Evaluating AHDriFT Camera Traps and Traditional Survey Methods for Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) Presence-Absence

Thesis

Presented in Partial Fulfillment of the Requirements for the Degree of Master of Science in the Graduate School of The Ohio State University

By

Evan Douglas Amber

Graduate Program in Environment and Natural Resources

The Ohio State University

2021

Thesis Committee

William E. Peterman, Advisor

Christopher M. Tonra

Stanley Gehrt

Abstract

The Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) is Federally threatened and Ohio endangered. Accepted Ohio survey protocols includes visual encounter surveys (VES) and artificial cover (corrugated tin sheets) surveys. Although effective, these traditional methods require intensive field effort (~25 weekly visits). The Adapted-Hunt Drift Fence Technique (AHDriFT) is a new low-effort camera trap and drift method for ectotherms and small mammals. However, the method has not been applied for Massasauga or in their habitats, or even evaluated beyond proof-of-concept.

The objectives of this study were to: (1) assess AHDriFT as a wildlife survey tool; (2) compare AHDriFT efficacy for Massasauga presence-absence surveys to VES and tin surveys in terms of detection rates, detection probability, and cost-efficiency; (3) determine optimal AHDriFT deployment for Massasauga in terms of camera trap timing and length, array spatial placement, and weather influence; and (4) provide preliminary recommendations for a Massasauga survey protocol using AHDriFT.

I deployed 15 Y-shaped AHDriFT arrays in fields with known Massasauga populations from March – October 2019 and 2020. In 2019, I compared arrays to prior VES and tin surveys, and assessed between-field detection covariates. In 2020, I evaluated concurrent surveys and assessed within-field detection covariates.

Equipment for each array cost approximately US$1,570. Construction and deployment of each array took about three hours, with field servicing requiring 15 minutes per array. Arrays proved durable under wind, ice, snow, flooding, and heat. Processing two-weeks of images of 45 cameras averaged 13 person-hours. In 2019, arrays obtained 9,018 detections of 41 vertebrate species comprised of 5 amphibians, 13 reptiles (11 snakes), 16 mammals, and 7 birds. Arrays cumulatively detected all amphibians and 92% of expected snakes and small mammals.

Arrays obtained a total of 206 Massasauga detections, 2 – 4 times that of traditional methods. In 2019, arrays detected 0.48 snakes/person-hour, surpassing prior VES (0.11) and tin surveys (0.28). In 2020, arrays exceeded tin catch-per-person-hour by at least 2.6 – 6 times. Weekly array detection probability equated to maximum tin detection probability per survey (0.5) using only 1 array/~15 ha. Additional arrays increased weekly detection probability to 0.6 – 0.9. However, arrays have lower weekly detection probability (0.1 – 0.4) in small population sites. Such sites therefore required longer camera trapping timeframes and higher array densities to achieve low error rates.

Arrays were most effective from June – October, requiring as few as five field visits for 16 weeks of camera trapping. Optimal array placement is in dense vegetation away from predator perch trees. After equipment purchases, AHDriFT was more cost-effective than tin. Overall, AHDriFT was an effective snake and small mammal survey and inventory tool. The method also demonstrates high promise as a more effective Massasauga survey tool than traditional surveys. Still, AHDriFT needs to be tested in Massasauga sites more representative of their typically small population sizes in Ohio.

Acknowledgments

I thank my advisor, Bill Peterman, for his continuous support and enthusiasm of this project, and for his patience, direction, and encouragement as I developed my scientific skills. I thank my co-advisor on this project, Gregory J. Lipps Jr., for his mentorship and substantial contributions to this research and my professional development. I also thank Drs. Tonra and Gerht for kindly agreeing to serve on my thesis committee.

I would like to acknowledge the agencies and people that made this project possible. First, I thank my lab mate, Jennifer M. Myers, for her dedication to the project and tireless contributions with field work, processing camera trap images, and writing manuscripts. I extend my gratitude to all of the undergraduate and graduate students, volunteers, and my colleagues at The Ohio Department of Transportation for their incredible help constructing and hauling the equipment needed for this project into and out of the field. I thank Matthew Perlik for his enthusiasm of this project and for his flexibility in balancing my internship and thesis work. I give a special thanks to Nicholas A. Smeenk and Douglas Wynn for sharing the traditional survey method data necessary to complete my analyses, and to Scott Martin and Andrew Grosse for their advice on deploying AHDriFT.

This study was funded by The Ohio Department of Transportation as part of on-going research (PID 107308). I thank Chris Staron, Kate Parsons, Kelly Nye, Lindsey Korfel, Marci Lininger, Matt Raymond, and Jacqueline Martindale for their input. I thank Adam Wohlever, Bob Ford, Kate Parsons, Melissa Moser, and Jacqueline Bilello for supporting site access and permitting.

Last but certainly not least, I thank all of my friends and family who have given me incredible support throughout my collegiate career. Mom, Dad, Jenna, Candida, Daniel, and all of my wonderful family, I could not ask for a better support network. Thank you to my lab mates for always listening, helping me overcome analytical problems, reviewing manuscripts, and making Columbus a fun place to be. Thank you to my friends for putting up with my long rants about snakes, even though most of you don't like them yourselves. Annalee, I thank you so much for always being by my side, and filling my graduate student days with laughter.

Vita

B.S. Biology – Ecology, Evolution, and Behavior...12/2014

Summa Cum Laude

State University of New York at Binghamton

Publications

**denotes corresponding author*

Amber, E.D.*, G.J. Lipps Jr., J.M. Myers, N.A. Smeenk, and W.E. Peterman. Accepted. Use of AHDriFT to efficiently survey for *Sistrurus catenatus*. Herpetological Conservation and Biology.

Amber, E.D.*, J.M. Myers, G.J. Lipps Jr., and W.E. Peterman. 2021. Small mammal daily activity periods derived using AHDriFT camera traps. Mammal Research. Available at: http://link.springer.com/article/10.1007/s13364-021-00560-z

Amber, E.D.*, G.J. Lipps Jr., and W.E. Peterman. 2020. Evaluation of the AHDriFT camera trap system to survey for small mammals and herpetofauna. Journal of Fish and Wildlife Management: Available at: https://doi.org/10.3996/JFWM-20-016

Marshall, B.M., C.T. Strine*, M.D. Jones, A. Theodorou, **E.D. Amber**, et al. 2018. Hits close to home: repeated persecution of king cobras (*Ophiophagus hannah*) in northeastern Thailand. Tropical Conservation Science 11: doi 10.1177.

Hodges, C., **E.D. Amber**, and C.T. Strine*. 2018. *Boiga guangxiensis* In, 1998 (Squamata: Colubridae) feeding on *Draco blanfordii* in Yunnan, China. Herpetological Notes 11:981–984.

Amber, E.D.*, C.T. Strine, P. Suwanwaree, and S. Waengsothorn. 2017. Intra-population color dimorphism of *Ahaetulla prasina* (Serptenes: Colubridae) in northeastern Thailand. Current Herpetology 36:1–7.

Amber, E.D.*[*], S. Waengsothorn, and C.T. Strine. 2017. *Calotes mystaceus* (Moustached Crested Lizard). Defensive behaviors. Herpetological Review 48:134.

Fields of Study

Major Field: Environment and Natural Resources

Table of Contents

List of Tables

List of Figures

Chapter 1. Evaluation of the AHDriFT Camera Trap System to Survey for Small Mammals and Herpetofauna

Abstract

Traditional surveys for small mammals and herpetofauna require intensive field effort because these taxa are often difficult to detect. Field surveys are further hampered by dynamic environmental conditions and dense vegetative cover, which are attributes of biodiverse wet meadows. Camera traps may be a solution, but commonly used passive infrared game cameras face difficulties photographing herpetofauna and small mammals. The Adapted-Hunt Drift Fence Technique (AHDriFT) is a camera trap and drift fence system designed to overcome traditional limitations, but has not been extensively evaluated. I deployed 15 Y-shaped AHDriFT arrays (three cameras per array) in northern Ohio wet meadows from March 10 to October 5, 2019. Equipment for each array cost approximately US$1,570. Construction and deployment of each array took about three hours, with field servicing requiring 15 minutes per array. Arrays proved durable under wind, ice, snow, flooding, and heat. Processing two-weeks of images of 45 cameras averaged about 13 person-hours. Arrays obtained 9,018 captures of 41 vertebrate species comprised of 5 amphibians, 13 reptiles (11 snakes), 16 mammals and 7 birds. Arrays imaged differing animal size classes ranging from invertebrates to weasels. I assessed detection efficacy using expected biodiversity baselines. I determined snake communities

from three years of traditional surveys. I estimated potential small mammal and amphibian biodiversity from prior observations and species ranges and habitat requirements. Arrays cumulatively detected all amphibians and 92% of snakes and small mammals that were expected to be present. Arrays also imaged four mammal and two snake species where they were not previously observed. However, capture consistency was variable by taxa and species. Low-mobility species or species in low densities may not be detected. In its current design, AHDriFT proved to be effective for terrestrial vertebrate biodiversity surveying.

Introduction

Biological surveys often focus on select taxa due to species-specific activity and behavioral patterns, detection (the probability of documenting a present organism), and established sampling methods. Broad biodiversity surveys thus necessitate researchers or teams with a multitude of skills and can consume considerable time and resources (Garden et al. 2007). Camera trapping is increasingly popular in conservation research and monitoring to reduce field effort. Camera traps are remotely operated cameras that photographs an area either on a trigger or timer to document passing wildlife, and are typically used to image species that are difficult to visually observe (Swann et al. 2004).

Researchers have a number of options when considering camera trap deployment (Rovero et al. 2013). Laser active trigger camera traps record an image when a constant laser is interrupted. Environmental conditions such as vegetation or mud splashes from precipitation can block the laser and trigger the camera trap without animals present (Guyer et al. 1997; Hobbs and Brehme 2017). Time-lapse camera traps are set to record at or over predetermined time intervals regardless of animal presence (Geller 2012). These cameras can consume substantial battery power and need to be frequently serviced (Glen et al. 2013; Rovero et al. 2013; Meek et al. 2014). Passive infrared (PIR) camera traps ideally only trigger when the sensor detects a thermal infrared differential caused by a passing animal. This limits PIR camera battery usage and generally minimizes the number of images without animals (Swann et al. 2004). They also outperform some other passive triggers, such as microwave sensors (Glen et al. 2013). These properties have established PIR camera traps as the most commonly used commercial game cameras (Swann et al. 2004; Rovero et al. 2013; Meek et al. 2014).

Passive infrared sensors are often misunderstood to detect body temperature, core temperature, ambient temperature, or heat-in-motion. Rather, they detect an infrared discrepancy caused by an object surface that is sufficiently hotter or colder than the background surfaces (Welbourne et al. 2016). This is not typically an issue for large-bodied endotherms. However, ectothermic and small-bodied animals (e.g., herpetofauna, mice, voles, shrews) can have surface temperatures too similar to background surfaces to trigger PIR sensors (Welbourne 2014). Passive infrared camera sensitivity (propensity to trigger when an animal is under the camera sensor) is thus a challenge when applied to these taxa (Glen et al. 2013; Merchant et al. 2013; Welbourne 2014). As such, researchers may choose active laser (Hobbs and Brehme 2017) or time-lapse (Geller 2012) cameras or rely on traditional methods, especially for ectotherms. Indeed, reptile surveys rarely apply camera traps and instead typically use traditional visual encounter, artificial cover, or live trapping (pitfall or funnel) methods (Dorcas and Willson 2009; McDiarmid et al.

2012). Still, PIR camera traps compare favorably to traditional small mammal snap or live-trapping (De Bondi et al. 2010).

Researchers have also needed to compromise between the area of camera coverage (i.e., detection zone) versus the detail of the images for species identification (DeSa et al. 2012; Glen et al. 2013). Most camera traps are set in open environments with a wide detection zone (Swann et al. 2004). This can result in images where it is difficult to identify small-bodied animals to the species-level. Narrow detection zones are better for acquiring photos capable of identifying small-bodied species but may miss more animals (Glen et al. 2013).

There have been recent attempts to solve the PIR sensitivity and detection zone issues when camera trapping small mammals and herpetofauna. Drift fences combined with traps are a favored method to capture species of herpetofauna (Campbell and Christman 1982; Greenberg et al. 1994; Ryan et al. 2002; McDiarmid et al. 2012) and small mammals (Williams and Braun 1983; Mitchell et al. 1993) that are otherwise difficult to observe. The Camera Overhead Augmented Temperature (COAT) system uses drift fences to concentrate animals into a central gap (Welbourne 2013). Thermally-homogeneous background surfaces are necessary for ideal PIR sensitivity (Welbourne et al. 2016). The COAT camera is therefore aimed downwards at a cork board, which provides a somewhat thermally-homogeneous background surface. This increases PIR sensitivity compared to cameras aimed at the ground or into open space (Welbourne 2013; Welbourne et al. 2016). Even so, COAT has limited sensitivity, operates best only during certain hours, and doesn’t capture animals moving outwards along the fence

(Welbourne 2014). Meanwhile, the Hunt Trap places a PIR camera inside of an inverted bucket housing unit equipped with bait (McCleery et al. 2014). The bucket results in a narrow detection zone and the lid is thermally-homogeneous. Buckets also provide cameras with consistent shade, protection, and stable environmental conditions relative to the open air. This set-up should remove or alleviate PIR camera problems at high ambient temperatures seen in conventional deployment (Swann et al. 2004). Overall, these factors allow Hunt Trap cameras to be durable, sensitive, and able to obtain clear pictures for species identification. Yet the system omits species not attracted to the bait and can capture many images of an individual (McCleery et al. 2014).

The Adapted-Hunt Drift Fence Technique (AHDriFT) combines the strengths of the COAT and Hunt Trap methods (Martin et al. 2017). Drift fences funnel animals under PIR cameras inside of modified Hunt Traps. This system encompasses the biodiversity sampling benefits of traditional drift fences (McDiarmid et al. 2012), enhances PIR sensitivity (Welbourne at al. 2016), and allows for detailed images (McCleery et al. 2014). Martin et al. (2017) photographed 32 vertebrate species and identified species in 98% of AHDriFT images. As with Hunt Traps, ambient temperatures due to night, sunny, or cloudy conditions should not strongly influence camera durability or sensitivity. Camera batteries and SD cards can also be easily changed in the field without deconstructing equipment. Martin et al. (2017) asserts that AHDriFT reduced their field time by 95% compared to drift fences and traps. Camera traps are also non-invasive, which removes the ethical issue of animal trapping mortality (De Bondi et al. 2010; Edwards and Jones 2014) as well as permit restrictions for listed or venomous species.

Taken together, these traits make AHDriFT a potential alternative to traditional drift fence and trapping. Yet, while conceptual testing has produced promising results, the method has not been extensively evaluated. For example, the original design was for Florida sand dunes, which may experience static and fair environmental conditions relative to some other ecosystems. Even so, the original cameras only operated 84% of deployment time (Martin et al. 2017). Whether the method is durable enough for widespread application under more strenuous environmental conditions is unresolved. Further, the method's ability to adequately capture biodiversity also remains untested.

Northern Ohio wet meadows are open-canopy systems characterized by organic-rich mineral soils, high and fluctuating water tables, and herbaceous vegetation (Sears 1926). Unlike Florida sand dunes, they experience a range of environmental conditions over a typical biological field season (March – October), such as strong winds, snow, ice, rain, flooding, heat, fast vegetative growth, and dynamic water tables. Wet meadows also have greater biodiversity than sand dunes, including rare and imperiled species in Ohio (ODNR 2020), but dense vegetation hampers traditional detection of many species (Slaughter and Kost 2010). Burrowing species present an additional potential challenge for AHDriFT maintenance and efficiency. Holes or tunnels under the drift fences or buckets reduce the likelihood that animals are coaxed into the camera traps. These characteristics make northern Ohio wet meadows ideal for camera trap deployment and for testing AHDriFT in strenuous and biodiverse environments.

I modified AHDriFT for wet meadow conditions and assessed its durability and required effort. I compared our small mammal and herpetofauna detections to biodiversity baselines, including established snake community data. I then generally compared AHDriFT species capture efficiency to other traditional and PIR camera trap methods. I also provide detailed methodological instructions, practical information, and recommendations for researchers and managers interested in AHDriFT.

Methods

I selected 15 wet meadow fields across northern Ohio in Wyandot, Huron, and Ashtabula Counties, with a mean size of 10.39 ha (median = 3.50 ha; range = 0.39 – 71.78 ha). I chose fields with known snake communities in order to assess detection efficacy against an established biodiversity baseline because snakes are traditionally difficult to detect (Steen 2010; Durso and Seigel 2015), and their biodiversity can be challenging to capture without employing multiple methods or long-term studies (Kéry 2002; Dorcas and Willson 2009; McDiarmid et al. 2012). I determined snake communities in each field from at least three years of traditional visual encounter and artificial cover (corrugated tin sheets) surveys (Gregory J. Lipps Jr. and Nicholas A. Smeenk, unpubl. data). I did not have field-level amphibian and small mammal community information from prior surveys. Instead, I used previous opportunistic observations, Ohio range maps, and species habitat requirements (Bokman et al. 2016; Parsons et al. 2019) to determine species that could potentially occur in these fields.

I modified AHDriFT from the original design (Martin et al. 2017) to an omni-directional Y-shape configuration, with an "array" defined as three camera traps connected by drift fences (Figure 1A). I considered an entire array as one sampling unit (i.e., the three cameras as non-independent). I used 1.27 cm thick oriented strand board for the drift fences and metal fence posts for support. Each array arm measured 4.88 m in length. Construction materials and detailed deployment instructions are available as an open-source online publication (https://doi.org/10.6084/m9.figshare.12685763.v1). I deployed one array at the geometric center of each field (15 arrays; 3 cameras per array, 45 total cameras) from March 10 to October 5, 2019. I used Reconyx Hyperfire 2 Professional PIR camera traps (model: HP2X Gen3) with custom flash and 28 cm focal-lengths modified by the manufacturer. These adjustments increased image clarity by focusing the cameras and flash to the distance to the bucket lid. I selected camera settings of highest sensitivity and three-image burst per trigger event. I used rechargeable NiMH AA batteries (EBL 1.2V HR 6; 2,800 mAh) and 32-GB SD cards to allow the cameras to operate continuously. I examined arrays every 7 – 14 days for damage and gaps under the fences, buckets, guide boards, and fence joints. I changed camera SD cards and batteries every two-weeks.

I broadly defined a camera “false-trigger” as any image that did not capture an animal or animal part. I manually processed raw images by removing false-triggered images and assigning species images into designated folders. I used the R package ‘camtrapR’ (Niedballa et al. 2017, version 1.1; R Core Team 2019, version 3.6.1) to compute a species capture record table. I determined species captures using a 60-minute interval between images of the same species at a given array. This framework ensured that the dataset was not inflated by an individual rapidly moving around a camera or an array (Martin et al. 2017).

Results

Deployment, operation, and servicing

The equipment cost of each array was about US$1,570 (**Table 1**). The arrays withstood all environmental fluctuations, including wind, ice, flooding, freezing, and heat (daily temperatures ranged from -10 – 36°C). The only operational maintenance required was minor fence back-filling of gaps with mud in the first weeks following deployment. After the water tables settled, I did not need to conduct repairs. Arrays remained operational despite vegetative growth and I did not observe any holes or tunnels created by burrowing species. Paper Wasps (*Polistes* spp.) and Mud Daubers (*Sceliphron caementarium*) sometimes built nests in the buckets or on the cameras. New vegetation also occasionally grew into the buckets. While these factors resulted in more false-triggers, they were easily removed and did not impair array operation. The 45 cameras operated 9,198 of the 9,204 trap-nights (one camera malfunctioned for six days). The malfunction appeared to be due to a hardware issue. I did not observe camera problems or changes in their efficiency due to overheating or general environmental conditions.

I constructed each camera trap housing unit in about one-hour and deployed each array in about two-hours (**Table 2**). When checking the cameras, batteries typically read "full" charge with only one occasion showing 50%. The 32-GB SD cards usually read 0% full, although two unusual occasions each used 16% of capacity (~22,500 and 28,000 images). Those occasions were due to false-triggers by one camera. I resolved the problem by lowering that camera's sensitivity setting by one level. I suspect that the camera's oversensitivity was caused by a preexisting mechanical issue. Swapping SD cards and batteries averaged 13.96 minutes (± 3.21) per array for one researcher, typically faster in warm and dry weather. Two weeks' worth of images of all 45 cameras required 6 – 19 person-hours to process ($\bar{x}$ = 13.08 ± 3.84). The shortest processing times were in the spring (March – May) when animals were less active. The longest processing times resulted from when there were unusually large amounts of false-triggers.

Species captures

Arrays recorded 190,851 false-triggered images (52.57 GB). The primary causes of false-triggering were flooding and daylight shifts, influenced by bucket orientation on the landscape. Arrays obtained 75,477 species images (18.4 GB) with a per camera mean of 1,679 (± 830) species images. Discounting the two unusual false-trigger occasions by one camera, arrays had approximately two false-trigger images per species image. This compares to an upwards of 50:1 false-trigger to species image ratio during original AHDriFT testing (Scott Martin, The Ohio State University, pers. comm.). Arrays obtained excellent image quality (**Figure 2**) and I identified all vertebrate images to the species-level. Arrays recorded a total of 9,018 captures from 41 species, including 5 amphibian, 13 reptile (11 snake), 16 mammal, and 7 avian species (**Table 3**). Arrays imaged an average of 21 species per array, with a range of 16 – 24. I also recorded the total number of invertebrate detections which included ants, bees, wasps, beetles, flies, moths, mantids, and spiders. Mammals had the most captures (4,595), followed by reptiles (2,495), invertebrates (987), birds (889), and amphibians (52). Array captures per unit effort (array trap nights) were comparable to or sometimes greater than traditional methods (**Table 4**).

Discussion

My AHDriFT design (**Figure 1**) has some potential limitations. The biggest obstacle is the upfront cost of the equipment per array (**Table 1**). Camera trapping generally requires more initial investment than traditional survey methods (Garden et al. 2007). Nonetheless, AHDriFT is substantially less expensive than some other camera trap systems for small mammals and ectotherms (Hobbs and Brehme 2017). There are also some areas where costs can be reduced or minimized. Equipment costs can be reduced by a third by deploying a two-camera linear array in narrow areas where the drift fence will effectively intercept moving animals. Researchers can also purchase SD cards with smaller memory than I used.

While some material costs can be lowered, I do recommend investing in high-quality cameras. The professional-grade cameras operated continuously except for one camera for six days, outperforming the consumer-grade cameras used by Martin et al. (2017). I recognize that our enhanced camera performance may also be attributed in part to my modified design. For example, I attached the cameras to opaque acrylic rather than to transparent plexiglass (Martin et al. 2017), which may have better prevented overheating.

I also achieved much lower false-trigger rates compared to the original design, but this is likely due to using professional-grade cameras (Glen et al. 2013). I recommend field research comparing different camera trap models in both my and the original AHDriFT designs. For the drift fences, sturdy materials allowed them to endure dynamic conditions and remain suitable for a second field season. I also note that cameras can be a long-term investment. Multi-season studies can therefore benefit by investing in quality materials despite upfront costs.

Further, in some cases AHDriFT may be more cost-efficient than traditional methods because arrays minimize field effort (**Table 2**). Traditional methods may need low upfront investment, but their field requirements can ultimately lead to higher costs than camera trapping (Garden et al. 2007). Although I changed SD cards and batteries every two-weeks, arrays likely only need to be serviced every 4 – 8 weeks. Reducing field person-hours may be particularly cost-effective for labor-intensive surveys for diverse taxa or research in dynamic ecosystems. As such, research targeting multiple species may particularly benefit by using AHDriFT to simultaneously survey for numerous species. Image processing effort can also be reduced if researchers are interested only in certain species. Much of my processing time was spent sorting every species image, particularly of common species such as Deer Mice (*Peromyscus* spp.), Common Five-lined Skinks (*Plestiodon fasciatus*), and Song Sparrows (*Melospiza melodia*).

A second obstacle of my array design is transporting and deploying materials. The oriented strand board drift fences are heavy, especially after soaking up water. Erecting arrays also entailed strenuous physical effort. Using light-weight corrugated plastic for fences may reduce physical strain, and its durability is currently being tested. Silt fencing, metal flashing, or wildlife exclusion fencing may be viable options as well. I also dug trenches by hand using a mattock, but fences may be installed quicker and easier using a powered trencher. This limitation is not inherent of AHDriFT and is equivalent to traditional drift fence deployment.

Thirdly, researchers interested in a particular species or taxa should consider life history traits to select the most appropriate survey method. Although I imaged seven avian species, AHDriFT is designed for ground-dwelling species and does not adequately capture avian biodiversity. Of the avian captures, 75% were Song Sparrows and 21% were Northern House Wrens (*Troglodytes aedon*). Drift fences also rely on animals encountering and moving along them. Thus, AHDriFT is most effective at imaging highly mobile species or species present in dense populations. For example, Eastern Gartersnakes (*Thamnophis sirtalis*) and Masked Shrews (*Sorex cinereus*) had the most captures, and arrays frequently imaged mice and voles (*Microtus* spp.; likely *M. pennsylvanicus*; **Table 3**). All of these species are numerous in these fields and actively forage for food (Bokman et al. 2016; Gibbons 2017).

Meanwhile, species in low densities or low-mobility species likely have reduced probability of encountering the drift fences. For example, arrays imaged 7 of the 12 possible snake species in all fields where they are known to occur (**Table 3**). Snake species not imaged in a field typically had only one, and no more than five, prior observations in that field over three years of traditional surveys (Gregory J. Lipps Jr., unpubl. data). The exception is Kirtland's Snakes (*Clonophis kirtlandii*), which are abundant in two of our fields. Kirtland's Snakes have fossorial life histories, low-mobility, and tend to move through or under the vegetative thatch (Gibbons 2017). These traits likely reduce the probability that they move along drift fences or under the camera traps.

Taken together, AHDriFT can miss low-mobility species or species in low densities. Nonetheless, I contend that this limitation is generally applicable to camera trapping (De Bondi et al. 2010) and traditional drift fence and trapping (Steen 2010). I also note that I did not test camera sensitivity of all species in all environmental circumstances. For example, I suspect that amphibians moving during rain events may not have been consistently captured (Martin et al. 2017). This may explain why arrays did not detect amphibians in all expected fields and the generally low capture counts for the taxa, despite that the arrays cumulatively captured all amphibian biodiversity (**Table 3**). Of course, no single survey method is without flaws or biases towards specific taxa. I encourage research into AHDriFT detection of specific target species.

Lastly, data derived from a single array in a field is likely best used for presence-absence research. Species occupancy modelling can be a potential application of camera trap data and combined with environmental, climatic, and spatial covariates (Tobler et al. 2015). However, I obtained too few captures per field for population-level analyses of some species. Researchers seeking to infer species abundance or activity should carefully consider potential limitations to detection when designing a study. On-going research is investigating the cost-efficiency of deploying multiple arrays per field to increase detections.

The use of AHDriFT images for capture-mark-recapture studies would also present a challenge. One reason is due to the variability in how animals entered the buckets or the physical condition inside of the buckets (leaves, water, etc.). These conditions sometimes made unique patterns difficult to discern, especially at night. Automated identification software also needs a degree of image standardization and much larger datasets (Schneider et al. 2019). Furthermore, while Passive Integrated Transponders (PIT tags) are commonly used in capture-mark-recapture (Gibbons and Andrews 2004), readers placed in the camera trap buckets may not be effective because animals did not always fully enter the buckets, and so may not activate the PIT reader. The efficacy of PIT readers combined with AHDriFT can nonetheless be a valuable route for future research. As of this writing, I recommend traditional survey methods such as trapping to identify individuals.

Despite limitations, I found that AHDriFT is an effective new method in general small mammal and herpetofauna surveying. Traditional survey methods can vary in the biodiversity observed of small mammals (Sealander and James 1958) and herpetofauna (Dorcas and Willson 2009). Meanwhile, arrays detected a wide range of multi-taxa biodiversity and 92% of expected snakes and small mammals (**Table 3**). Importantly, this biodiversity included species of different size classes, ranging from invertebrates and mice to weasels and mink. I also imaged many species that are traditionally difficult to detect, such as moles and snakes. This includes four mammal and two snake species in fields where they were not previously observed or expected (**Table 3**). Although I did not image Least Shrews (*Cryptotis parva*), I note that they are rare in Ohio (Bokman et al. 2016), and whether the species truly occurs in these fields is unknown. Using camera traps also removed the serious issues of animal mortality and small mammal bait bias associated with traditional trapping (Beer 1964; De Bondi et al. 2010; Edwards and Jones 2014). Further, traditional survey methods often have few or highly variable captures per unit effort (**Table 4**). I found that AHDriFT was generally equitable in this metric compared to traditional techniques. I could also have decreased the frequency of my field visits, which would have increased array captures per unit effort. However, I caution against stringent interpretation of capture rates across studies of different ecosystems, populations, and species. More research is needed to better quantitatively compare detection rates of different methods in the same geographic and temporal settings.

Nonetheless, AHDriFT generally performed well compared to other PIR camera trap systems for small mammals and herpetofauna. While the Hunt Trap is bait-biased (McCleery et al. 2014), arrays captured diverse species and size classes (**Table 3**). Still, my array design is not suitable for the tidal environments that the Hunt Trap was designed for (McCleery et al. 2014). Additionally, in 300 days COAT imaged 118 reptiles (Welbourne 2014), while in just 210 days arrays averaged 166 reptile captures per array. This may be in part because COAT primarily worked during the day after the cork was sufficiently warmed (Welbourne 2014) and more thermally-homogeneous (Welbourne et al. 2016). The arrays operated continuously and were extremely sensitive, even capturing small invertebrates. The distance of the COAT camera to the ground (70 cm) and size of the detection zone also limited its image quality (Welbourne 2015). Arrays obtained superb species-level images using custom focal-length cameras (**Figure 2**).

Overall, I recommend utilizing AHDriFT to establish site terrestrial vertebrate biodiversity or to target multiple species concurrently. Surveyors seeking to limit person-hours can camera trap numerous sites that would traditionally require intensive field effort. These applications can be especially beneficial to land trusts, permitting agencies, wildlife managers, developers, and environmental consultants. There is also the possibility of incorporating the method into citizen science programs, which could reduce the time required by researchers to verify species identifications (McShea et al. 2016; Schuttler et al. 2019). I conclude that AHDriFT can be a powerful research, management, and conservation tool for small mammals and herpetofauna.

Literature Cited

Beer, J.R. 1964. Bait preferences of some small mammals. Journal of Mammalogy 45:632–634.

Bokman, H., J. Emmert, J. Dennison, J. McCormac, J. Norris, K. Parsons, and A. Rhodedeck. 2016. Mammals of Ohio: field guide. Ohio Department of Natural Resources, Division of Wildlife pub. 5344 R0216.

Bruseo, J.A., and R.E. Barry Jr. 1995. Temporal activity of syntopic *Peromyscus* in the central Appalachians. Journal of Mammalogy 76:78–82.

Campbell, H.W., and S.P. Christman. 1982. Field techniques for herpetofaunal community analysis. Pp. 193–200 *In* Herpetological communities, USDI Fish and Wildlife Service Wildlife Research Report 13. N.J. Scott Jr (Ed).

De Bondi, N., J.G. White, M. Stevens, and R. Cooke. 2010. A comparison of the effectiveness of camera trapping and live trapping for sampling terrestrial small-mammal communities. Wildlife Research 37:456–465.

DeSa, M.A., C.L. ZIig, H.F. Percival, W.M. Kitchens, and J.W. Kasbohm. 2012. Comparison of small-mammal sampling techniques in tidal salt marshes of the central Gulf Coast of Florida. Southeastern Naturalist 11.

Dorcas, M.E., and J.D. Willson. 2009. Innovative methods for studies of snake ecology and conservation. Pp. 5–30 *In* Snakes: Ecology and Conservation, Mullin, S.J., and R.A. Seigal (Eds.). Cornell University Press, New York, USA.

Durso, A.M., and R.A. Seigel. 2015. A snake in the hand is worth 10,000 in the bush. Journal of Herpetology 49:503–506.

Edwards, K.E., and J.C. Jones. 2014. Trapping efficiency and associated mortality of incidentally captured small mammals during herpetofaunal surveys of temporary Itlands. Wildlife Society Bulletin 38:530–535.

Garden, J.G., C.A. McAlpine, H.P. Possingham, and D.N. Jones. 2007. Using multiple survey methods to detect terrestrial reptiles and mammals: what are the most successful and cost-efficient combinations? Wildlife Research 34:218–227.

Geller, G.A. 2012. Notes on the nesting ecology of Ouachita map turtles (*Graptemys ouachitensis*) at two Wisconsin sites using trail camera monitoring. Chelonian Conservation and Biology 11:206–213.

Gibbons, J.W. 2017. Snakes of the eastern United States. University of Georgia Press, Athens, Georgia, USA.

Gibbons, J.W., and K.M. Andrews. 2004. PIT tagging: simple technology at its best. Bioscience 54:447–454.

Glen, A.S., S. Cockburn, M. Nichols, J. Ekanayake, B. Warburton. 2013. Optimising camera traps for monitoring small mammals. PloS One 8.

Greenberg, C.H., D.G. Neary, and L.D. Harris. 1994. A comparison of herpetofaunal sampling effectiveness of pitfall, single-ended, and double-ended funnel traps used with drift fences. Journal of Herpetology:319–324.

Guyer, C., C.T. Meadows, S.C. Townsend, and L.G. Wilson. 1997. A camera device for recording vertebrate activity. Herpetological Review 28:135–140.

Hobbs, M.T., and C.S. Brehme. 2017. An improved camera trap for amphibians, reptiles, small mammals, and large invertebrates. PloS one 12(10): p.e0185026.

Kéry, M. 2002. Inferring the absence of a species: a case study of snakes. The Journal of Wildlife Management:330–338.

Kjoss, V.A., and J.A. Litvaitis. 2001. Comparison of 2 methods to sample snake communities in early successional habitats. Wildlife Society Bulletin:153–157.

Martin, S.A., R.M. Rautsaw, F. Robb, M.R. Bolt, C.L. Parkinson, and R.A. Seigel. 2017. Set AHDriFT: applying game cameras to drift fences for surveying herpetofauna and small mammals. Wildlife Society Bulletin 41(4):804–809.

McCleery, R.A., C.L. ZIig, M.A. DeSa, R. Hunt, W.M. Kitchens, and H.F. Percival. 2014. A novel method for camera-trapping small mammals. Wildlife Society Bulletin 38(4):887–891.

McDiarmid, R.W., M.S. Foster, C. Guyer, N. Chernoff, and J.W. Gibbons. 2012. Reptile biodiversity: standard methods for inventory and monitoring. University of California Press, Berkeley, California, USA.

McShea, W.J., T. Forrester, R. Costello, Z.H. He, and R. Kays. 2016. Volunteer-run cameras as distributed sensors for macrosystem mammal research. Landscape Ecology 31:55–66.

Meek, P.D., G. Ballard, A. Claridge, R. Kays, K. Moseby, T. O’Brien, A. O’Connell, J. Sanderson, D.E. Swann, M. Tobler, and S. Townsend. 2014. Recommended guiding principles for reporting on camera trapping research. Biodiversity and Conservation 23:2321–2343.

Merchant, M., Z. Li, J.A. Sullivan, and A. Cooper. 2013. Modification of camera traps for the study of ectothermic vertebrates. Herpetological Review 44:62–65.

Mitchell, J.C., S.Y. Erdle, and J.F. Pagels. 1993. Evaluation of capture techniques for amphibian, reptile, and small mammal communities in saturated forested wetlands. Wetlands 13:130–136.

Niedballa, J., A. Courtiol, R. Sollman. 2017. camtrapR: camera trap data management and preparation of occupancy and spatial capture-recapture analyses. R package version 0.99.9.

[ODNR] Ohio Department of Natural Resources, Division of Wildlife. 2020. Ohio's listed species. Available at: https://ohiodnr.gov/wps/portal/gov/odnr/discover-and-learn/safety-conservation/about-ODNR/wildlife/state-listed-species (October 2020).

Parsons, K., J. Davis, G.J. Lipps Jr., R. Pfingsten, A. Mann, and G. Denny. 2019. Amphibians of Ohio: field guide. Ohio Department of Natural Resources, Division of Wildlife pub. 5348-0019.

R Core Team. 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Rovero, F., F. Zimmermann, D. Berzi, and P. Meek. 2013. "Which camera trap type and how many do I need?" A review of camera features and study designs for a range of wildlife research applications. Hystrix 24.

Ryan, T.J., T. Philippi, Y.A. Leiden, M.E. Dorcas, T.B. Wigley, and J.W. Gibbons. 2002. Monitoring herpetofauna in a managed forest landscape: effects of habitat types and census techniques. Forest Ecology and Management 167:83-90.

Schneider, S., G.W. Taylor, S. Linquist, and S.C. Kremer. 2019. Past, present and future approaches using computer vision for animal re-identification from camera trap data. Methods in Ecology and Evolution 10:461–470.

Schuttler, S.G., R.S. Sears, I. Orendain, R. Khot, D. Rubenstein, N. Rubenstein, R.R. Dunn, E. Baird, K. Kandros, T. O'Brien, and R. Kays. 2019. Citizen science in schools: students collect valuable mammal data for science, conservation, and community engagement. Bioscience 69:69–79.

Sealander, J.A., and D. James. 1958. Relative efficiency of different small mammal traps. Journal of Mammalogy 39:215–223.

Sears, P.B. 1926. The natural vegetation of Ohio II, the prairies.

Slaughter, B.S., and M.A. Kost. 2010. Natural community abstract for It prairie. Michigan Natural Features Inventory, Lansing, MI:12.

Steen, D.A. 2010. Snakes in the grass: secretive natural histories defy both conventional and progressive statistics. Herpetological Conservation and Biology 5:183–188.

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

Tobler, M.W., A. Zúñiga-Hartley, S.E. Carrillo-Percastegui, and G.V. PoIll. 2015. Spatiotemporal hierarchical modelling of species richness and occupancy using camera trap data. Journal of Applied Ecology 52:413–421.

Welbourne, D.J. 2013. A method for surveying diurnal terrestrial reptiles with passive infrared automatically triggered cameras. PloS One 6:p.e18965.

Welbourne, D.J. 2014. Using camera traps to survey diurnal terrestrial reptiles: a proof of concept. Pp. 225–232 *In* Camera Trapping: Wildlife Management and Research, Meek, P.D. et al. (Eds.). CSIRO Publishing, Melbourne, Victoria, Australia.

Welbourne, D.J., A.W Claridge, D.J. Paull, and A. Lambert. 2016. How do passive infrared triggered camera traps operate and why does it matter? Breaking down common misconceptions. Remote Sensing in Ecology and Conservation 2:77–83.

Welbourne, D.J., C. MacGregor, D. Paull, and D.B. Lindenmayer. 2015. The effectiveness and cost of camera traps for surveying small reptiles and critical weight range mammals: a comparison with labour-intensive complementary methods. Wildlife Research 42:414–425.

Williams, D.F., and S.E. Braun. 1983. Comparison of pitfall and conventional traps for sampling small mammal populations. The Journal of Wildlife Management 47:841–845.

Tables

Table 1. Estimated material cost (USD) per AHDriFT array (Y-shaped). Camera traps were customized by the manufacturer to a focal-length of 28 cm. I include double the SD cards and batteries needed to set the cameras so that they can be swapped and allow for continuous camera operation. The total number of units needed of each piece of equipment is provided (in parentheses). Estimated costs represent the approximate total sum needed to purchase all the units needed of each piece of equipment.

Equipment	Estimated cost (USD)
Camera trap supplies	
Reconyx PIR custom cameras (3)	1,200
Rechargeable AA batteries (72)	90
SD cards (6)	60
TOTAL	**1,350**
Camera trap housing unit supplies	
5-gallon buckets and lids (3)	20
Acrylic sheets (3)	40
Spray paint (1)	4
L-brackets (9)	4
Machine screws / hex nuts (39)	10
Washers (12)	2
Wing nuts (9)	3

Table 1 Continued

Equipment	Estimated cost (USD)
Drywall screws (24)	4
Metal rods (3)	8
Wood studs (2)	5
TOTAL	**100**
Drift fence supplies	
Oriented strand boards (3)	60
Metal fence posts (13)	45
Zip-ties / screws / nuts	15
TOTAL	**120**
TOTAL	**1,570**

Table 2. Typical effort breakdown for constructing and servicing arrays, and the image processing time for all three cameras used in an array. Time range (minutes) minimums and maximums are approximated for array construction and for the final record table. Time range (minutes) minimums and maximums are exact for data acquisition and processing effort (mean ± standard deviation).

Task per array	Time (mins)
AHDriFT array construction	
Build three camera trap housing units	135 – 180
Deploy one array (one person)	90 – 120
Deploy one array (two people)	60 – 90
Deploy one array (three people)	30 – 50
Deploy one array (four people)	30 – 45
Data acquisition and processing	
Change batteries and SD cards	9 – 25 (13.96 ± 3.21)
Process two-weeks of images	24 – 76 (52.32 ± 12.84)
Final record table (‘camtrapR’)	5 – 10

Table 3. Species image capture events (Captures) using AHDriFT. The number of fields that a species was imaged in (Fields) is followed by the total number of possible fields in which the species is known or expected to occur (in parentheses). Field values marked with an asterisk (*) indicate imaged species that are not known or expected to be in these fields, but have been observed in or could potentially inhabit adjacent areas. Listed species have designations after their common names (E = Ohio Endangered; SC = Ohio Species of Concern; R = Rare in Ohio; LT = Federally Threatened).

Species	Common name / status	Captures	Fields
Amphibians			
Ambystoma texanum	Small-mouthed Salamander	1	1(2)
Anaxyrus americanus	American Toad	11	6(15)
Lithobates catesbeianus	American Bullfrog	1	1*
Lithobates clamitans	Green Frog	15	9(15)
Lithobates pipiens	Northern Leopard Frog	24	9(15)
Reptiles			
Chrysemys p. marginata	Midland Painted Turtle	3	3*
Clonophis kirtlandii	Kirtland’s Snake	0	0(2)
Lampropeltis triangulum	Eastern Milksnake	10	5(8)
Nerodia s. sipedon	Northern Watersnake	9	8(8)
Opheodrys vernalis	Smooth Greensnake[E]	15	2(2)
Pantherophis spiloides	Gray [Black] Ratsnake	8	5(1)
Plestiodon fasciatus	Common Five-lined Skink	490	10(12)

Table 3 Continued

Species	**Common name / status**	**Captures**	**Fields**
Sistrurus catenatus	Eastern Massasauga Rattlesnake[E, LT]	72	12(13)
Storeia dekayi	Dekay's Brownsnake	69	12(15)
Storeia occipitomaculata	Northern Red-bellied Snake	3	2(4)
Thamnophis butleri	Butler's Gartersnake	24	1(1)
Thamnophis radix	Plains Gartersnake[E]	26	2(2)
Thamnophis sauritus	Eastern Ribbonsnake	21	6(1)
Thamnophis sirtalis	Eastern Gartersnake	1,745	15(15)
Mammals			
Blarina brevicauda	Northern Short-tailed Shrew	152	15(15)
Condylura cristata	Star-nosed Mole[SC]	16	9(12)
Cryptotis parva	Least Shrew[R]	0	0(15)
Didelphis virginiana	Virginia Opossum	58	13(15)
Marmota monax	Groundhog	7	5*
Mephitis mephitis	Striped Skunk	7	4*
Microtus spp.	Voles	1,390	15(15)
Mustela frenata	Long-tailed Iasel	97	12(15)
Napaeozapus insignis	Woodland Jumping Mouse[SC]	396	13(13)
Neovision vision	American Mink	11	4(12)
Peromyscus spp.	Deer Mice	1,031	15(15)
Procyon lotor	Raccoon	8	5*

Table 3 Continued

Species	**Common name / status**	**Captures**	**Fields**
Rattus norvegicus	Brown Rat	1	1*
Sorex cinereus	Masked Shrew	1,135	14(15)
Sylvilagus floridanus	Eastern Cottontail	212	11(15)
Tamias striatus	Eastern Chipmunk	32	7(10)
Zapus hudsonius	Meadow Jumping Mouse[R]	41	3(3)
Birds and invertebrates			
Dumetella carolinensis	Gray Catbird	5	2
Geothlypis trichas	Common Yellowthroat	58	12
Melospiza melodia	Song Sparrow	633	14
Passerina cyanea	Indigo Bunting	5	1
Porzana carolina	Sora[SC]	1	1
Siala sialis	Eastern Bluebird	1	1
Troglodytes aedon	Northern House Wren	186	12
Invertebrate spp.	Invertebrates	987	15

Table 4. Comparison of catch per unit effort (CPUE) of traditional survey techniques and passive infrared (PIR) camera trapping for common taxa across published studies. Camera trap methods include the Adapted-Hunt Drift Fence Technique (AHDriFT) and PIR game cameras conventionally deployed without drift fences. Sherman livetrap method refers to deployment without drift fences. Drift fence and live-trap combinations (DF + live-trap) for small mammals employ either Sherman, Elliot, or cage live-traps. Drift fence and live-trap combinations (DF + live-trap) for snakes employ pitfall or funnel traps. I estimated CPUE from total captures divided by total trap nights of all sampling units or independent surveys. A single array or traditional drift fence and trap plot, regardless of the number of cameras or traps, is considered as one sampling unit for the purpose of generalizing data. Snake visual and artificial cover surveys categories define each survey of a site as one unit of effort, regardless of walking transect or cover object densities.

Species	**Method**	**CPUE**	**Ecosystem**	**Reference**
Mouse spp.	AHDriFT	0.47	Wet meadow	This study
		0.42	Sand dune	Martin et al. (2017)
	PIR game cameras	0.02	Tidal salt marsh	DeSa et al. (2012)
	Snap-trap	2.20	Forest	Williams and Braun (1983)
	Sherman live-trap	0.25	Forest	Williams and Braun (1983)
		0.13	Forest	Bruseo and Barry Jr. (1995)
	DF + live-trap	0.70	Forest	Williams and Braun (1983)
		0.05	Ephemeral pool	Edwards and Jones (2014)

Table 4 Continued

Species	Method	CPUE	Ecosystem	Reference
Vole spp.	AHDriFT	0.44	Wet meadow	This study
	PIR game cameras	0.00	Tidal salt marsh	DeSa et al. (2012)
	Snaptrap	0.00	Forest	Williams and Braun (1983)
	Sherman live-trap	0.00	Forest	Williams and Braun (1983)
	DF + live-trap	0.25	Forest	Williams and Braun (1983)
		<0.01	Ephemeral pool	Edwards and Jones (2014)
Shrew spp.	AHDriFT	0.41	Wet meadow	This study
		0.02	Sand dune	Martin et al. (2017)
	Snap-trap	0.05	Forest	Williams and Braun (1983)
	Sherman live-trap	0.00	Forest	Williams and Braun (1983)
	DF + live-trap	3.25	Forest	Williams and Braun (1983)
		0.16	Ephemeral pool	Edwards and Jones (2014)
Snake spp.	AHDriFT	0.64	wet meadow	This study
		0.16	Sand dune	Martin et al. (2017)
	PIR game cameras	0.01	Cliff / beach	Ilbourne (2014)
	Visual survey	0.22–0.74	Variable	Kéry (2002)
	Artificial cover	0.37	Grass / scrub	Kjoss and Litvaitis (2001)
	DF + live-trap	0.05	Grass / scrub	Kjoss and Litvaitis (2001)
		0.02	Sand pine scrub	Greenberg et al. (1994)

Figures

Figure 1. (A) Y-shaped Adapted-Hunt Drift Fence Technique (AHDriFT) array in a recently mowed wet meadow field in mid-March, 2019 in Ashtabula County, northern Ohio. An "array" consisted of three passive infrared (PIR) camera traps each set inside of a modified inverted bucket housing unit and placed at the ends of three 4.88 m long drift fences; (B) the entrance of the modified inverted bucket housing unit that connects to the drift fence, with external wooden guide boards; and (C) a downward-facing PIR camera trap attached to a white acrylic sheet over the internal wooden guide boards inside of a bucket housing unit.

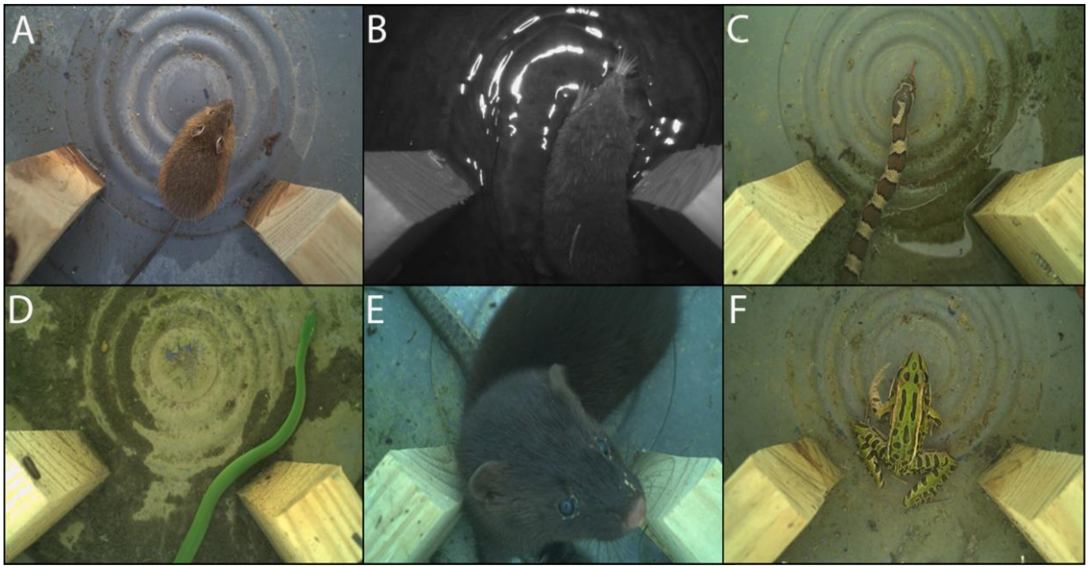

Figure 2. Sample species-level camera trap images captured using AHDriFT. (A) Woodland Jumping Mouse *Napaeozapus insignis*; (B) Star-nosed Mole *Condylura cristata*; (C) Eastern Milksnake *Lampropeltis triangulum*; (D) Smooth Greensnake *Opheodrys vernalis*; (E) American Mink *Neovision vision* consuming an Eastern Gartersnake *Thamnophis sirtalis*; and (F) Northern Leopard Frog *Lithobates pipiens*.

Chapter 2. Use of AHDriFT to Efficiently Survey for *Sistrurus catenatus*

Abstract

The Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) is Federally threatened. Traditional visual encounter and artificial cover object survey techniques are effective but require intensive field effort. The Adapted-Hunt Drift Fence Technique (AHDriFT) is a camera trap and drift fence system that effectively images reptiles, including snakes. I assessed AHDriFT as a potential new Massasauga survey tool relative to traditional methods. Colleagues derived Massasauga population size estimates in 13 wet meadow fields in northern Ohio from 3-y of traditional capture-mark-recapture surveys. I deployed one AHDriFT array (three cameras) per field from March to October 2019. Arrays obtained a total of 72 Massasauga detections across 12 fields. My data suggest that total detection counts may increase with greater population density. Detection probability estimates in each field were typically under 0.30 per week. However, weekly detection probability rose to 0.40 during peak periods of Massasauga activity in the fall. Weekly detection probability also varied by as much as 0.10 due to temperature fluctuations. I estimated 0.48 snakes per person-hour using AHDriFT. This figure is comparable to published surveys and greater than the detection rates from traditional surveys in the same fields. Further, AHDriFT may be better suited for a wider

range of habitat types than traditional methods. Overall, I found that AHDriFT is an effective new Massasauga occupancy survey technique.

Introduction

The Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) is a small (<70 cm) stout-bodied rattlesnake with populations centered around the North American Great Lakes region. They are considered endangered across nearly all of their historic range (Syzmanski et al. 2016) and are Federally threatened (USFWS 2016). The species requires open-canopy early-successional mixed-herbaceous grassland, meadow, or prairie that encompasses or is adjacent to wetlands that host burrowing crayfish (Moore and Gillingham 2006; Smith 2009; Ernst and Ernst 2011; Gibbons 2017; Lipps Jr and Smeenk 2017). Narrow habitat requirements make Massasauga vulnerable to habitat loss through vegetative succession, a primary driver of population declines (Szymanski et al. 2016). Today, extant populations are generally small, isolated, and located on protected properties (Lipps Jr and Smeenk 2017).

Rapid population declines have prompted extensive Massasauga spatial and habitat research (Szymanski et al. 2016), leading to the development of numerous habitat suitability models (Bissell 2006; Harvey and Weatherhead 2006; Moore and Gillingham 2006; Bailey et al. 2012). The models aim to identify areas where Massasauga may occur so that conservation sites can be quickly delineated. However, the habitat suitability models are unable to reliably predict Massasauga occurrence and the predicted suitable habitat typically overestimates actual occupancy (McCluskey 2016; Lipps Jr and Smeenk 2017). The discrepancy between predicted and actual occurrence may in part be because the models do not incorporate historical land uses or landscape resistances. Such influences include localized persecution of the species and barriers to movement such as roads and unsuitable habitat matrices (Chiucci and Gibbs 2010; Willson 2016; McCluskey et al. 2018). Therefore, effective Massasauga field surveys are critical to establish or validate site occupancy and monitor declining or fragmented populations.

The balance between field effort and obtaining snake detections is a common issue faced by researchers (McDiarmid et al. 2012). Snakes are generally difficult to observe because they are secretive (Steen 2010; Durso and Seigal 2015), cryptic, and can move slowly and infrequently (Greene 1997). Traditional visual encounter surveys (VES) and artificial cover object (ACO) surveys are effective at detecting snakes and obtaining detailed data on individuals, but require considerable time investment (Kéry 2002; Dorcas and Willson 2009; McDiarmid et al. 2012).

Visual encounter surveys entail walking sites or transects (McDiarmid et al. 2012). Detection rates and probability can be influenced by observer identity if variation in detection skill among multiple observers is not adequately accounted for in the models (Dorcas and Willson 2009; Albergoni et al. 2016). Artificial cover object surveys typically place plywood or corrugated metal sheets flat on the ground (McDiarmid et al. 2012). Temperate snakes thermoregulate by moving to areas of relative warmth or coolness compared to the ambient conditions (Greene 1997). The ACO create attractive refugia for thermoregulation and congregates snakes that are otherwise difficult to find (McDiarmid et al. 2012). However, detection probability is variable by species, cover material, and length of deployment (Parmelee and Fitch 1995; Fitzgerald 2012; Willson

2016). Whether snakes are observed under ACO is also influenced by survey timing and environmental conditions (Joppa et al. 2009).

The U.S. Fish and Wildlife Service endorsed Massasauga survey protocol recommends at least 40 person-hours of VES per year and 10-y before declaring species absence (Casper et al. 2001). The Ohio ACO (corrugated tin sheets) survey protocol for Massasauga requires about 25 weekly surveys without detections at a site to assume species absence (Lipps Jr and Smeenk 2017). Studies encompassing numerous sites or with limited time or resources may be unable to meet such requirements. Further, not all studies require identification of individual animals or aim to obtain detailed data on individuals (e.g., sex, snout-vent-length, mass, reproductive state). Therefore, camera trapping has been increasingly applied to herpetofauna surveys to reduce field effort when detection/non-detection data are of primary interest for more broadscale inference (e.g., occupancy; Guyer et al. 1997; Merchant et al. 2013; Welbourne 2014; Colley et al. 2017).

Camera traps are remotely operated cameras that image passing wildlife using a trigger, sensor, or timer. Frequently used passive infrared (PIR) cameras activate when the sensor detects an infrared emission differential between the background and animal surfaces. Thus, PIR sensors may not trigger if the infrared differential is less than the sensor's sensitivity threshold (Welbourne et al. 2016). Ectotherm surface temperatures can be similar to background surface temperatures, resulting in small infrared differentials that PIR sensors can fail to detect. Due to trigger sensitivity issues, conventional open-air deployment of PIR camera traps is often ineffective for imaging ectotherms (Merchant et al. 2013; Welbourne 2014; Welbourne et al. 2016). Indeed, PIR camera traps have only had limited success when surveying for Massasauga in confined target areas such as eco-passages (Colley et al. 2017).

A recently developed camera trap system, the Adapted-Hunt Drift Fence Technique (AHDriFT), was designed to image small-bodied mammals (e.g., mice, voles, shrews) and ectotherms in Florida sand dunes (Martin et al. 2017). Modified inverted buckets containing PIR trail cameras are placed at the ends of a drift fence. The buckets concentrate animals into a small detection zone, allowing for species-level identification (McCleery et al. 2014; Martin et al. 2017). Further, the bucket lids raise PIR sensitivity by providing thermal homogeneity under the camera sensors (Welbourne et al. 2016). Martin et al. (2017) found that AHDriFT reduced field effort compared to traditional techniques by 95% in surveys of small mammals and herpetofauna. Amber et al. 2020 also demonstrated this benefit but identified the trade-off of not obtaining detailed data on individual animals.

The AHDriFT system has shown great potential for implementation in snake occupancy surveys by detecting a range of species and size-classes (Martin et al. 2017; Amber et al. 2020). During pilot testing, AHDriFT recorded three Pygmy Rattlesnake (*Sistrurus miliarius*) detections (Martin et al. 2017). Pygmy Rattlesnakes are closely related to Massasauga, are of a comparable size, and have similar natural history characteristics (Ernst and Ernst 2011). The detections provide preliminary evidence that AHDriFT can detect Massasauga, but AHDriFT has never been specifically deployed for Massasauga occupancy surveys. There remains an unresolved potential for AHDriFT to reduce the field effort demanded by traditional Massasauga survey techniques (Lipps Jr and Smeenk 2017). Here, I report a novel application of AHDriFT as a new Massasauga survey tool. The objectives of this study were to: (1) determine Massasauga detection rate and detection probability using a single AHDriFT array per field; (2) assess how temporal, environmental, and spatial covariates influence AHDriFT detection probability; and (3) quantitatively compare AHDriFT to traditional Massasauga survey methods.

Methods

Study sites

I selected northern and northeastern Ohio fields where colleagues have previously conducted 3-y (2015-2017) of Massasauga capture-mark-recapture traditional surveys (Gregory J Lipps Jr., Nicholas A. Smeenk, Douglas Wynn, unpubl. data). I chose one 8.82 ha field in Huron County that is isolated by agriculture. I chose a 26.83-ha field and a 71.78-ha field in Wyandot County that are separated by about 500-m of developed or agricultural matrix. I chose 10 fields in Ashtabula County within a 14-km^2 area of the Grand River Lowlands, of which eight fields are isolated by roads or agriculture (mean size = 2.77 ha; range = 0.39 – 6.52 ha). I considered two partially connected fields as separate because prior research has shown limited exchange of individuals and high field fidelity (Gregory J. Lipps Jr., unpubl. data). I therefore considered all of the fields in this study as independent. The fields are covered by herbaceous vegetation such as goldenrods (*Solidago* spp.) and other forbs, with limited numbers of shrubs and small trees.

I categorized the fields as two different geographic regions. I grouped the Wyandot and Huron County fields as the southern region. These fields are located in the prairie peninsula (Transeau 1935) and include species such as Cordgrass (*Spartina pectinata*), Big Bluestem (*Andropogon gerardii*), Little Bluestem (*Schizachyrium scoparium*), Indiangrass (*Sorghastrum nutans*), and Reed Canary Grass (*Phalaris arundinacea*). I categorized the Ashtabula County fields as the northern region. These fields are mostly sedge meadows dominated by sedges (*Carex* spp.) and rushes (*Juncus* spp.).

Traditional surveys

I synthesized data from over 400 traditional VES and ACO surveys, totaling about 650 person-hours (Gregory J Lipps Jr., Nicholas A. Smeenk, Douglas Wynn, unpubl. data). Colleagues conducted VES and ACO surveys concurrently during each field visit. They recorded a single number of person-hours for the field visit, but tracked captures separately by method of observation. They conducted surveys over about 25 weeks per year, following established Massasauga survey protocol in Ohio (Lipps Jr and Smeenk 2017). The VES entailed one or more researchers walking fields for approximately 30-min on average. The ACO surveys consisted of corrugated tin sheets (2.4 x 0.6-m) set in linear transects (1–2 tin sheets/ha) that were checked at least once per week while concurrently conducting VES (Lipps Jr and Smeenk 2017). Colleagues estimated Massasauga population size (number of individuals) in each field following the Schnabel method (Chapman and Overton 1966) using the R package ‘fishmethods’ (Nelson 2019, version 1.1; R Development Core Team 2019, version 3.6.1).

AHDriFT data collection

I deployed 13 AHDriFT arrays from 10 March to 06 October 2019. Each array operated for 210 survey days (30 survey weeks). I built omni-directional Y-shaped AHDriFT arrays (**Figure 3A**) and placed one array at the geometric center of each field (three cameras per array, 39 total cameras) with one wing oriented to true north. This construction protocol standardized the array deployment between fields and simulated the use of AHDriFT by researchers surveying a new location (i.e., without the prior field-level knowledge of Massasauga distributions and movements that I had available from previous studies). I constructed arrays to withstand the dynamic environmental conditions of wet meadows, including wind, ice, flooding, and heat. Detailed construction and deployment instructions are described elsewhere (Amber et al. 2020) and are also available as an open-source online publication (https://doi.org/10.6084/m9.figshare.12685763.v1). I used Reconyx Hyperfire 2 Professional PIR camera traps (model: HP2X Gen3; Reconyx, Holmen, Wisconsin, USA) with focal lengths and flash customized by the manufacturer to 28 cm. I selected camera settings of highest PIR sensitivity and three-round image burst. I serviced arrays every two-weeks to ensure that they were operating continuously.

I equipped an iButton Hygrochron temperature/humidity logger (model: DS1923; Maxim Integrated, San Jose, California, USA) at each array, which recorded ground temperature (°C) and relative humidity (%) data every 45-min. I set iButtons 5 cm above ground-level with sensors aimed groundward to avoid submersion under water. However, equipment malfunctions lost data prior to 11 June 2019. Therefore, I downloaded hourly ambient temperature (°C) and relative humidity (%) data from the nearest National Oceanic and Atmospheric Administration (NOAA) weather stations starting from 10 March 2019. Since overlapping iButton and NOAA data captured similar weather patterns in each field (Pearson's r = 0.89–0.93, P <<0.01), I determined that NOAA data was acceptable to use in my models for the dates prior to iButton malfunction. I also downloaded daily NOAA precipitation (mm) data for the entire study period. I averaged all weather data into weekly bins.

I assessed eight covariates to account for spatial variation in detection probability (**Table 11**). I quantified vegetation height and density at each array using a Digital Imagery Vegetation Analysis (DIVA; Jorgensen et al. 2013) in mid-July 2019. I imaged the vegetation against a white poster board placed approximately 3 m from the ends of each array arm. I set the camera at about 0.5 m above the ground to image ground-level vegetation. I processed images in Adobe Photoshop (version CC-2018) by converting the vegetation to black pixels and recording the proportion of black pixels in the image (Jorgensen et al. 2013). I then averaged the black pixel proportions of the images from each array arm to obtain a single DIVA score per array. Higher DIVA scores represent taller and denser vegetation than lower scores.

I extracted elevation, slope, and hydrologic flow rate using U.S. Geological Survey (USGS) 3x3 m digital elevation models (DEM) in ArcMap (version 10.0). I determined the dominant land cover at each array from field observations as either shrub/scrub or herbaceous cover. Colleagues created a GIS polygon layer of the fields in ArcMap and I input the layer into the R package 'landscapemetrics' (Hesselbarth et al.

2019, version 1.2.2) to determine field total areas, field edge habitat percentage, and distance of the arrays to forest edges.

Analysis

I processed AHDriFT camera trap images using the R package 'camtrapR' (Niedballa et al. 2017, version 1.1) and considered all three cameras at an array as one sampling unit. I defined detections as Massasauga images at a single array that were taken at least 60-min apart. The interval reduced the likelihood that detections were inflated by one individual moving around an array within a short timeframe (Martin et al. 2017). On five occasions, cameras imaged two snakes within a 60-min interval at the same array (i.e., 10 total potential detections). On these occasions, I attempted to use dorsal patterns to differentiate individuals. However, I could not individually identify all snakes using this method since snakes were not imaged under standardized conditions. Five snakes only partially entered the buckets, the dorsal patterns of two snakes were obscured by water and debris, and one snake moved through the bucket at an angle along the internal guide boards. Under these conditions where I could not reliably differentiate individuals, I only included only one of the two potential detections in the dataset. I was able to confidently differentiate individuals on one occasion and counted both of those detections.

I fit generalized linear mixed effects models (glmm) to test the effects of spatial and temporal covariates on AHDriFT detection probability. I built glmms using a Bayesian framework to account for small sample sizes using the R package 'brms' (Bürkner 2018, version 2.9). I modeled detection probability using separate spatial and temporal models (**Table 12**). The spatial models fit non-temporal field-level covariates (N fields = 13) with Massasauga population size estimates grouped by geographic region (see *Study sites* above) as random slopes, and with geographic region as random intercepts. I fit two models under this framework. First, I modeled the number of Massasauga detections at each field using a Poisson glmm. Second, I assessed the number of weeks that AHDriFT detected Massasauga over the 30-week study period using a binomial glmm.

The temporal model used a Bernouilli glmm to predict weekly detection probability from averaged weather covariates and the sampling season. I defined the season that each detection occurred in by evenly dividing the 30-week study period into three survey sessions. I considered the first 10-week survey session as spring (10 March–19 May 2019), the second as summer (20 May–28 July 2019), and the last as fall (29 July–06 October 2019). I binned temporal covariates and detections by week in order to account for infrequent daily detections. I set a random intercept of field nested within geographic region (i.e., 13 fields nested within northern (10) and southern (3) regions), and a random slope of Massasauga population size estimates grouped by geographic region.

I scaled and centered all continuous predictors to have a mean of zero and standard deviation of one. I manually set all models with normally-distributed priors with a mean of zero and standard deviation of ten. I visually inspected model chains for mixing and used Gelman-Rubin statistics (Rhat < 1.1) to confirm convergence (Cowles and Carlin 1996). I then assessed model fit with posterior predictive checks (Bürkner 2018).

I reduced the global additive models and selected the best-supported final models (**Table 12**) using the R packages ‘bayestestR’ (Makowski et al. 2019, version 0.3) and ‘ggeffects’ (Lüdecke 2018, version 0.12). I fit eight additive models for each of the spatial analyses, step-wise removing insignificant parameters (see below). I reduced both spatial analyses to an additive model of population size estimate and field area. I then fit models with these variables as an interactive effect. I considered the global, reduced additive, and reduced interactive spatial models as candidate models for selection. I fit four additive models for the temporal analyses, step-wise removing parameters. For the global model and after each parameter removed, I fit all combinations of interactive effects. I considered all temporal models (n = 14) as candidate models for selection.

To step-wise reduce the models, I retained the variables whose posterior distributions did not or only marginally included zero. I also checked if the variable had less than 11% of its posterior distribution within the Region of Practical Equivalence (ROPE; Piironen and Vehtari 2017). A small proportion of the distribution within ROPE suggests that the variable likely had a meaningful effect on the response. However, I only used ROPE as a secondary assessment to inform decisions on potentially marginally significant or insignificant variables, and did not necessarily remove all variables with above 11% ROPE.

I conducted model selection of the candidate spatial and temporal models using Watanabe-Akaike information criterion (WAIC) and leave-one-out (LOO) model weights, with the largest weight attributed to the most supported model (Vehtari et al. 2017). I also used Bayes Factors to compare the likelihood of a model correctly capturing data variation relative to another (alternative) model. Large values (>100) can be interpreted as extremely strong evidence supporting the tested model over the alternative model (Lee and Wagenmakers 2014). I selected the best-supported model from among the global and candidate models as the final models for analysis.

In order to compare detection rates from AHDriFT and traditional methods, I considered one-week intervals as one AHDriFT "survey". I chose a one-week interval because VES and ACO surveys are usually conducted on weekly timeframes for Ohio Massasauga (Lipps Jr and Smeenk 2017). Further, AHDriFT is designed to be serviced infrequently rather than daily (Martin et al. 2017), and so it would be impractical to consider one day of camera trap data as one "survey". I determined the AHDriFT detection rate from detections divided by person-hours of effort in the field and spent processing images specifically for Massasauga. I generated the detection rate of concurrent traditional surveys by totaling VES and ACO captures, and dividing by field person-hours. I generated detection rates for VES and ACO separately by dividing captures from each method by the same field person-hours (since the traditional surveys were conducted concurrently). I estimated detection rates from the Massasauga literature using the average or typically conducted survey effort reported. Effort and detection data were not consistently or uniformly reported and so my estimates from the published literature may contain additional error.

Results

Traditional surveys

For each of the three years, colleagues averaged 11 ± (5 SD) surveys per field (range, 5–27 surveys per field) and a mean = 17.79 ± (14.54 SD) total person-hours per field (range, 3.75–67.42 total person-hours per field). I obtained 0.46 Massasauga per person-hour when totaling VES and ACO captures from concurrent surveys (**Table 5**). The VES detections in each field averaged 2 ± (4 SD) Massasauga per year (range, 0–16 Massasauga per year), with a mean of 0.11 Massasauga per person-hour. The ACO surveys in these fields were generally more effective than VES, accounting for 37.5–100% of weekly detections. The ACO survey detections in each field averaged 5 ± (7 SD) Massasauga per year (range, 0–28 Massasauga per year), with a mean of 0.28 Massasauga per person-hour. Each field typically required a mean = 3 ± (3 SD) ACO surveys to obtain the first Massasauga detections within a year (range, 1–13 ACO surveys). Colleagues estimated a mean Massasauga population size = 36 ± (33 SD) individuals per field (range, 3–166 individuals per field). One field had only four detections over 3-y of traditional surveys (21.33 person-hours of survey effort). Three of these detections occurred in 2015 by VES and one occurred in 2017 by ACO survey.

AHDriFT surveys

Arrays imaged Massasauga in 12 of the 13 fields (92%) and obtained 72 Massasauga detections, including eight neonates (**Figure 3B–E**). The field that failed to image a Massasauga only had four prior traditional survey detections. Individual arrays obtained a mean = 6 ± (5 SD) detections (range, 1–20 detections). Ten arrays obtained less than 10 detections each, with two of those arrays each obtaining a single Massasauga detection. All detections occurred between 1000 and 1900 hours, peaking at 1600 hours. After summing array deployment, servicing, and image processing time, I approximated 150 person-hours of total effort (11.5 person-hours per array). Thus, I estimated an average detection rate of 0.48 Massasauga detections per person-hour using AHDriFT (**Table 5**).

Spatial analysis

I reduced the spatial global models to an interaction between population size estimate and field area (**Table 12**), which had a negative relationship but a relatively small effect (20.9% of posterior distribution in ROPE; **Table 6**). Total detection counts increased with larger population size estimates (**Figure 4**), especially in smaller fields (<5 ha) relative to medium-sized fields (5–15 ha), and large fields (>15 ha). However, the estimates had large and overlapping 95% credible intervals (CI). The binomial model predicted Massasauga detections in a mean = 5 weeks (CI = 2–10 weeks) out of a 30-week study period in each field. This equates to a mean of 20% (CI = 5–33%) weekly chance of imaging a Massasauga in a given field based on non-temporal variables.

Temporal analysis

Arrays detected Massasauga in 57 of 390 (14.6%) possible field weeks (13 fields sampled for 30 weeks each; **Table 5**). Four field weeks with detections occurred in spring, 18 field weeks in summer, and 35 field weeks in fall. I detected Massasauga in no more than two and three different fields per week in spring and summer, respectively. Fall had a mean number of fields per week with Massasauga detections = 4 ± (1 SD) fields (range, 2–8 fields), and a weekly detection probability per field as high as 0.40 (**Figure 5**). Mean detection probability of a means-parameterized model that isolated season was 0.28 (CI = 0.00–0.62) in fall, 0.13 (CI = 0.00–0.29) in summer, and 0.15 (CI = 0.00–0.44) in spring. Arrays detected Massasauga on 65 of 2,730 (2.4%) possible field days (13 fields sampled for 210 days each).

The best-supported temporal model included an interaction of season and weekly average temperature (**Table 12**). I only imaged Massasauga in weeks with average temperatures ranging from 10–26° C (**Figure 5**). The data suggest that detection probability in spring may be positively correlated with weekly average temperature, while in summer it may be negatively correlated. However, the credible intervals for these interaction parameters did somewhat overlap zero (**Table 5**). Temperature did not produce a meaningful effect in fall. Overall, weekly average temperature may influence weekly detection probability in each field by up to 0.10, albeit with notable uncertainty in the estimates.

Discussion

The Adapted-Hunt Drift Fence Technique shows promising results as a new Massasauga survey method. Arrays imaged Massasauga at a similar, and often higher, detection rate compared to traditional survey methods while requiring less person-hours (**Table 5**). Shaffer et al. (2019) only surpassed AHDriFT weekly detection probabilities by VES when two surveyors actively searched for over 75-min. Crawford et al. (2020) had greater VES success, but effort influenced detection rates and surveyors walked tight transects only 2–3 m apart. Prior surveys in my fields typically observed only two

Massasauga in each field per year using VES. Comparatively, each AHDriFT array averaged six Massasauga detections.

Bartman et al. (2016) had relatively high detection rates using ACO surveys (**Table 5**). However, the authors deployed ACO in very high densities (14 ACO per 0.06 ha) in conjunction with a drift fence. Such deployment protocol is uncommon and standard Ohio Massasauga survey protocol calls for linear transects of only 1–2 tin sheets/ha (Lipps Jr and Smeenk 2017). In my fields, average yearly ACO (tin) survey detections per field were about equal to AHDriFT detections, but ACO surveys obtained lower detections per person-hour (**Table 5**). Further, surveyors typically needed at least three ACO surveys to first observe a Massasauga each year. The AHDriFT detections per field were also comparable to previous traditional ACO surveys (168 total tin sheets) in two of my fields in 2002 and 2003 (Douglas Wynn, Ohio Department of Natural Resources, unpubl. report, 2003). The first year of ACO surveys obtained 36 Massasauga detections and the second obtained 31 detections. In the same two fields, arrays obtained 31 detections.

Colleagues did yield more detections per year than AHDriFT when combining VES and ACO detections, with a roughly equal detection rate. However, VES and ACO survey efficacy is variable and both methods may not be applicable at all locations or times. Visual encounter surveys work best when vegetation is low (Olson and Warner 2003), making VES most effective in routinely managed fields. Wet meadow vegetation is dense by mid-summer, even in well-maintained fields, which impairs visual detection and reduces VES efficacy in the second half of the active season (Olson and Warner

2003; Crawford et al. 2020). Meanwhile, AHDriFT was not influenced by vegetation density and removed VES observer bias (Dorcas and Willson 2009; Albergoni et al. 2016) by placing arrays at each site's geometric center. Therefore, AHDriFT may be more widely applicable than VES for detecting Massasauga.

Artificial cover object surveys are also not always effective. For example, about 30 tin sheets checked daily through the first half of the active season at Carlyle Lake, Illinois yielded only two Massasauga per year. Late summer checks detected more gestating females and neonates, but overall ACO appears ineffective at this site. Carlyle Lake has a robust Massasauga population and what causes the ACO inefficiency is unclear (Dr. Michael J. Dreslik, Illinois Natural History Survey, pers. comm., July 2020). I suspect in northern Ohio wet meadows that ACO may be less effective where there are numerous alternative cover objects (e.g., downed trees, rocks, dense brush) or where ACO becomes flooded. Conversely, AHDriFT only requires Massasauga to move and encounter the drift fences rather than to congregate under desired cover objects. Further, I observed that Massasauga and other species moved through buckets even if they contained standing water, suggesting that AHDriFT may be less affected by flooding than tin sheets. It is therefore possible that AHDriFT is applicable to a wider range of field habitat types than ACO surveys. I encourage future research that directly compares ACO and AHDriFT efficacy in different Massasauga habitats. Further, ACO surveys are influenced by the time of day, temperature, and sky cover during the survey (Joppa et al. 2009). If ACO surveys cannot be conducted during optimal conditions then they may be ineffective. Researchers and managers surveying many sites or with limited resources can instead deploy continuously active AHDriFT arrays.

Overall, I found that AHDriFT can compare to or exceed the detection efficacy of traditional Massasauga survey methods. The major strengths of AHDriFT are that it is widely applicable and can obtain detections using minimal field effort. However, AHDriFT was ineffective for identifying individuals and I recommend traditional methods for this purpose. Combining Passive Integrated Transponders (PIT tags; Gibbons and Andrews 2004) with arrays remains a potential avenue of research. However, PIT tags are usually placed towards the tail of snakes, so individuals that do not fully enter the buckets may not trigger the PIT reader. In its current design, AHDriFT may be best applied for Massasauga presence-absence surveys or occupancy modeling in numerous fields or in fields where traditional methods are ineffective. Alternatively, AHDriFT can be combined with traditional methods to capture heterogeneity in detection and increase overall encounter success.

Additionally, AHDriFT could be used with N-mixture models or incorporated into integrated population models to make abundance estimates or track population dynamics. However, the total number of snakes observed at sites was typically quite low. As such, counts will need to be summarized over a period of time, requiring some subjective decisions about what constitutes a closed survey period. Researchers may consider deploying multiple arrays per field to increase detections, but AHDriFT costs may be limiting (Amber et al. 2020). The cost-efficiency of this strategy is being assessed as part of on-going research. I also note that AHDriFT captures a wide diversity of small mammal species (Martin et al. 2017; Amber et al. 2020), including Massasauga prey such as Meadow Voles (*Microtus pennsylvanicus*; Keenlyne and Beer 1973). Thus, AHDriFT may potentially be used for concurrent Massasauga prey abundance surveys and I encourage research that examines this application.

Regardless of the survey objectives, researchers that deploy AHDriFT are likely aiming to maximize detection rates. I provide several recommendations to optimize AHDriFT deployment for Massasauga surveys. First, I serviced arrays every two-weeks, but likely could have halved or quartered my field visits. Second, most of the array detections occurred in the fall when detection probability was highest. The fall is when Massasauga breed, give birth, and prepare for overwintering (Ernst and Ernst 2011; Gibbons 2017). Heightened Massasauga activity in late July through September (DeGregorio et al. 2018) increases their likelihood of encountering the AHDriFT drift fences. However, I note that the detection probability estimates across seasons have substantial uncertainty. As such, researchers can likely activate cameras in late summer through the fall when Massasauga are most likely to be imaged, but more research is needed to examine the detection success of a shortened survey season (refer to **Chapter 3**).

Lastly, surveyors can refine AHDriFT deployment by considering temperature. Arrays imaged Massasauga only when weekly average temperatures were between 10–26° C (**Figure 5**). Temperature has been previously shown to affect Massasauga detection (Shaffer et al. 2019; Crawford et al. 2020), likely because ground temperature influences Massasauga movement activity (Moore and Gillingham 2006). Northern

Massasauga populations have the most movement activity when daily temperatures are 30–34° C and show constrained movement below 20° C (Harvey and Weatherhead 2010). Likewise, AHDriFT detections increased in the spring with higher average temperatures (**Figure 5**) that are more suitable to Massasauga movement. Meanwhile, high temperatures during summer exceeded 34° C and potentially reduced Massasauga movements and AHDriFT detections. Overall, researchers can likely focus effort when temperatures are not at their seasonal extremes. For example, my results suggest that when spring temperatures are below 10° C, Massasauga are unlikely to be detected by AHDriFT in northern Ohio. Spring emergence of Massasauga is triggered when temperatures at or near the surface become warmer than the underground hibernacula (Smith 2009; Hileman 2016). In my fields the required underground-surface temperature inversion did not occur until early April.

I identify some important limitations of this study. I focused on landscape-level differences between fields (e.g., topography, hydrology, Massasauga population size, overall field habitat and area) that may affect AHDriFT detections. However, Massasauga spatial ecology and movements may be more strongly influenced by microhabitats than macrohabitats (Harvey and Weatherhead 2010). I did not investigate how array placement within a field or how Massasauga microhabitat preferences (Moore and Gillingham 2006) affected AHDriFT detection as part of this study (refer to **Chapter 3**). Further, large seasonal Massasauga movements occur when Massasauga move from lowland winter hibernacula in the spring to drier upland areas in the active season (Gibbons 2017; DeGregorio et al. 2018). Deploying AHDriFT along these movement corridors or in preferred microhabitats may yield higher detection rates than arrays in field geometric centers.

My statistical analyses are also limited due to low numbers of Massasauga detections at most arrays. Detection rates of Massasauga using AHDriFT is low, particularly in fields with very sparse Massasauga densities (**Figure 4**). Low detections per field may have led to ineffective accounting for variation in detections, resulting in large credible intervals (**Table 6**). I emphasize that the modelling results should be considered as preliminary. Still, I expect that the overall effects of temperature and season reflect real patterns (**Figure 5**). My results are in-line with the expected influence of season and temperature on Massasauga movement (Moore and Gillingham 2006; Harvey and Weatherhead 2010; Gibbons 2017; DeGregorio et al. 2018), Massasauga detection (Shaffer et al. 2019; Crawford et al. 2020), and drift fence efficiency for snakes (Greene 1997; Dorcas and Willson 2009).

Conclusions

Deploying a single AHDriFT array can reduce the field effort of conducting intensive traditional Massasauga surveys and obtain higher detection rates. Thus, surveyors that need to minimize field hours, have limited resources, or need to survey many locations can especially benefit from AHDriFT. I assert that AHDriFT can be of particular use for researchers and managers interested in determining presence-absence or estimating occupancy. Surveyors can also deploy AHDriFT in conjunction with traditional methods to increase Massasauga detections with minimal additional field effort. For example, low-density fields where a single AHDriFT array failed to image

Massasauga can then be specifically targeted using traditional methods. Another option is to conduct VES in the spring while vegetation is low (Olson and Warner 2003), and then AHDriFT in summer and fall when Massasauga are more likely to be imaged (**Figure 5**). Combining AHDriFT and traditional methods may be particularly beneficial since use of multiple survey methods is suggested to strengthen Massasauga monitoring (Bartman et al. 2016). I conclude that AHDriFT is an effective new tool for widespread, non-invasive, and time-efficient surveying of the Federally threatened Massasauga.

Literature Cited

Albergoni, A., I. Bride, C.T. Scialfa, M. Jocque, and S. Green. 2016. How useful are volunteers for visual biodiversity surveys? An evaluation of skill level and group size during a conservation expedition. Biodiversity and Conservation 25(1):133–149.

Amber, E.D., G.J. Lipps, and W.E. Peterman. 2020. Evaluation of the AHDriFT camera trap system to survey for small mammals and herpetofauna. Journal of Fish and Wildlife Management: doi.org/10.3996/JFWM-20-016

Bailey, R.L., H. Campa III, K.M. Bissell, and T.M. Harrison. 2012. Resource selection by the Eastern Massasauga Rattlesnake on managed land in southwestern Michigan. The Journal of Wildlife Management 76(2):414–421.

Bartman, J.F., N. Kudla, D.R. Bradke, S. Otieno, and J.A. Moore. 2016. Work smarter, not harder: comparison of visual and trap survey methods for the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). Herpetological Conservation and Biology 11:451–458.

Bissell, K.M. 2006. Modeling habitat ecology and population viability of the Eastern Massasauga Rattlesnake in southwestern lower Michigan. M.Sc. Thesis, Michigan State University, Department of Fisheries and Wildlife, East Lansing, Michigan, USA. 124 p.

Bürkner, P. 2018. Advanced Bayesian multilevel modeling with the R package brms. The R Journal 10(1):395–411. doi:10.32614/RJ-2018-017.

Casper, G.S., T.G. Anton, R.W. Hay, A.T. Holycross, R.S. King, B.A. Kingsbury, D. Mauger, C. Parent, C.A. Phillips, A. Resetar, and R.A. Seigel. 2001. Recommended standard survey protocol for the Eastern Massasauga, *Sistrurus catenatus catenatus*. U.S. Fish and Wildlife Service:10.

Chapman, D.G., and W.S. Overton. 1966. Estimating and testing differences between population levels by the Schnabel estimation method. The Journal of Wildlife Management 1966:173–180.

Chiucchi, J.E., and H.L. Gibbs. 2010. Similarity of contemporary and historical gene flow among highly fragmented populations of an endangered rattlesnake. Molecular Ecology 19(24):5345–5358.

Colley, M., S.C. Lougheed, K. Otterbein, and J.D. Litzgus. 2017. Mitigation reduces road mortality of a threatened rattlesnake. Wildlife Research 44(1):48–59.

Cowles, M.K., and B.P. Carlin. 1996. Markov chain Monte Carlo convergence diagnostics: a comparative review. Journal of the American Statistical Association 91: 883–904

Crawford, J.A., M.J. Dreslik, S.J. Baker, C.A. Phillips, and W.E. Peterman. 2020. Factors affecting the detection of an imperiled and cryptic species. Diversity 12(5):177.

DeGregorio, B.A., M. Ravesi, J.H. Sperry, S.J. Tetzlaff, J. Josimovich, M. Matthews, and B.A. Kingsbury. 2018. Daily and seasonal activity patterns of the Massasauga (*Sistrurus catenatus*): an automated radio-telemetry study. Herpetological Conservation and Biology 13(1):10–16.

Dorcas, M.E., and J.D. Willson. 2009. Innovative methods for studies of snake ecology and conservation. Pp. 5–37 *In* Snakes: Ecology and Conservation, Mullin, S.J., and R.A. Seigal (Eds.). The Cornell University Press, Ithaca, New York, USA.

Dreslik, M.J., S.J. Wylie, M.A. Davis, D.B. Wylie, and C.A. Phillips. 2011. Demography of the Eastern Massasauga (*Sistrurus c. catenatus*) at Carlyle Lake, Illinois. Illinois Natural History Survey, Champaign, Illinois, USA.

Durso, A.M., and R.A. Seigel. 2015. A snake in the hand is worth 10,000 in the bush. Journal of Herpetology 49(4):503–506.

Ernst, C.H., and E.M. Ernst. 2011. Venomous Reptiles of the United States, Canada, and Northern Mexico, Volume 1: *Heloderma, Micruroides, Micrurus, Pelamis, Agkistrodon, Sistrurus*. The Johns Hopkins University Press, Baltimore, Maryland, USA.

Fitzgerald, L.A. 2012. Finding and capturing reptiles. Pp. 77–80 *In* Reptile Biodiversity: Standard Methods for Inventory and Monitoring, McDiarmid, R.W., M.S. Foster, C. Guyer, J.W. Gibbons, and N. Chernoff (Eds.). The University of California Press, Los Angeles, California, USA.

Gibbons, J.W. 2017. Snakes of the Eastern United States. The University of Georgia Press, Athens, Georgia, USA.

Gibbons, J.W., and K.M. Andrews. 2004. PIT tagging: simple technology at its best. Bioscience 54:447–454.

Greene, H.W. 1997. Snakes: The Evolution of Mystery in Nature. The University of California Press, Berkeley, California, USA.

Guyer, C., C.T. Meadows, S.C. Townsend, and L.G. Wilson. 1997. A camera device for recording vertebrate activity. Herpetological Review 28(3):135–140.

Harvey, D.S., and P.J. Weatherhead. 2006. A test of the hierarchical model of habitat selection using Eastern Massasauga Rattlesnakes (*Sistrurus c. catenatus*). Biological Conservation 130(2):206–216.

Harvey, D.S., and P.J. Weatherhead. 2010. Habitat selection as the mechanism for thermoregulation in a northern population of Massasauga Rattlesnakes (*Sistrurus catenatus*). Ecoscience 17(4):411–419.

Hesselbarth, M.H.K., M. Sciaini, K.A. With, K. Wiegand, and J. Nowosad. 2019. Landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography 42:1–10

Hileman, E.T. 2016. Filling in the gaps in demography, phenology, and life history of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). Ph.D. Dissertation, Northern Illinois University, Dekalb, IL, USA. 128 + appendix p.

Joppa, L.N., C.K. Williams, S.A. Temple, and G.S. Casper. 2009. Environmental factors affecting sampling success of artificial cover objects. Herpetological Conservation and Biology 5(1):143–148.

Jorgensen, C.F., R.J. Stuzman, L.C. Anderson, S.E. Decker, L.A. Powell, W.H. Schacht, and J.J. Fontaine. 2013. Choosing a DIVA: a comparison of emerging digital imagery vegetation analysis techniques. Applied Vegetation Science 16:552–560.

Keenlyne, K.D., and J.R. Beer. 1973. Food habits of *Sistrurus catenatus catenatus*. Journal of Herpetology 7(4):382–384.

Kéry, M. 2002. Inferring the absence of a species: a case study of snakes. The Journal of Wildlife Management 66(2):330–338.

Lee, M.D., and E.J. Wagenmakers. 2014. Bayesian Cognitive Modelling: A Practical Course. Cambridge University Press, Cambridge, UK.

Lipps Jr, G.J., and N.A. Smeenk. 2017. Ohio conservation plan: Massasauga, *Sistrurus catenatus*. Ohio Division of Wildlife:44 + appendices p.

Lüdecke, D. 2018. ggeffects: tidy data frames of marginal effects from regression models.Journal of Open Source Software 3(26):772. doi: 10.21105/joss.00772.

Makowski, D., M. Ben-Shachar, and D. Lüdecke. 2019. bayestestR: describing effects and their uncertainty, existence and significance within the Bayesian framework. Journal of Open Source Software 4(40):1541. doi:10.21105/joss.01541.

Martin, S.A., R.M. Rautsaw, F. Robb, M.R. Bolt, C.L. Parkinson, and R.A. Seigel. 2017. Set AHDriFT: applying game cameras to drift fences for surveying herpetofauna and small mammals. Wildlife Society Bulletin 41(4):804–809.

McCleery, R.A., C.L. Zweig, M.A. Desa, R. Hunt, W.M. Kitchens, and H.F. Percival. 2014. A novel method for camera-trapping small mammals. Wildlife Society Bulletin 38(4):887–891.

McCluskey, E.M. 2016. Landscape ecology approaches to Eastern Massasauga Rattlesnake conservation. Ph.D. Dissertation, The Ohio State University, Columbus, Ohio, USA. 111 p.

McCluskey, E.M., S.N. Matthews, I.Y. Ligocki, M.L. Holding, G.J. Lipps Jr, and T.E. Hetherington. 2018. The importance of historical land use in the maintenance of early successional habitat for a threatened rattlesnake. Global Ecology and Conservation 13: p.e00370.

McDiarmid, R.W., M.S. Foster, C. Guyer, N. Chernoff, and J.W. Gibbons. 2012. Reptile Biodiversity: Standard Methods for Inventory and Monitoring. The University of California Press, Berkeley, California, USA.

Merchant, M., Z. Li, J.A. Sullivan, and A. Cooper. 2013. Modification of camera traps for the study of ectothermic vertebrates. Herpetological Review 44(1):62–65.

Moore, J.A., and J.C. Gillingham. 2006. Spatial ecology and multi-scale habitat selection by a threatened rattlesnake: the Eastern Massasauga (*Sistrurus catenatus catenatus*). Copeia 2006(4):742–751.

Nelson, G.A. 2019. Package ‘fishmethods’. https://CRAN.Rproject.org/package=fishmethods.

Niedballa, J., A. Courtiol, and R. Sollman. 2017. camtrapR: camera trap data management and preparation of occupancy and spatial capture-recapture analyses. R package version 0.99.9. https://CRAN.R-project.org/package=camtrapR.

Parmelee, J.R., and H.S. Fitch. 1995. An experiment with artificial shelters for snakes: effects on material, age, and surface preparation. Herpetological Natural History 3(2):187–191.

Piironen, J., and A. Vehtari. 2017. Comparison of Bayesian predictive methods for model selection. *Statistics and Computing 27*(3):711–735.

R Development Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.

Shaffer, S.A., G.J. Roloff, and H. Campa III. 2019. Survey methodology for detecting Eastern Massasauga Rattlesnakes in southern Michigan. Wildlife Society Bulletin 43(3):508–514.

Smith, C.S. 2009. Hibernation of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus catenatus*) in northern Michigan. M.Sc. Thesis, Purdue University, West Lafayette, Indiana, USA. 34 p.

Steen, D.A. 2010. Snakes in the grass: secretive natural histories defy both conventional and progressive statistics. Herpetological Conservation and Biology 5(2):183–188.

Szymanski, J., C. Pollack, L. Ragan, M. Redmer, L. Clemency, K. Voorhies, and J. JaKa. 2016. Species status assessment for the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). SSA report version 2. United States Fish and Wildlife Service, Fort Snelling, Minnesota. p 103.

Transeau, E.N. 1935. The Prairie Peninsula. Ecology 16(3):423–437.

[USFWS]. U.S. Fish and Wildlife Service. 2016. Endangered and threatened wildlife and plants; threatened species status for the Eastern Massasauga Rattlesnake. Federal Register 81:67193-67214.

Vehtari, A., A. Gelman, and J. Gabry. 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and Computing 27(5):1413–1432.

Welbourne, D.J. 2014. Using camera traps to survey diurnal terrestrial reptiles: a proof of concept. Pp. 225–232 *In* Camera Trapping: Wildlife Management and Research, Meek, P.D., P. Fleming, G. Ballard, P. Banks, A.W. Claridge, J. Sanderson, and D. Swann (Eds.). CSIRO Publishing, Melbourne, Victoria, Australia.

Welbourne, D.J., A.W. Claridge, D.J. Paull, and A. Lambert. 2016. How do passive infrared triggered camera traps operate and why does it matter? Breaking down common misconceptions. Remote Sensing in Ecology and Conservation 2(2):77–83.

Willson, J.D. 2016. Surface-dwelling reptiles. Pp. 125–138 *In* Reptile Ecology and Conservation: A Handbook of Techniques, Dodd, C.K. (Ed.). The Oxford University Press, Oxford, UK.

Tables

Table 5. Comparison of sample detection rates of Massasauga using AHDriFT, visual encounter surveys (VES), and artificial cover object (ACO) surveys. Detection rate metrics from the literature are from published data and only represent the estimated average or typically conducted survey effort reported.

Method	Proportion of surveys with detections	Effort per survey (person-hours)	Snakes per person-hour	Detection probability	Reference
AHDriFT	**14.6%**	**0.38**	**0.48**	**0.00–0.40**	**This study**
VES	20.2%	0.65	0.11	0.18	This study – prior surveys
	20.4%	2.13	0.16	0.08	Shaffer et al. 2019
	44.2%	2.00	0.22	0.40	Crawford et al. 2020
	NA	4.07	0.41	NA	Bartman et al. 2016
	NA	NA	0.41	NA	Dreslik et al. 2011
ACO	45.7%	0.65	0.28	0.45	This study – prior surveys
	NA	NA	0.58	NA	Bartman et al. 2016

Table 6. Parameter estimates of the final generalized linear mixed effect models to assess Massasauga detections using AHDriFT. Estimates presented with 95% credible intervals (CI), probability of direction (pd) which indicates the probability that a parameter estimate has the effect (±) indicated by the mean of the posterior, and percentage of the parameter's posterior distribution that falls within the Region of Practical Equivalence (% ROPE) using 95% of the distribution.

Parameter	Estimate	CI low	CI high	pd	% ROPE
Spatial Binomial					
(number of weeks with a detection)					
Population	0.963	-5.13	7.19	0.663	4.8
Field Size	0.088	-2.04	2.05	0.530	13.2
Population * Field Size	-0.409	-1.48	0.40	0.845	20.9
Spatial Poisson					
(total counts)					
Population	0.798	-4.84	7.59	0.647	3.6
Field Size	0.656	-1.37	2.38	0.718	5.4
Population * Field Size	-0.633	-1.72	0.10	0.956	4.4
Temporal Bernoulli					
(weekly detection probability)					
Average Temperature	0.265	-0.99	1.44	0.637	19.7
Spring Season	-3.414	-6.76	0.66	0.921	1.5

Table 6 Continued

Parameter	Estimate	CI low	CI high	pd	% ROPE
Summer Season	-1.629	-5.20	2.09	0.808	3.9
Fall Season	-0.684	-4.10	3.10	0.672	7.6
Temperature * Spring	2.351	-0.22	5.24	0.942	3.4
Temperature * Summer	-0.748	-2.11	0.79	0.788	11.2
Temperature * Fall	-0.920	-4.71	4.04	0.695	6.3

Figures

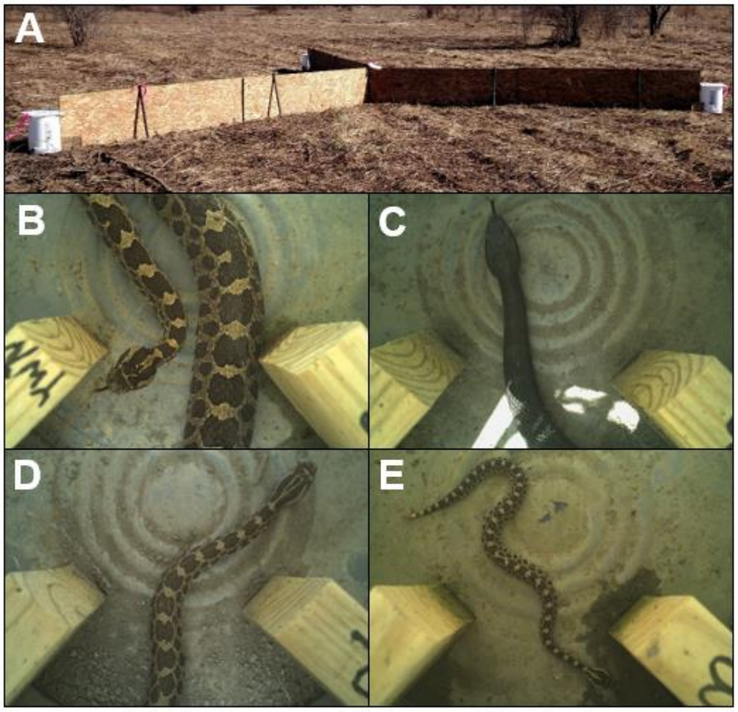

Figure 3. Sample Massasauga images taken using AHDriFT: (A) Y-shaped AHDriFT array with inverted bucket units containing passive infrared trail camera traps; (B) adult with the typical patterning; (C) melanistic adult; (D) juvenile or young adult; (E) neonate.

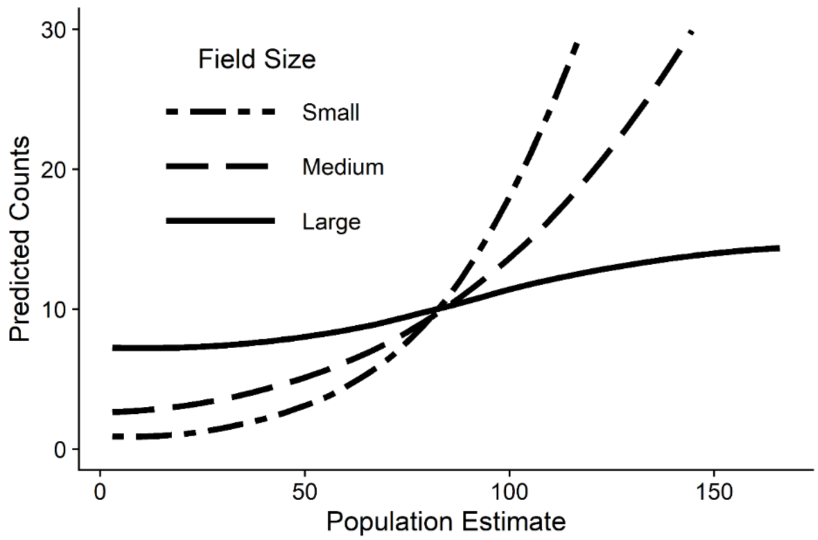

Figure 4. Relationship of Massasauga population size estimate (number of individuals) and field size on predicted total detection counts using AHDriFT. Three general categorizations of field sizes as small (< 5 ha), medium (5–15 ha), and large (> 15 ha). I omitted 95% credible intervals (CI) to more clearly display general patterns but report them here for field sizes of: small (CI = 0–162); medium (CI = 0–88); and large (CI = 0–44).

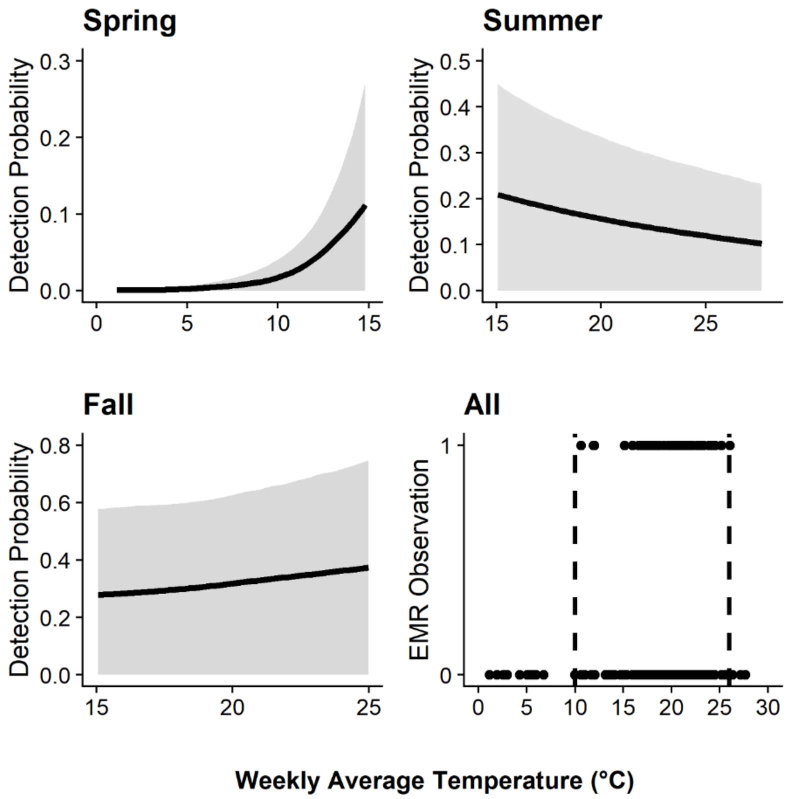

Figure 5. Influence of weekly average temperature on weekly detection probability per AHDriFT array of Massasauga (EMR) across seasons. I defined spring as 10 March–19 May 2019, summer as 20 May–28 July 2019, and fall as 29 July–06 October 2019. Vertical dashed lines indicate the temperature range of Massasauga detections across all seasons combined. Shaded regions indicate 95% credible intervals around mean estimated responses.

Chapter 3. Optimal Deployment and Concurrent Comparison of Tin Artificial Cover and AHDriFT Camera Traps to Survey for *Sistrurus catenatus*

Abstract

The Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) is Federally threatened and Ohio endangered. Artificial cover (corrugated tin sheets) surveys are the primary method used for Ohio Massasauga, but require intensive field effort. The Adapted-Hunt Drift Fence Technique (AHDriFT) is a camera trap method that is effective for detecting Massasauga. These two methods have not been directly compared. I evaluated 20 concurrent weekly surveys for Massasauga using AHDriFT and tin sheets in Wyandot County, Ohio. I evaluated detection rates (detection probability and catch-per-unit-effort) and cost-efficiency, and assessed spatial and temporal detection covariates. I generated error rates from previously collected AHDriFT data to evaluate if my results are generalizable. Arrays obtained 123 Massasauga detections during concurrent surveys, 2 – 4 times that of tin, and exceeded tin catch-per-person-hour by 2.6 – 6 times. The tin surveys achieved a maximum detection probability per survey of 0.5, which was matched using 2 – 4 arrays. Tin was more cost-effective if including initial equipment purchases, while arrays were more cost-effective afterwards. Arrays obtained 92% of captures from May – October, with 74 – 81% of captures after mid-July. Arrays required five field visits for 16 weeks of camera trapping to achieve a confidence of absence >90%. Optimal

array placement is in dense vegetation away from predator perch trees and field edges. Overall, AHDriFT was more effective than tin surveys at detecting Massasauga in these sites. However, these data may not be generalizable and further research is needed in locations with less dense populations. I conclude with preliminary recommendations for an AHDriFT protocol for Massasauga presence-absence surveys in Ohio, pending on-going research.

Introduction

The Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) is a small (<70 cm) stout-bodied rattlesnake with populations centered around the North American Great Lakes region. They are considered endangered across nearly all of their historic range (Syzmanski et al. 2016) and are Federally threatened (USFWS 2016). The species requires open-canopy early-successional mixed-herbaceous grassland, meadow, or prairie that encompasses or is adjacent to wetlands that host burrowing crayfish (Moore and Gillingham 2006; Gibbons 2017; Lipps Jr and Smeenk 2017). Narrow habitat requirements make Massasauga vulnerable to habitat loss through vegetative succession, a primary driver of population declines (Szymanski et al. 2016). Today, extant populations are generally small, isolated, and located on protected properties (Lipps Jr and Smeenk 2017).

In Ohio, where the species is state endangered, currently accepted survey protocols predominantly rely on artificial cover object surveys (corrugated tin sheets; Lipps Jr and Smeenk 2017). Tin sheets create attractive refugia for thermoregulation and congregate snakes that are otherwise difficult to find (McDiarmid et al. 2012). The tin sheets are deployed in linear transects or grids, and then carefully flipped during each survey by permitted specialists who are experienced with venomous snake research. However, whether snakes are observed under cover objects is influenced by survey timing and environmental conditions (Joppa et al. 2009), and tin may not be suitable in all Massasauga habitats (Amber et al. Accepted).

Although effective for detecting Massasauga over a study season (Lipps Jr and Smeenk 2017), tin surveys require intensive field effort since individual tin surveys have low detection rates (McDiarmid et al. 2012). Current protocols in Ohio require about 25 weekly tin surveys before considering the species as absent from a study location (Lipps Jr and Smeenk 2017). Given the expense of venomous snake-specialist researcher or consultant hours, the required field visits can incur high survey costs. Low detection per survey and high survey costs can complicate environmental reviews of development project impacts to the Massasauga (Lipps Jr and Smeenk 2017).

The Adapted-Hunt Drift Fence Technique (AHDriFT) is a drift fence and camera trap system designed to image small mammals and ectotherms (Martin et al. 2017). Prior research has found that AHDriFT is highly sensitive and operates efficiently in Massasauga habitat in Ohio and captures high-quality images (Amber et al. 2020). Amber et al. (Accepted) further demonstrated that AHDriFT is an effective new survey tool for Massasauga and that it compared favorably to previously conducted traditional surveys. However, AHDriFT has not been directly compared to tin surveys by deploying and assessing the methods concurrently. It remains unresolved which method is the more effective technique for Massasauga surveys in terms of detection rates and cost-efficiency. Further, there is ambiguity of how to best deploy AHDriFT to optimize Massasauga detection (Amber et al. Accepted), and a recommended deployment protocol for Massasauga surveys has not yet been established.

The objectives of this study are to: (1) compare the detection rates (detection probability and catch-per-unit-effort) and cost-efficiency of concurrent AHDriFT and tin surveys for Massasauga in northern Ohio; (2) evaluate how within-field spatial covariates influence Massasauga detection for both methods; (3) determine the amount and timing of camera trapping effort required using AHDriFT to achieve a desired confidence of absence; and (4) provide protocol recommendations for AHDriFT deployment density and survey length for Massasauga presence-absence surveys.

Methods

Massasauga surveys

I chose two wet meadow fields in Wyandot County, Ohio, that are separated by approximately 500-m of developed or agricultural matrix and known to host Massasauga populations. I deployed 15 omni-directional Y-shaped AHDriFT arrays (**Figure 1**) from 16 March – 03 October, 2020. Detailed construction and deployment instructions are described elsewhere (Amber et al. 2020) and are also available as an open-source online publication (https://doi.org/10.6084/m9.figshare.12685763.v1). Colleagues deployed 181 corrugated tin sheets (2.4 x 0.6-m) from 17 May – 07 October, 2020 (Douglas Wynn, unpubl. data). University research limitations in response to the COVID-19 pandemic prevented earlier tin surveys. Tin density was set between 1.5 – 2 tin/ha, in accordance with accepted Ohio protocols for Massasauga (Lipps Jr and Smeenk 2017). Although colleagues conducted a total of 41 tin surveys (multiple surveys in some weeks), I selected only the first survey of the week to include in method comparison analyses. Therefore, I constrained the comparison analyses to 20 equal weeks of concurrent surveys for both methods from 14 May – 07 October, 2020. To compare the two methods, I defined a "survey" as one week of camera trapping or one weekly check of all available tin. Since no single definition of a survey can perfectly compare methods that operate on different time schedules (i.e., camera traps are continuous and checked infrequently, while tin surveys are single time points), we recognize that our framework is a subjective attempt to compare these methods using a practical and equitable survey definition.

Typical Massasauga sites in northern and northeast Ohio range from 0.39 – 8.82 ha, with a mean Massasauga density of 3.40 snakes/ha (range of 0.60 – 10.80 snakes/ha; Lipps Jr and Smeenk 2017). I deployed six arrays and 1.5 tin/ha in a 27-ha field that is adjacent to a known major overwintering area (Field A; **Figure 9**), which has a mean estimate of Massasauga density of 3.53 snakes/ha (Amber et al. Accepted). I deployed nine arrays and 2 tin/ha in a 72-ha field (Field B**),** which has a mean estimate of Massasauga density of 2.67 snakes/ha. The deployed arrays and tin encompassed approximately equivalent effective trap areas of available suitable habitat (~90%; based on a 350 m home range from prior telemetry and Ohio Department of Natural Resources Massasauga suitable habitat GIS layer, Gregory J. Lipps Jr., unpubl. data; Lipps Jr and Smeenk 2017).

I processed camera trap images using the R package ‘camtrapR’ (Niedballa et al. 2017, version 1.1; R Development Core Team 2019, version 3.6.1) and considered all three cameras at an array as one sampling unit. I defined AHDriFT detections as Massasauga images at a single array that were taken at least 60-min apart. The interval reduced the likelihood that Massasauga detections were inflated by one individual moving around an array within a short timeframe (Martin et al. 2017). I recorded the individual array and sheet of tin for each Massasauga capture. I also maintained detailed logs of project effort and expenses. I found that the number of captures was significantly different between the two fields (Kolmogorov-Smirnov test, $P < 0.01$). Thus, I conducted separate statistical analyses for each field.

Detection rate analysis

I computed catch-per-unit-effort based on the field time spent checking tin and the field time spent servicing arrays plus the image processing time specifically for Massasauga. To equitably compare detection probabilities of tin and arrays, I generated detection accumulation curves for both methods. To accomplish this, I created weekly detection/non-detection (1/0) datasets from one to the maximum number of units deployed. For instance, I first assumed that only a single unit of tin was deployed, and fit a binomial model for the 20-week detection history for each tin. Next, I assumed two units of tin were used, and looked at all possible combinations of two units of tin. I repeated this process until all units of tin were included. I conducted the same process for AHDriFT arrays. When the number of tin or array combinations exceeded 5,000, I randomly selected 5,000 combinations. I fit maximum likelihood binomial models to all generated datasets in R and calculated the mean and 95% confidence intervals.

I then plotted the AHDriFT accumulation curves along with the mean detection probability estimate per survey for tin densities of 1 – 2 tin/ha. I determined the number of arrays that produced a survey detection probability equivalent to that of the maximum tin density in each field. I then computed the number of weeks needed for that number of arrays to be deployed to achieve a 95% and 99% confidence of Massasauga absence.

Spatial and temporal models

For each array and unit of tin, I recorded the dominant land cover as either herbaceous or mixed vegetation, the distance to the nearest predator perch tree, and the distance to the nearest known or suspected hibernacula area. I delineated hibernacula areas from prior telemetry and observations of muddy snakes around the known spring emergence dates at these sites (Gregory J. Lipps Jr., pers. comm.). For each array, I also quantified vegetation density using a Digital Imagery Vegetation Analysis (DIVA; Jorgensen et al. 2013) in mid-July, 2020. I imaged the vegetation against a 0.6 x 1-m white poster board placed approximately 3 m from the ends of each array arm. I set the camera at about 0.5 m above the ground to image ground-level vegetation. I processed images in Adobe Photoshop (version CC-2018) by converting the vegetation to black pixels and recording the proportion of black pixels in the image (Jorgensen et al. 2013). I then averaged the black pixel proportions of the images from each array arm to obtain a single DIVA score per array. Higher DIVA scores represent taller and denser vegetation than lower scores.

I fit generalized linear mixed effects models (glmm) to test the effects of spatial covariates and week-of-year on total captures per unit of tin or array. Because these models evaluate AHDriFT and tin surveys separately, I used all available data for these analyses (i.e., array data starting in March, and tin data of all 41 surveys). I built glmms using a Bayesian framework using the R package 'brms' (Bürkner 2018, version 2.9). I modelled each surveyed field as a random intercept. I scaled and centered all continuous predictors to have a mean of zero and standard deviation of one. I manually set all models with normally-distributed priors with a mean of zero and standard deviation of ten.

I visually inspected model chains for mixing and used Gelman-Rubin statistics to confirm convergence (Rhat < 1.1; Cowles and Carlin 1996). I then assessed model fit with posterior predictive checks (Bürkner 2018). I reduced our global models and selected our best-supported final models (**Table 13**) using the R packages 'bayestestR' (Makowski et al. 2019, version 0.3). Model support, and subsequently selection was based on Watanabe-Akaike information criterion (WAIC) and leave-one-out (LOO) model weights, with the largest weight attributed to the most supported model (Vehtari et al. 2017). I retained variables whose posterior distributions did not or only marginally included zero. I also checked if the variable had less than 11% of its posterior distribution within the Region of Practical Equivalence (Piironen and Vehtari 2017; ROPE). A small proportion of the distribution within ROPE suggests that the variable likely had a meaningful effect on the response.

Array density and deployment length analysis

I synthesized Massasauga capture data from a prior study in 2019, in which I deployed one AHDriFT array in the centers of 10 fields in northern and northeastern Ohio where colleagues have previously obtained at least one Massasauga detection (Amber et al. Accepted; refer to **Chapter 2**). Using these data, I conducted bootstrap simulation analysis to determine the potential error rate (i.e., failing to detect a Massasauga when it was present) at three confidence thresholds when 1–6 arrays are deployed for three different durations. The steps of this analysis are as follows. First, I fit an intercept-only binomial glm to the 20-week detection history for each of 10 sites. I then calculated 1,000 detection probabilities for each site by sampling from a normal distribution with a mean and standard deviation equal to the estimated intercept and standard error from the fitted model. I then generated 20-week detection histories for the each of the 1,000 detection probabilities, which are equivalent to detection history generated by a single AHDriFT camera array. I then fit binomial models to each detection history to simulate deployment of a single array, or 1,000 random combinations of 2–6 detection histories to simulate deployment of multiple arrays. This resulted in 60,000 detection probability estimates (1,000 estimates for 1–6 arrays deployed * 10 sites). To generalize results, I pooled all detection estimates across sites for each array number combination. Then, given each estimated detection probability, I determined the number of weeks arrays would need to be deployed to achieve 90, 95, and 99% confidence as:

$$weeks = \frac{\log(-confidence + 1)}{\log(1 - detection)}.$$

Finally, I determined the proportion of surveys that would fail to detect a Massasauga, given they were present, using the empirical cumulative distribution function. I assessed survey lengths of 12, 16, and 20 weeks. Because I pooled all sites and equally weighted sites in this simulation, the estimated error rates are independent of patch size or population density and should be a general estimate for most Massasauga populations in Ohio.

Results

Method detection rates and cost-efficiency

Over the 20 weeks of concurrent surveys, 14 arrays (93%) cumulatively obtained 123 Massasauga detections, with a mean of nine per array (**Table 7**). Tin surveys obtained 34 detections from 33 units of tin (18%), with a mean of 0.2 detections per unit of tin. Array detection rate averaged 5.6 snakes per hour of effort, while tin averaged 1.2 snakes per hour of effort. Both methods, but particularly arrays, obtained more captures and greater detection rates in Field A compared to Field B. Arrays obtained about 4.7 times more detections and six times greater catch per unit effort than tin in Field A. Arrays obtained about two times more detections and 2.6 times greater catch per unit effort than tin in Field B. Arrays also recorded greater captures of other species that are traditionally difficult to observe or are species of interest in Ohio (**Table 15**).

In Field A, all six arrays combined achieved a maximum detection probability per survey of 0.9 (**Figure 6A**). Tin surveys achieved a maximum detection probability per survey of 0.5, equivalent to deploying two arrays (0.074 arrays/ha). Deploying two arrays in Field A would obtain a 95% confidence of Massasauga absence after a mean of three weeks of camera trapping (95% confidence interval = 2 – 6 weeks), and 99% confidence after a mean of five weeks (95% confidence interval = 3 – 9 weeks). In Field B, all nine arrays combined achieved a maximum detection probability per survey of 0.6 (**Figure 6B)**. Tin surveys achieved a maximum detection probability per survey of 0.43, equivalent to deploying four arrays (0.056 arrays/ha). Four arrays in Field B would obtain a 95% confidence of Massasauga absence after a mean of five weeks of camera trapping (95% confidence interval = 3 – 11 weeks), and 99% confidence after a mean of eight weeks (95% confidence interval = 5 – 17 weeks). Overall, arrays matched the detection probability of all deployed tin using only about 1 array/15-ha.

The dollar cost (USD) of 20 tin surveys was $5,469, equating to $160.85 per snake detection (**Table 8**). Deploying 15 arrays for 20 weeks of surveys cost $9,496, equating to $211.02 per snake detection. However, 92% of the AHDriFT costs were the initial equipment purchases, particularly the camera materials (86% of total cost), which can be used for multiple seasons (detailed equipment cost breakdown provided in Amber et al. 2020; refer to **Chapter 1**). After removing equipment purchases, the tin surveys cost $72.62 per snake detection while arrays cost $16.58 per snake detection. These figures assume a consultant rate of only $15/hour for the purposes of comparing the methods equably, and likely do not reflect the true costs of a contracted survey or differences in specialist and generalist biologist consultant rates.

Optimal method deployment

Over the full period of AHDriFT deployment, arrays obtained 134 Massasauga detections with 97 from Field A and 37 from Field B. Across all 41 tin surveys, tin obtained 52 Massasauga detections with 31 from Field A and 21 from Field B. I provide as supplemental material the global and best-supported spatial and temporal models (**Table 13**), and details of final parameter results (**Table 14**). Here, I report parameter estimates and 95% credible intervals (CI). Tin survey captures were not significantly influenced by any of the spatial covariates. For arrays, vegetation density (0.51, CI = -0.04 – 1.12; **Figure 7A**) and distance to a predator perch tree (0.51, CI = -0.12 – 1.11; **Figure 7B**) were the best-supported spatial covariates for predicting captures.

Tin surveys in Field A increased captures with increasing week-of-year (0.44, CI = -0.12 – 1.01), with 63% of captures after 15 July, 2020. However, tin in Field B did not produce this effect (-0.03, CI = -0.62 – 0.55; 29% in ROPE), with 53% of captures after 15 July. Arrays obtained 92% of total captures from May – October, with captures after 15 July accounting for 74% of captures in Field A and 81% of captures in Field B. Arrays in Field A obtained 40% of its captures from 20 August – 09 September. The week-of-year model parameter had a positive effect on array captures in both Field A (0.10, CI = 0.06 – 0.15; **Figure 8A**) and Field B (0.08, CI = 0.02 – 0.13; **Figure 8B**). Still, we caution that the week-of-year parameter for arrays exceeded 11% ROPE in Field A (12.3%) and Field B (23.7%; **Table 14**).

Previously deployed arrays in 2019 in sites with smaller Massasauga populations achieved substantially lower detection probabilities per survey of only 0.1 – 0.4 (**Figure 6C**). At these sites, I found that a minimum of three arrays deployed for 16 weeks or four arrays deployed for 12 weeks are necessary to achieve above 90% confidence of absence with less than 10% error rate (**Table 9**).

Discussion

The AHDriFT arrays outperformed concurrent tin surveys for Massasauga at these sites in terms of total captures, detection rates, and cost-efficiency after initial equipment investment (**Table 10**). I conducted double or nearly double array field visits than is strictly necessary for the method (Amber et al. 2020), so the array catch-per-person-hour could have been even higher (**Table 7**). However, I conducted these surveys in sites with Massasauga populations that are atypically high for Ohio. Massasauga population size positively correlates with captures using AHDriFT (Amber et al. Accepted). Further, the synthesis of prior AHDriFT surveys demonstrated that small population sites need to deploy arrays for longer timeframes and in greater densities to achieve an equivalent confidence of absence and low error rate (**Table 9**). As such, although these data suggest that deploying 1 array/15-ha for an eight-week survey period is sufficient, I suspect that this protocol is not generalizable.

Therefore, I recommend a conservative approach to AHDriFT deployment in its current form. I encourage researchers to deploy a minimum of three arrays per field, independent of field area, and then an additional 1 array/10-ha (e.g., a 20-ha field would have five arrays). However, due to the species decline, habitat fragmentation, and that most fields able to be purchased, managed, or surveyed for conservation are small (<3 ha; Lipps Jr. and Smeenk 2017), fields that host extant Massasauga will likely only require three arrays. I suggest at least 16 weeks of camera trapping to ensure the greatest confidence in assessment of absence. Although arrays should be built in early spring prior to Massasauga emergence (Amber et al. Accepted), I recommend activating cameras from June through September to minimize image processing effort (**Figure 8**). This period corresponds to when Massasauga movement activity is greatest (DeGregorio et al. 2018), and thus when they are most likely to be imaged. On-going research is examining AHDriFT deployment protocols across numerous sites in Ohio that are more representative of typical Massasauga population sizes in the state.

Researchers following my recommended array deployment density and survey length may face the obstacle of the high initial equipment costs per array (Amber et al. 2020). Still, AHDriFT has the potential to ultimately lower the costs of environmental reviews for Massasauga by requiring far fewer field person-hours than traditional methods (Martin et al. 2017; **Table 8**). Arrays require about 15-min of servicing every 4 – 8 weeks (Amber et al. 2020), so deploying additional arrays does not substantially increase field effort. Further, researchers only need to conduct about five field visits for 16 weeks of AHDriFT surveys. Meanwhile, tin surveys require about 25 weekly visits in Ohio, which may incur a significant cost of researcher hours. Camera traps are also non-invasive, which is less stressful on the snakes and removes the obstacles of acquiring handling permits and hiring or training staff proficient in venomous snake handling. Therefore, AHDriFT is a technique that can be applied by any wildlife biologist, removing the potentially significant expense of contracting specialist consultants.

In sum, investing in AHDriFT is best when cameras will be utilized for multiple seasons or projects. I encourage researchers conducting tin surveys for Massasauga to evaluate their field effort costs to determine if AHDriFT will be more cost-efficient for their study designs. Further, deployment of two-camera arrays (Martin et al. 2017) rather than my three camera arrays could potentially reduce both equipment costs and image processing effort. On-going research is evaluating if there is a meaningful difference in detection rates between linear and omni-directional designs.

I did not discern spatial or temporal covariates that meaningfully influenced tin detections for Massasauga. I suspect that this is in part because tin survey efficacy is primarily influenced by the environmental conditions on the survey date (Joppa et al. 2009). Further, the dense and linear deployment of the tin units may not have captured enough spatial heterogeneity between tin units to discern potential spatial effects on detection (**Figure 9**). I therefore strongly caution against an interpretation that Massasauga captures are not affected by tin placement, and I encourage future research using fine-scale spatial parameters and different tin placement configurations.

I did find that AHDriFT detection rates for Massasauga were greatest when arrays were set in dense, herbaceous vegetation, away from field edges and predator perch trees (**Figure 7**). Further, Field A obtained far greater captures and detection rates than Field B (**Table 7**; **Figure 6**). These observations are likely explained by the location of Field A immediately adjacent to a major overwintering area for the species. Massasauga make seasonal movements from lowland hibernacula in the spring to drier upland areas during the active season, and back again in the fall (Gibbons 2017; DeGregorio et al. 2018). As AHDriFT relies on animals encountering the drift fences, the method is most efficient when species are moving more frequently and over larger distances (Amber et al. 2020).

Therefore, placing arrays between suspected hibernacula and active season habitats may increase detections by intercepting snakes during their seasonal movements.

However, the covariate of array distance to hibernacula did not yield a significant effect on captures. I suspect that this may be because I roughly estimated most hibernacula areas from prior observations. Further, prior telemetry reveals that some individuals active in Field B actually overwinter next to Field A (Gregory J. Lipps Jr., pers. comm.), which could have confounded the model term. I encourage further research of array placement using confident delineations of hibernacula areas across numerous, fully independent populations.

I also recognize that the spatial metrics may have been too coarse to best evaluate differences in Massasauga movements (i.e., array captures) within each field. Massasauga movement activity is more strongly driven by microhabitat preferences than macrohabitat characteristics (Moore and Gillingham 2006; Harvey and Weatherhead 2010). Although I recorded spatial metrics at each array, the number of array sample points may not have been adequate to capture microhabitat heterogeneity in these fields. In addition to my recommended array placement protocol, I encourage researchers to consider Massasauga microhabitat preferences and movement activity predictors.

Overall, this study suggests that AHDriFT may be a more effective survey method for Massasauga than traditional tin surveys, as well as for numerous other species (**Table 15;** Martin et al. 2017; Amber et al. 2020; Amber et al. Accepted). By investing in cameras for multiple seasons of use, wildlife biologists can have a time and cost-efficient means to non-invasively conduct presence-absence Massasauga surveys. Additionally, researchers can benefit from the larger sample sizes obtained using AHDriFT for use in more sophisticated analyses than presence-absence. Future research is warranted to further develop AHDriFT protocols that are more generalizable for typical Massasauga population sizes across their range.

Literature Cited

Albergoni, A., I. Bride, C.T. Scialfa, M. Jocque, and S. Green. 2016. How useful are volunteers for visual biodiversity surveys? An evaluation of skill level and group size during a conservation expedition. Biodiversity and Conservation 25:133–149.

Amber, E.D., G.J. Lipps Jr., and W.E. Peterman. 2020. Evaluation of the AHDriFT camera trap system to survey for small mammals and herpetofauna. Journal of Fish and Wildlife Management: doi.org/10.3996/JFWM-20-016

Amber, E.D., G.J. Lipps Jr., J.M. Myers, N.A. Smeenk, and W.E. Peterman. Accepted. Use of AHDriFT to efficiently survey for *Sistrurus catenatus*. Herpetological Conservation and Biology.

Bürkner, P. 2018. Advanced Bayesian multilevel modeling with the R package brms. The R Journal 10(1):395–411. doi:10.32614/RJ-2018-017.

Cowles, M.K., and B.P. Carlin. 1996. Markov chain Monte Carlo convergence diagnostics: a comparative review. Journal of the American Statistical Association 91(434):883–904.

DeGregorio, B.A., M. Ravesi, J.H. Sperry, S.J. Tetzlaff, J. Josimovich, M. Matthews, and B.A. Kingsbury. 2018. Daily and seasonal activity patterns of the Massasauga (*Sistrurus catenatus*): an automated radio-telemetry study. Herpetological Conservation and Biology 13:10–16.

Gibbons, J.W. 2017. Snakes of the Eastern United States. The University of Georgia Press, Athens, Georgia, USA.

Harvey, D.S., and P.J. Weatherhead. 2010. Habitat selection as the mechanism for thermoregulation in a northern population of Massasauga Rattlesnakes (*Sistrurus catenatus*). Ecoscience 17:411–419.

Joppa, L.N., C.K. Williams, S.A. Temple, and G.S. Casper. 2009. Environmental factors affecting sampling success of artificial cover objects. Herpetological Conservation and Biology 5(1):143–148.

Jorgensen, C.F., R.J. Stuzman, L.C. Anderson, S.E. Decker, L.A. Powell, W.H. Schacht, and J.J. Fontaine. 2013. Choosing a DIVA: a comparison of emerging digital imagery vegetation analysis techniques. Applied Vegetation Science 16:552–560.

Lipps Jr, G.J., and N.A. Smeenk. 2017. Ohio conservation plan: Massasauga, *Sistrurus catenatus*. Ohio Division of Wildlife:44 + appendices p.

Makowski, D., M. Ben-Shachar, and D. Lüdecke. 2019. bayestestR: describing effects and their uncertainty, existence and significance within the Bayesian framework. Journal of Open Source Software 4(40):1541. doi:10.21105/joss.01541.

Martin, S.A., R.M. Rautsaw, F. Robb, M.R. Bolt, C.L. Parkinson, and R.A. Seigel. 2017. Set AHDriFT: applying game cameras to drift fences for surveying herpetofauna and small mammals. Wildlife Society Bulletin 41(4):804–809.

McDiarmid, R.W., M.S. Foster, C. Guyer, N. Chernoff, and J.W. Gibbons. 2012. Reptile Biodiversity: Standard Methods for Inventory and Monitoring. The University of California Press, Berkeley, California, USA.

Moore, J.A., and J.C. Gillingham. 2006. Spatial ecology and multi-scale habitat selection by a threatened rattlesnake: the Eastern Massasauga (*Sistrurus catenatus catenatus*). Copeia 2006:742–751.

Niedballa, J., A. Courtiol, and R. Sollman. 2017. camtrapR: camera trap data management and preparation of occupancy and spatial capture-recapture analyses. R package version 0.99.9. https://CRAN.R-project.org/package=camtrapR.

Piironen, J., and A. Vehtari. 2017. Comparison of Bayesian predictive methods for model selection. *Statistics and Computing 27*(3):711–735.

R Development Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.

Szymanski, J., C. Pollack, L. Ragan, M. Redmer, L. Clemency, K. Voorhies, and J. JaKa. 2016. Species status assessment for the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). SSA report version 2. United States Fish and Wildlife Service, Fort Snelling, Minnesota. p 103.

[USFWS] U.S. Fish and Wildlife Service. 2016. Endangered and threatened wildlife and plants; threatened species status for the Eastern Massasauga Rattlesnake. Federal Register 81:67193-67214.

Vehtari, A., A. Gelman, and J. Gabry. 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and Computing 27(5):1413–1432.

Tables

Table 7. Comparison of Massasauga captures and detection rates of concurrent AHDriFT and tin surveys. The field identifier is provided after the method type (in parentheses). Field A has a very high Massasauga density relative to most sites in Ohio and is adjacent to a major overwintering area. Field B has a moderately high Massasauga density relative to most sites in Ohio. I conducted double or nearly double array field visits than is strictly necessary for the method, denoted by an asterisk (*), which lowered our potential catch-per-unit-effort (CPUE; captures/person-hours). I defined effort as the time spent in the field checking tin, and the time spent in the field servicing arrays plus image processing time specifically for Massasauga.

Metric	Tin (A)	Arrays (A)	Tin (B)	Arrays (B)
Total captures	19	91	15	32
Density (units/ha)	1.5	0.22	2.0	0.13
Effort hours (field visits)	13 (20)	10 (6*)	20 (20)	15 (6*)
Estimated CPUE	1.5	9.1	0.8	2.1

Table 8. Approximate dollar cost (USD) expense comparison of tin and AHDriFT surveys for Massasauga. Twenty field visits for tin surveys of 181 tin units resulted in 34 Massasauga captures. Only about five field visits of five arrays (three cameras per array) were needed to equate to the tin maximum detection probability, with a mean of nine Massasauga captures per array (five arrays would achieve an estimated 45 captures). I note that Ohio protocol typically calls for ~25 tin surveys, which would increase the travel and field expenses presented here. Estimates assume that each method employs a single researcher paid $15 (USD) per hour, who is based out of the Columbus, Ohio area (~120-mile roundtrip per field visit). Tin survey costs do not include miscellaneous equipment (i.e., snake tongs, bags) or time to process captured snakes.

Expense	Estimated cost – tin	Estimated cost – AHDriFT
Equipment	3,000 (181 tin sheets)	8,750 (five arrays)
Mileage ($0.56/mile)	1,344	336
Travel time pay	750	165
Field time pay	375	95
Image sorting pay	NA	150
Totals with equipment purchase		
Sum	5,469	9,496
Cost per snake	160.85	211.02
Totals without equipment purchase		
Sum	2,469	746
Cost per snake	72.62	16.58

Table 9. Estimated error rate in failing to detect a Massasauga when present, independent of field size or population density, that a given number of AHDriFT arrays will have at a desired confidence of absence threshold (90%, 95%, or 99%) and when arrays are deployed for 12, 16, or 20 weeks. Bolded values in the table highlight when the error rate is ≤0.10. Values are generated from an analysis of 2019 AHDriFT data (Amber et al. Accepted; refer to **Chapter 2**).

	12 weeks			**16 weeks**			**20 weeks**		
Arrays	**90%**	**95%**	**99%**	**90%**	**95%**	**99%**	**90%**	**95%**	**99%**
1	0.51	0.61	0.79	0.38	0.51	0.71	0.38	0.38	0.61
2	0.23	0.31	0.48	0.16	0.23	0.39	0.16	0.16	0.31
3	0.13	0.18	0.31	0.08	0.13	0.24	0.08	0.08	0.18
4	0.08	0.12	0.20	0.04	0.08	0.16	0.04	0.04	0.12
5	0.05	0.07	0.14	0.02	0.05	0.11	0.02	0.02	0.07
6	0.02	0.05	0.10	0.01	0.02	0.07	0.01	0.01	0.05

Table 10. Summary comparison matrix of tin surveys and AHDriFT arrays for Massasauga. The AHDriFT detection probability lower range is using the array density needed to equate to the detection probability of 1.5 – 2 tin/ha, and the upper range is using all deployed arrays.

Method aspect	Tin	AHDriFT
Typical length of survey season	25 weeks	16 weeks
Total field visits per season	25	5
Expected captures per season	17	62
USD per snake after equipment	72.62	16.58
Snakes per person-hour	1.2	5.6
Detection probability per survey	~0.50	0.50 – 0.90
Researcher experience and skill	Snake specialist	Wildlife biologist
USFWS and OH Div. of Wildlife endangered species permits	Required	None

Figures

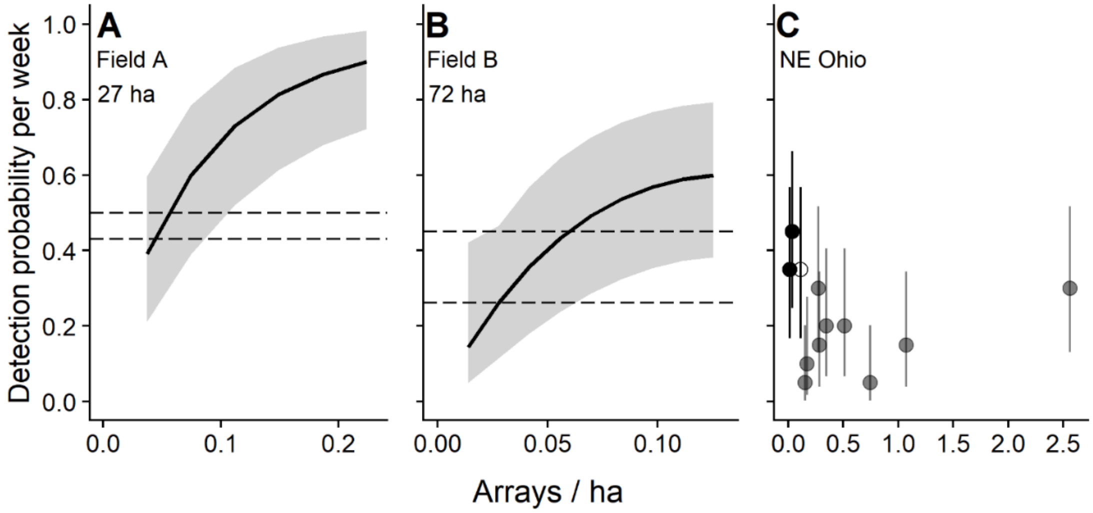

Figure 6. (A, B) Massasauga weekly detection probability accumulation curves of increasing AHDriFT array density. Dashed horizontal lines represent the minimum and maximum detection probability per survey of concurrent tin surveys within the unit density range acceptable in the current Ohio Massasauga protocol (1 – 2 tin/ha). Field A has a relaitvely high Massasauga density relative to most sites in Ohio and is adjacent to a major overwintering area. Field B has a moderately high Massasauga density relative to most sites in Ohio. (C) Massasauga weekly detection probability means and 95% confidence intervals using AHDriFT arrays in northern and northeastern Ohio sites from a prior study (Amber et al. Accepted; refer to **Chapter 2**). Shading represents relative categorizations of Massasauga population size estimates, including: large (black), moderate (hollow), and small (grey).

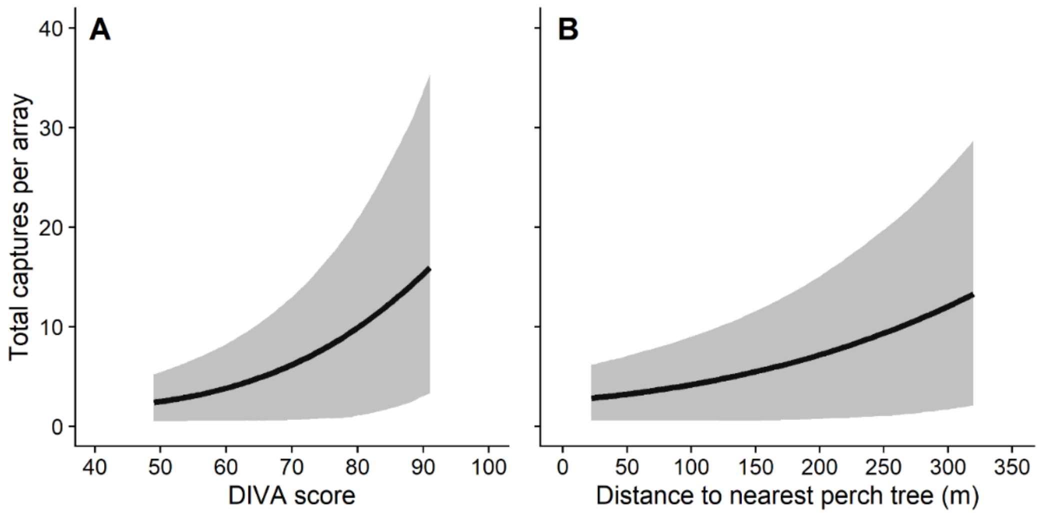

Figure 7. Influence on Massasauga weekly total captures per AHDriFT array of (A) vegetation density, with higher Digital Imagery Vegetation Analysis (DIVA) scores corresponding to denser wet meadow vegetation; and (B) the distance of the array from the nearest tree suitable for avian predators to perch on.

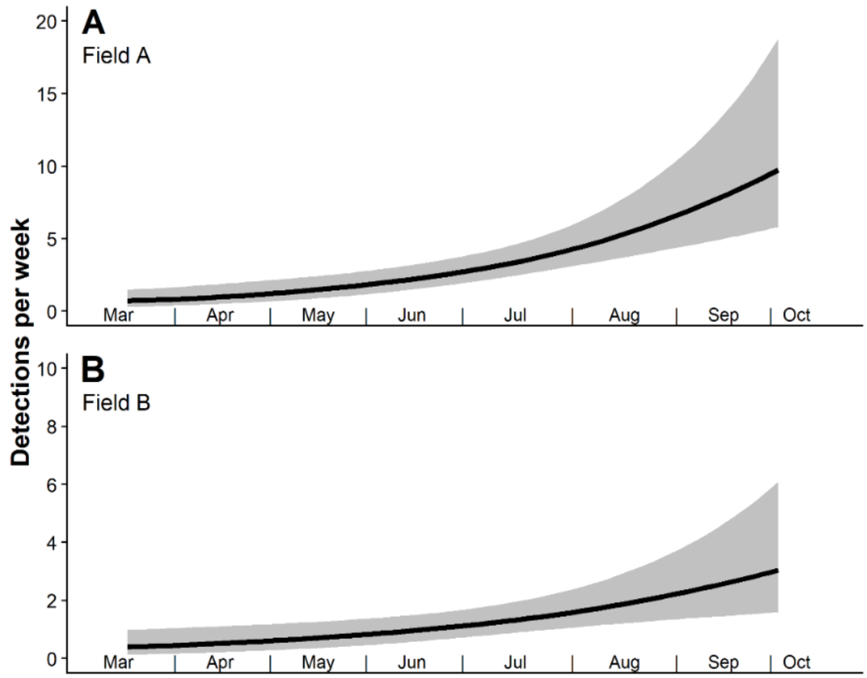

Figure 8. Influence of week of year on Massasauga weekly total captures per AHDriFT array. Field A has a higher Massasauga density relative to mean estimates for most sites in northern Ohio and is adjacent to a major overwintering area. Field B has a moderately high Massasauga density relative to most sites in northern Ohio.

References

Albergoni, A., I. Bride, C.T. Scialfa, M. Jocque, and S. Green. 2016. How useful are volunteers for visual biodiversity surveys? An evaluation of skill level and group size during a conservation expedition. Biodiversity and Conservation 25:133–149.

Amber, E.D., G.J. Lipps Jr., and W.E. Peterman. 2020. Evaluation of the AHDriFT camera trap system to survey for small mammals and herpetofauna. Journal of Fish and Wildlife Management: doi.org/10.3996/JFWM-20-016

Amber, E.D., G.J. Lipps Jr., J.M. Myers, N.A. Smeenk, and W.E. Peterman. Accepted. Use of AHDriFT to efficiently survey for *Sistrurus catenatus*. Herpetological Conservation and Biology.

Bailey, R.L., H. Campa III, K.M. Bissell, and T.M. Harrison. 2012. Resource selection by the Eastern Massasauga Rattlesnake on managed land in southwestern Michigan. The Journal of Wildlife Management 76(2):414–421.

Bartman, J.F., N. Kudla, D.R. Bradke, S. Otieno, and J.A. Moore. 2016. Work smarter, not harder: comparison of visual and trap survey methods for the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). Herpetological Conservation and Biology 11:451–458.

Beer, J.R. 1964. Bait preferences of some small mammals. Journal of Mammalogy 45:632–634.

Bissell, K.M. 2006. Modeling habitat ecology and population viability of the Eastern Massasauga Rattlesnake in southwestern lower Michigan. M.Sc. Thesis, Michigan State University, Department of Fisheries and Wildlife, East Lansing, Michigan, USA. 124 p.

Bokman, H., J. Emmert, J. Dennison, J. McCormac, J. Norris, K. Parsons, and A. Rhodedeck. 2016. Mammals of Ohio: field guide. Ohio Department of Natural Resources, Division of Wildlife pub. 5344 R0216.

Bruseo, J.A., and R.E. Barry Jr. 1995. Temporal activity of syntopic *Peromyscus* in the central Appalachians. Journal of Mammalogy 76:78–82.

Bürkner, P. 2018. Advanced Bayesian multilevel modeling with the R package brms. The R Journal 10(1):395–411. doi:10.32614/RJ-2018-017.

Campbell, H.W., and S.P. Christman. 1982. Field techniques for herpetofaunal community analysis. Pp. 193–200 *In* Herpetological communities, USDI Fish and Wildlife Service Wildlife Research Report 13. N.J. Scott Jr (Ed).

Casper, G.S., T.G. Anton, R.W. Hay, A.T. Holycross, R.S. King, B.A. Kingsbury, D. Mauger, C. Parent, C.A. Phillips, A. Resetar, and R.A. Seigel. 2001. Recommended standard survey protocol for the Eastern Massasauga, *Sistrurus catenatus catenatus*. U.S. Fish and Wildlife Service:10.

Chapman, D.G., and W.S. Overton. 1966. Estimating and testing differences between population levels by the Schnabel estimation method. The Journal of Wildlife Management 1966:173–180.

Chiucchi, J.E., and H.L. Gibbs. 2010. Similarity of contemporary and historical gene flow among highly fragmented populations of an endangered rattlesnake. Molecular Ecology 19(24):5345–5358.

Colley, M., S.C. Lougheed, K. Otterbein, and J.D. Litzgus. 2017. Mitigation reduces road mortality of a threatened rattlesnake. Wildlife Research 44(1):48–59.

Cowles, M.K., and B.P. Carlin. 1996. Markov chain Monte Carlo convergence diagnostics: a comparative review. Journal of the American Statistical Association 91(434):883–904.

Crawford, J.A., M.J. Dreslik, S.J. Baker, C.A. Phillips, and W.E. Peterman. 2020. Factors affecting the detection of an imperiled and cryptic species. Diversity 12(5):177.

DeGregorio, B.A., M. Ravesi, J.H. Sperry, S.J. Tetzlaff, J. Josimovich, M. Matthews, and B.A. Kingsbury. 2018. Daily and seasonal activity patterns of the Massasauga (*Sistrurus catenatus*): an automated radio-telemetry study. Herpetological Conservation and Biology 13:10–16.

DeSa, M.A., C.L. ZIig, H.F. Percival, W.M. Kitchens, and J.W. Kasbohm. 2012. Comparison of small-mammal sampling techniques in tidal salt marshes of the central Gulf Coast of Florida. Southeastern Naturalist 11.

Dorcas, M.E., and J.D. Willson. 2009. Innovative methods for studies of snake ecology and conservation. Pp. 5–30 *In* Snakes: Ecology and Conservation, Mullin, S.J., and R.A. Seigal (Eds.). Cornell University Press, New York, USA.

Durso, A.M., and R.A. Seigel. 2015. A snake in the hand is worth 10,000 in the bush. Journal of Herpetology 49:503–506.

Edwards, K.E., and J.C. Jones. 2014. Trapping efficiency and associated mortality of incidentally captured small mammals during herpetofaunal surveys of temporary Itlands. Wildlife Society Bulletin 38:530–535.

Ernst, C.H., and E.M. Ernst. 2011. Venomous Reptiles of the United States, Canada, and Northern Mexico, Volume 1: *Heloderma, Micruroides, Micrurus, Pelamis, Agkistrodon, Sistrurus*. The Johns Hopkins University Press, Baltimore, Maryland, USA.

Fitzgerald, L.A. 2012. Finding and capturing reptiles. Pp. 77–80 *In* Reptile Biodiversity: Standard Methods for Inventory and Monitoring, McDiarmid, R.W., M.S. Foster, C. Guyer, J.W. Gibbons, and N. Chernoff (Eds.). The University of California Press, Los Angeles, California, USA.

Garden, J.G., C.A. McAlpine, H.P. Possingham, and D.N. Jones. 2007. Using multiple survey methods to detect terrestrial reptiles and mammals: what are the most successful and cost-efficient combinations? Wildlife Research 34:218–227.

Geller, G.A. 2012. Notes on the nesting ecology of Ouachita map turtles (*Graptemys ouachitensis*) at two Wisconsin sites using trail camera monitoring. Chelonian Conservation and Biology 11:206–213.

Gibbons, J.W. 2017. Snakes of the Eastern United States. The University of Georgia Press, Athens, Georgia, USA.

Gibbons, J.W., and K.M. Andrews. 2004. PIT tagging: simple technology at its best. Bioscience 54:447–454.

Glen, A.S., S. Cockburn, M. Nichols, J. Ekanayake, B. Warburton. 2013. Optimising camera traps for monitoring small mammals. PloS One 8.

Greenberg, C.H., D.G. Neary, and L.D. Harris. 1994. A comparison of herpetofaunal sampling effectiveness of pitfall, single-ended, and double-ended funnel traps used with drift fences. Journal of Herpetology:319–324.

Greene, H.W. 1997. Snakes: The Evolution of Mystery in Nature. The University of California Press, Berkeley, California, USA.

Guyer, C., C.T. Meadows, S.C. Townsend, and L.G. Wilson. 1997. A camera device for recording vertebrate activity. Herpetological Review 28:135–140.

Harvey, D.S., and P.J. Weatherhead. 2006. A test of the hierarchical model of habitat selection using Eastern Massasauga Rattlesnakes (*Sistrurus c. catenatus*). Biological Conservation 130(2):206–216.

Harvey, D.S., and P.J. Weatherhead. 2010. Habitat selection as the mechanism for thermoregulation in a northern population of Massasauga Rattlesnakes (*Sistrurus catenatus*). Ecoscience 17:411–419.

Hesselbarth, M.H.K., M. Sciaini, K.A. With, K. Wiegand, and J. Nowosad. 2019. Landscapemetrics: an open-source R tool to calculate landscape metrics. Ecography 42:1–10

Hileman, E.T. 2016. Filling in the gaps in demography, phenology, and life history of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). Ph.D. Dissertation, Northern Illinois University, Dekalb, IL, USA. 128 + appendix p.

Hobbs, M.T., and C.S. Brehme. 2017. An improved camera trap for amphibians, reptiles, small mammals, and large invertebrates. PloS one 12(10): p.e0185026.

Joppa, L.N., C.K. Williams, S.A. Temple, and G.S. Casper. 2009. Environmental factors affecting sampling success of artificial cover objects. Herpetological Conservation and Biology 5(1):143–148.

Jorgensen, C.F., R.J. Stuzman, L.C. Anderson, S.E. Decker, L.A. Powell, W.H. Schacht, and J.J. Fontaine. 2013. Choosing a DIVA: a comparison of emerging digital imagery vegetation analysis techniques. Applied Vegetation Science 16:552–560.

Keenlyne, K.D., and J.R. Beer. 1973. Food habits of *Sistrurus catenatus catenatus*. Journal of Herpetology 7(4):382–384.

Kéry, M. 2002. Inferring the absence of a species: a case study of snakes. The Journal of Wildlife Management:330–338.

Kjoss, V.A., and J.A. Litvaitis. 2001. Comparison of 2 methods to sample snake communities in early successional habitats. Wildlife Society Bulletin:153–157.

Lee, M.D., and E.J. Wagenmakers. 2014. Bayesian Cognitive Modelling: A Practical Course. Cambridge University Press, Cambridge, UK.

Lipps Jr, G.J., and N.A. Smeenk. 2017. Ohio conservation plan: Massasauga, *Sistrurus catenatus*. Ohio Division of Wildlife:44 + appendices p.

Lüdecke, D. 2018. ggeffects: tidy data frames of marginal effects from regression models.Journal of Open Source Software 3(26):772. doi: 10.21105/joss.00772.

Makowski, D., M. Ben-Shachar, and D. Lüdecke. 2019. bayestestR: describing effects and their uncertainty, existence and significance within the Bayesian framework. Journal of Open Source Software 4(40):1541. doi:10.21105/joss.01541.

Martin, S.A., R.M. Rautsaw, F. Robb, M.R. Bolt, C.L. Parkinson, and R.A. Seigel. 2017. Set AHDriFT: applying game cameras to drift fences for surveying herpetofauna and small mammals. Wildlife Society Bulletin 41(4):804–809.

McCleery, R.A., C.L. ZIig, M.A. DeSa, R. Hunt, W.M. Kitchens, and H.F. Percival. 2014. A novel method for camera-trapping small mammals. Wildlife Society Bulletin 38(4):887–891.

McCluskey, E.M. 2016. Landscape ecology approaches to Eastern Massasauga Rattlesnake conservation. Ph.D. Dissertation, The Ohio State University, Columbus, Ohio, USA. 111 p.

McCluskey, E.M., S.N. Matthews, I.Y. Ligocki, M.L. Holding, G.J. Lipps Jr, and T.E. Hetherington. 2018. The importance of historical land use in the maintenance of early successional habitat for a threatened rattlesnake. Global Ecology and Conservation 13: p.e00370.

McDiarmid, R.W., M.S. Foster, C. Guyer, N. Chernoff, and J.W. Gibbons. 2012. Reptile Biodiversity: Standard Methods for Inventory and Monitoring. The University of California Press, Berkeley, California, USA.

McShea, W.J., T. Forrester, R. Costello, Z.H. He, and R. Kays. 2016. Volunteer-run cameras as distributed sensors for macrosystem mammal research. Landscape Ecology 31:55–66.

Meek, P.D., G. Ballard, A. Claridge, R. Kays, K. Moseby, T. O'Brien, A. O'Connell, J. Sanderson, D.E. Swann, M. Tobler, and S. Townsend. 2014. Recommended guiding principles for reporting on camera trapping research. Biodiversity and Conservation 23:2321–2343.

Merchant, M., Z. Li, J.A. Sullivan, and A. Cooper. 2013. Modification of camera traps for the study of ectothermic vertebrates. Herpetological Review 44:62–65.

Mitchell, J.C., S.Y. Erdle, and J.F. Pagels. 1993. Evaluation of capture techniques for amphibian, reptile, and small mammal communities in saturated forested wetlands. Wetlands 13:130–136.

Moore, J.A., and J.C. Gillingham. 2006. Spatial ecology and multi-scale habitat selection by a threatened rattlesnake: the Eastern Massasauga (*Sistrurus catenatus catenatus*). Copeia 2006:742–751.

Nelson, G.A. 2019. Package 'fishmethods'. https://CRAN.Rproject.org/package=fishmethods.

Niedballa, J., A. Courtiol, and R. Sollman. 2017. camtrapR: camera trap data management and preparation of occupancy and spatial capture-recapture analyses. R package version 0.99.9. https://CRAN.R-project.org/package=camtrapR.

[ODNR] Ohio Department of Natural Resources, Division of Wildlife. 2020. Ohio's listed species. Available at: https://ohiodnr.gov/wps/portal/gov/odnr/discover-and-learn/safety-conservation/about-ODNR/wildlife/state-listed-species (October 2020).

Parmelee, J.R., and H.S. Fitch. 1995. An experiment with artificial shelters for snakes: effects on material, age, and surface preparation. Herpetological Natural History 3(2):187–191.

Parsons, K., J. Davis, G.J. Lipps Jr., R. Pfingsten, A. Mann, and G. Denny. 2019. Amphibians of Ohio: field guide. Ohio Department of Natural Resources, Division of Wildlife pub. 5348-0019.

Piironen, J., and A. Vehtari. 2017. Comparison of Bayesian predictive methods for model selection. *Statistics and Computing 27*(3):711–735.

R Development Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org.

Rovero, F., F. Zimmermann, D. Berzi, and P. Meek. 2013. "Which camera trap type and how many do I need?" A review of camera features and study designs for a range of wildlife research applications. Hystrix 24.

Ryan, T.J., T. Philippi, Y.A. Leiden, M.E. Dorcas, T.B. Wigley, and J.W. Gibbons. 2002. Monitoring herpetofauna in a managed forest landscape: effects of habitat types and census techniques. Forest Ecology and Management 167:83-90.

Schneider, S., G.W. Taylor, S. Linquist, and S.C. Kremer. 2019. Past, present and future approaches using computer vision for animal re-identification from camera trap data. Methods in Ecology and Evolution 10:461–470.

Schuttler, S.G., R.S. Sears, I. Orendain, R. Khot, D. Rubenstein, N. Rubenstein, R.R. Dunn, E. Baird, K. Kandros, T. O'Brien, and R. Kays. 2019. Citizen science in schools: students collect valuable mammal data for science, conservation, and community engagement. Bioscience 69:69–79.

Sealander, J.A., and D. James. 1958. Relative efficiency of different small mammal traps. Journal of Mammalogy 39:215–223.

Sears, P.B. 1926. The natural vegetation of Ohio II, the prairies.

Shaffer, S.A., G.J. Roloff, and H. Campa III. 2019. Survey methodology for detecting Eastern Massasauga Rattlesnakes in southern Michigan. Wildlife Society Bulletin 43(3):508–514.

Smith, C.S. 2009. Hibernation of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus catenatus*) in northern Michigan. M.Sc. Thesis, Purdue University, West Lafayette, Indiana, USA. 34 p.

Slaughter, B.S., and M.A. Kost. 2010. Natural community abstract for It prairie. Michigan Natural Features Inventory, Lansing, MI:12.

Steen, D.A. 2010. Snakes in the grass: secretive natural histories defy both conventional and progressive statistics. Herpetological Conservation and Biology 5:183–188.

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

Szymanski, J., C. Pollack, L. Ragan, M. Redmer, L. Clemency, K. Voorhies, and J. JaKa. 2016. Species status assessment for the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*). SSA report version 2. United States Fish and Wildlife Service, Fort Snelling, Minnesota. p 103.

Tobler, M.W., A. Zúñiga-Hartley, S.E. Carrillo-Percastegui, and G.V. PoIll. 2015. Spatiotemporal hierarchical modelling of species richness and occupancy using camera trap data. Journal of Applied Ecology 52:413–421.

Transeau, E.N. 1935. The Prairie Peninsula. Ecology 16(3):423–437.

[USFWS] U.S. Fish and Wildlife Service. 2016. Endangered and threatened wildlife and plants; threatened species status for the Eastern Massasauga Rattlesnake. Federal Register 81:67193-67214.

Vehtari, A., A. Gelman, and J. Gabry. 2017. Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC. Statistics and Computing 27(5):1413–1432.

Welbourne, D.J. 2013. A method for surveying diurnal terrestrial reptiles with passive infrared automatically triggered cameras. PloS One 6:p.e18965.

Welbourne, D.J. 2014. Using camera traps to survey diurnal terrestrial reptiles: a proof of concept. Pp. 225–232 *In* Camera Trapping: Wildlife Management and Research, Meek, P.D. et al. (Eds.). CSIRO Publishing, Melbourne, Victoria, Australia.

Welbourne, D.J., A.W Claridge, D.J. Paull, and A. Lambert. 2016. How do passive infrared triggered camera traps operate and why does it matter? Breaking down common misconceptions. Remote Sensing in Ecology and Conservation 2:77–83.

Welbourne, D.J., C. MacGregor, D. Paull, and D.B. Lindenmayer. 2015. The effectiveness and cost of camera traps for surveying small reptiles and critical weight range mammals: a comparison with labour-intensive complementary methods. Wildlife Research 42:414–425.

Williams, D.F., and S.E. Braun. 1983. Comparison of pitfall and conventional traps for sampling small mammal populations. The Journal of Wildlife Management 47:841–845.

Willson, J.D. 2016. Surface-dwelling reptiles. Pp. 125–138 *In* Reptile Ecology and Conservation: A Handbook of Techniques, Dodd, C.K. (Ed.). The Oxford University Press, Oxford, UK.

Appendix A. AHDriFT Construction and Deployment Instructions

Available as an open-source online publication:

https://doi.org/10.6084/m9.figshare.12685763.v1

Appendix B. Chapter 2 Supplementary Material

Table 11. The eight covariates used to determine the spatial variation of detection success of Massasauga using AHDriFT. Columns represent the field identification number, with field 1 in Huron County, fields 2 and 3 in Wyandot County, and fields 4–13 in Ashtabula County. Higher DIVA scores represent denser vegetation. Land cover is classified as either shrub/scrub (SS) or herbaceous cover (HC).

Metric	1	2	3	4	5	6	7	8	9	10	11	12	13
Dist. to Forest edge (m)	30	442	274	71	113	8	70	38	27	25	28	60	7
DIVA	10.5	16.8	35.5	18.7	29.6	81.5	45.3	32.1	37.6	67.5	80.3	75.8	88.2
Elevation (m)	283	272	271	245	245	244	241	245	245	245	244	246	246
Field edge area (%)	70	40	20	65	75	100	95	100	100	100	80	75	100
Field total area (ha)	8.82	26.8	71.8	3.50	2.89	0.74	5.76	1.34	0.39	1.95	6.52	3.64	0.93

Table 11 Continued

Metric	1	2	3	4	5	6	7	8	9	10	11	12	13
Hydrologic flow rate (m^3/s)	0.01	0.02	0.01	0.02	0.01	0	0.01	0	0.03	0.01	0.01	0.02	0.01
Land cover	HC	HC	HC	SS	HC	SS	SS	HC	HC	SS	SS	HC	SS
Slope (°)	0.46	0.36	0.45	0.03	0.22	0.07	1.12	0.23	0.02	0.50	0.33	0.26	0.10

Table 12. Generalized linear mixed effect models to assess Massasauga detections using AHDriFT. Global models [A] and reduced final models [B] of the two spatial models and the temporal model. Watanabe-Akaike information criterion (WAIC) model weight, leave-one-out (LOO) model weight, and Bayes Factors (BF) as model selection criteria. Bayes Factors with large values (>100) represent extremely strong evidence for support of the reduced final model relative to the global model (BF = 1).

Model	WAIC	LOO	BF
Spatial Binomial (number of weeks with a detection out of 30 possible weeks)			
[A] (weeks | 30) ~ population + hydrologic flow rate + land cover + field area + edge area + vegetation height and density + distance to forest + elevation^2 + slope + (population | region)	1.1	0.1	1
[B] (weeks | 30) ~ population * field area + (population | region)	98.9	99.9	1.04^6
Spatial Poisson (total observation counts)			
[A] counts ~ population + hydrologic flow rate + land cover + field area + edge area + vegetation height and density + distance to forest + elevation^2 + slope + (population | region)	2.4	0.1	1
[B] counts ~ population * field area + (population | region)	97.6	99.9	1.51^7

Table 12 Continued

Model	WAIC	LOO	BF
Temporal Bernoulli (weekly detection probability)			
[A] detection ~ average temperature + precipitation + relative humidity + season + (population | region / field)	3.3	3.3	1
[B] detection ~ average temperature * season + (population | region / field)	96.7	96.7	1.2^3

Appendix C. Chapter 3 Supplementary Material

Table 13. Global and best-supported (**bold**) spatial and temporal models of captures per deployed unit of Massasauga using tin surveys and AHDriFT. I built models using Poisson and negative binomial (NB) distributions. Model selection analyses included Watanabe-Akaike information criterion (WAIC) and leave-one-out (LOO) model weights, with the largest weight attributed to the most supported model.

Method	Model	Formula	WAIC	LOO
AHDriFT	Spatial	NB: Captures ~ DIVA + Dis. Hibernacula + Dis. Perch + Land cover + (1 | Field)	3.3	1.1
		Poisson: Captures ~ DIVA + Dis. Hibernacula + Dis. Perch + Land cover + (1 | Field)	1.5	0.1
		NB: Captures ~ DIVA + Dis. Perch + (1 | Field)	60.5	71.8
		NB: Captures ~ DIVA * Dis. Perch + (1 | Field)	34.7	27.0
	Temporal	**NB: Captures ~ Week**	99.8	99.8
		Poisson: Captures ~ Week	0.2	0.2
Tin	Spatial	**NB: Captures ~ Dis. Hibernacula + Dis. Perch + Land cover + (1 | Field)**	99.6	99.7
		Poisson: Captures ~ Dis. Hibernacula + Dis. Perch + Land cover + (1 | Field)	0.4	0.3
	Temporal	**NB: Captures ~ Week**	82.0	81.7
		Poisson: Captures ~ Week	18.0	18.3

Table 14. Parameter results of the best-supported spatial and temporal models of captures per deployed unit of Massasauga using tin surveys and AHDriFT. Estimates presented with 95% credible intervals (CI), probability of direction (pd) which indicates the probability that a parameter estimate has the effect (+/-) indicated by the mean of the posterior, and percentage of the parameter's posterior distribution that falls within the Region of Practical Equivalence (% ROPE) using 95% of the distribution. Field A has a very high Massasauga density relative to most sites in Ohio and is adjacent to a major overwintering area. Field B has a moderately high Massasauga density relative to most sites in Ohio. Higher Digital Imagery Vegetation Analysis (DIVA) scores represent denser vegetation. The Dis. Perch parameter refers to the array distance from the nearest predator perch tree.

Method	Model	Parameter	Field	Estimate	CI low	CI high	% Cross 0	Pd	% ROPE
AHDriFT	Spatial	Dis. Perch	A + B	0.51	-0.04	1.12	3.1	0.95	5.17
		DIVA	A + B	0.51	-0.12	1.11	5.0	0.98	5.58
	Temporal	Week	A	0.10	0.06	0.15	0.0	1.00	12.3
			B	0.08	0.02	0.13	<1.0	1.00	23.7
Tin	Temporal	Week	A	0.44	-0.12	1.01	6.2	0.94	9.7
			B	-0.03	-0.62	0.55	45.6	0.54	29.0

Table 15. Notable captures of other species of interest, conservation concern using concurrent AHDriFT (Array) and 41 tin (Tin) surveys. Field identifier is denoted after the method type (in parentheses). Field A is a 27-ha field surrounded wetland. Field B is a 72-ha field with a constructed pond adjacent to one end. Ohio state listed species have designations after their Latin name (E = Ohio Endangered; T = Ohio Threatened).

Species	Tin (A)	Array (A)	Tin (B)	Array (B)
Clonophis kirtlandii[T]	3	0	14	13
Opheodrys vernalis[E]	1	16	0	112
Thamnophis radix[E]	0	22	39	268

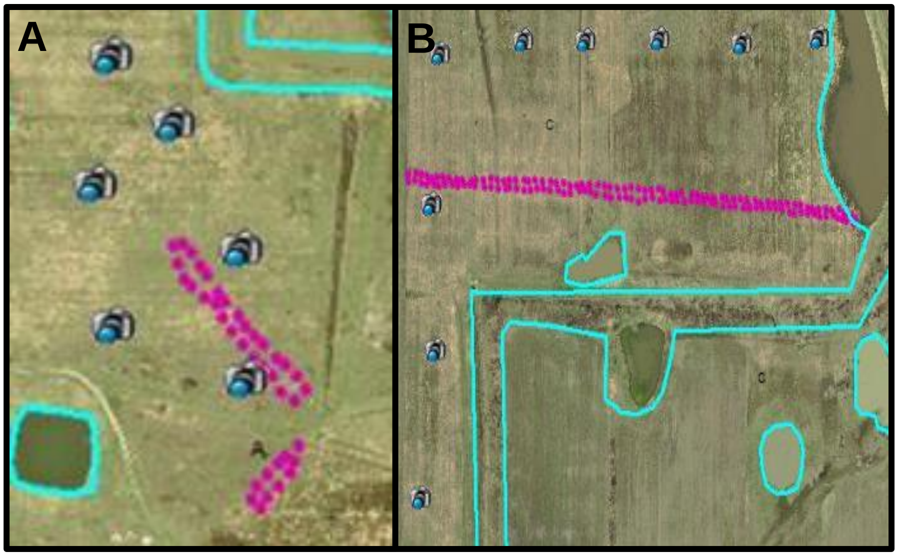

Figure 9. Deployment locations AHDriFT (cameras) and tin sheets (purple points). (A) A 27-ha field with a relatively dense Massasauga density and adjacent to a major overwintering area (Field A); and (B) a 72-ha field with a relatively sparse Massasauga density, although still denser than most sites in Ohio (Field B).