top binomial logistic regression model predicting whether the algorithm would flag the images of the snakes captured by camera traps in the Kisatchie National Forest in Louisiana, USA during 28 March to 15 October 2019. SE = standard error, CI = confidence intervals.

Parameter	β	SE	95% CI	z	p	Odds ratio
Intercept	−2.111	0.369	−2.856 to −1.408	−5.726	≤0.001	0.121
Relative size						
Medium	−0.345	0.261	−0.848–0.179	−1.321	0.186	0.708
Large	1.386	0.302	0.802–1.989	4.589	≤0.001	3.997
Snake amount						
Some	0.664	0.327	0.027–1.313	2.029	0.042	1.942
Most	0.286	0.283	−0.255–0.857	1.012	0.311	1.331
Covered (Y)	0.599	0.229	0.157–1.058	2.616	0.009	1.821

DISCUSSION

Our time-lapse triggered camera trapping technique performed well with respect to *P. ruthveni* detection accuracy. All but one of the pit-tagged *P. ruthveni* crossings were detected, and the single miss occurred because the image included only a small portion of the snake's tail (i.e., the camera caught the snake, but the manual image reviewers did not). Even with the missed observation, our camera trapping technique detected the same number of pit-tagged *P. ruthveni* as the tag reader, because one individual captured on camera did not cross the tag reader. Importantly, the camera-detected, but tag reader-missed, individual was the only observation of a *P. ruthveni* at that camera site (C4) during the study. Camera trapping detection accuracy suggests a 30 second time-lapse interval set to take pictures during daylight hours was sufficient for monitoring large-bodied snakes like *P. ruthveni*. Indeed, all the cameras detected at least one *P. ruthveni* while operational, albeit with considerable variation in detection rates. While the causes of variation in detection rates in our study are unknown (Rovero and Marshall 2009), the range of variation in detection rates is extremely important for drawing inferences about survey and monitoring results from other studies on the species.

A previous camera trapping study using time-lapse triggered camera trapping technique to survey for *P. ruthveni* in potentially suitable habitats in Texas was also successful at detecting large-bodied snake species but failed to detect the target species (Anderson et al. 2020, Neuharth et al. 2020). Neuharth et al. (2020) recorded >8 million images from 26 cameras at 7 sites, taking pictures at similar intervals to our study, between February and October 2016. The 2016 Texas study had an average of 172.5 ± 19.8 (SD) camera trap days/camera (range = 120–228 trap days; unpublished data). Comparing the studies based on camera trap days to detection (i.e., from deployment, how many days it took to observe *P. ruthveni*, range 0–153 in our study), between 88–100% of the cameras in the Texas study should have detected *P. ruthveni*, if present. Alternatively, if using the catch per unit effort (i.e., observations/camera trap days, range = 1/29–1/171), then 50–100% of the Texas cameras should have detected *P. ruthveni*, if present. However, one factor impacting the detection is the abundance of the species in each study area (McCarthy et al. 2013). The translocation site in our study has had *P. ruthveni* released annually from 2010 to 2019 (123 unique individuals released), likely resulting in inflated detection rates. Comparatively, the last known *P. ruthveni* observation from the Texas study was 2012, thus if *P. ruthveni* are still present, they are present at very low densities, suggesting that much more effort may be required to detect them (Rudolph et al. 2018). Clearly more research is needed to understand variation in detection rates of *P. ruthveni* using time-lapse triggered camera trapping technique, but the results of our study can begin to help discern inferences of absence from inadequate sampling for rare species like *P. ruthveni*.

In addition to recording species' detections, camera traps have been considered useful in recording information on individuals, in particular recaptures. Individual identifications work well with species that have unique markings or scars and have been used for large cats (e.g., bobcats, Mendoza et al. 2011; tigers, Karanth et al. 2011; leopards, Hedges et al 2015). Camera traps have been less used among reptiles; Welbourne 2013 had limited success identifying Jacky Dragons (*Amphibolurus muricatus*), although Moore et al. (2020) was successful at identifying individual perentie (*Varanus giganteus*), larger lizards with distinct spot patterns on their backs. Although *P. ruthveni* have distinctive patterns potentially allowing for the identification of individuals, the amount of the animal showing in pictures from our work (e.g., anterior body, posterior body), as well as body positioning, cover and lighting impeded the identification of individuals. For example, one *P. ruthveni* individual was captured 5 times on tag reader/camera C11 and tag reader/camera C12 during the study, but changes in lighting and different portions of the animal showing made it challenging to determine visually that this was the same animal (Figure 3). More frequent removal of vegetation and other cover and reducing the time-lapse interval should produce more pictures of individual *P. ruthveni* that are identifiable and increase the probability of scoring recaptures. Small changes in application could expand population monitoring and modeling of *P. ruthveni* beyond that which is feasible with tag readers, which require initial capture of individuals to implant the pit-tag. The camera trapping drift fence arrays described here can monitor new individuals that do not have pit-tags implanted, such as young produced on site or immigrants to the site. In bypassing the initial capture requirement for pit-tagging, the camera trapping drift fence arrays could fully automate the mark-recapture sampling of *P. ruthveni* populations, where individuals are never physically captured but instead are monitored through image recapture potentially capable of tracking body condition, growth, movement, and survival over time.

Using the change detection algorithm we developed, we found approximately a 50% success rate in the detection of both *P. ruthveni* and other similarly sized snakes (Table 3). Given the low rate of snake observations in general, and *P. ruthveni* in particular (i.e., 2 camera sites had only a single *P. ruthveni* detection), increasing the success rate should be a major focus of future research. However, an average reduction of 78.5% of pictures to evaluate (~1.17 million fewer) potentially saves 175 hours of evaluation time, assuming a manual evaluation rate of 10,000 pictures per 1.5 hours (Adams et al. 2017). The potential reduction in effort is also worth further evaluation of the program to see if the picture setup and algorithm could be further refined.

The algorithm was successful at reducing false positives across all sites, but it also reduced true positives of both *P. ruthveni* and other snake species at 4 of 5 sites. At the remaining site, camera C9, the algorithm performed extremely well by flagging the single true positive *P. ruthveni* detection at that camera while also eliminating 87.9% of true negative images. The variation in algorithm snake detections observed across sites is likely due to the background noise in the images (e.g., moving vegetation, changing cloud cover), which complicated threshold determination. We expected that snakes that were not covered would present more of a pixel change and thus be more likely to be flagged by the algorithm, but the opposite was true. The positive association of cover in images shows that vegetation may have played 2 specific roles. First, it influenced the brightness band we used to calculate the change detection threshold (i.e., [0.1–0.2]); snakes in the reference images that had partial cover had a smaller change in pixel brightness, compared to snakes that were in the open, thus pixel changes from snakes in the open was not necessarily included in the threshold calculation. Additionally, it suggests that background noise may have played a larger than preferred role in the flagging of the images (i.e., snakes entering the field of view are not the sole cause of pixel change calculated by the algorithm). For our study, we attempted to keep the trapping area as natural as possible to minimize disturbance to the landscape. However, future camera trapping efforts could work on ways to reduce background noise, such as creating and maintaining an open, uniform space beneath the camera to reduce the noise and cover of vegetation, in order to achieve a more efficient threshold and one that could potentially be applied across multiple cameras.

For the current version of the change detection algorithm presented here, finding the best threshold across sites for maximizing true positives and minimizing false negatives while optimizing the number of false positives was a challenge. There is clearly a large amount of further research to be performed in order to improve quality assurances of camera trap image filtering and object recognition algorithms across different sites or environments (Shahinfar et al. 2020). Nonetheless, our research provides detailed information supporting the establishment of long-term monitoring sites with a high degree of visual similarity in the image background. In addition, our study provides another source of labelled images for snake species that are necessary for the practical implementation of deep learning algorithms in the field of camera trapping (Shahinfar et al. 2020). Our study remains equivocal regarding comparisons between PIR and TL camera trapping approaches, but we suggest advancements in TL approaches are more feasible for researchers, as most researchers cannot improve sensor technology to increase trapping success, but they can improve algorithm success.

MANAGEMENT IMPLICATIONS

For many rare and secretive species requiring conservation actions like *P. ruthveni*, non-detections can be just as important as detections in guiding allocation of resources. The results on variation in detection rates of our study can begin to help discern robust inferences of absence from inadequate sampling for rare species like *P. ruthveni*, as well as improve our understanding of how best to apply time-lapse triggered camera trapping technique with a change detection algorithm for monitoring of biodiversity more broadly. Long-term trapping for *P. ruthveni* indicates that trapping success is highly variable across years (Rudolph et al. 2018) and, given the large home ranges of this species (Himes et al. 2006, Pierce et al. 2014), longer term camera studies should be undertaken before declaring *P. ruthveni* absent from an area. From the results of our study, we were able to suggest a potential detectability window of camera trap days with non-detections to help infer absence, and in doing so, we hope to help guide the application of conservation resources where they can be most beneficial to the species.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

ETHICS STATEMENT

The authors confirm that all methods and experiments were performed in accordance with the relevant federal and state guidelines and regulations, under federal Native Endangered and Threatened Species Recovery Permit No. TE007748-5 and Louisiana Department of Wildlife and Fisheries Scientific Research and Collecting Permit No. WDP-19-046.

DATA AVAILABILITY STATEMENT

Data available from authors upon reasonable request.

ORCID

Danielle K. Walkup http://orcid.org/0000-0001-6836-4212

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SUPPORTING INFORMATION

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APPENDIX A: CHANGE DETECTION ALGORITHM R CODE

```
## Install and load packages
pkgs <- c("jpeg", "rasterImage", "sp", "rgdal")
pkgsMiss <- pkgs[!(pkgs %in% installed.packages()[, "Package"])] # Extract not installed packages
if(length(pkgsMiss)) install.packages(pkgsMiss)
lapply(pkgs, require, character.only = TRUE)

## Identify location of image folders
basepath <- NULL #Replace NULL with the folder path for the original images
path <- NULL #Replace NULL with the folder path to copy images to
folder.names <- dir(basepath, full.names = TRUE)
destination.names <- dir(path, full.names = TRUE)

## Run Algorithm
threshold <- NULL #Replace null with the threshold calculated
for(i in 1:(length(file.names) – 1)) {
    file1 <- readJPEG(file.names[i])
    file2 <- readJPEG(file.names[i + 1])
    gray1 <- ((file1[,,1]+file1[,,2]+file1[,,3])/3)
    gray2 <- ((file2[,,1]+file2[,,2]+file2[,,3])/3)
    change <- abs(gray2 - gray1)
   if(sum(change > 0.1 & change < 0.2) > threshold) {
   file.copy(file.names[i + 1], path)
   } else {
   NULL
   }
}
```