Herpetological Conservation and Biology 20(1):82–93.
Submitted: 24 January 2024; Accepted: 29 January 2025; Published: 30 April 2025.

Experimental Evaluation of Eastern Box Turtle (*Terrapene carolina carolina*) Detectability in Visual Search Surveys

William F. Heinle[1,4], Noelle Beswick[1], Emily Wapman[2], and J. Andrew Royle[3]

[1]Department of Biology, University of Richmond, 28 Westhampton Way, Richmond, Virginia 23173, USA
[2]University of California Santa Barbara, 494 UCEN Road, Santa Barbara, California 93106, USA
[3]U.S. Geological Survey, Eastern Ecological Science Center, 12100 Beech Forest Road, Laurel, Maryland 20708, USA
[4]Corresponding author; e-mail: will.heinle@richmond.edu

***Abstract*.—Understanding how detection probability varies over time, space, or in response to measurable covariates is important to inform the monitoring and assessment of many species. A standard model to understand detectability, the availability/perception model, admits that detection probability is the composite of two components: availability and ability of surveyors to detect the target. Availability is largely affected by environmental and behavioral factors, whereas perception is primarily affected by attributes of individual observers and survey protocols, and thus can potentially be partially controlled by survey design. We designed and implemented a field study to understand the perception component of detection for Eastern Box Turtles (*Terrapene carolina carolina*) using visual encounter surveys. We obtained and deployed museum specimens of Eastern Box Turtle shells and subjected them to visual search surveys by observers in realistic field situations. Overall, about 50% of the box turtle shells were detected by observers, including 41.5% in what we categorized as partially visible and 63.0% as fully visible. There were significant differences among observers, which may be due to observer-specific variation in search technique; the observers varied in how well they achieved the protocol guidance. Therefore, in visual search surveys, care in study design and analysis should be taken to account for variation in perception to determine detectability, as our study suggests 37% of perceptible targets are missed by surveyors.**

Key Words.—detection probability; perception; spatial capture-recapture; temporary emigration; visual encounter survey

Introduction

The southeastern U.S. is a global hotspot for Chelonian diversity, ranking second only to Southeast Asia in species richness (Mittermeier et al. 2015). Turtles are threatened by human development in key habitats, climate change, and the illegal wildlife trade, with a 38% decline possible by 2080 (Ihlow et al. 2011). Eastern Box Turtles (*Terrapene carolina carolina*) are native to the Eastern U.S., and like other turtle species, face threats from human development, road collisions, and illegal collection (Converse et al. 2005; Nazdrowicz et al. 2008; Currylow et al. 2011). According to the International Union for Conservation of Nature (IUCN), populations of all species of box turtles have declined 30% in the previous 100 y (van Dijk, 2011). Their longevity, late maturation, and high juvenile mortality exacerbate the effects of newly introduced stressors from the human environment (Lori Erb and H. Patrick Roberts, unpubl. report). At the Patuxent Research Refuge of the U.S. Fish and Wildlife Service (USFWS) in central Maryland, USA, Eastern Box Turtle population densities have dropped from 10–12 turtles per ha in the 1940s to about 1.4 turtles per ha today (Royle and Turner 2022). Declines at the Patuxent Research Refuge are consistent with range-wide declines of the species (Hall et al. 1999; Kemp et al. 2022). As a result of these trends, there has been increased attention focused on developing monitoring efforts for Eastern Box Turtle populations (Lori Erb and H. Patrick Roberts, unpubl. report).

Collecting data in a statistically rigorous manner is the first step towards understanding population status and achieving meaningful conservation of threatened species. For turtles, population data are often collected using Visual Search Surveys (Willson, 2016), and the resulting data are analyzed in one of two ways: Capture-recapture (CR) and related models (such as distance sampling) to estimate population size or density (Converse et al. 2005; Royle and Turner 2022), or Occupancy Models to estimate distribution and factors that affect probability of species occurrence (Langtimm et al. 1996; Erb et al. 2015). Probability of detection is a central concept in both classes of methods, and it is important to understand how detection probability varies over space, time, and habitat (Refsnider et al. 2011). Studies of reptiles and amphibians are particularly subject to detection bias and undercounting (Mazerolle et al. 2007). While visual surveys and occupancy methods remain popular with mammals, both methods may miss small and rare species that tend to have lower encounter rates, like many reptiles and amphibians. Mazerolle et al. (2007) found that methods involving marking or resighting individuals underestimated population metrics when failing to account for detection probability. In addition to the nature of herpetofauna, observer bias, habitat, and seasonality may also skew detection rates (Gardner et al. 1999; Anderson et al. 2001; Kéry et al. 2011).

A useful conceptual model of detectability in animal populations is the Availability/Perception Conceptual Model (Marsh and Sinclair 1989; Kendall et al. 1997; Bailey et al. 2004; Diefenbach et al. 2007) under which it is recognized that detection bias arises from two distinct processes: availability and perception. The availability (or its complement, temporary emigration) process determines when individuals in the population are available for detection by observers because of conspicuous behaviors (such as basking or foraging) or, conversely, are unavailable for detection because they are engaging in unsuitable behaviors such as brumation. The second process, perception, is the visual detection of animals by the observer given that they are available to be detected. In aerial surveys of waterfowl, Marsh and Sinclair (1989) defined perception bias as the proportion of groups of the target species that are visible in the transect yet missed. In the context of aerial surveys (and terrestrial turtle surveys), an animal being available for detection is one that is physically conspicuous to the observer. Such individuals may therefore be detected, or not, by the observer. Animals that are not available by virtue of being underground or buried in leaf litter cannot be detected by observers in ordinary visual search surveys. The precise interpretation of available differs between search methods (e.g., humans versus dogs). For example, in studies of salamanders (Bailey et al. 2004), individuals are inconspicuous on the ground but become detectable once a cover object is lifted. It is important to understand both components of detectability because availability is driven largely by biological processes related to behavior and environmental conditions, whereas perception is driven more by factors related to observer and survey method.

One way to investigate detection probability experimentally is to simulate live population survey techniques with a controllable or measurable proxy (Fuentes et al. 2015). Two components are required to measure detection probability: a count of detections, via a systematic search method, and a known pool of available objects from which detections are made. Although various detection methods exist, simulating a known pool for an open system has proven more difficult. Previous studies reported low turtle detection probabilities using radio-tagged live turtles (Refsnider et al. 2011), and others have corrected inflated population estimates using human-constructed model turtles to quantify human perception bias (Fuentes et al. 2015).

We initiated a field experiment to evaluate perception bias in visual search surveys of Eastern Box Turtles. We surveyed plots with randomly placed museum collection box turtle shells in visible and partially visible states. Use of museum shells simulate a closed population where individual behavior is known and controlled. Our experience with surveys of live free-ranging Eastern Box Turtles is that most detected turtles are conspicuous on the forest floor, although we expect some conspicuous turtles are not detected. Partially visible turtles in above-ground cover or mostly buried in leaf litter, however, appear to be detected at a much lower frequency. Here, we attempt to determine if there are significant causes for variation in detection of box turtles during visual search-encounter surveys and quantify the percentage of conspicuous box turtles that may go undetected by observers. We expect that individuals that occupy a study site may inhabit one of three states, consistent with the availability/perception model of detection probability: (1) completely invisible to observers, and undetectable without invasive searching (moving leaf litter, debris, etc.); (2) conspicuous and observable, on the surface of the leaf litter, foraging, basking or moving about their home ranges; or (3) an intermediate state, which is partially observable, comprising individuals that have some portion of their bodies exposed and thus susceptible to individual detection. We expect that partially observable shells of box turtles should be detected at a lower rate than fully visible shells, and that detectability of shells will not differ among experienced observers but that any differences among observers should be explainable by measurable attributes of their search method, which we attempted to characterize using GPS search track data.

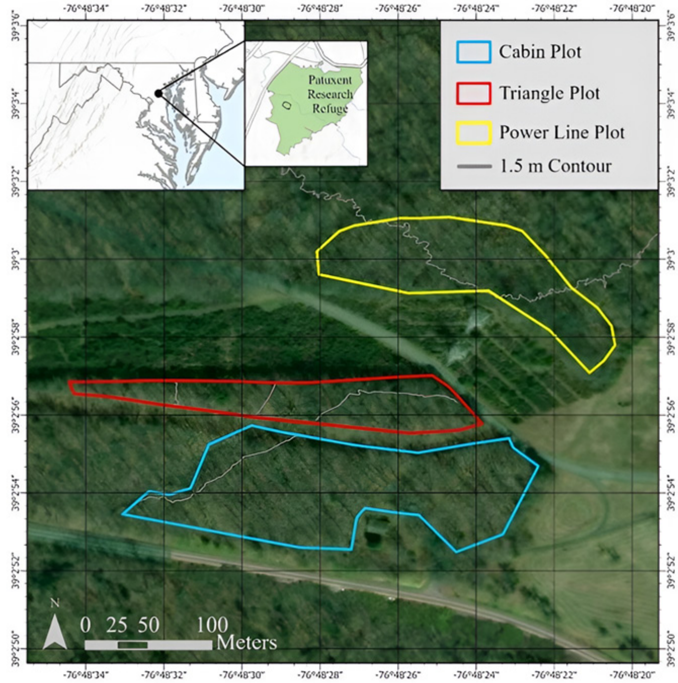


Figure 1. Map of survey plots for Eastern Box Turtles (*Terrapene carolina carolina*) on the Patuxent Research Refuge of the U.S. Fish and Wildlife Service, Laurel, Maryland, USA.

Materials and Methods

Study site.—Detection surveys occurred in three plots delineated by orange flagging (Fig. 1). All plots were adjacent to powerline clearings on the Patuxent Research Refuge of the U.S. Fish and Wildlife Service in Laurel, Maryland, USA. The refuge is located in a suburban area between Baltimore, Maryland, and Washington, D.C. (approximate refuge centroid 39°03’50.4”N, 76°47’02.4”W). Eastern Box Turtle monitoring has occurred on the refuge since the 1940s (Stickel 1950).

Two plots (Triangle and Cabin, see Fig. 1 and 2) were long and narrow totaling approximately 0.69 and 1.56 ha, respectively. Both consisted of American Beech (*Fagus grandifolia*) dominated upland with minimal understory, limited ground cover, fallen logs, and a small seasonal stream flowing through both. The third plot (Powerline) was rectangular totaling 0.94 ha and was adjacent to a seasonal wetland. Beeches and American Sweetgum (*Liquidambar styraciflua*) predominated, with minimal understory but some dense patches of ferns.

Shell placement.—We obtained museum collection shells of Eastern Box Turtles from Towson University (Towson, Maryland) and Jug Bay Wetlands Sanctuary (Lothian, Maryland). The shells, varying in size and color, were previously coated in a clear adhesive for preservation. We do not believe this significantly affected their detectability, although some effect may be possible. The number of shells we placed varied each week and varied by plot, with a minimum of three shells and a maximum of 13 in any one plot during a survey event (defined here as the search of a single plot by a single observer). Typically, we deployed shells to the three study plots on a weekend or Monday, and the shells remained for the week so that each observer could survey each plot during the week at their convenience. The fourth author generated the number and locations of shells pseudo-randomly with an effort to minimize the knowledge by surveyors about shell placement. Specifically, we simulated points and plotted them using R (R Development Core Team 2019). The first and second authors distributed shells and the third and fourth authors were two of the four surveyors. In total, we placed 116 shells within three plots across the five weeks (Table 1) between 13 June and 15 July 2022. The distribution of shells slightly favored the partially visible state, 64 versus 52. We randomly chose shells every week to ensure different ones were used in each plot and we placed them in one of two states to imitate how live box turtles are encountered

Figure 2. Example of the Upland Beech (*Fagus grandifolia*) habitat of Eastern Box Turtles (*Terrapene carolina carolina*) in the Cabin survey plot in the Patuxent Research Refuge, Laurel, Maryland, USA. (Photographed by Emily Wapman).

in population surveys based on our experience. We placed what we called visible shells on top of the forest floor, representing foraging, basking, or moving turtles. Partially visible shells were nestled against nearby logs or trees or buried in leaves covering the marginal scutes to a variable degree (Fig. 3).

Shell detection.—Up to four biologists surveyed the three plots each week. Surveyors documented their search track with GPS (Gaia GPS, Bozeman, Montana, USA) on their smartphone, and achieved

Table 1. Number of shells of Eastern Box Turtles (*Terrapene carolina carolina*) deployed per week in each of three survey plots between 13 June and 15 July 2022 in the Patuxent Research Refuge, Laurel, Maryland, USA. See Figure 1 for mapped location of the survey plots.

Week	Cabin Plot	Power Line Plot	Triangle Plot	Total
1	8	9	3	20
2	8	7	4	19
3	10	9	3	22
4	10	11	4	25
5	13	12	5	30

Figure 3. Example of a (A) partially visible versus (B) fully visible shell placements of Eastern Box Turtles (*Terrapene carolina carolina*) for the experimental evaluation of box turtle detection in visual search surveys. (Photographed by William Heinle).

uniform coverage of the plot by envisioning a 5-m buffer on either side of their search track. There was no formal data-based reason for choosing this 5-m instruction other than for observers to have a consistent instruction to follow, although it was close to the mean detection distance (about 4.3 m) reported in Royle and Turner (2022). Detection almost surely depends on distance and thus no specific buffer will yield equal detection of box turtles. We did not impose any search time constraints, consistent with our operational field protocol. When a surveyor detected a shell, they measured the distance between their location and the shell (not analyzed here), took photographs of the shell *in situ*, and recorded whether they determined it was visible or partially visible. Surveyors (except the fourth author) had no prior knowledge of the number of shells in each plot and did not survey plots where they had placed shells. All four surveyors were experienced box turtle searchers and have conducted operational surveys in these plots.

Statistical methods.—We used observer search tracks to define covariates that might account for heterogeneity in detection probability of shells. Specifically, we placed a 5 × 5 m box around each of the deployed shells and used this to define covariates of searcher proximity to each shell. First, we computed coverage, which we defined as the area of the 5 × 5 m box covered by a 5-m buffered track, which was a single buffered track (2-m buffer shown for a clearer graphic) for one of the observers during their search of the powerline plot (Fig. 4). We made all geographic analysis calculations in the R package rgeos (R Development Core Team 2019).

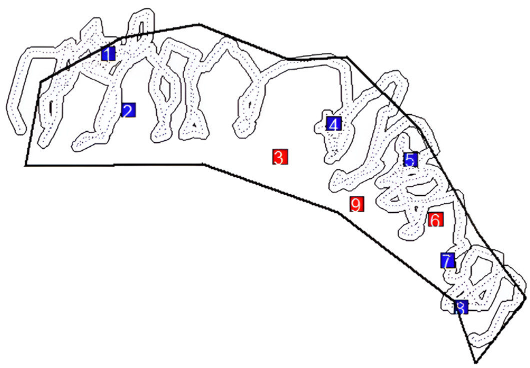


Figure 4. Example of a search track with a 2-m buffer for one of the searches of the Powerline survey plot between 13 June and 15 July 2022 in the Patuxent Research Refuge, Laurel, Maryland, USA. Detected Eastern Box Turtle (*Terrapene carolina carolina*) shells are shown in blue, shells that were not detected are shown in red. Bounding boxes around each shell are 5 × 5 m square polygons.

We created a second covariate we called points, where we represented each search track by a set of regularly spaced points, using a constant intensity of 20 points per search minute. We tallied up the number of points in each 5 × 5 m shell grid box as a surrogate measure of composite time and effort spent in the vicinity of each shell. In the model fitting (see below), we used a square-root transformation of this variable due to extreme right skew. To evaluate differences in search efficacy among observers, we also computed two plot-level covariates for the search of each observer as a summary of their overall search efficiency. We did this by using the total proportion of plot area covered, computed by intersecting the 5-m buffered track with the plot polygon, and the total time spent surveying the plot.

We used Logistic Regression to model the probability of detecting shells. The variable y_{ij} denotes the observed outcome (y = 1 if detected, y = 0 if not detected) for shell i = 1–116 (total shell sets over the five-week study) and observer j = 1–4. We assumed that y_{ij} is a Bernoulli outcome with parameter p_{ij} , the probability that a shell is detected. Covariates are modeled as a linear function on the logit-transformation of p as follows:

$$logit(p_{ij}) = \beta_0 + \beta_1 \times x_i$$

where x_i is the value of some covariate for shell i. We considered the covariates related to the observer search effort as defined above: (1) coverage is the area of the 5 × 5 m box around each shell that intersects the 5-m buffered search track; (2) points is the number of track points within the 5 × 5 m box (using a 20 point-per-minute density of regularly spaced points to define the GPS track); and (3) state, which is the visible or partially visible state of each shell. We modeled the first two covariates as continuous covariates, and we coded covariate state as a factor with the intercept of the model corresponding to the level partially visible. We also considered an observer effect (a factor having four levels), and we considered a plot effect (three levels). We carried-out model selection in two stages. In the first stage, we defined models that included various combinations of the experimental design variables: (1) plot; (2) observer; and (3) state (seven models total, including the null model having no effects). We used the top two models from stage one as a basis for stage two model selection, including combinations of the shell-level covariates. Models were ranked using Akaike Information Criterion (AIC) score (with small-sample correction, AICc) to evaluate important effects and produce a best model.

Results

Four observers participated in at least six total plot searches (out of 15 plot-week sets). The number of shells each observer was exposed to was: 116, 60, 56, 55. The variation among observers is because observer one was always a searcher (all five weeks and three plots) whereas observers two and three alternated setting up shells each week, and observer four only participated in the last two weeks of the study as a trained observer. Overall, surveyors detected 49.8% of placed shells (143 of 287). Visible shells were detected 21.5% more often than partially visible shells (63.0% for visible vs. 41.5% for partially visible; Fig. 5). Observers detected visible

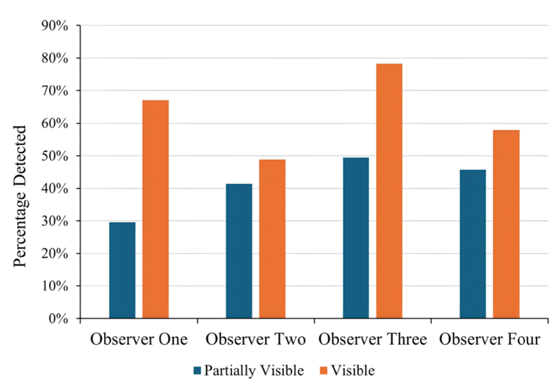


Figure 5. Proportion of partially visible and (fully) visible Eastern Box Turtle (*Terrapene carolina carolina*) shells detected by each of four observers between 13 June and 15 July 2022 in the Patuxent Research Refuge, Laurel, Maryland, USA.

and partially visible shells in differing proportions. The largest difference between visible and partially visible shells was for observer one, who detected visible shells at a rate 37.5% higher than partially visible shells. The other observers had more similar detection rates among visible and partially visible shells. During the experimental surveys of the three plots, 12 live box turtles were incidentally encountered.

Survey-specific covariates (total time and fraction of plot area covered using the 5-m GPS track buffer) differed for each observer (Appendix Table). Total survey time ranged from 68 to 111 min for the Cabin plot with a mean = 88.7 ± (standard deviation) 13.8 min, 46 to 169 min for the Powerline plot (mean = 73.2 ± 32.9 min), and 40 to 87 min for the Triangle plot (mean = 61.3 ± 17.3 min). With the 5-m buffered tracks, the proportion of plot area covered ranged from 0.77 to 0.99 (mean = 0.89 ± (SD) 0.08%) for the Cabin plot, 0.70 to 1.00 (mean = 0.92 ± (SD) 0.09%) for the Powerline plot, and 0.70 to 0.95 (mean = 0.86 ± (SD) 0.07%) for the Triangle plot. Thus, there was variation in observer effectiveness searching plots, with considerable variation both in search time and the fraction of the plot covered by the observer (Table 2). For example, observer one and observer two achieved better coverage than observers three and four, on average. Observer one typically had the lowest time per unit area compared to the other three observers but covered more of the plot.

Table 2. Observer (Obs) summaries of the proportion of area coverage and the time searching (minutes) per ha for Eastern Box Turtle (*Terrapene carolina carolina*) shells on four study plots by four observers between 13 June and 15 July 2022 in the Patuxent Research Refuge, Laurel, Maryland, USA.

Plot	Obs1	Obs2	Obs3	Obs4
Proportion				
Cabin	0.948	0.956	0.817	0.811
Power Line	0.962	0.972	0.873	0.847
Triangle	0.890	0.917	0.756	0.886
Time				
Cabin	52.48	64.30	65.38	47.59
Power Line	64.64	121.5	83.23	67.11
Triangle	69.14	94.35	118.9	87.86

For phase one of the model fitting, the top model contains state only, and the second-best model has state + observer (Table 3). We used the top two models (m1 having state only and m5 having state + observer) as initial models for the second stage of model fitting where we considered combinations of the two shell-level effort covariates (Table 3). This

Table 3. Logistic Regression model selection results for the detection study of Eastern Box Turtle (*Terrapene carolina carolina*) at the Patuxent Research Refuge, Laurel, Maryland, USA. Stage one considered models with the following effects on the probability of detecting a shell: (1) visibility state (partially and fully visible); (2) observer (four levels); and (3) plot (three levels). Stage two of the model fitting included covariates related to effort and search efficacy: points is the number of GPS track points within a 5 × 5 m bounding box around each shell; and coverage is the amount of the 5-m buffered GPS track that covers the bounding box. Abbreviations are K = the number of parameters in the model, AICc = Akaike Information Criterion (AIC) score with small sample correction, AICc Wt = Akaike Information Criterion weights, Cum Wt = cumulative weight, and LL = log-likelihood.

Model		K	AICc	Δ AICc	AICc Wt	Cum Wt	LL
Stage one							
m1	State	2	387.86	0.00	0.45	0.45	-191.91
m5	State + Observer	5	388.89	1.03	0.27	0.72	-189.34
m6	Observer × State	8	389.60	1.74	0.19	0.91	-186.54
m3	State + Pilot	4	391.16	3.30	0.09	1.00	-191.51
m0	Null	1	399.88	12.02	0.00	1.00	-198.93
m4	Observer	4	401.27	13.41	0.00	1.00	-196.57
m2	Plot	3	403.31	15.45	0.00	1.00	-198.61
Stage two							
m11	State + Points + Observer	6	375.32	0.00	0.33	0.33	-181.51
m7	State + Points	3	375.33	0.01	0.33	0.66	-184.62
m10	State + Points + Observer + Overlap	7	377.38	2.06	0.12	0.78	-181.49
m9	State + Points + Overlap	4	377.38	2.06	0.12	0.90	-184.62
m12	State × Observer + Points	9	378.30	2.98	0.07	0.97	-179.82
m8	State + Overlap	3	380.44	5.12	0.03	1.00	-187.18

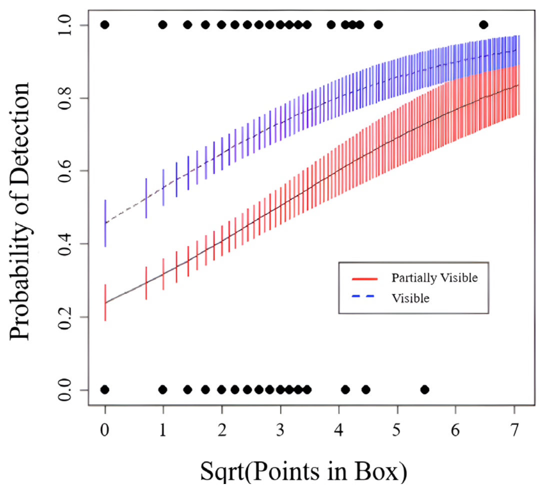


Figure 6. Fitted response curve for probability of detection of box turtle shells as a function of the search effort variable points. The points variable represents the number of square-root transformed (Sqrt) track points within a 5 × 5 m polygon surrounding each box turtle shell. Fitted response is shown for both visible and partially visible observation states. Solid points are the observed detection (y = 1.0) or non-detection (y = 0) events. Vertical lines are predicted response ± 1 standard error.

produced a top model (m11) that had state, points (square-root transformed), and observer effects. The effect on detection probability of a shell being in the visible state was highly positive, 1.02 (± standard error 0.26). The coefficient on the square-root of points was 0.43 (± 0.11). According to a fitted response curve of detection probability to sqrt(points), the detection probability of a shell in the visible state rose above 50% with fewer than one square-root transformed track point, compared to nearly three for shells in the partially visible state (Fig. 6). The second-best model did not contain observer effects, and the coefficients of state and points changed little in that model relative to the top model (Appendix Table).

Discussion

We implemented an experimental study to investigate the perception component of detection probability in visual search surveys of Eastern Box Turtle shells. Overall, about 50% of shells were detected across four observers (143 detections during 287 trials), and this varied by visibility state (63.0% of visible shells, 41.5% for partially visible shells detected). This variation in detectability suggests that trained observers using our search protocol may miss about 37% of conspicuous box turtles in plain sight on leaf litter in a forest with predominantly open under-story. Furthermore, our results indicate there is variation among observers in the perception component of detection probability. Although trained, the four observers in our study varied in age and experience detecting box turtles, and we believe this may explain some of the variation in detection among observers. There was also clear variation among observers, however, in how effectively they surveyed the plots according to our protocol of achieving uniform coverage subject to a 5-m transect width. Both coverage of the plot and time-per-unit area varied among observers, and many shells were not well exposed to detection by the observer, and thus not detected (i.e., some shells were beyond the buffered search track). This demonstrates that spatial coverage bias (i.e., incomplete spatial sampling) is an important component of perception, analogous to non-detection of distant objects in line-transect surveys.

Our results also suggest that observer variation in perception may be important even when accounting for spatial coverage. That is, our top model favored observer effects in addition to the spatial variable of points. Care should be taken when comparing count-based relative abundance indices that are not properly adjusted for observer variation.

Our observers missed a much larger proportion of partially visible shells compared to fully visible shells. These partially visible shells were meant to mimic turtles emerging, or otherwise partially visible due to inactivity (i.e., resting or in-form rather than foraging, basking, or mating). Presumably this partially visible state represents a relatively smaller fraction of turtles that are observed in the field, but we have not collected specific data on this during our operational surveys. We cannot, however, determine from our study the fraction of the population that might be in the different availability states at any given time, either partially or fully visible. The probability of availability could be quantified with telemetry, as individuals could be located by observers and then the availability status of the individual recorded. Indeed, Refsnider et al. (2011) studied a population of Ornate Box Turtles (*Terrapene ornata ornata*) with telemetry and estimated the probability of detection of available individuals (i.e., perception). Specifically, they referred to detection probability as the detection probability of available individuals, confirmed by telemetry. They estimated the perception probability to be 0.03. We are skeptical of that estimate given our own estimate, which is more than 15 times larger (about 50% averaged over visible and partially visible states). Moreover, consistent with our findings, two other studies (Gardner et al. 1999; Anderson et al. 2001) calculated much higher estimates of the perception component of detection probability.

Besides Refsnider et al. (2011), to our knowledge there are two other studies that characterize the perception component of detection probability for tortoises. Gardner et al. (1999) used plaster molds of Geometric Tortoise (*Psammobates geometricus*) shells and had a group of observers simultaneously search plots using standardized transect searches. They achieved about 60% detection of tortoise shells in open habitat and 57% in denser habitat. Their individual searcher results were more variable, but no observer detected more than 50% of the model shells, similar to our overall detection rate of 50% (across partially and fully visible states). Detection probability in Gardner et al. (1999) varied by the size of the model shells and habitat denseness although the authors did not conduct formal model selection or hypothesis testing to gauge the statistical significance of these effects. In our study, there was not a wide variation in shell sizes, but we believe the variation in size was consistent with adult live turtles in the study area. Anderson et al. (2001) used styrofoam models to study the detection of Desert Tortoises (*Gopherus agassizii)* using line-transect survey protocols. Their sub-adult size models were only slightly larger than the adult-sized box turtles in our study (18 cm versus about 13–15 cm for box turtles). The proportion of sub-adult tortoises detected ranged from 0.39 to 0.65 for 12 teams of three people searching a long transect. On average, 17% of models on or near (within 5 m) the centerline were not detected. Therefore, we believe the results of both Gardner et al. (1999) and Anderson et al. (2001) are consistent with our results demonstrating that a significant proportion of visible shells are missed by observers (or teams of observers), including shells in close proximity to the search tracks of observers.

We recognize some important limitations in our study. First, because our box turtle shells were museum specimens, most of them were treated with a coating of shellac to varying degrees. Overall, we did not feel that their appearance was much different from shells we observed in the field; although we cannot be certain of this, and it is possible that the real detection frequency could be less than what we observed in the field experiment. We hope to evaluate this question using unmodified shells if a supply can be obtained. Second, as with Gardner et al. (1999) and Anderson et al. (2001), we conducted our detection study with a higher density of shells than the natural density of turtles in our study area, which is about 1.4 turtles per ha (Royle and Turner 2022). Thus, our plots are expected to contain between zero and three turtles on average. Data from our study from 1999 to 2022 indicate that 17 individuals have been captured in the Powerline plot since 2019, seven in the Cabin plot (since 2020), and 12 in the Triangle plot (since 2020). An experimental design with natural densities would use only one to three shells per plot, thereby requiring many more weeks to obtain a similar number of detection events as we obtained under very high densities of box turtle shells. Therefore, our choice to use a higher density of shells in the study was pragmatic, but one might expect different detection rates under more realistic density settings. Moreover, as noted by Gardner et al. (1999), use of higher experimental densities allows for finer distinctions to be made in the experimental results. Essentially, we expect higher statistical power to detect effects for the limited time we had to conduct the experiment.

Finally, we only used two observable states, what we called visible and partially visible. We imagine that the unobservable state in which turtles are in-form or otherwise obscured is the most common state for turtles to be in on any given day. For practical concerns, we did not study fully obscured shells because during an experimental study, the probability of observing a shell in this state should be close to zero. We occasionally, however, detected a small number (1–3) of fully obscured (i.e., what we would define as unobservable or unavailable) turtles every year by random chance (e.g., by stepping on them). The best way to study the availability of turtles (that is, the proportion of time they are not in the unobservable state) is with telemetry. With telemetry turtles can be detected nearly 100% of the time, and their availability, degree of conspicuousness, or some other measure of how available individuals are can be recorded.

In summary, total proximity of the search track of an observer to the turtle shell as measured by our points covariate was a key factor affecting probability of detecting a box turtle shell. Visibility state was also significant, but this variable is not controllable by surveyors. On the other hand, proximity is essentially a design feature that can be controlled; observers can spend more time and do a better job systematically searching a plot, thereby increasing proximity for all possible shell locations and realizing a concomitant increase in detection probability. Increases in detection probability, however, cost time and money and, in practice, you can moderate time/effort and still estimate population parameters, like density, population size, or occupancy, in a manner that incorporates imperfect detection. As in many other wildlife monitoring systems, we found variation in detection probability among observers; however, this effect was not significant. Nevertheless, investigators should consider accounting for observer effects in models whether for relative abundance based on count indices (e.g., Sauer and Link 2011), or capture-recapture to estimate population size, especially when multiple observers are used who may be highly variable in their skill levels and experience. When feasible, evaluating search protocols that use experimental trials may help understand the efficacy of a monitoring program, and provide insight into plausible models for wildlife status and trend assessments.

Acknowledgments.—We thank Steve Kimble, Towson University, Mike Quinlan, and Jug Bay Wetlands Sanctuary for contributing box turtle shells. We are grateful to Haley Turner, Jackie Guzy, and Meg Lamont for providing reviews of a draft. We thank the Cooperative Summer Fellowship Program of the U.S. Geological Survey that provided funding for Emily Wapman, and the Department of Biology of the University of Richmond, who provided funding for William Heinle and Noelle Beswick. We thank Sandy Spencer and the Patuxent Research Refuge of the U.S. Fish and Wildlife Service for access to the refuge for box turtle research. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Literature Cited

Anderson, D.R., K.P. Burnham, B.C. Lubow, L. Thomas, P.S. Corn, P.A. Medica, and R.W. Marlow. 2001. Field trials of line transect methods applied to estimation of Desert Tortoise abundance. Journal of Wildlife Management 65:583–597.

Bailey, L.L., T.R. Simons, and K.H. Pollock. 2004. Estimating site occupancy and species detection probability parameters for terrestrial salamanders. Ecological Applications 14:692–702.

Converse, S.J., J.B. Iverson, and J.A. Savidge. 2005. Demographics of an Ornate Box Turtle population experiencing minimal human-induced disturbances. Ecological Applications 15:2171–2179.

Currylow, A.F., P.A. Zollner, B.J. MacGowan, and R.N. Williams. 2011. A survival estimate of Midwestern adult Eastern Box Turtles using radiotelemetry. American Midland Naturalist 165:143–149.

Diefenbach, D.R., M.R. Marshall, J.A. Mattice, and D.W. Brauning. 2007. Incorporating availability for detection in estimates of bird abundance. Auk 124:96–106.

Erb, L.A., L.L. Willey, L.M. Johnson, J.E. Hines, and R.P. Cook. 2015. Detecting long-term population trends for an elusive reptile species. Journal of Wildlife Management 79:1062–1071.

Fuentes, M.M.P.B., I. Bell, R. Hagihara, M. Hamann, J. Hazel, A. Huth, J.A. Seminoff, S. Sobtzick, and H. Marsh. 2015. Improving in-water estimates of marine turtle abundance by adjusting aerial survey counts for perception and availability bias. Journal of Experimental Marine Biology and Ecology 471:77–83.

Gardner, S., E.H.W. Baard, N.J. Le Roux. 1999. Estimating the detection probability of the Geometric Tortoise. South African Journal of Wildlife Research 29:62–71.

Hall, R.J., P.F. Henry, and C.M. Bunck. 1999. Fifty-year trends in a box turtle population in Maryland. Biological Conservation 88:165–172.

Ihlow, F., J. Dambach, J.O. Engler, M. Flecks, T. Hartmann, S. Nekum, H. Rajaei, and D. Rödder. 2011. On the brink of extinction? How climate change may affect global chelonian species richness and distribution. Global Change Biology 18:1520–1530.

Kemp, S.J., M.J. Kemp, and C. Guers. 2022. Decline of Woodland Box Turtles (*Terrapene carolina carolina*) over 40 years in southeastern Pennsylvania, USA. Herpetological Conservation and Biology 17:196–203.

Kendall, W.L., J.D. Nichols, and J.E. Hines. 1997. Estimating temporary emigration and breeding proportions using capture-recapture data with Pollock's robust design. Ecology 78:563–578.

Kéry, M., B. Gardner, T. Stoeckle, D. Weber, and J.A. Royle. 2011. Use of spatial capture-recapture modeling and DNA data to estimate densities of elusive animals. Conservation Biology 25:356–36.

Langtimm, C.A., C.K. Dodd, Jr., and R. Franz. 1996. Estimates of abundance of box turtles (*Terrapene carolina buari*) on a Florida island. Herpetologica 52:496–504.

Marsh, H., and D.F. Sinclair. 1989. Correcting for visibility bias in strip transect aerial surveys of aquatic fauna. Journal of Wildlife Management 53:1017–10724.

Mazerolle, M.J., L.L. Bailey, W.L. Kendall, J.A. Royle, S.J. Converse, and J.D. Nichols. 2007. Making great leaps forward: accounting for detectability in herpetological field studies. Journal of Herpetology 41:672–689.

Mittermeier, R.A., P.P. van Dijk, A.G.J. Rhodin, and S. Nash. 2015. Turtle hotspots: an analysis of the occurrence of tortoises and freshwater turtles in biodiversity hotspots, high-biodiversity wilderness areas, and turtle priority areas. Chelonian Conservation and Biology 14:2–10.

Nazdrowicz, N.J., J.L. Bowman, and R.R. Roth. 2008. Population ecology of the Eastern Box Turtle in a fragmented landscape. Journal of Wildlife Management 72:745–753.

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

Refsnider, J.M., T.S. Mitchell, H.M. Streby, J.T. Strickland, D.A. Warner, and F.J. Janzen. 2011. A generalized method to determine detectability of rare and cryptic species using the Ornate Box Turtle as a model. Wildlife Society Bulletin 35:93–100.

Royle, J.A., and H. Turner. 2022. Density estimation in terrestrial chelonian populations using spatial capture-recapture and search-encounter surveys. Journal of Herpetology 56:341–348.

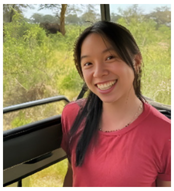
Sauer, J.R., and W.A. Link. 2011. Analysis of the North American Breeding Bird Survey using hierarchical models. Auk 128:87–98.

Stickel, L.F. 1950. Populations and home range relationships of the box turtle, *Terrapene c. carolina* (Linnaeus). Ecological Monographs 20:351–378.

van Dijk, P.P. 2011. *Terrapene carolina*. The IUCN Red List of Threatened Species 2011. International Union for the Conservation of Nature. http://www.iucnredlist.org.

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

William F. Heinle received his B.S. in Biology and Environmental Studies and B.A. in Geography from the University of Richmond, Virginia, USA. His research interests include using spatial statistics and technologies to explain patterns in ecosystems and wildlife. His recent work has evaluated effects of disturbance and multiuse management on ecosystem services as well as rural and urban community health. William has a history of herpetological experience in Virginia, Maryland, and West Virginia, USA, including habitat delineation, phylogenetics, and distribution extensions. (Photograph courtesy of the University of Richmond).



Noelle Beswick is an Assistant Researcher at New Mexico State University, Las Cruces, USA, studying and monitoring the large game mammals of San Andres National Wildlife Refuge in Las Cruces, New Mexico. Noelle graduated from the University of Richmond, Virginia, USA, with a B.S. in Environmental Studies with a minor in Mathematics. Her research interests include ecology, climate change, and human-wildlife interactions. Her experience consists of positions at Fort Matanzas National Monument, Florida, USA, Patuxent Wildlife Research Center, Maryland, USA, and the Center for Wildlife and Human Dimensions of Conservation in Kimana, Kenya. (Photographed by Reece Pauling).

Emily Wapman earned her B.Sc. in Biological Sciences from U.C. Santa Barbara, California, USA, and has a range of experience spanning fisheries sustainability research, fieldwork with the Oregon Department of Fish and Wildlife and the U.S. Geological Survey, and molecular biology at Lawrence Livermore National Laboratory, California, USA. (Photographed by Jacob Ogawa).

J. Andrew Royle is a Senior Scientist and Research Statistician at the Eastern Ecological Science Center of the U.S. Geological Survey in Laurel, Maryland, USA. He has made contributions to quantitative and statistical ecology, particularly in the development of hierarchical models for animal abundance and occurrence. His recent research focuses on spatial capture-recapture methods, which are pivotal in estimating wildlife population densities. Andrew holds a Ph.D. in Statistics from North Carolina State University, Raleigh, USA, and has a B.S. in Fisheries and Wildlife from Michigan State University, East Lansing, USA. (Photographed by J. Andrew Royle).

Appendix

Experimental evaluation of Eastern Box Turtle (Terrapene carolina carolina) detectability in visual search surveys

(Disclaimer: Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.)

Summary results (R output) for the top two models fitted to the Eastern Box Turtle (*Terrapene carolina carolina*) detection data.

summary(m11)
Call:
glm(formula = cbind(y,one- y) ~ observer + points + state, family = binomial(), data = newdata2)
Coefficients:

	Estimate	Std. Error	Z value	Pr(>|Z|)
(Intercept)	-1.3104	0.3060	-4.283	1.85e -05 ***
observerE	-0.3915	0.3514	-1.114	0.265174
observerN	0.5981	0.3477	1.720	0.085384 .
observerW	0.1461	0.3413	0.428	0.668671
points	0.4251	0.1116	3.809	0.000139 ***
statev	1.0266	0.2566	4.002	6.29e -05 ***

—-
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1
AIC: 375.02

---

summary(m7)
Call:
glm(formula = cbind(y,one- y) ~ state + points, family = binomial(), data = newdata2)

Coefficients:

	Estimate	Std. Error	Z value	Pr(>|Z|)
(Intercept)	-1.1769	0.2707	-4.347	1.38e -05 ***
statev	0.9882	0.2521	3.919	8.87e -05 ***
points	0.4002	0.1086	3.685	0.000229 ***

—-
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1
AIC: 375.25

Appendix Table. Survey attributes of the search track for each observer. Plot values are Pow = Powerline, Cab = Cabin, and Tri = Triangle plots as referenced in the main text. Observer references the individual conducting the survey (values 1–4). Survey is an integer representing the replicate sample of each plot (values 1–5). Total time is the time in minutes it took the observer to complete the search. Areafrac2 is the total plot coverage using a 2-m track buffer, Areafrac5 is the same using a 5-m buffer, Area.cov2 is the total area covered using the 2-m buffer, and Area.cov5 is the total area covered using the 5-m buffer. Models reported in the text use the 5-m buffer, although we evaluated both buffers and found that similar results were produced.

	plot	observer	survey	Total time	Areafrac2	Area.cov2	Areafrac5	Area.cov5
1	Pow	1	1	59.0	0.563	4,445	0.861	6,796
2	Pow	4	1	46.6	0.230	1,819	0.703	5,551
3	Pow	1	2	46.0	0.764	6,032	0.977	7,717
4	Pow	3	2	79.1	0.630	4,971	0.892	7,040
5	Pow	1	3	55.1	0.734	5,799	0.988	7,804
6	Pow	4	3	57.3	0.704	5,561	0.886	6,997
7	Pow	1	4	80.8	0.867	6,845	0.986	7,784
8	Pow	2	4	168.7	0.797	6,295	0.975	7,698
9	Pow	3	4	77.4	0.658	5,193	0.854	6,741
10	Pow	1	5	62.9	0.944	7,454	0.999	7,888
11	Pow	2	5	59.8	0.842	6,644	0.969	7,651
12	Pow	4	5	85.3	0.180	1,418	0.952	7,518
13	Cab	1	1	74.0	0.794	12,378	0.948	14,785
14	Cab	3	1	107.8	0.702	10,949	0.864	13,482
15	Cab	1	2	84.6	0.812	12,665	0.973	15,183
16	Cab	4	2	68.3	0.544	8,489	0.773	12,053
17	Cab	1	3	86.5	0.792	12,355	0.929	14,489
18	Cab	3	3	87.1	0.571	8,906	0.815	12,712
19	Cab	1	4	83.9	0.792	12,358	0.943	14,709
20	Cab	2	4	109.0	0.762	11,888	0.988	15,406
21	Cab	4	4	80.2	0.626	9,765	0.849	13,251
22	Cab	1	5	80.4	0.637	9,942	0.949	14,800
23	Cab	2	5	91.6	0.820	12,791	0.924	14,410
24	Cab	3	5	111.1	0.490	7,651	0.771	12,025
25	Tri	1	1	43.9	0.608	4,907	0.916	7,387
26	Tri	3	1	87.3	0.444	3,584	0.697	5,624
27	Tri	1	2	64.0	0.694	5,595	0.885	7,139
28	Tri	4	2	46.5	0.595	4,802	0.836	6,746
29	Tri	1	3	41.2	0.591	4,766	0.876	7,061
30	Tri	3	3	87.4	0.535	4,316	0.818	6,596
31	Tri	1	4	49.7	0.739	5,963	0.903	7,284
32	Tri	2	4	71.6	0.701	5,656	0.881	7,104
33	Tri	4	4	74.8	0.729	5,879	0.936	7,546
34	Tri	1	5	39.6	0.494	3,983	0.872	7,033
35	Tri	2	5	58.6	0.825	6,652	0.953	7,689
36	Tri	3	5	71.4	0.514	4,148	0.754	6,079