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Visual head counts: a promising method for efficient monitoring of diamondback terrapins

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Abstract: Generating a range-wide population status of the diamondback terrapin (*Malaclemys terrapin* spp.) is challenging due to a combination of species ecology and behavior, and limitations associated with traditional sampling methods. Visual counting of emergent heads offers an efficient, non-invasive and promising method for generating abundance estimates of terrapin populations across broader spatial scales and can be used to explain spatial variation in population size. We conducted repeated visual head count surveys at 38 predetermined sites along the shoreline of Wellfleet Bay in Wellfleet, Massachusetts. We analyzed the count data using a hierarchical modeling framework designed specifically to analyze repeated count data: the so-called N-mixture model. This approach allows for simultaneous modeling of imperfect detection to generate estimates of true terrapin abundance. We found detection probability was lowest when skies were overcast and when wind speed was highest. Site specific abundance varied but we found that abundance estimates were, on average, higher in unexposed sites compared to exposed sites. We demonstrate the utility of pairing visual head counts and N-mixture models as an efficient method for estimating terrapin abundance and show how the approach can be used to identifying environmental factors that influence detectability and distribution.

Keywords: abundance, detection, diamondback terrapin, *Malaclemys terrapin*, monitoring, N-mixture, salt marsh, visual head count

1. Introduction

The diamondback terrapin (DBT; *Malaclemys terrapin* spp.) is the only estuarine obligate turtle species in North America [1], and as a result, has a long but fragmented coastal range that extends from Cape Cod, Massachusetts, to the Texas Gulf Coast [2]. DBT are currently listed as protected or regulated in every range state [3]. Despite their conservation status, population assessments have been limited to local scales, and as a result, range wide inference about the status of this imperiled species is generally lacking [3,4].

As salt marsh specialists, DBT have specific life history and behavioral traits that determine which monitoring techniques are suitable and how that data can be used. For example, DBT have highly seasonal phenology in their northern range [5], form mating aggregations [6], and have highly specialized terrestrial nesting habitat requirements. The species is highly mobile [1] responding locally to disturbance when at the surface but also making larger movements with the tides, and they use regular surface breathing bouts as a behavioral adaptation to brackish conditions [3]. A variety of methods are used to monitor DBT, including modified crab traps [7–9], hoop traps [10,11], trammel nets [4,10–12], fyke nets [13,14], seines [12,15,16] and dip nets [8,11]. While each method takes some

aspects of DBT ecology into consideration, their success, in terms of consistent, reliable, and scalable population estimates has been variable. For example, in Wellfleet Bay (MA), almost four decades of monitoring using capture mark recapture (CMR) has resulted in over 3,000 marked individuals [17], but failed to produce reliable estimates of population sizes due to low detection rates (see also: [9,11,16]), mature female biased captures (see also: [7,18]), and variable and opportunistic search effort. These challenges often result in extensive sampling effort being concentrated in very small study areas that are not representative of the landscape, and therefore are not appropriate for landscape of range scale inferences [16,18,19].

A promising, but vastly under-utilized, monitoring method for DBT is visual counting of emergent heads (hereafter, *visual head counts*), which offers an efficient, non-invasive method for generating abundance estimates of local populations. Because DBT are the only turtle species to inhabit coastal estuarine habitats, must surface to breathe air, and perform seasonal staging behavior where both sexes congregate to initiate courtship and mating, their biology and behavior lend themselves naturally to count-based methods that do not require individual recognition. Visual (point) count surveying is a well-established monitoring method in avian ecology [20], with well-developed field protocols that can easily be modified for DBT; and well-developed statistical models, the so-called N-mixture model, for analyzing exactly the type of data that arise from such point-based count surveys. Although there is some support for the use of visual head counting for estimating relative DBT abundance [4,7], the concept has yet to gain traction and has not yet taken full advantage of the well-established canonical coupling of data generated from repeated counts and analysis using hierarchical ‘detection’ models.

In this study, we conducted visual head count surveys at 38 locations throughout Wellfleet Bay, Massachusetts. Using efficient spatially- and temporally-replicated visual head count surveys and well-established statistical models we were able to produce estimates of local population size, including lining abundance to shoreline exposure, and estimates of how environmental conditions (wind and cloud cover) influence detectability. Our results suggest that visual head count surveys are a promising method for monitoring of diamondback terrapins.

2. Materials and Methods

2.1 Study Area

This study is focused on approximately 50 km of shoreline around Wellfleet Bay (WB), a protected area located in the town of Wellfleet, within Cape Cod Bay, Massachusetts, USA (Figure 1). Wellfleet Bay is a marsh dominated system comprised of many creeks and inlets with an extensive intertidal zone that can exceed 3 meters during spring high tides.

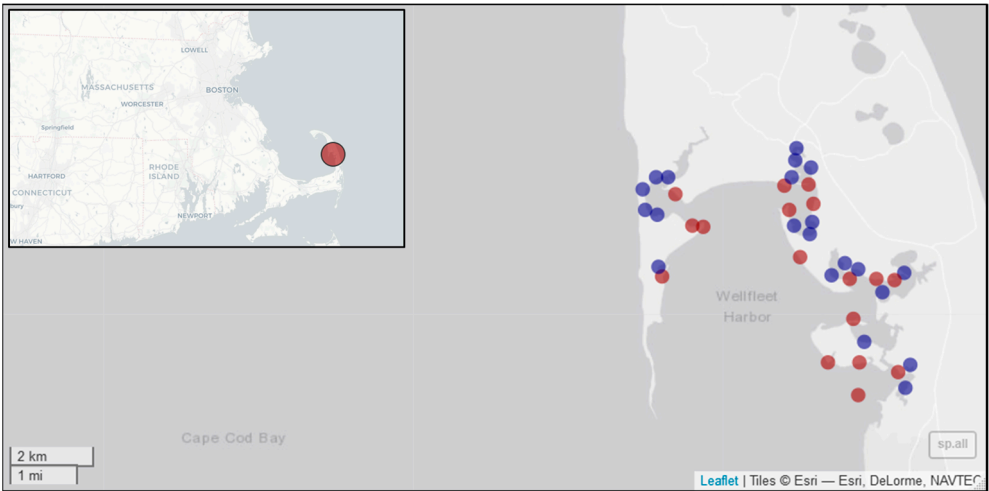


Figure 1. The Wellfleet Bay study area. Circles in the main figure shows the location of the 38 visual head count surveys (Red: exposed, Blue: sheltered), while the inset shows the geographic location of Wellfleet Bay in the greater Cape Cod Bay, Massachusetts.

We conducted visual head count surveys (visual surveys from here) at 38 locations along the shoreline of WB. Sites were selected using the following approach: First, points were generated every 500 meters along the entire shoreline of WB using the *Generate Points Along Lines* tool in ArcMap 10.6 (ESRI 2018). We used 500 m between points to ensure that on any given day, we would avoid double counting of individuals (i.e., to ensure independence among the sampling locations). Next, we removed points that were located in unsuitable DBT habitat, leaving 44 potential survey sites. We note that ‘unsuitable habitat’ was defined as areas with no marsh habitat, and thus, our surveys were focused on areas where DBT would, in theory, be expected to occupy at some point during the tide cycle. Upon initial visits to these 44 sites, 6 were deemed either inaccessibility or unsuitable for surveying (e.g. not enough open water visible to detect surfaced heads), leaving the final 38 suitable sites (Figure 1).

2.2 Visual Head Count Surveys

We conducted visual surveys at each of the 38 predetermined visual survey locations, that were navigated to exactly using a handheld GPS unit (Garmin GPSMAP 78, Olathe, Kansas). Visual surveys were conducted, using binoculars, by scanning the water from shoreline to shoreline and recording the number of DBT heads that were observed inside a 100 m radius from the survey point. During each site visit, we conducted five (5) such scans with a 1-minute break between the end of one scan and the beginning of the next. Each site was visited at least once each month from May through August 2018 (median number of site visits: 4, range: 3 - 13). Thus, the data generated from each site visit are five (5) imperfect counts of a population assumed to be constant during the period of counting, but that can vary between site visits and between sites. In total, there were 184 five-scan head count surveys conducted at 38 sites (i.e., 184 unique site-visit combinations).

The area sampled was approximately a 100 m radius semi-circle around the sampling location from the shoreline, extending into the water. This area was identified using a rangefinder (Halo, XL450-7, Grand Prairie). Rangefinders cannot reliably or efficiently detect DBT heads, which are too small, and therefore were not used to count heads. Instead, proficiency in observer distance estimation was achieved through extensive self-calibration prior to, and regularly during, the sampling season by comparing estimated distances with rangefinder distances of objects easily detected by rangefinders in the water (e.g. boats, buoys).

2.3 Statistical Analysis

The canonical analytical framework for analyzing repeated counts that are assumed to come from a population that does not change over the period during which counts are made (here the 5 scans) is the so-called N-mixture model [21]. Formally, the counts y_{ik} , which are the number of heads observed in scan k , where $k = 1, \dots, 5$, from site i , where $i = 1, \dots, 184$, are assumed to be binomial random variables with a trial size of N_i , i.e., the true population size at site i , and success probability, p_{ik} , which is the probability of detecting an individual in the population at site i during scan k . This can be written as follows:

$$y_{ik} \sim \text{Bin}(N_i, p_{ik}). \tag{1}$$

The N-mixture model assumes that individuals are equally detectable, but does allow detectability to be modelled using scan- or site-specific covariates that are assumed to influence detectability. In our case, for this pilot study, we considered three environmental covariates we felt would influence our ability to detect DBT heads: wind speed (miles per hour, ‘Wind’), cloud cover (clear, <50%, ~50%, >50%, or Overcast, ‘Cloud’), and the air temperature (Celcius, ‘Temp’). Each covariate was measured immediately prior to conducting the visual surveys and the same covariate value was used for each

scan at a site during a single visit. Detection probability can be modelled using a logit-linear model as follows:

$$\text{logit}(p_{ik}) = \beta_0 + \beta_{\text{wind}} \times \text{Wind}_{ik} + \beta_{\text{cloud}} \times \text{Cloud}_{ik} + \beta_{\text{temp}} \times \text{Temp}_{ik}, \tag{2}$$

where the intercept (β_0) and the coefficient for the effect of wind (β_{wind}), cloud cover categories (β_{cloud}), and air temperature (β_{temp}) are parameters to be estimated.

The N-mixture model is a ‘hierarchical model’, which means that the detection process (p_{ik} above) can be modelled conditional on, and independent of, the true abundance at a site N_i . This ability to explicitly account for imperfect detection while simultaneously estimating variation in true abundance is what makes these types of observation-state hierarchical models so appealing. Formally, we describe the abundance at a site, N_i , as a Poisson distributed random variable with expected value λ_i :

$$N_i \sim \text{Pois}(\lambda_i). \tag{3}$$

The Poisson distribution is an appropriate distribution for non-negative discrete variable such as abundance. As with detection, variation in abundance can be modeled as a function of site-specific covariates using an appropriate generalized linear model (GLM). For this pilot study, we quantified sites as exposed (i.e., sampling sites were located on a stretch of shoreline that were exposed to the open water of the larger bay), or unexposed (i.e., sampling sites were located on a stretch of shoreline that were sheltered to the open water of the larger bay), and used this categorical measure of exposure as a covariate on abundance (‘Exposure’, Figure 1). For Poisson regression, an appropriate GLM is a log-linear model:

$$\log(\lambda_i) = \alpha_0 + \alpha_{\text{exposure}} \times \text{Exposure}_i, \tag{4}$$

where the intercept (α_0), which is the expected abundance, on the log scale, for exposed sites, and the coefficient measuring the difference between the expected abundance at exposed and unexposed locations (α_{exposure}) are parameters to be estimated.

Because we were interested in exploring which covariate effects were most important in explaining both detection (i.e., Wind, Cloud, and Temp) and abundance (i.e., Exposure), we fit all possible combinations of covariate effects models. For detection, this included a null model (constant detection across all sites), univariate models for each of the three covariates, all possible pairs of covariates, and a model with all three covariates included (eight detection models, Table 1). For abundance, this included a null model (constant abundance across all sites), and an Exposure model (two abundance models, Table 1). Thus, in total, we considered 16 models. We treated each of the 184 unique site-visit samples as independent sites, acknowledging that the system is highly dynamic and that the assumption of closure between visits is very likely to be violated (see Discussion). All models we fitted in R (R citation), using the package unmarked [22], and were ranked according to AIC values where lowest is best [23].

3. Results

A total of 184 head count surveys were conducted at 38 spatially distinct sites, each of which was visited at least once each month from May through August 2018 (median number of site visits: 4, range: 3 - 13). Of the 38 sites, 17 were categorized as exposed and 21 were categorized as unexposed (Figure 1). Twenty-nine percent (29%) of surveys were conducted under clear skies, 28% conducted in <50% cloud cover, 5% in 50% cloud cover, 20% in <50% and 17% in overcast conditions. Surveys were conducted in wind speeds that ranged from 1 mph to 16 mph. The mean head count in a single scan was 2.65 (median = 0) and ranged from 0 to 91 individuals. DBT were detected at 36 out of the 38 sites surveyed.

Based on model evaluation using AIC [23], the best supported model allowed detection to vary as a function of both wind and cloud cover and abundance to vary by exposure category (i.e., this

model had the lowest AIC, Table 1). Although a model with air temperature was close in terms of AIC ($\Delta AIC = 0.64$, Table 1), and following recommendations in [24], the air temperature term can be considered non-informative because the addition of the effect did not improve the support relative to the top model which was simpler by one term. Therefore, below we report our findings based on the top model.

Detection probability was lowest when surveys were conducted in overcast conditions ($pr[\text{detection}|\text{avg wind}] = 0.11$, 95% CI: 0.08 – 0.15) and were similar when the sky was clear, had less than, about, and above 50% cloud cover ($pr[\text{detection}|\text{avg wind}] \approx 0.5$, Figure 2). Detection probability was negatively influenced by wind ($\beta_{\text{wind}} = -0.20$, 95% CI: -0.24 – -0.16, Figure 3). For example, in clear sky conditions, this effect relates to detection probability ranging from 0.80 (95% CI: 0.77 – 0.83, Figure 3) when there is no wind, to 0.16 (95% CI: 0.11 – 0.23, Figure 3) when wind speed is 16 mph (the highest recorded during surveys). Thus, maximum detection probability is achieved when sampling in conditions where the sky is not overcast and there is no wind.

Our classification of whether we determined sites to be located on exposed versus sheltered stretches of shoreline (exposure classification) was selected as the best model based on AIC (Table 1). Unexposed sites had a significantly higher expected abundance than exposed sites ($\alpha_{\text{exposure}} = 1.03$, 95% CI: 0.85 – 1.21, estimates on the log scale). This translates to an expected abundance of 2.68 (95% CI: 0.23 – 3.16, Figure 4) at exposed sites and 7.50 (95% CI: 6.87 – 8.20, Figure 4) at unexposed sites. Note that the estimate of λ are the mean of the Poisson distribution, i.e., the *expected* value, from which observed estimates of site specific abundances are assumed to be distributed. We can use the count data, and estimates of detection, to estimate a ‘conditional on observation data’ abundance for each site [22] (Figure 4). Local abundance at exposed sites ranged from 0 (95% CI: 0 – 1) to 51 (95% CI: 51 – 53), and local abundance at unexposed sites ranged from 0 (95% CI: 0 – 1) to 106 (95% CI: 101 – 110). Expected and realized estimates are shown in Figure 4.

Table 1. Model selection table showing all 16 models ranked according to their AIC score (lowest is better). The Detection (p) and Abundance (λ) model formulations are provided, as is the number of parameters in the model (K), the AIC score, the difference in AIC relative to the top model (ΔAIC), the AIC weight (ωAIC) which is a measure of relative model support, and the cumulative AIC weights ($\Sigma \omega AIC$).

Detection	Abundance	K	AIC	ΔAIC	ωAIC	$\Sigma \omega AIC$
$p(\text{wind}+\text{ccov})$	$\lambda(\text{expo})$	8	4382.69	0.00	0.58	0.58
$p(\text{airtemp}+\text{wind}+\text{ccov})$	$\lambda(\text{expo})$	9	4383.33	0.64	0.42	1.00
$p(\text{airtemp}+\text{ccov})$	$\lambda(\text{expo})$	8	4475.53	92.84	0.00	1.00
$p(\text{airtemp}+\text{wind})$	$\lambda(\text{expo})$	5	4476.29	93.60	0.00	1.00
$p(\text{ccov})$	$\lambda(\text{expo})$	7	4477.81	95.12	0.00	1.00
$p(\text{wind})$	$\lambda(\text{expo})$	4	4478.46	95.77	0.00	1.00
$p(\text{wind}+\text{ccov})$	$\lambda(\cdot)$	7	4539.74	157.05	0.00	1.00
$p(\text{airtemp}+\text{wind}+\text{ccov})$	$\lambda(\cdot)$	8	4540.46	157.77	0.00	1.00
$p(\text{airtemp})$	$\lambda(\text{expo})$	4	4554.15	171.45	0.00	1.00
$p(\cdot)$	$\lambda(\text{expo})$	3	4558.73	176.03	0.00	1.00
$p(\text{airtemp}+\text{wind})$	$\lambda(\cdot)$	4	4640.62	257.93	0.00	1.00
$p(\text{wind})$	$\lambda(\cdot)$	3	4644.02	261.33	0.00	1.00
$p(\text{airtemp}+\text{ccov})$	$\lambda(\cdot)$	7	4645.78	263.09	0.00	1.00
$p(\text{ccov})$	$\lambda(\cdot)$	6	4647.29	264.60	0.00	1.00
$p(\text{airtemp})$	$\lambda(\cdot)$	3	4722.14	339.44	0.00	1.00
$p(\cdot)$	$\lambda(\cdot)$	2	4725.64	342.95	0.00	1.00

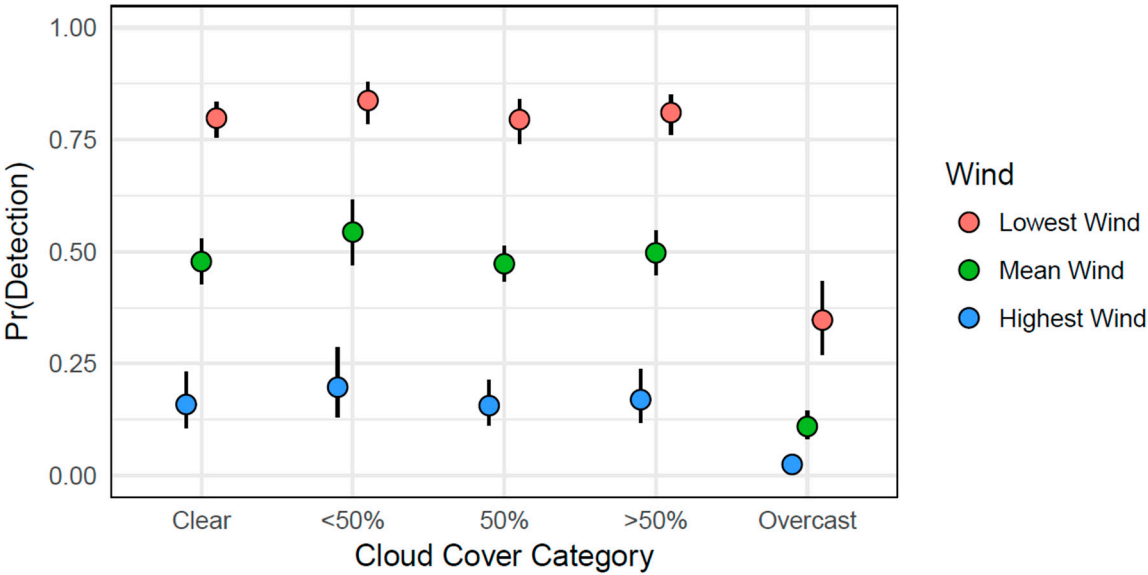


Figure 2. Per individual detection probability of diamondback terrapin heads as a function of the five cloud cover categories. Estimates are reported at the lowest (1.00 mph), average (8.21 mph), and highest (16.00 mph) wind speeds recorded during the head count surveys. Points are maximum likelihood estimates, and solid black lines represent 95% confidence intervals.

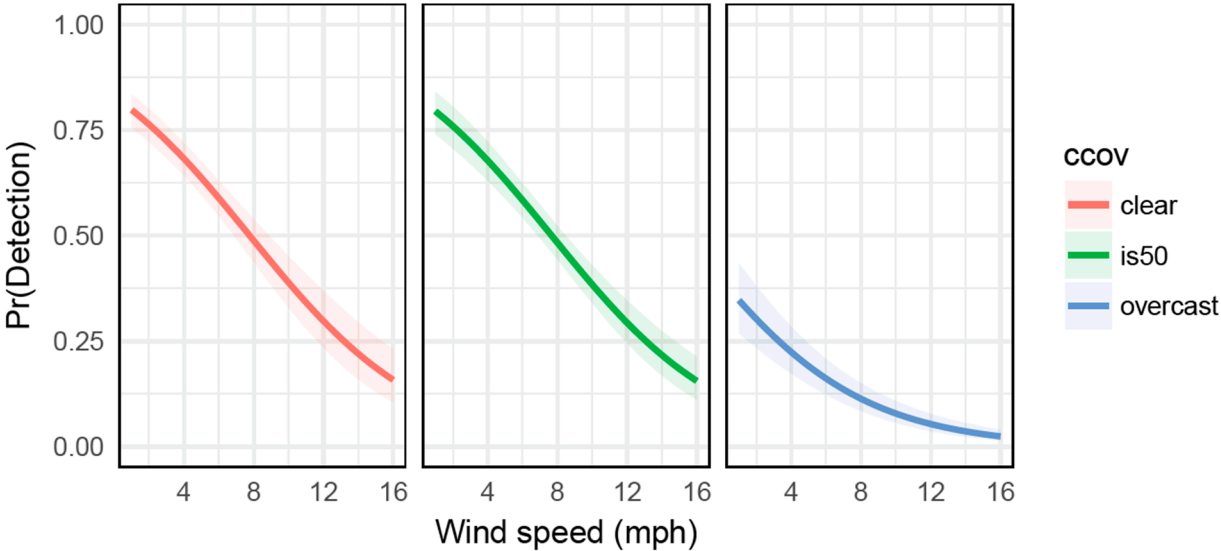


Figure 3. Per individual detection probability of diamondback terrapin heads as a function of wind speed at three (of the five) cloud cover categories. Solid lines are maximum likelihood estimates, and polygons represent 95% confidence intervals.

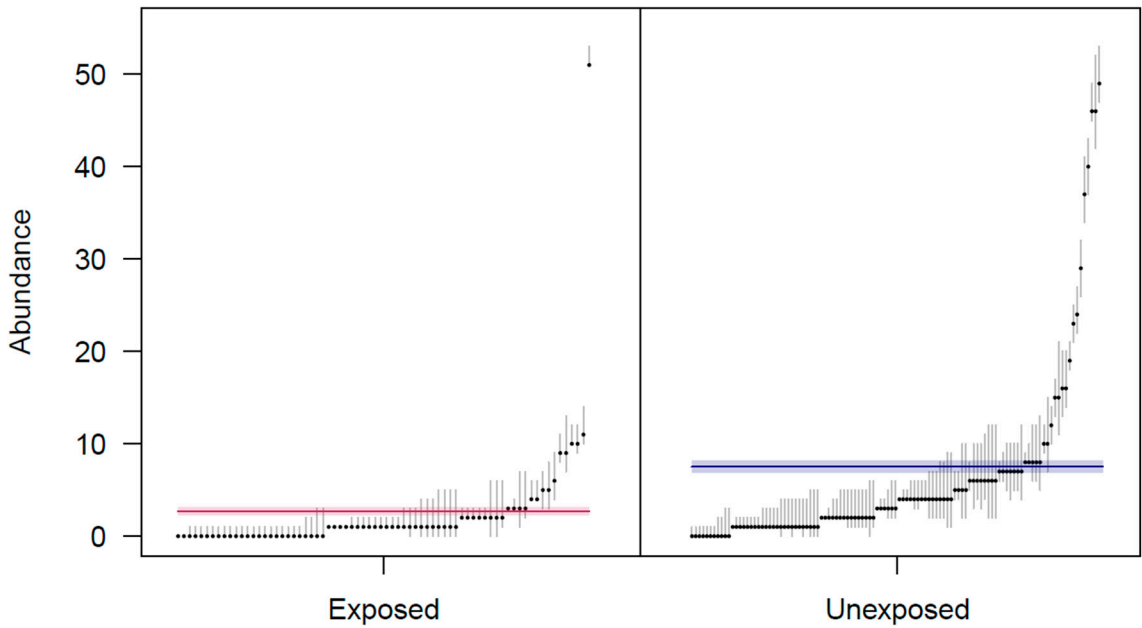


Figure 4. Model estimates of expected (solid horizontal lines) and conditional (black points) estimates of abundance. Expected abundance is the mean, or expected, abundance at an exposed (red line with polygon representing 95% confidence intervals) and unexposed (blue line with polygon representing 95% confidence intervals) sites. Realized abundances are assumed to be populations sizes assumed to come from a Poisson distribution with a mean $\lambda_{\text{exposed/unexposed}}$ and thus vary by site. Site specific counts allow the generation of realized site-specific population estimates which are conditional on the observed data. Note, that the Y-axis has been truncated at 55 for enhanced visual representation of the data – there is one unexposed stite (N=106) not shown here.

4. Discussion

In this study, we demonstrate how pairing visual head count surveys with N-mixture modeling offers a complimentary data collection and analysis framework for efficiently estimating local diamondback terrapin population sizes while simultaneously accounting for factors that affect detectability and explain spatial variation in abundance. We found that, as expected, detection probability was negatively influenced by wind speed and overcast skies, and our results suggest that abundance was higher at sites along sheltered stretches of shoreline relative to sites that were exposed. Visual head count surveys are indeed a promising and efficient method of estimating abundance for this important estuarine obligate turtle.

Studies of DBT have been largely focused on capture mark recapture and are plagued with reported issues of detectability [7,16,17]. Our study confirms that this challenge is not restricted to CMR, but also impacts visual head counts. However, repeat-survey designs such as those called for under the N-mixture model, are developed specifically to capture variability in imperfect counts and relate that variability to variation in factors (e.g., environmental) recorded during each survey. While robust design CMR is designed in the same way, an important distinction is that visual head counts do not require physical capture and are designed in line with the species surfacing and aggregation behavior to maximize detection, and this appears to yield far greater sample sizes. While this precludes the estimation of demographic rates (survival and fecundity) that typically require individual identity to be known, when the inference objective is to estimate abundance, something that is lacking throughout the range, then abundance estimates from unmarked individuals as we have presented here has obvious value (see Figure 4).

Applying the N-mixture model to repeated head count surveys, we were able to both identify, and correct for, factors that influenced detectability and therefore estimate population size free of these specific biases. Specifically, for DBT in Wellfleet Bay, wind reduced detectability (Figure 2) and detection was poorest in overcast conditions relative to any other cloud cover category (Figure 3). It

was interesting, and contrary to our expectations, that there was no substantial difference in detectability with increasing cloud cover, but rather it appeared that the main difference was between completely overcast and all other categories where there was at least some blue sky. This may be due to the significant decrease in contrast between emergent DBT heads and the water, as both become darker in color under overcast skies. The negative effect of wind on detection was expected, and likely related to either increase wave chop making heads more difficult to observe or, behavior-related, that DBT surface less in higher winds. While we cannot disentangle the effect of wind and cloud cover on observer ability versus DBT behavioral response *per se*, N-mixture models do allow us to test hypotheses about detectability in general. This has potential implications for other capture methods that rely on visual detection of terrapins (e.g. dip netting, drones). Our study suggests that the ideal conditions for conducting visual head count surveys in this system is are in low-to-no wind when it is not overcast.

One of the most appealing features of our use of the visual head counts and N-mixture models is the ability to generate estimates of population size for several, 38, locations within Wellfleet bay and link those estimates to spatially varying covariates. This is in contrast with intensive CMR efforts, which often require multiple seasons to generate sufficient recaptures [16,17], and have been restricted to just two locations within the bay [17]. This is common throughout the range where CMR estimates of abundance are typically, and justifiably, made over a spatially restricted area relative to the local or regional distribution of the species [9,10]. Moreover, this improvement in the spatial coverage and the statistical inference about DBT population status, at least in Wellfleet Bay, is achieved far more efficiently than traditional methods [7,25], and arguably yields more management-relevant results. For example, the ability to move beyond point estimates of abundance and start to relate spatial variation in abundance to habitat characteristics or environmental conditions is potentially far more valuable information to inform proactive species- and habitat-specific conservation action.

Our focus here was to demonstrate the utility of visual head counts and N-mixture models as an efficient method for estimating abundance, and as such, we did not exhaustively explore all potential predictors of abundance. Instead, we focused on differences between sheltered and exposed shorelines as a simple catch-all proxy for a wide range of environmental disturbance. As expected, we found that abundances at exposed sites were on average lower than at sheltered sites. Despite being a crude measure of habitat quality, these model predictions are in line with what we would expect: unexposed sites experience less environmental disturbance (e.g., turbidity) where intact saltmarsh habitat is more likely to be found. Also as expected, there was a great deal of variation in site-specific abundances over and above the ‘exposure effect’ (Figure 4), likely reflecting unmodeled spatiotemporal variation in population size arising from additional habitat preference and phenologically driven changes. While not included in this effort, the next step is to focus on developing a suite of potential spatiotemporal covariates to formally identity drivers of population sizes in both space and time.

5. Conclusion

The visual head count methodology described here naturally matches the ecology of DBT, they are easy to conduct and require very little training (i.e., low intensive), and, as demonstrated here, generate spatially referenced estimates of local abundance over a large spatial extent. This contrasts substantially with the widely used CMR approaches, which involve substantial effort, both in terms of time and expertise (i.e., highly intensive), they often suffer from extremely low capture rates requiring multiple sampling seasons to generate abundance estimates, and as a result are typically limited in terms of spatial coverage. Further, we demonstrate the application of N-mixture models, the canonical analytical framework for analyzing such repeated count data, and were able to identify ideal survey conditions that will maximize detection in future surveys, and revealed substantial site-specific variation in estimates of abundance likely due to habitat preferences and phenology. We propose visual head count surveys and associated hierarchical modeling framework as a promising

method for generating spatially explicit estimates of diamondback terrapin abundance, and drivers of spatiotemporal variation in abundance that has the potential to scale up DBT population assessments across their range.

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