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Use of AHDriFT to Efficiently Survey for *Sistrurus catenatus*

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Abstract.—**The Eastern Massasauga Rattlesnake (EMR; *Sistrurus catenatus*) is Federally listed in the USA as Threatened. Traditional visual encounter and artificial cover object survey techniques for this species are effective but require intensive field effort. The Adapted-Hunt Drift Fence Technique (AHDriFT) is a camera trap and drift fence system able to effectively image reptiles, including snakes. We modified AHDriFT for use in EMR habitats and assessed its potential as a new EMR survey tool relative to traditional methods. We derived EMR population size estimates in 13 wet meadow fields in northern Ohio, USA, from 3 y of traditional capture-mark-recapture surveys. We deployed one AHDriFT array (three cameras) per field from March to October 2019. We obtained 72 EMR detections across 12 fields. Our 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. Weekly detection probability, however, rose to 0.40 during peak periods of EMR activity in the fall. Weekly detection probability also varied by as much as 0.10 due to temperature fluctuations. We estimated 0.48 EMR per person-hour using AHDriFT. This detection rate is comparable to published EMR survey data and greater than the detection rates from our traditional surveys. Further, AHDriFT may be better suited for a wider range of habitat types than traditional methods. Overall, we found that AHDriFT is an effective new EMR occupancy survey technique.**

Key Words.—camera trap; detection; Eastern Massasauga Rattlesnake; occupancy; presence

Introduction

The Eastern Massasauga Rattlesnake (EMR; *Sistrurus catenatus*) is a small (typically < 70 cm total length) stout-bodied rattlesnake with populations centered around the North American Great Lakes region. They are considered endangered across nearly all of their historical range (Syzmanski et al. 2016) and are Federally listed as Threatened (U.S. Fish and Wildlife Service [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 and Smeenk 2017). Narrow habitat requirements make EMR 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 and Smeenk 2017).

Rapid population declines have prompted extensive EMR 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 EMR may occur so that conservation sites can be quickly delineated. The habitat suitability models, however, are unable to reliably predict EMR occurrence and the predicted suitable habitat typically overestimates actual occupancy (McCluskey 2016; Lipps 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 (Chiucchi and Gibbs 2010; Willson 2016; McCluskey et al. 2018). Therefore, effective EMR 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 Seigel 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 congregate snakes that are otherwise difficult to find (McDiarmid et al. 2012). Detection probability, however, 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 EMR survey protocol that has been endorsed by the USFWS recommends at least 40 person-hours of VES per year for 10 y before the species can be declared absent (Gary Casper et al., unpubl. report). The ACO (corrugated tin sheets) survey protocol for EMR by the state of Ohio, USA, requires about 25 weekly surveys without detections at a site to assume species absence (Lipps 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 sensitivity threshold of the sensor (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 EMR in confined target areas such as ecopassages (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 sand dunes in Florida, USA (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 EMR, are of a comparable size, and have similar natural history characteristics (Ernst and Ernst 2011). The detections provide preliminary evidence that AHDriFT can detect EMR, but AHDriFT has never been specifically deployed for EMR occupancy surveys. There remains an unresolved potential for AHDriFT to reduce the field effort demanded by traditional EMR survey techniques (Lipps and Smeenk 2017). Here, we report a novel application of AHDriFT as a new EMR survey tool. Our objectives were to: (1) determine EMR 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 EMR survey methods.

Materials and Methods

Study sites.—We selected fields where we or colleagues had previously conducted 3 y (2015–2017) of EMR capture-mark-recapture traditional surveys (unpubl. data). We chose three areas in Ohio, USA, to deploy AHDriFT: one field in Huron County that was isolated by agriculture; two fields in Wyandot County that were separated by about 500 m of developed or agricultural matrix; and 10 fields in Ashtabula County within a 14-km^2 area of the Grand River Lowlands of which eight fields were isolated by roads or agriculture. We considered two partially connected fields as separate because prior research has shown limited exchange of individuals and high field fidelity (unpubl. data). We therefore considered all of the fields in this study as independent. The fields were covered by herbaceous vegetation such as goldenrods (*Solidago* spp.) and other forbs, with limited numbers of shrubs and small trees.

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

Traditional surveys.—We completed over 400 traditional VES and ACO surveys, totaling about 650 person-hours. We conducted VES and ACO surveys concurrently during each field visit. We recorded a single number of person-hours for the field visit but tracked captures separately by method of observation. We conducted surveys over about 25 weeks per year, following established EMR survey protocols in Ohio (Lipps 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 × 0.6 m) set in linear transects that we checked at least once per week while conducting VES. We set a tin density of 1–2 tin sheets/ha (Lipps and Smeenk 2017). We estimated EMR population size (number of individuals) in each field following the Schnabel method (Chapman and Overton 1966) using the R package fishmethods (Nelson 2019; R Development Core Team 2019).

AHDriFT data collection.—We deployed 13 AHDriFT arrays from 10 March to 6 October 2019. Each array operated for 210 survey days (30 survey weeks). We built omni-directional Y-shaped AHDriFT arrays (Fig. 1) 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 our 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 EMR distributions and movements that we had available from previous studies). We 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). We 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. We selected camera settings of highest PIR sensitivity and three-round image burst. We serviced arrays every two weeks to ensure that they were operating continuously.

We 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 (%) every 45 min. We set iButtons 5 cm above ground-level with sensors aimed groundward to avoid submersion under water. Equipment malfunctions, however, lost data prior to 11 June 2019. Therefore, we 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. Because overlapping iButton and NOAA data captured similar weather patterns in each field (Pearson's r = 0.89–0.93, P < 0.001), we determined that NOAA data was acceptable to use in our models for the dates prior to iButton malfunction. We also downloaded daily NOAA precipitation (mm) data for the entire study period. We averaged all weather data into weekly bins.

We assessed eight covariates to account for spatial variation in detection probability (Appendix 1). We quantified vegetation height and density at each array using a Digital Imagery Vegetation Analysis (DIVA; Jorgensen et al. 2013) in mid-July 2019. We imaged the vegetation against a white poster board placed approximately 3 m from the ends of each array arm. We set the camera at about 0.5 m above the ground to image ground-level vegetation. We processed images in Adobe Photoshop (version CC-2018; Adobe Inc., San Jose, California, USA) by converting the vegetation to black pixels and recording the proportion of black pixels in the image (Jorgensen et al. 2013). We 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.

We extracted elevation, slope, and hydrologic flow rate using U.S. Geological Survey (USGS) 3 × 3 m digital elevation models (DEM) in ArcMap (version 10.0; Esri, Redlands, California, USA). We determined the dominant land cover at each array from field observations as either shrub/scrub or herbaceous cover. We created a GIS polygon layer of our fields in ArcMap and input the layer into the R package landscapemetrics (Hesselbarth et al. 2019) to determine field total areas, field edge habitat percentage, and distance of the arrays to forest edges.

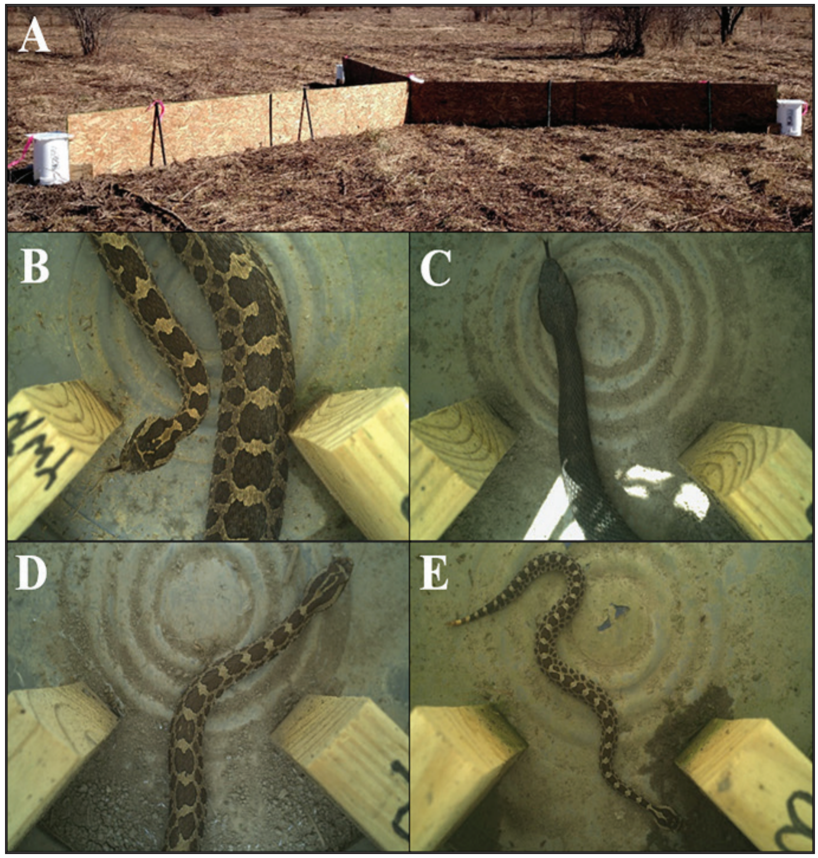

Figure 1. Sample Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) images taken using the Adapted-Hunt Drift Fence Technique (AHDriFT) in northern Ohio, USA, wet meadows: (A) Y-shaped AHDriFT array with inverted bucket units containing passive infrared trail camera traps; (B) adult with the typical patterning; (C) melanistic adult; (D) juvenile or young adult; (E) neonate. (Photographed by Evan D. Amber).

Analytical framework.—We processed AHDriFT camera trap images using the R package camtrapR (Niedballa et al. 2017) and considered all three cameras at an array as one sampling unit. We defined detections as EMR images at a single array that were taken at least 60 min apart. The interval reduced the likelihood that EMR detections were inflated by one individual moving around an array within a short timeframe (Martin et al. 2017). On five occasions, we imaged two snakes within a 60 min interval at the same array (i.e., 10 total potential detections). On these occasions, we attempted to use dorsal patterns to differentiate individuals. We could not individually identify all snakes using this method, however, because 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 we could not reliably differentiate individuals, we only included only one of the two potential detections in the dataset. We were able to confidently differentiate individuals on one occasion and counted both of those detections.

We fit Generalized Linear Mixed Effects models (glmm) to test the effects of spatial and temporal covariates on AHDriFT detection probability. We built glmms using a Bayesian framework to account for small sample sizes using the R package brms (Bürkner 2018). We modeled detection probability using separate spatial and temporal models (Appendix 2). We scaled and centered all continuous predictors to have a mean of zero and standard deviation of one. We manually set all models with normally distributed priors with a mean of zero and standard deviation of 10. We visually inspected model chains for mixing and used Gelman-Rubin statistics (Rhat < 1.1) to confirm convergence (Cowles and Carlin 1996). We then assessed model fit with posterior predictive checks (Bürkner 2018).

We reduced our global additive models and selected our best-supported final models (Appendix 2) using the R packages bayestestR (Makowski et al. 2019) and ggeffects (Lüdecke 2018). To step-wise reduce our models, we retained the variables whose posterior distributions did not or only marginally included zero. We also checked if the variable had < 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, we 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 > 11% ROPE.

We conducted model selection of the candidate 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). We 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). We selected the best-supported model from among the global and candidate models as our final models for analysis.

To compare detection rates from AHDriFT and traditional methods, we considered one-week intervals as one AHDriFT survey. We chose a one-week interval because VES and ACO surveys are usually conducted on weekly timeframes for Ohio EMR (Lipps 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. We determined our AHDriFT detection rate from detections divided by person-hours of effort in the field and spent processing images. We generated the detection rate of concurrent traditional surveys by totaling VES and ACO captures and dividing by field person-hours. We generated detection rates for VES and ACO separately by dividing captures from each method by the same field person-hours (because we conducted traditional surveys concurrently). We estimated detection rates from the EMR literature using the average or typically conducted survey effort reported. Effort and detection data were not consistently or uniformly reported and so our estimates from the published literature may contain additional error.

Spatial analysis.—The spatial models fit non-temporal field-level covariates (N fields = 13) with EMR population size estimates grouped by geographic region (see Study sites above) as random slopes and with geographic region as random intercepts. We fit two models under this framework. First, we modeled the number of EMR detections at each field using a Poisson glmm. Second, we assessed the number of weeks that AHDriFT detected EMR over the 30-week study period using a binomial glmm. We fit eight additive models for each of the spatial analyses, step-wise removing insignificant parameters. We reduced both spatial analyses to an additive model of population size estimate and field area. We then fit models with these variables as an interactive effect. We considered the global, reduced additive, and reduced interactive spatial models as candidate models for selection.

Temporal analysis.—The temporal model used a Bernoulli glmm to predict weekly detection probability from averaged weather covariates and the sampling season. We defined the season that each detection occurred in by evenly dividing the 30-week study period into three survey sessions. We considered the first 10-week survey session as spring (10 March to 19 May 2019), the second as summer (20 May to 28 July 2019), and the last as fall (29 July to 6 October 2019). We binned temporal covariates and detections by week to account for infrequent daily detections. We 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 EMR population size estimates grouped by geographic region. We fit four additive models for the temporal analyses, step-wise removing parameters. For the global model and after each parameter removed, we fit all combinations of interactive effects. We considered all temporal models (n = 14) as candidate models for selection.

Results

Traditional surveys.—For each of the three years, we averaged 11.55 ± 5.08 (standard deviation) surveys per field (range, 5–27 surveys per field) and a mean = 17.79 ± 14.54 total person-hours per field (range, 3.75–67.42 total person-hours per field). We obtained 0.46 EMR per person-hour when totaling VES and ACO captures from concurrent surveys (Table 1). Our VES detections in each field averaged 2.33 ± 3.86 EMR per year (range, 0–16 EMR per year), with a mean of 0.11 EMR per person-hour. The ACO surveys in our fields were generally more effective than VES, accounting for 37.5–100% of weekly detections. Our ACO survey detections in each field averaged 5.27 ± 6.71 EMR per year (range, 0–28 EMR per year), with a mean of 0.28 EMR per person-hour. Each field typically required a mean = 3.23 ± 2.94 ACO surveys to obtain the first EMR detections within a year (range, 1–13 ACO surveys). We estimated a mean EMR population size = 36.07 ± 33.23 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.—We imaged EMR in 12 of the 13 fields (92%) and obtained 72 EMR detections,

Table 1. Comparison of sample detection rates of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) using the Adapted-Hunt Drift Fence Technique (AHDriFT), visual encounter surveys (VES), and artificial cover object (ACO) surveys. We considered one week of camera trapping by an AHDriFT array as one survey. Detection rate metrics from the literature are from published data and only represent the estimated average or typically conducted survey effort reported. The abbreviation NA = not available.

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

including eight neonates (Fig. 1). The field that failed to image an EMR only had four prior traditional survey detections. Individual arrays obtained a mean = 5.54 ± 4.36 detections (range, 1–20 detections). Ten arrays obtained fewer than 10 detections each, with two of those arrays each obtaining a single EMR detection. All detections occurred between 1000 and 1900, peaking at 1600. After summing array deployment, servicing, and image processing time, we approximated 150 person-hours of total effort (11.5 person-hours per array). Thus, we estimated an average detection rate of 0.48 EMR detections per person-hour using AHDriFT (Table 1).

Spatial analysis.—We reduced the spatial global models to an interaction between population size estimate and field area (Appendix 2), which had a negative relationship but a relatively small effect (20.9% of posterior distribution in ROPE; Table 2). Total detection counts increased with larger population size estimates (Fig. 2), especially in smaller fields (< 5 ha) relative to medium-sized fields (5–15 ha) and large fields (> 15 ha). The estimates, however, had large and overlapping 95% credible intervals (CI). The binomial model predicted EMR detections in mean = 5.08 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 an EMR in a given field based on non-temporal variables.

Temporal analysis.—We detected EMR in 57 of 390 (14.6%) possible field weeks (13 fields sampled for 30 weeks each; Table 1). Four field weeks with detections occurred in spring, 18 field weeks in summer, and 35 field weeks in fall. We detected EMR 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 EMR detections = 4.19 ± 1.42 fields (range, 2–8 fields), and a weekly detection probability per field as high as 0.40 (Fig. 3). 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. We detected EMR on 65 of 2,730 (2.4%) possible field days (13 fields sampled for 210 d each).

The best-supported temporal model included an interaction of season and weekly average temperature (Appendix 2). We only imaged EMR in weeks with average temperatures ranging from 10°–26° C (Fig. 3). Our data suggest that detection probability in spring may be positively correlated with weekly average

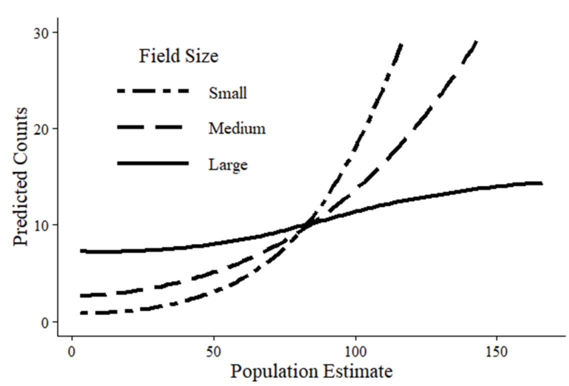

Figure 2. Relationship of Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) population size estimate (number of individuals) and field size on predicted total detection counts using the Adapted-Hunt Drift Fence Technique (AHDriFT) from the field-level spatial model. Total predicted counts are representative for the entire sampled active season (10 March to 6 October 2019) using one AHDriFT array per wet meadow field in northern Ohio, USA. We defined three general categorizations of field sizes as small (< 5 ha), medium (5–15 ha), and large (> 15 ha). We 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).

Table 2. Parameter estimates of the final Generalized Linear Mixed Effect models to assess Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) detections using the Adapted-Hunt Drift Fence Technique (AHDriFT) in northern Ohio, USA, wet meadows. Analyses include two spatial models (non-temporal field-level covariates) and a temporal model (season and weekly averaged weather covariates). 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 posterior distribution of the parameter 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
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

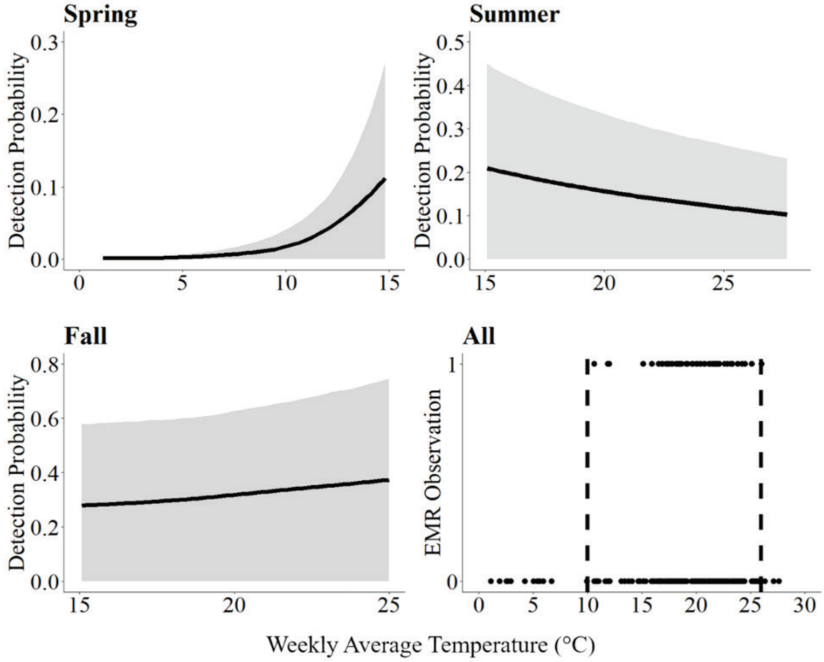

Figure 3. Influence of weekly average temperature on weekly detection probability per Adapted-Hunt Drift Fence Technique (AHDriFT) array of Eastern Massasauga Rattlesnakes (*Sistrurus catenatus;* EMR) across seasons in northern Ohio, USA, wet meadows. We defined spring as 10 March to 19 May 2019, summer as 20 May to 28 July 2019, and fall as 29 July to 6 October 2019. Vertical dashed lines indicate the temperature range of EMR detections across all seasons combined. Shaded regions indicate 95% credible intervals around mean estimated responses.

temperature, while in summer it may be negatively correlated; however, the credible intervals for these interaction parameters did somewhat overlap zero (Table 1). 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 EMR survey method. We imaged EMR at a similar, and often higher, detection rate compared to traditional survey methods while requiring fewer person-hours. 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. We typically observed only two EMR in each field per year using VES. Comparatively, each AHDriFT array averaged six EMR detections.

Bartman et al. (2016) had relatively high detection rates using ACO surveys (Table 1). The authors, however, 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 EMR survey protocol calls for linear transects of only 1–2 tin sheets/ha (Lipps and Smeenk 2017). Our average yearly ACO (tin) survey detections per field were about equal to AHDriFT detections, but ACO surveys obtained lower detections per person-hour. Further, we typically needed at least three ACO surveys to first observe an EMR each year. Our AHDriFT detections per field were also comparable to previous traditional ACO surveys (168 total tin sheets) in two of our fields in 2002 and 2003 (Douglas Wynn, unpubl. report). The first year of ACO surveys obtained 36 EMR detections and the second obtained 31 detections. In the same two fields, we obtained 31 detections using AHDriFT.

We 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 our DIVA vegetation scores and removed VES observer bias (Dorcas and Willson 2009; Albergoni et al. 2016) by placing arrays at the geometric center of each site. Therefore, AHDriFT may be more widely applicable than VES for detecting EMR.

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, USA, yielded only two EMR per year (Michael Dreslik, pers. comm.). Late summer checks detected more gestating females and neonates, but overall ACO appears ineffective at this site. Carlyle Lake has a robust EMR population and what causes the ACO inefficiency is unclear (Michael Dreslik, pers. comm.). We suspect in our 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 EMR to move and encounter the drift fences rather than to congregate under desired cover objects. Further, we observed that EMR 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. We encourage future research that directly compares ACO and AHDriFT efficacy in different EMR 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, we found that AHDriFT can compare to or exceed the detection efficacy of traditional EMR 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 we recommend traditional methods for this purpose. Combining Passive Integrated Transponders (PIT) tags (Gibbons and Andrews 2004) with arrays remains a potential avenue of research. PIT tags, however, 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 EMR detection-nondetection 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. The total number of snakes observed at sites, however, 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. We also note that AHDriFT captures a wide diversity of small mammal species (Martin et al. 2017; Amber et al. 2020), including EMR prey such as Meadow Voles (*Microtus pennsylvanicus*; Keenlyne and Beer 1973). Thus, AHDriFT may potentially be used for concurrent EMR prey abundance surveys and we encourage research that examines this application.

Regardless of the survey objectives, researchers that deploy AHDriFT are likely aiming to maximize detection rates. To optimize AHDriFT deployment for EMR surveys, we recommend servicing arrays every 3-6 weeks, rather than every two-weeks as we did. Second, most of our detections occurred in the fall when detection probability was highest. The fall is when EMR breed, give birth, and prepare for overwintering (Ernst and Ernst 2011; Gibbons 2017). Heightened EMR activity in late July through September (DeGregorio et al. 2018) increases their likelihood of encountering the AHDriFT drift fences; however, we note that our detection probability estimates across seasons have substantial uncertainty. As such, we recommend that researchers activate cameras in late summer through the fall when EMR are most likely to be imaged, but more research is needed to examine the detection success of a shortened survey season.

Lastly, we recommend that surveyors refine AHDriFT deployment by considering temperature. We imaged EMR only when weekly average temperatures were between 10°–26° C. Temperature has been previously shown to affect EMR detection (Shaffer et al. 2019; Crawford et al. 2020), likely because ground temperature influences EMR movement activity (Moore and Gillingham 2006). Northern EMR 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 that are more suitable to EMR movement. Meanwhile, high temperatures during summer exceeded 34° C and potentially reduced EMR movements and AHDriFT detections. Overall, researchers can likely focus effort when temperatures are not at their seasonal extremes. For example, our results suggest that when spring temperatures are below 10° C, EMR are unlikely to be detected by AHDriFT in northern Ohio. Spring emergence of EMR is triggered when temperatures at or near the surface become warmer than the underground hibernacula (Smith 2009; Hileman 2016). In our fields the required underground-surface temperature inversion did not occur until early April.

We identify some important limitations to our study. We focused on landscape-level differences between fields (e.g., topography, hydrology, EMR population size, overall field habitat and area) that may affect AHDriFT detections. Eastern Massasauga Rattlesnake spatial ecology and movements, however, may be more strongly influenced by microhabitats than macrohabitats (Harvey and Weatherhead 2010). We did not investigate how array placement within a field or how EMR microhabitat preferences (Moore and Gillingham 2006) affected AHDriFT detection. Further, large seasonal EMR movements occur when EMR 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. We are investigating microhabitat and seasonal movement influence on AHDriFT detection rates as part of on-going research.

Our statistical analyses are also limited due to low numbers of EMR detections at most arrays. Detection rates of EMR using AHDriFT is low, particularly in fields with very low EMR densities. Low detections per field may have led to ineffective accounting for variation in detections, resulting in large credible intervals. We emphasize that our modeling results should be considered as preliminary. Still, we expect that the overall effects of temperature and season reflect real patterns. Our results are in-line with the expected influence of season and temperature on EMR movement (Moore and Gillingham 2006; Harvey and Weatherhead 2010; Gibbons 2017; DeGregorio et al. 2018), EMR 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 EMR 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. We 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 EMR detections with minimal additional field effort. For example, low-density fields where a single AHDriFT array failed to image EMR 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 EMR are more likely to be imaged. Combining AHDriFT and traditional methods may be particularly beneficial since use of multiple survey methods is suggested to strengthen EMR monitoring (Bartman et al. 2016). We conclude that AHDriFT is an effective new tool for widespread, non-invasive, and time-efficient surveying of the Federally threatened EMR.

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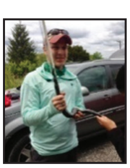

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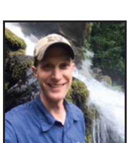

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Appendices

Appendix 1. The eight covariates used in our spatial models to determine the spatial variation of detection success of the Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) using the Adapted-Hunt Drift Fence Technique (AHDriFT) in northern Ohio, USA, wet meadows. 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 Digital Imagery Vegetation Analysis (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
Distance to forest edge	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
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

Appendix 2. Generalized Linear Mixed Effect models built under a Bayesian framework to assess Eastern Massasauga Rattlesnake (*Sistrurus catenatus*) detections using the Adapted-Hunt Drift Fence Technique (AHDriFT) in northern Ohio, USA, wet meadows. We present global models [A] and reduced final models [B] of the two spatial models (non-temporal field-level covariates) and the temporal model (season and weekly averaged weather covariates). We used 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
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