

AN ASSESSMENT OF VISUAL ENCOUNTER SURVEYS FOR AN ELUSIVE
SPECIES - THE DUNES SAGEBRUSH LIZARD (*SCELOPORUS ARENICOLUS*)

by

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DEDICATION

To my parents – Travis and Tammy Kiehne, my sisters – Kadie and Haley Kiehne, and my grandmother – Dorothy Ake. Without you, I would not have had the courage nor the strength to travel away from everything I know to pursue this dream. Thank you for everything you have done and everything that you continue to do for me. I love you more than you will ever know.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AICc	Akaike Information Criterion – corrected for small sample size
<i>A. marmoratus</i>	<i>Aspidoscelis marmoratus</i>
at.....	Air temperature
bp.....	Barometric pressure
CPUE	Catch-per-unit-effort
DSL	Dunes Sagebrush Lizard
GLMM	Generalized linear mixed model
<i>Q. harvardii</i>	<i>Quercus harvardii</i>
rh	Relative humidity
<i>S. arenicolus</i>	<i>Sceloporus arenicolus</i>
st.....	Substrate temperature
TCP	Texas Conservation Plan
<i>U. stansburiana</i>	<i>Uta stansburiana</i>
USFWS	United States Fish and Wildlife Service
VES	Visual encounter survey
WND	Weighted naïve detection
ws	Wind speed
YDWMA.....	Yoakum Dunes Wildlife Management Area
Δ AIC	Delta AIC value

ABSTRACT

The Dunes Sagebrush Lizard (*Sceloporus arenicolus* - DSL) is a highly cryptic, habitat specialist that shows a preference for environments comprised of large wind-blown sand dune complexes and dense arrays of shinnery oak (*Quercus harvardii*). This species occupies a narrow range in the Monahans Sandhills of Texas and the Mescalero Sands of New Mexico and like many habitat specialists, they are sensitive to disturbances within their environment. Conservation of this species relies upon precise assessments of the occurrence, abundance, and the trends in both metrics for this lizard. The standard method for detecting the DSL, visual encounter surveys (VES), was utilized to estimate the probability of detection, across sites that had varying degrees of reported suitability. Three separate VES methodologies were analyzed: 1) plot size: 200m x 200m; survey duration: 15 minutes, 2) plot size: 400m x 400m; survey duration: 60 minutes, and 3) plot size: 200m x 200m; survey duration: 30 minutes. The probability of detection, for *S. arenicolus*, was compared to two more commonly detected species, *Uta stansburiana* and *Aspidoscelis marmoratus*. The minimum number of surveys, needed to reliably detect these species, was then calculated from detection estimates. A total of 1,135 individual lizards were recorded, 12 of which were *S. arenicolus*. The mean detection probability for *U. stansburiana* = 0.38, followed by *A. marmoratus* = 0.28, and finally the DSL = 0.13 to 0.19. Less surveys were needed to be 95% confident that a lizard was detected, if that lizard had a higher probability of detection. Results of the study indicated that while VES may be suitable for many common species of lizards, it may not be the most efficient method for accurately determining presence of rarer species of lizards (i.e., the DSL). This could indicate that a more intensive survey methodology (i.e., pitfall traps) may be needed when trying to make reliable occupancy or abundance estimates.

I. AN ASSESSMENT OF VISUAL ENCOUNTER SURVEYS FOR AN ELUSIVE SPECIES - THE DUNES SAGEBRUSH LIZARD (*Sceloporus arenicolus*)

Introduction

Many long-term wildlife management plans focus on evaluating trends in animal populations. As a result, many plans necessitate extensive monitoring programs that will

- 1) accurately assess the number of individuals in a given population (i.e., abundance) and
- 2) identify areas where those individuals occur (i.e., occupancy) (Pollock, 2002; MacKenzie and Royle, 2005; Pellet and Schmidt, 2005; MacKenzie et al., 2006; Olea and Mateo-Tomás, 2011). This framework can be particularly important for species of conservation concern. Categorizing potential habitats for threatened/endangered species can be difficult, not only because these species are rare (low occupancy), but also because some species are highly cryptic and are therefore not easily encountered (low detection probabilities) (Shannon et al., 2014). The effects of imperfect detection rates are profound, especially when managing species of concern. If biologists misunderstand population parameters, it can create complications that ultimately affect their management decisions. For example, imperfect detections can lead to 1) underestimation of naïve occupancy (MacKenzie et al., 2002), 2) erroneous or biased abundance counts (Royle et al., 2005) 3) poor predictive performance of species distribution models (Lahoz-Monfort et al., 2014), and 4) inaccurate estimates of local colonization and extinction events (MacKenzie et al., 2003). Concluding a species is absent, when it is really present, is a form of sampling error that must be avoided in order to make effective management decisions. It is therefore imperative that biologists and managers utilize protocols that will 1) accurately determine the occupancy of a species and 2) allow individuals of the species to be routinely detected for population monitoring.

The characteristics of a species and the environment that it resides in, are not the only factors that can cause variation in detection probabilities. In fact, the type of survey methodology may affect the overall detectability of a species (Mazerolle et al., 2007; Martin et al., 2007; Williams et al., 2002). Specific survey methods might be ineffective in some circumstances but when applied in the proper situation, they can be considered useful [e.g., point count surveys (Mazerolle et al., 2007)]. For example, visual transect surveys have been deemed unreliable when targeting rare or elusive species (Barea-Azcón et al., 2006), but this methodology can also be extremely useful when targeting other species (Sung et al., 2011). The success of a study can, therefore, rely heavily upon knowing the costs and benefits of different survey methods in various situations.

There are numerous survey methods that are frequently utilized for the detection of reptile species. These methods can be classified into two main categories: passive sampling methods (animals captures are accumulated over time, with marginal human intervention) and active sampling methods (observers search for and sometimes physically capture animals) (Willson and Gibbons, 2010; Hubert et al., 2012). Pitfall and camera traps are prime examples of conventional passive trapping methods that have been utilized for surveying herpetofaunal species, specifically lizards (Degenhardt, 1966). Pitfall traps and camera traps alike, may be effective for obtaining high numbers of captures (Townsend, 1991; Greenberg et al., 1994; Welbourne et al., 2015). While these methodologies are both highly successful, neither is unbiased. Pitfall traps, for example, may have disadvantages such as high mortality rates (Todd et al., 2007) and the inability to accurately detect certain ecological groups (i.e. arboreal and fossorial species) (Greenberg et al., 1994). Unfortunately, camera traps are also imperfect, as this method

may be problematic with regard to species identification (Welbourne et al., 2015). These types of issues can contribute to the appeal for using active sampling methods such as visual encounter surveys (VES). VES has proven to be effective over other sampling methods in situations where there are time and/or cost restraints because VES is relatively inexpensive and can be completed in short timespans (Smolensky and Fitzgerald, 2010). VES, while useful, is also largely dependent upon the sampling effort and the expertise of the individuals conducting the survey (Ribeiro-Júnior et al., 2008). Acknowledging these types of strengths and weaknesses among methodologies is crucial to the success of any study and should not be overlooked when making management decisions.

The Dune Sagebrush Lizard (*Sceloporus arenicolus*: DSL, hereafter; Figure 1) is listed as endangered by the New Mexico Department of Game and Fish (2016) and was a candidate for federal listing in 2012 (U.S. Fish and Wildlife Service, 2012). The DSL occupies a narrow geographic range that encompasses the Monahans Sandhills of Texas and the Mescalero Sands of New Mexico (Figure 2) (Smolensky and Fitzgerald, 2010; Center for Biological Diversity and Defenders of Wildlife, 2018). Studies have explicitly suggested that the current range of this endemic lizard, is relatively small when compared to other North American lizard species (Fitzgerald et al., 1997). The DSL is categorized as a habitat specialist showing a strong preference for environments comprised of large dune complexes and dense arrays of shinnery oak (*Quercus harvardii*) (Chan et al., 2009). In addition to restricted habitat types, individuals can routinely go undetected because of their behavior [i.e., basking and retreating into the shade for thermoregulation purposes (Sartorius et al., 2002)] and low abundances that are mostly due to habitat

fragmentation (Leavitt and Fitzgerald, 2013). The DSL, like many habitat specialists, is sensitive to disruptions in its environment (Leavitt and Fitzgerald, 2013). A substantial network of roads and oil pads (infrastructure for the expanding energy industries) is currently dispersed throughout the habitat, fragmenting and destabilizing the homogeneous sand dune landscape (Walkup et al., 2017). Studies suggest that these roads block connectivity between dunes and disrupt the dispersal of the species (Hibbitts et al., 2017; Young et al., 2018). Hibbitts et al. (2017) indicated that most individuals will avoid the industrial caliche roads altogether. This type of extreme behavior can confine individuals to noncoastal islands, ultimately increasing the likelihood for local extirpations to occur (Young et al., 2018). Overall, anthropogenic changes to habitat and landscapes, coupled with the potential to inefficiently detect and estimate occupancy, is detrimental to the conservation of this species.

Unfortunately, there are few studies that provide reliable survey guidelines for detecting the DSL. Moreover, there are not many studies that utilize the current standard for locating this species (i.e., visual encounter surveys). In fact, prior studies are mainly focused on utilizing capture-mark-recapture methods for evaluating abundance and other demographic factors (Leavitt and Fitzgerald, 2013; Ryberg et al., 2013; Ryberg et al., 2015). Additionally, the few studies that do employ VES were predominately conducted within habitats that were categorized as highly suitable for the DSL (Fitzgerald et al., 2011; Ryberg et al., 2016). This implies that efforts are mainly focused within large dune blowouts that are surrounded by *Q. harvardii* (Fitzgerald et al., 1997; Fitzgerald et al., 2011). While this technique may be effective for detecting DSL individuals, it does not evaluate the true ability of VES across habitat types. The primary goals of this study were

1) to assess the efficiency and accuracy of VES for detecting the DSL and 2) to determine the minimum survey effort needed to reliably infer absence, of various lizard species, within the Shinnery – Sands ecoregion. Visual encounter surveys may be less labor intensive when compared to other more robust survey methodologies (i.e., pitfall trap arrays), but they can provide highly variable detection rates, especially when attempting to detect highly cryptic species (Olsen et al., 2016; Willson and Gibbons, 2010). As stated before, there is concern for the proper conservation management of the DSL and any inaccurate occupancy estimates could be detrimental for this species. Understanding the trade-offs of any survey method could inform biologists of the biases associated with that specific method. Once those biases are acknowledged, surveyors could use that information to potentially 1) increase the probability of detecting this species when it is present or 2) minimize the probability of non-detection when a population is actually present at a given location or habitat type. Therefore, it is possible that assessing VES as a detection method, for this elusive species, will provide biologists with better information that is necessary to mitigate the issues surrounding this method. The amendments could then be used to improve conservation and management efforts, by ensuring that the most efficient form of this method is being utilized when monitoring and surveying populations.

Methods

Study Site. – The sites for this study are located in the Monahan Sandhills of Texas (Andrews, Ward, and Winkler counties). All sites were either 1) properties that were owned by the University of Texas System 2) within the Monahans Sandhills State Park or

3) privately-owned parcels that were enrolled in the now defunct Texas Conservation Plan (TCP) for the DSL (Office of the Texas Comptroller, 2012). This region is characterized by a variety of habitat types, including open dune blowouts, open active dunes, shinnery oak and grassland dune complexes, and mesquite flats. In order to avoid potential detection biases, this study was conducted on sites that had varying degrees of reported suitability for the DSL. The sites ranged from highly suitable to those considered to represent unsuitable habitat. An equal number of sites were selected, for each habitat suitability type, using a stratified random sampling approach (Table 1; Forstner et al., 2018). It is important to note that the number of sites were not uniform between the two sampling years because of additional site access restrictions (2017, $n = 60$; 2018, $n = 30$). In addition to the 60 sites that were originally selected in 2017, access was also granted within other Permian Basin locations ($n = 43$). It is also important to note, that while all sites in 2017 were surveyed once per month, the sites in 2018 were actually visited twice per month because of limited access to sites.

Sampling. – Visual encounter surveys were conducted for two sampling seasons (May – September 2017; May – July 2018) in the Monahans Sandhills ecosystem. In addition to these two periods, another sampling interval was completed during July of 2017 in the Yoakum Dunes Wildlife Management Area (YDWMA). A total of 15 individual observers conducted the VES over the two survey years. Those 15 individuals were randomly arranged into pairs, with the intention of having every plot assessed by two observers simultaneously and independently. Observers were randomly partnered, before sampling was initiated, to prevent creating bias among observer pairs. Each pair of

observers used a Kestrel 2500 Weather Meter to record abiotic environmental conditions (i.e., air temperature, wind speed, humidity and barometric pressure). The only abiotic condition not recorded with the Kestrel was substrate temperature. Instead, this factor was recorded with an infrared laser thermometer. Surveyors were also equipped with a GPS unit (GPSMAP 64st – Garmin) to record the quasi-random path they walked throughout the survey. Observers were required to record every individual lizard that they encountered (including non-target species) and document their locations on both the GPS and on AppSheet (i.e., a customizable mobile app building program) (Seshadri et al., 2019).

Initially, in the 2017 sampling period, surveys were conducted for 15 minutes, in a 4-hectare plot (200m x 200m or 40,000 m²) (15'200 m² hereafter). The best estimates of the home range, for the DSL (average = 436 m²), were used to determine plot size (Hill and Fitzgerald, 2007). Thus, 400 m² was used as the starting point for plot size in this study, mimicking that of Crump and Forstner (2019). In an attempt to maximize survey efficiency, alterations were made to the study design. Beginning in May 2018, plot size and survey time were quadrupled (i.e., plot size: 400m x 400m or 160,000 m²; survey time: 60 minutes; 60'400 m² henceforth). A catch-per-unit-effort (CPUE) analysis was then performed to determine the effectiveness of the modified study design. The remaining surveys in the 2018 sampling period (i.e., June – July), were subsequently conducted for 30 minutes, in a 4-hectare plot (30'200 m² hereafter).

Statistical Analysis. – A suite of generalized linear mixed models (GLMM) were analyzed in Program R (R Core Team, 2013; Package: lme4), to compare detection

probabilities among the various lizard species in the Monahans Sandhills complex. Several environmental factors were included to account for heterogeneity among the detection probability estimates. Substrate temperature (st), air temperature (at), barometric pressure (bp), relative humidity (rh), wind speed (ws), and the survey type were included in the models to determine if they had any effect on the overall detections of lizards, at sites known to be occupied. Moreover, the survey type was added, along with these environmental covariates, to account for any variation among the three survey treatments (i.e., 15'200 m², 30'200 m² and 60'400 m²). All of the models that were compared included observer, as a random effect, to account for presumed observer biases (Crump and Forstner, 2019). Observer and survey type were both coded as factors, before the analysis began, to indicate the type of survey that was utilized and who completed the survey. These two variables were considered the independent variables and were added to test the effects they might have on the dependent variable (i.e. lizard detections). Once the models were built, an Akaike Information Criterion analysis, corrected for small sample size (AICc), was executed for model selection (R package: AICcmodavg). A full model (e.g., including all of the covariates) was selected for the AICc analysis, along with six models that excluded one of each of the covariates, six univariate models, and an intercept model. All of the models selected included the random effect (i.e., observer). The delta AIC (ΔAIC) and Akaike weight values were used in the model selection process. A ΔAIC value of <2 is known to suggest strong evidence for the selection of that particular model, therefore this threshold was used when selecting the top model (Mazerolle, 2006). Note that these procedures were completed, not only for the species of interest, the DSL, but for two more common species of lizards (i.e., The Common Side-

blotched Lizard – *Uta stansburiana* and The Marbled Whiptail – *Aspidoscelis marmoratus*) as well. Furthermore, the analysis was only performed using the data from sites where a lizard was detected at least once by an observer. All other sites that did not have a prior detection were removed from the dataset. Finally, the YDWMA plots were removed from all analyses because the plot size and shape associated with these sites was not comparable to plots at other sites.

Initial attempts to analyze the DSL detections, with the GLMM, resulted in model convergence issues. Therefore, estimates were obtained by calculating the weighted naïve detection (WND) probabilities in Microsoft Excel. This was completed through the use of the following formula, where p_s was the proportion of surveys where at least one DSL was detected and p_r was the proportion of surveys conducted at that given site.

$$\text{WND} = \sum_{i=0}^n p_s * p_r$$

These values were then compared to detection probabilities that were estimated with a series of bootstrap analyses, conducted with 10,000 iterations. In order to account for differences among the three survey methodologies, the analyses were split into three groups (i.e., one for each VES configuration utilized in this study). After these values were verified, 95% confidence intervals were obtained from the bootstrap analysis. All bootstrap analyses were conducted in Program R (Code: Appendix A; R Core Team, 2013; R package: boot).

Finally, in order to further assess the efficiency of VES, the detection probabilities were used to determine the total number of surveys needed to be 95% confident that a species was absent at a given site. Utilizing the equation described by Pellet and Schmidt (2005), the average survey effort was calculated for the same three lizards

located in the sand dune ecoregion. Standard deviations (*U. stansburiana* and *A. marmoratus*) and confidence intervals (DSL) were used to obtain the maximum number of surveys needed to be 95% confident in the detection of these species. All statistical analyses were completed in Program R (Code: Appendix A; R Core Team, 2013).

Results

Total Lizard Observations. – There were 891 surveys conducted during the two years of survey work. The total number of detections varied greatly among species (Table 2). Raw detection counts showed that a total of 1,135 individual lizard observations were made, encompassing 7 genera and 13 species (Table 2). Among these lizard detections, 903 of the observations were identified at the species level (Figure 3). However, after the YDWMA sites were removed the total number of detections was 1,065, with 865 of those detections identified at the species level. *U. stansburiana* and *A. marmoratus* were the two most frequently reported lizard species, in both datasets, with 447 and 211 individual detections respectively (Table 2). All other lizards were reported less frequently, most of which had < 150 individual detections. The DSL, for instance, was recorded a total of 12 times throughout the entirety of the study (Table 2).

In addition to species, the total number of detections also varied among the three survey methods used in this study. *U. stansburiana* had the lowest number of detections within the 15'200 m² survey plots and greatest number of observations within the 60'400 m² survey design (n = 109 and n = 193 respectively; Figure 4). Similar to *U. stansburiana*, the 15'200 m² survey type yielded the lowest counts for *A. marmoratus* (n = 39; Figure 4). However, *A. marmoratus* was detected the most when the 30'200 m²

survey design was utilized ($n = 101$; Figure 4). Unlike the other two species, the relatively few detections of the DSL suggest that as time and plot size increased, the number of detections decreased. Moreover, the highest number of detections for the DSL was recorded when the 15'200 m² surveys were performed ($n = 6$; Figure 4).

As seen above, the DSL was detected a total of 12 times, within sites used in the analysis. Expectedly, all detections for the DSL occurred in areas where sand was the dominant substrate (Figure 5; Figure 6). Within those sites, the majority of the detections were located within open dune blowout habitats (Figure 5). However, the DSL was not restricted to the sites classified as open dune blowouts, as has often been portrayed in the literature for the species. In fact, individuals were detected within a variety of areas including: 1) sand flats dominated by thick expanses of *Q. harvardii*, 2) habitat on the edge of small open dunes, and 3) within sandy areas near roadways (Figure 6).

AICc Model Selection. – The ΔAIC and AICc model weights, calculated in the AICc analysis indicated that there were four competing detection models for *U. stansburiana* (Table 3). The highest ranked AICc model in the analysis, was the model that included all of the covariates except relative humidity ($\Delta AIC = 0.00$, AIC Weight = 0.42; Table 3). Substrate temperature, air temperature, and survey type were all considered important covariates for explaining the variation among *U. stansburiana* detections. In fact, these covariates were consistently selected for inclusion, not just within the highest ranked model, but in the top four models of the AICc analysis as well (Table 3).

Out of the six competing AICc models for *A. marmoratus*, the univariate model that included wind speed had the highest rank ($\Delta AIC = 0.00$, AIC Weight = 0.35; Table

4). Unlike the AICc analysis for *U. stansburiana*, substrate temperature was not included in any of the competing models (Table 4). Instead the top two competing models showed that wind speed and survey type were the two most important variables for detecting *A. marmoratus* (Table 4). Interestingly, for *A. marmoratus*, all of the univariate models were selected over the models that included combinations of the covariates. The higher ranked models, that did include more than one covariate however, consistently included wind speed and survey type (Table 4).

Probability of Detection Among Lizards. – The probability of detecting the lizards in this study varied greatly among species. The top model for, *U. stansburiana*, yielded a higher probability of detection than the other two lizard species (mean = 0.38 ± 0.17).

Barometric pressure and air temperature were identified as significant variables for detecting this *U. stansburiana* (bp: $p < 0.0001$; at: $p = 0.015$; Table 5). More specifically, as barometric pressure decreased and air temperature increased, the probability of detecting *U. stansburiana* increased (Table 5). The top model for *A. marmoratus*, on the other hand, yielded a mean detection rate of approximately 28% (mean = 0.28 ± 0.09). It was found that as wind speed increased, so did the probability of detecting *A.*

marmoratus ($p < 0.0305$; Table 6). Finally, after the bootstrap analyses were conducted for the DSL, there were three separate uncorrected detection probabilities, one for each of the survey types. It was observed that all three values were lower than the other two lizards.

When the values for the DSL were compared to one another however, all three were relatively close in value and the confidence intervals overlapped substantially. The

15'200 m² yielded the greatest mean probability of detection followed by the 30'200 m²

and then the 60'400 m², respectfully (15'200 m²: mean = 0.19, 95% C.I. = 0.039, 0.35; 30'200 m²: mean = 0.13, 95% C.I. = 0.00, 0.25; 60'400 m²: mean = 0.17, 95% C.I. = 0.00, 0.33).

Inferring Absence. – The absence analysis showed that less surveys were needed when trying to detect the more common species of lizards. In fact, it was found that a total of six surveys (mean = 6.30, max = 22.86) were needed to be 95% confident that *U. stansburiana* was truly absent from a site where it was known to occur (Figure 7). In addition to this, *A. marmoratus*, which was detected less frequently than *U. stansburiana*, needed a larger number of surveys for reliable detection. If *A. marmoratus* was present at a site, roughly 9 surveys would be needed to be 95% confident that this species was detected (mean = 9.03, max = 41.77; Figure 7).

The surveys needed to reliably detect the DSL, were divided into three groups based on survey methodology. When conducting a survey with the 15'200 m² methodology, the average number of surveys needed was approximately 19 (mean = 19.23; Figure 7). The confidence intervals also yielded a minimum of 7 surveys and a maximum of 76 surveys (95% C.I. = 7.05, 76.30). When utilizing the 30'200 m² survey design, roughly 22 surveys were needed to reliably detect a DSL in a positive site (mean = 22.43; 95% C.I. = 10.41, ∞; Figure 7). Finally, when conducting surveys using the 60'400 m² methodology, an average of 16 surveys were needed to be 95% confident that the DSL was detected, at a site of known occurrence (mean = 16.43; 95% C.I. = 7.39, ∞; Figure 7). However, judging by the confidence intervals, lack of detections and the

inability to assess environmental covariates for the DSL, may have confounded the results for this species.

Discussion

A critical aspect of any management strategy is the ability to accurately detect and monitor the species of concern (Kéry and Schmidt, 2008; Crump and Forstner, 2019). Threatened and endangered species should be regularly monitored using guidelines in conservation management plans. As above, species that fall within these categories can be difficult to monitor because they present unique challenges (i.e., low occupancy rates) (Shannon et al., 2014; Walkup et al., 2018). This does not however, change the fact that threatened or endangered species rely heavily upon the management strategies put in place for their recovery. It is therefore imperative, that the methods utilized when monitoring populations, are efficient in yielding accurate estimates. Results from this study emphasize the importance of tailoring survey methodologies to the species of concern, by highlighting the variation in detection probabilities among the different lizard species when using identical methods.

The main focus of this study was to assess the adequacy of VES as a tool for accurately detecting the DSL. To achieve this, the detection rates of the two most common lizards, *U. stansburiana* and *A. marmoratus* were compared to the species of interest. Results of the comparison showed varying rates of detection among the three species. *U. stansburiana* had the greatest probability of being encountered ($p = 0.38$), followed by *A. marmoratus* ($p = 0.28$) and DSL ($p = 0.13 - 0.19$). The results of this study coincide with other studies conducted in west Texas. Fitzgerald et al. (2011), also

found *U. stansburiana* and *A. marmoratus* to be the two most frequently encountered lizard species. While the initial pattern of the data is similar, the detection rates in this study were considerably lower than other rates presented in the literature. This is especially apparent when comparing the detection rates of the DSL. For example, one study showed that the probability of detecting DSL individuals was approximately 52%, a large difference when compared to 13% - 19% probability seen at sites in this study (Walkup et al., 2018). While this is strikingly different, the results from this study were collected using a different survey design. Recall that the DSL is a habitat specialist and is not commonly detected in habitats without large wind-blown dunes and *Q. harvardii* (Leavitt and Fitzgerald, 2013; Walkup et al., 2017; Walkup et al., 2018). This is important, as much of the current literature focuses the majority of the effort within areas classified as highly suitable for the DSL (Fitzgerald et al., 2011; Ryberg et al., 2016; Walkup et al., 2018). In the previously mentioned study, for instance, the majority of the surveys were conducted in highly suitable habitats, with only 13 surveys focused in the lower quality sites (Walkup et al., 2018). In this study, however, the surveys were conducted equally across a gradient of habitat types. The sites surveyed here included habitats considered unsuitable for the DSL (Table 1). This study more closely followed the methods published by Crump and Forstner (2019), which specifically encompassed a breadth of habitat types (i.e., mesquite grasslands, sand flats covered in dense vegetation, etc.). Furthermore, the results in that study, not unlike this one, report lower overall detection probabilities for the DSL than what is found in the literature (i.e. for studies that more often target blowout habitats) (Crump and Forstner, 2019).

Results of this study show that the DSL was not detected as frequently as other species. In fact, only 12 observations of DSL were made over the two years (i.e., 2017 = 6; 2018 = 6). This is a significant difference from the other two species in this analysis, both of which had over 200 individual observations. Furthermore, out of the 15 observers, less than half detected a DSL, with several of those observations being made exclusively by four observers. It is entirely possible that variation in detection rates could be attributed to the overall behavior of these species. While all three of these species occupy many of the same sites, their life history traits are different. The two more commonly detected lizards are generalist species that can thrive in many habitats, including fragmented areas (Sartorius et al., 2002; Walkup et al., 2017). In fact, one study, that compared capture rates in disturbed and undisturbed sites, found that *U. stansburiana* has been captured more frequently in fragmented areas (Leavitt and Fitzgerald, 2013). This is quite different from habitat specialists, such as the DSL. The DSL is highly sensitive to habitat alterations and is found less frequently in these fragmented areas (Leavitt and Fitzgerald, 2013). The fact that the more common lizard species are more abundant in some areas, makes these species readily available for observation. The behavior differences could be responsible for the extreme contrast in the total number of detections (Table 2).

It is possible that detection rate is altered by more than differences in habitat preference. It is also possible that some animal behaviors and the habitat that they reside in, might influence the observer's ability to detect the individual. The two more common species in this study, have a natural response to flee when threatened (Punzo, 2008; Zani et al., 2009). However, when the DSL is threatened, this species shows a natural desire to

burrow under the sandy surface (Fitzgerald et al., 1997; Smolensky and Fitzgerald, 2010). In addition to this behavior, many environmental variables were included in the models to account for any additional variation. The top model for *U. stansburiana*, for instance, emphasized the significance of barometric pressure and air temperature when attempting to detect that species of lizard (Table 5). However, it is possible that the analysis did not account for every possible source of variation. For example, the habitat of the DSL is colonized by an endemic species of oak shrub, *Q. harvardii*. According to the current literature, the DSL shows a preference for areas where this shrub is present (Walkup et al., 2018). Therefore, it could be assumed that occupancy rates would increase in sites containing *Q. harvardii*. However, this species of oak is unique in that it rarely surpasses a stature of one meter (Mayes et al., 1998). This presents a rare obstacle for scientists using a visual method of detection because seldom are visual types of observations attempted above the canopy cover in a forest. In this situation, the *Q. harvardii* “forest” is shorter than the human observer, ultimately obscuring the ground surface that the lizards are utilizing. Unfortunately, there is little literature that discusses the possible effects that vegetation cover can have on the visual detection of reptile species. The majority of studies that do discuss visibility bias are mainly focused on detecting large vertebrate species from the perspective of an aircraft. In these situations, vegetation cover was known to greatly affect the reliability of aerial surveys conducted on elk (*Cervus elaphus*) and other wildlife populations (Samuel et al., 1987; Fleming and Tracey, 2008). Future studies that utilize VES, for the DSL, may benefit from accounting for the variation in detection rates as a result of visibility bias. More importantly, both of the issues mentioned above demonstrate the how the DSL can occupy a site and not be available for

detection. This type of behavior can have adverse effects on detection, especially when observers are using a visual survey method. It is imperative that researchers are aware of this type of behavior, as it could potentially increase the likelihood of recording a lizard as absent when it is truly present (false negative).

Many studies have commented on the overall efficiency of VES for detecting certain species. Specifically, visual encounter surveys, were viewed as ineffective when trying to detect rare or elusive species (Barea-Azcón, 2006). In this study, VES was effective at detecting more common species of lizards and enough data was collected to make accurate model estimations. However, as previously stated, the DSL is a highly cryptic species (elusive), that is considered endangered (rare) in much of the currently occupied range. As a result, VES did not yield very many DSL detections and model convergence was not achieved for this species. Instead, values had to be separated by survey methodology and then bootstrapped to provide detection estimates. Unfortunately, the overall lack of sufficient data for this species, decreased the precision of estimates and made comparisons with other species difficult. Future studies may want to 1) apply a more robust survey method for detecting the DSL or 2) utilize a statistical analysis that is more suited for rare species. Pitfall traps are commonly praised for their ability to accumulate large capture numbers and could be beneficial for similar studies (Towns, 1991; Greenberg et al., 1994; Welbourne et al., 2015). Visual encounter surveys could also continue to be an option for detecting the DSL. However, based on results from this study, the total number of required surveys, needed to detect the species, should be considered when designing the study. Moreover, a GLMM may not be the most effective method for analyzing data collected for rare species. Occupancy covariates (i.e.,

vegetation type, substrate type, etc.) were not recorded throughout the course of this study. Future studies may benefit from recording this data so that an occupancy study can be performed. There have been various articles published that discuss occupancy models that target rare and elusive species (MacKenzie et al., 2002; MacKenzie et al., 2003). A model framework that follows these procedures should be considered for the DSL.

While little data was collected for the DSL, this study did in fact yield interesting results in regard to this species. The DSL is routinely reported to be restricted to large open dune blowouts and therefore many of the studies are focused in these areas (Fitzgerald et al., 1997; Fitzgerald et al., 2011). It is worth mentioning that while the DSL was, in fact, detected in areas that met this description (Figure 5), this study, contrary to some reporting, found that the DSL inhabited areas outside of large open dune blowouts (i.e., sand flats with dense shinnery, small dune complexes, near roadways, etc.; Figure 6). It is imperative that researchers and managers are aware of these occurrences, if the proper conservation methods are to be applied for this species. As stated earlier, the DSL is a highly cryptic species and many aspects make it difficult to visually detect. In addition to this, much of the current literature for this species can be misleading because it portrays large open dune blowouts to be the only areas where this species occurs (Fitzgerald et al., 1997; Fitzgerald et al., 2011). This is problematic because it may deter surveyors from searching the “non-suitable” areas. The DSL is located within the Permian Basin, one of the most popular areas for oil development in the world (Walkup et al., 2018). Not detecting the species in areas where it actually occurs, or worse only searching within the currently restricted areas, could be detrimental to this species and the habitat it relies upon. The results of this study show that areas often reported as

unsuitable for the DSL, are of equal importance, as they may represent habitat corridors or connectivity areas. Therefore, individuals should include these areas when making management or regulatory decisions.

Overall, efficient survey methods should be used to detect species of concern, especially if those species are considered rare or vulnerable. If the detection methods are not reliable for the species, population estimates may be inaccurate and inappropriate management decisions could be implemented. In this study, VES provided accurate results for two commonly encountered lizards, but did not provide accurate estimates for detection of the DSL. It is because of this, that VES should be thoroughly analyzed, and the most reliable survey method be utilized when making future management decisions. As stated before, the habitat of the DSL is located within the Permian basin, an area that is highly susceptible to anthropogenic alterations emanating from the oil industry. Therefore, any detection method that does not yield accurate results could prove destructive for this species and the surrounding habitat. It is important to note that this study did not address the scale at which VES will determine absence. Any inferences about scale in this study are restricted to the size of the plots that were utilized. A study similar to Chan et al. (2009), that uses microsatellite data, could be used to identify the level of genetic variation throughout the range of this species (Chan et al., 2009). This type of study, conducted in Texas, could be beneficial for not only identifying critical areas but for determining the size of occupied patches that are linked by dispersal. Such information can then better define the connectivity habitats, among the blowout dune fields, required for the persistence of this species overtime.

Tables

Table 1. Total number of sites selected for *Sceloporus arenicolus* – Dunes Sagebrush Lizard. The sites were selected using a stratified random approach within the Shinnery – Sands ecoregion. The number of surveys were kept equal across the suitability types.

Habitat Suitability	Total Sites – 2017	Total Sites – 2018
High	20	10
Medium	20	10
Low	20	10

* Does not include additional Permian Basin sites or the YDWMA sites.

Table 2. Total number of raw lizard observations recorded during visual encounter surveys. The table shows the number of lizards that were detected between the sampling periods and among the sampling months. Highlighted are the species used in data analyses. *Aspidoscelis* spp. = Lizards that could only be identified to the *Aspidoscelis* genus level. *Plestiodon* spp. = Lizards that could only be identified to the *Plestiodon* genus level. *Sceloporus* spp. = Lizards that could only be identified to the *Sceloporus* genus level. Spp. = Lizards that were not identified to a genus or species level. All surveys were conducted on sites located within the Shinnery – Sands ecoregion.

Lizard Species	2017				2018			Total
	May	June	July	Sept.	May	June	July	
<i>Aspidoscelis gularis</i>	5	0	1	0	3	9	17	35
<i>Aspidoscelis marmoratus</i>	3	27	4	5	71	53	48	211
<i>Aspidoscelis sexlineatus</i>	9	9	16	4	10	29	15	92
<i>Aspidoscelis tessellatus</i>	5	0	1	0	2	6	0	14
<i>Aspidoscelis</i> spp.	11	14	15	6	33	18	18	115
<i>Gambelia wislizenii</i>	0	0	0	0	1	0	0	1
<i>Holbrookia maculata</i>	11	0	6	0	10	0	4	31
<i>Phrynosoma cornutum</i>	1	0	0	0	3	2	0	6
<i>Plestiodon obsoletus</i>	0	0	2	0	0	0	0	2
<i>Plestiodon</i> spp.	0	0	1	0	0	0	0	1
<i>Sceloporus arenicolus</i>	0	4	0	2	2	3	1	12
<i>Sceloporus consobrinus</i>	0	0	25	2	12	5	2	46
<i>Sceloporus cowlesi</i>	0	1	0	0	1	0	0	2
<i>Sceloporus</i> spp.	3	0	30	3	6	2	1	45
<i>Urosaurus ornatus</i>	3	0	0	1	0	0	0	4
<i>Uta stansburiana</i>	12	30	41	26	193	75	70	447
Spp.	8	1	8	3	34	15	2	71
Total	71	86	150	52	381	217	178	1135

Table 3. AICc model selection results for *Uta stansburiana*. Models are ordered by their associated AICc rank. K = the number of parameters, AICc = Akaike Information Criterion value (corrected for small sample size), Δ AIC = the difference, in AICc value, from the top model, Wt. = likelihood the selected model represents the best supported model and Log. Lik. = log likelihood value for that model. Abbreviations are as follows: st = substrate temperature (°C), at = air temperature (°C), rh = relative humidity, bp = barometric pressure (inHg), ws = wind speed (km), and survey = type of survey performed.

Model*	<i>k</i>	AICc	Δ AIC	Wt.	Log. Lik.
<i>p</i> (st + at + bp + ws + survey)	8	712.96	0.00	0.42	-348.35
<i>p</i> (st + at + rh + bp + survey)	8	714.35	1.39	0.21	-349.05
<i>p</i> (st + at + rh + bp + ws + survey)	9	714.40	1.43	0.20	-348.04
<i>p</i> (at + rh + bp + ws + survey)	8	715.24	2.27	0.13	-349.49
<i>p</i> (st + rh + bp + ws + survey)	8	718.17	5.21	0.03	-350.96
<i>p</i> (st + at + rh + bp + ws)	7	723.27	10.31	0.00	-354.54
<i>p</i> (bp)	3	726.34	13.38	0.00	-360.15
<i>p</i> (st + at + rh + ws + survey)	8	736.99	24.03	0.00	-360.37
<i>p</i> (survey)	4	742.55	29.59	0.00	-367.24
<i>p</i> (ws)	3	745.31	32.35	0.00	-369.63
<i>p</i> (st)	3	747.28	34.32	0.00	-370.62
<i>p</i> (at)	3	748.29	35.33	0.00	-371.12
<i>p</i> (rh)	3	750.03	37.07	0.00	-371.99

*Observer was included as a random covariate in all models

Table 4. AICc model selection results for *Aspidoscelis marmoratus*. Models are ordered by their associated AICc rank. K = the number of parameters, AICc = Akaike Information Criterion value (corrected for small sample size), Δ AIC = the difference, in AICc value, from the top model, Wt. = likelihood the selected model represents the best supported model and Log. Lik. = log likelihood value for that model.

Abbreviations are as follows: st = substrate temperature (°C), at = air temperature (°C), rh = relative humidity, bp = barometric pressure (inHg), ws = wind speed (km), and survey = type of survey performed.

Model*	<i>k</i>	AICc	Δ AIC	Wt.	Log. Lik.
<i>p</i> (ws)	3	570.00	0.00	0.35	-281.97
<i>p</i> (survey)	4	570.17	0.17	0.32	-281.04
<i>p</i> (rh)	3	573.28	3.28	0.07	-283.62
<i>p</i> (bp)	3	574.29	4.29	0.04	-284.12
<i>p</i> (at)	3	574.30	4.30	0.04	-284.12
<i>p</i> (st)	3	574.30	4.30	0.04	-284.12
<i>p</i> (st + at + rh + ws + survey)	8	574.85	4.85	0.03	-279.27
<i>p</i> (st + rh + bp + ws + survey)	8	574.99	5.00	0.03	-279.34
<i>p</i> (st + at + bp + ws + survey)	8	575.20	5.20	0.03	-279.45
<i>p</i> (at + rh + bp + ws survey)	8	575.72	5.72	0.02	-279.71
<i>p</i> (st + at + rh + bp + survey)	8	576.77	6.78	0.01	-280.24
<i>p</i> (st + at + rh + bp + ws + survey)	9	576.92	6.93	0.01	-279.27
<i>p</i> (st + at + rh + bp + ws)	7	577.06	7.06	0.01	-281.41

*Observer was included as a random covariate in all models.

Table 5. Estimates for the top model selected for *Uta stansburiana*. Model was selected using an AICc model selection analysis. Observer was included as a random variable, to account for additional variation. Analysis included data from sites where *Uta stansburiana* was known to occur. All sites were located in the Monahans Sandhills complex.

Fixed Effects	Estimate	Std. Error	z-value	Pr(> z)
Intercept	-0.93	0.154	-6.056	<0.0001 ***
Substrate Temperature	0.12	0.080	1.520	0.13
Air Temperature	0.18	0.075	2.437	0.015 *
Barometric Pressure	-0.39	0.079	-4.909	<0.0001 ***
Wind Speed	0.12	0.076	1.623	0.10
30x200 – Survey	-0.16	0.180	- 0.907	0.36
Method				
60x400 – Survey	0.60	0.208	2.865	0.004 **
Method				

Table 6. Estimates for the top model selected for *Aspidoscelis marmoratus*. Model was selected using an AICc model selection analysis. Observer was included as a random variable, to account for additional variation. Analysis included data from sites where *Aspidoscelis marmoratus* was known to occur. All sites were located in the Monahans Sandhills complex.

Fixed Effects	Estimate	Std. Error	z-value	Pr(> z)
Intercept	-1.19	0.144	-8.325	<0.0001 ***
Wind Speed	0.18	0.083	2.163	0.0305*

Figures



Figure 1. Photographic image of the Dunes Sagebrush Lizard – *Sceloporus arenicolus*. This gravid female was scaling a dune bank, covered in dense shinnery oak, when she was captured. Females develop the characteristic yellow and orange markings during the breeding season. Images were obtained May 25, 2018 in New Mexico. Both images represent the same individual.



Figure 2. Total geographical range of the Dunes Sagebrush Lizard – *Sceloporus arenicolus*. This lizard encompasses a range that includes the Mescalero Sands of New Mexico and the Monahans Sandhills of Texas. Image obtained from a petition created by the Center of Biological Diversity and the Defenders of Wildlife in 2018.

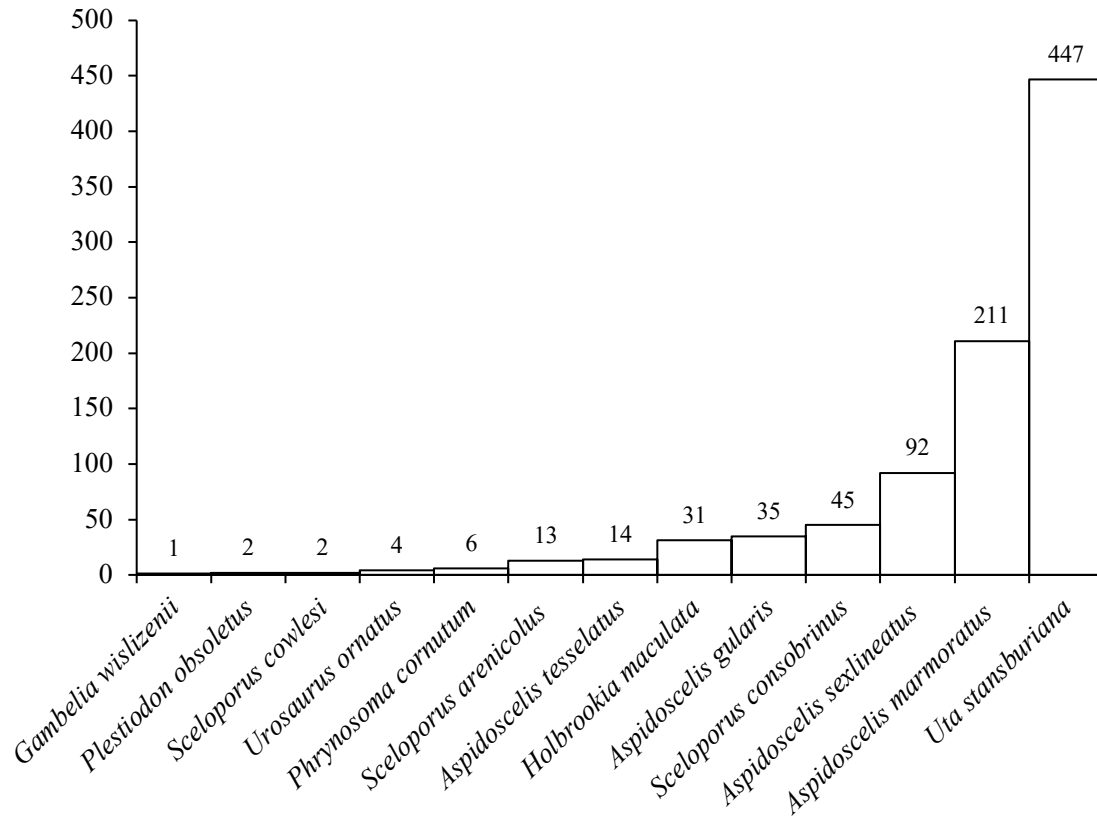


Figure 3. Lizard species level observations recorded during visual encounter surveys. This figure includes all of the detections recorded over the entire study. The number of observations for each species is shown above bars. All surveys were conducted on sites in the Monahans Sandhills complex.

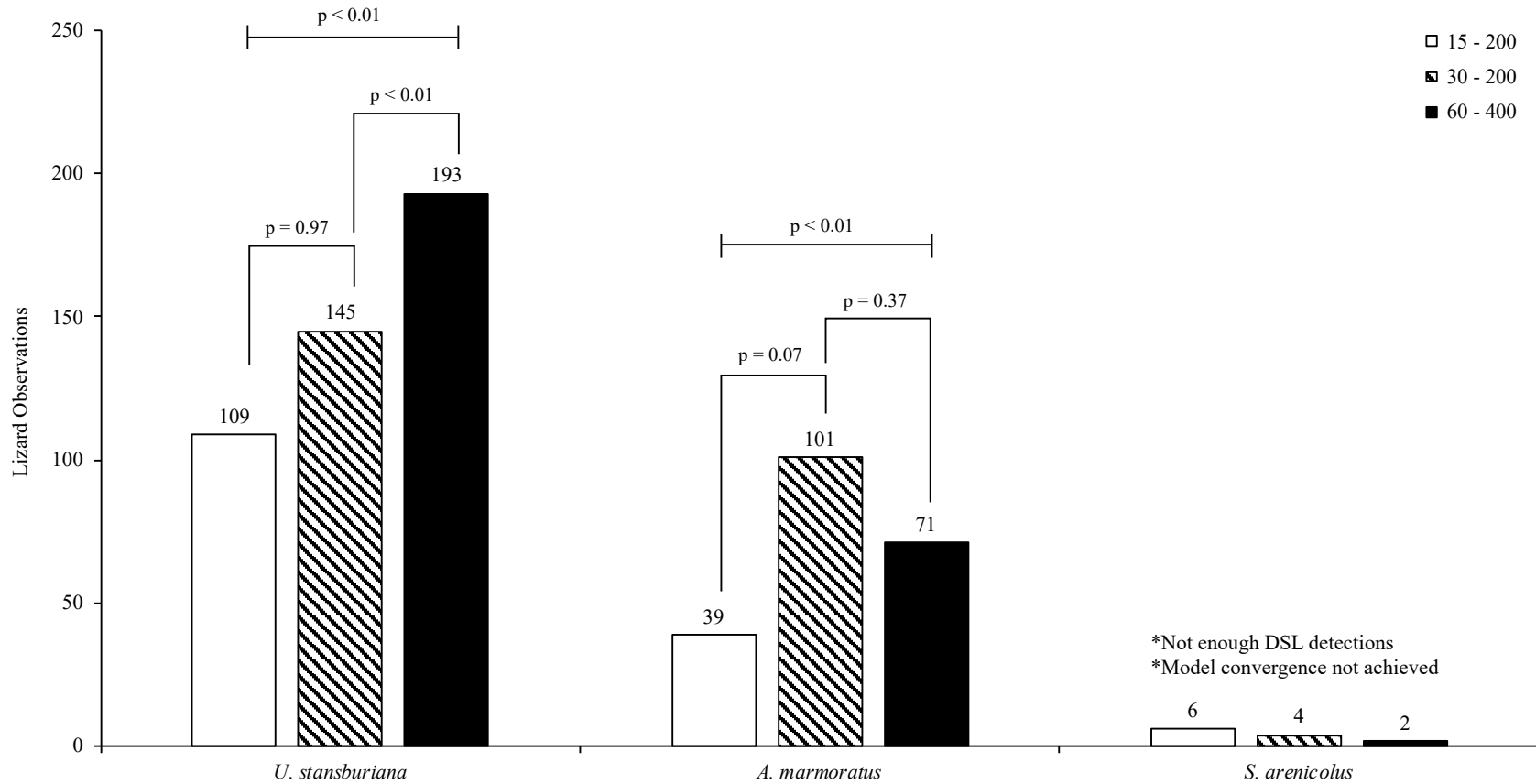


Figure 4. Individual lizard detections among survey types. This figure displays the total number of observations for each of the species analyzed in this study. The observations were separated into groups by the survey method that was used to obtain the observation. White = observations made with the 15'200 m² survey method. Stripes = observations made with the 30'200 m² survey method (n = 240). Black = observations made with the 60'400 m² survey method (n = 120). The number of observations is present above the bars in the graph. All surveys were conducted at sites within the Shinnery – Sands ecoregion. Species included in the analyses were *Uta stansburiana*, *Aspidoscelis marmoratus*, and *Sceloporus arenicolus*.

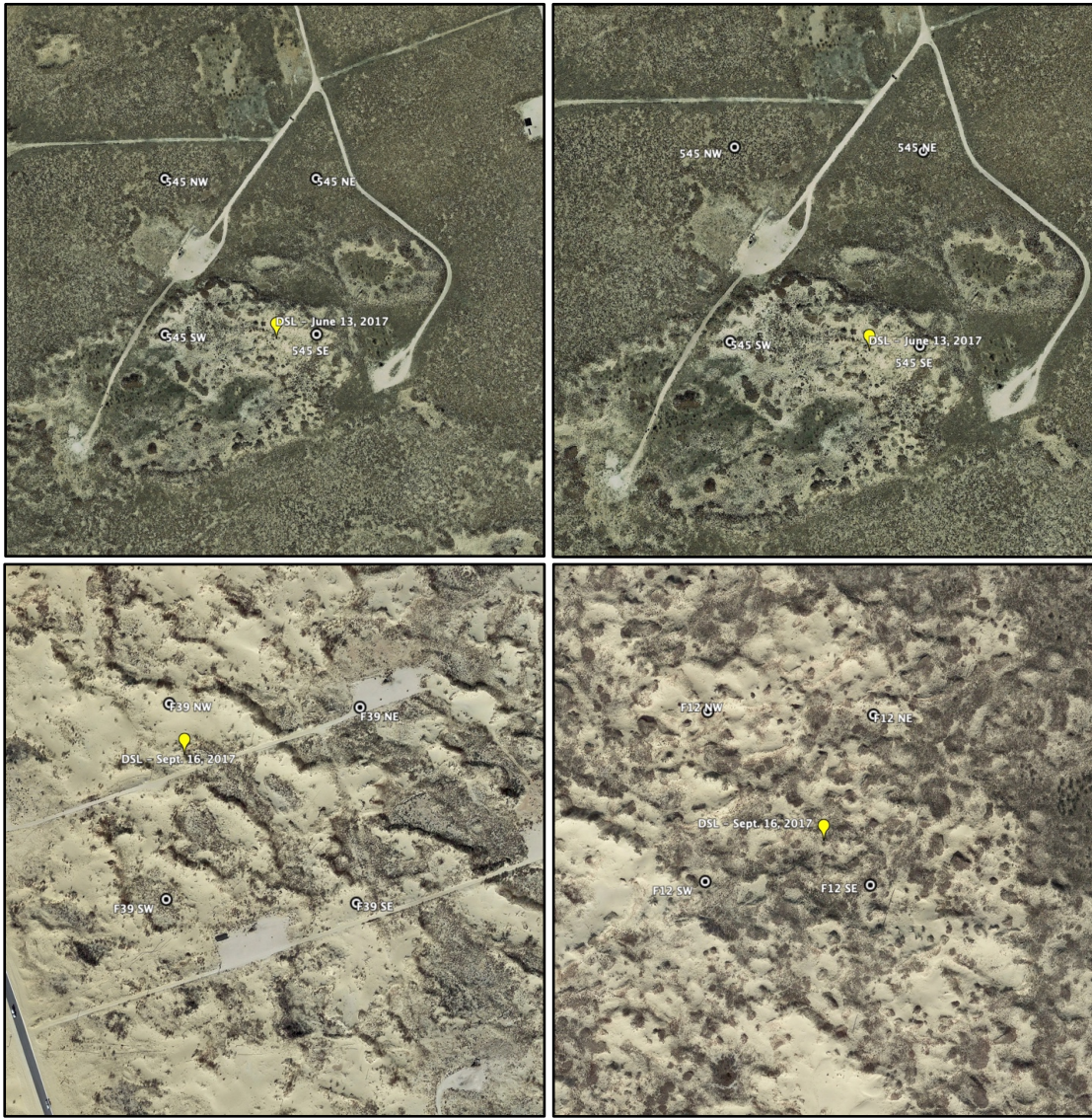


Figure 5. *Sceloporus arenicolus* detections located within large open dune blowouts. Exact locations of DSL individuals at the time of detection can be viewed in yellow. The white waypoints represent the corners of the plot. Detections were marked with a handheld GPS unit (i.e. Garmin GPSMAP 64st) and on AppSheet. Google Earth was used to obtain aerial images.



Figure 6. *Sceloporus arenicolus* detections located outside large open dune blowouts. Exact locations of DSL individuals at the time of detection can be viewed in yellow. The white waypoints represent the corners of the plot. Detections were marked with a handheld GPS unit (i.e. Garmin GPSMAP 64st) and on AppSheet. Google Earth was used to obtain aerial images.

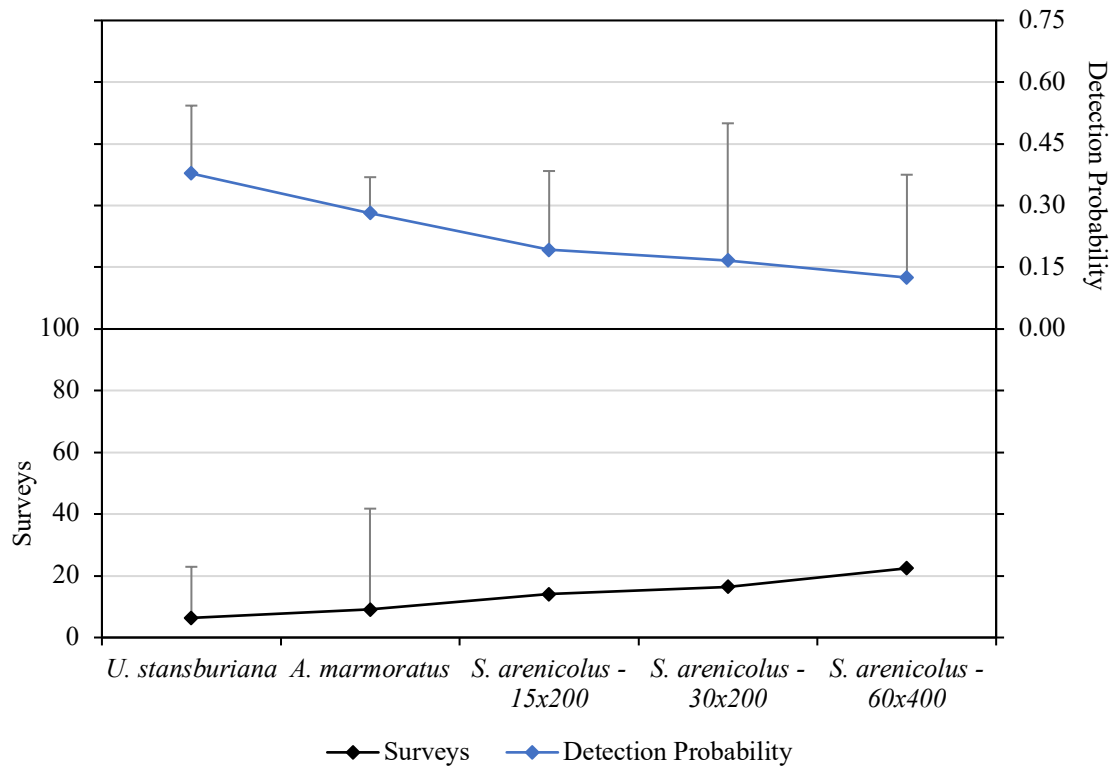


Figure 7. Comparison of lizard surveys to associated detection probability. This figure shows all of the detections for *Aspidoscelis marmoratus*, *Sceloporus arenicolus*, and *Uta stansburiana*. The surveys used to detect these lizards were conducted within the Monahans Sandhills complex. Detection probabilities are presented in the top panel. The number of surveys is presented in the bottom panel. As the probability of detection decreases, the number of surveys needed increases. Error bars for the number of surveys needed to detect *Sceloporus arenicolus* are not shown because numbers reach infinity.

APPENDIX SECTION

APPENDIX A: R – Code

```
library(lme4)
library(AICcmodavg)
library(boot)

#Raw Data - UTA#
URAW = read.csv(file.choose())
URAW
str(URAW)

#Uta detections
UDF = data.frame(URAW$U..stansburiana)
UDFu = UDF
UDFu[(UDF)!=0] = 1
str(UDFu)

#Observation Covariates UTA
date = data.frame(scale(URAW$julian_day))
stemp = data.frame(scale(URAW$substrate_temp))
atemp = data.frame(scale(URAW$air_temp))
rhum = data.frame(scale(URAW$X._relative_humidity))
baro = data.frame(scale(URAW$barometric_pressure))
windsp = data.frame(scale(URAW$mean_wind_speed..km.h.))
observer = data.frame(as.factor(URAW$observer))
survey = data.frame(as.factor(URAW$survey_type)) ## converts to a factor

lizardUTA <- cbind(stemp,atemp,rhum,baro,windsp,observer,survey,UDFu)
names(lizardUTA) <-
c("stemp","atemp","rhum","baro","windsp","observer","survey","detect")
unique(lizardUTA$observer)
lizardUTA = data.frame(lizardUTA)
str(observer)
## check for correlations
str(lizardUTA)
cor(lizardUTA[,1:5])

#GLMM - UTA
control=glmerControl(optimizer="bobyqa",optCtrl=list(maxfun=2e4))

#FULL MODEL split to prevent the drop of a variable
#PLOT MODELS
```

```

UTA1 = glmer(formula =
detect~stemp+atemp+rhum+baro+windsp+survey+(1|observer), data=lizardUTA, family
= binomial(link="cloglog"))
summary(UTA1)

```

```

UTA2 = glmer(formula = detect~stemp+atemp+rhum+baro+windsp+(1|observer),
data=lizardUTA, family = binomial(link="cloglog"))
UTA3 = glmer(formula = detect~stemp+atemp+rhum+baro+survey+(1|observer),
data=lizardUTA, family = binomial(link="cloglog"))
UTA4 = glmer(formula = detect~stemp+atemp+rhum+windsp+survey+(1|observer),
data=lizardUTA, family = binomial(link="cloglog"))
UTA5 = glmer(formula = detect~stemp+atemp+baro+windsp+survey+(1|observer),
data=lizardUTA, family = binomial(link="cloglog"))
UTA6 = glmer(formula = detect~stemp+rhum+baro+windsp+survey+(1|observer),
data=lizardUTA, family = binomial(link="cloglog"))
UTA7 = glmer(formula = detect~atemp+rhum+baro+windsp+survey+(1|observer), data =
lizardUTA, family = binomial(link="cloglog"))

```

```

UTA8 = glmer(formula = detect~stemp+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))
UTA9 = glmer(formula = detect~atemp+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))
UTA10 = glmer(formula = detect~rhum+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))
UTA11 = glmer(formula = detect~baro+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))
UTA12 = glmer(formula = detect~windsp+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))
UTA13 = glmer(formula = detect~survey+(1|observer), data=lizardUTA, family =
binomial(link="cloglog"))

```

```

Cand.mod<-list()
Cand.mod[[1]]=UTA1
Cand.mod[[2]]=UTA2
Cand.mod[[3]]=UTA3
Cand.mod[[4]]=UTA4
Cand.mod[[5]]=UTA5
Cand.mod[[6]]=UTA6
Cand.mod[[7]]=UTA7
Cand.mod[[8]]=UTA8
Cand.mod[[9]]=UTA9
Cand.mod[[10]]=UTA10
Cand.mod[[11]]=UTA11
Cand.mod[[12]]=UTA12
Cand.mod[[13]]=UTA13

```

```

ModnamesUTA1=c(1:13)
AICuFIN=aictab(cand.set=Cand.mod,modnames=ModnamesUTA1,second.ord=T)
evidence(AICuFIN)
summary(AICuFIN)
AICuFIN

#detection probability for top models
detection_probFINAL = predict(object = UTA5, newdata = lizardUTA, type =
"response", allow.new.levels =TRUE)
summary(UTA1)
#Avg/observer - UTA
UTA1 <- cbind(observer,detection_probFINAL)

names(UTA1) = c("observer","det_prob")
UTA1 = data.frame(UTA1)

avg1 = aggregate(~observer,data=UTA1, FUN = mean)
avg1

sd1 = aggregate(~observer,data=UTA1, FUN = sd)
sd1

#Avg/sd_DP
Umean = mean(detection_probFINAL)
Umean
sdU = sd(detection_probFINAL)
sdU

#Mean no. of Surveys for both of the top Models
#UTA#
dU = log(0.05)
fU = log(1-0.378273)
mnU = dU/fU
mnU

#Confidence Interval
ubU = log(1-0.1654683)
uU = dU/ubU
uU

#RAW DATA - MAR#
MARMRAW2 = read.csv(file.choose())
MARMRAW2
str(MARMRAW2)

```

```

#Marmoratus detections
AM = data.frame(MARMRAW2$A..marmoratus)
AM1 = AM
AM1[(AM)!=0] = 1
str(AM1)

#Observation Covariates MAR
DATEM = data.frame(scale(MARMRAW2$julian_day))
STEMPM = data.frame(scale(MARMRAW2$substrate_temp))
ATEMPM = data.frame(scale(MARMRAW2$sair_temp))
RHUMM = data.frame(scale(MARMRAW2$X._relative_humidity))
BAROM = data.frame(scale(MARMRAW2$barometric_pressure))
WINDSM = data.frame(scale(MARMRAW2$mean_wind_speed..km.h.))
OBSERM = data.frame(as.factor(MARMRAW2$observer))
SURVEYM = data.frame(as.factor(MARMRAW2$survey_type))

LAM =
cbind(STEMPM,ATEMPM,RHUMM,BAROM,WINDSM,OBSERM,SURVEYM,AM1)
names(LAM)=c("STEMPM","ATEMPM","RHUMM","BAROM","WINDSM","OBSER
M","SURVEYM","AM1")
LAM = data.frame(LAM)
unique(LM$OM)

## check for correlations
cor(LAM[1:5])

#GLMM - MAR
MRa = glmer(formula =
AM1~STEMPM+ATEMPM+RHUMM+BAROM+WINDSM+SURVEYM+(1|OBSER
M), data=LAM, family = binomial(link="cloglog"))

MRb = glmer(formula =
AM1~STEMPM+ATEMPM+RHUMM+BAROM+WINDSM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))
MRc = glmer(formula =
AM1~STEMPM+ATEMPM+RHUMM+BAROM+SURVEYM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))
MRd = glmer(formula =
AM1~STEMPM+ATEMPM+RHUMM+WINDSM+SURVEYM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))
MRe = glmer(formula =
AM1~STEMPM+ATEMPM+BAROM+WINDSM+SURVEYM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))

```

```

MRf = glmer(formula =
AM1~STEMPM+RHUMM+BAROM+WINDSM+SURVEYM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))
MRg = glmer(formula =
AM1~ATEMPM+RHUMM+BAROM+WINDSM+SURVEYM+(1|OBSERM),
data=LAM, family = binomial(link="cloglog"))

MRh = glmer(formula = AM1~STEMPM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))
MRi = glmer(formula = AM1~ATEMPM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))
MRj = glmer(formula = AM1~RHUMM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))
MRk = glmer(formula = AM1~BAROM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))
MRl = glmer(formula = AM1~WINDSM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))
MRm = glmer(formula = AM1~SURVEYM+(1|OBSERM), data=LAM, family =
binomial(link="cloglog"))

summary(MRm)

#Marm
Cand.modAM<-list()
Cand.modAM[[1]]=MRa
Cand.modAM[[2]]=MRb
Cand.modAM[[3]]=MRc
Cand.modAM[[4]]=MRd
Cand.modAM[[5]]=MRe
Cand.modAM[[6]]=MRf
Cand.modAM[[7]]=MRg
Cand.modAM[[8]]=MRh
Cand.modAM[[9]]=MRi
Cand.modAM[[10]]=MRj
Cand.modAM[[11]]=MRk
Cand.modAM[[12]]=MRl
Cand.modAM[[13]]=MRm

ModnamesAM=c('a','b','c','d','e','f','g','h','i','j','k','l','m')
AICAM=aictab(cand.set=Cand.modAM,modnames=ModnamesAM,second.ord=T)
evidence(AICAM)
AICAM #AIC Model selection#

detection_probM <- predict(MRl, newdata=LAM, type="response") #calculate dp for
Model 10#
detection_probM

```

```

summary(MR1)

#Avg/observer - MAR
MAR <- cbind(OBSERM,detection_probM)
names(MAR) = c("observer","det_prob")
MAR = data.frame(MAR)

avgM2 = aggregate(.~observer,data=MAR, FUN = mean) #avg dp/observer Model 10#
avgM2
sdM2 = aggregate(.~observer,data=MAR, FUN = sd) #sd dp/observer Model 10#
sdM2

Mmean = mean(detection_probM)
Mmean #mean Model 10#
sdM=sd(detection_probM)
sdM #sd Model 10#

#Mean no. of Surveys
#MAR#
dM = log(0.05)
fM = log(1-0.08742864) #mean number of surveys Model 10#
mnM = dM/fM
mnM

#Confidence Interval
ubM = log(1-0.08742864) #confid. interv. surveys Model 10#
uM = dM/ubM
uM

#DSL
#BOOT
DSLRAW2= read.csv(file.choose())
DSLRAW2

DDF = data.frame(DSLRAW2$S..arenicolus)
DDF1= DDF
DDF1[(DDF)!=0] = 1

DDF1 = c()
names(DDF1) = c("Detections", "Survey")

d = data.frame(scale(DSLRAW1$julian.day))
s_temp = data.frame(scale(DSLRAW1$substrate_temp))
a_temp = data.frame(scale(DSLRAW1$air_temp))
hum = data.frame(scale(DSLRAW1$X._relative_humidity))

```

```

barom = data.frame(scale(DSLRAW1$barometric_pressure))
c_c = data.frame(scale(DSLRAW1$X._cloud_cover))
windspd = data.frame(scale(DSLRAW1$mean_wind_speed..km.h.))
obs = data.frame(DSLRAW1$Observer)
detection = DDF1

```

```

detection = data.frame(detection)

```

```

DSL15 = c(0,0,0,0,1,0,0,0,1,1,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0)
b = DSL15
b1 = function(b, i) {mean(b[i])}
bootdump = boot(b,b1,R=10000)
summary(bootdump)
bootdump
boot.ci(bootdump,conf = 0.95, type = "bca")

```

```

quartz(h=6,w=6)
hist(bootdump$t, main = "", xlab = "", breaks = 12, xlim = c(0.0,0.6))
abline(v = mean(bootdump$t), col = "blue", lty = 2)
abline(v = 0.0455, col="blue", lty = 2)
abline(v = 0.4091, col = "blue", lty = 2)
Smean1 = bootdump$t0
Smean1

```

```

dM = log(0.05)
fM = log(1-0.125) #mean number of surveys Model 10#
mnM = dM/fM
mnM

```

```

#Confidence Interval
ubM = log(1-0.3) #confid. interv. surveys Model 10#
uM = dM/ubM
uM

```

```

DSL400 = c(0,0,0,0,0,0,0,0,0,1,0,1)
b2 = DSL400
b3 = function(b2, i) {mean(b2[i])}
bootdumpU = boot(b2,b3,R=10000)
summary(bootdumpU)
bootdumpU
boot.ci(bootdumpU,conf = 0.95, type = "bca")
Smean2 = bootdumpU$t0
Smean2

```

```

DSL30 = c(0,1,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0)

```



```

str(DSL30)
b4 = DSL30
b5 = function(b4, i) {mean(b4[i])}
bootdumpA = boot(b4,b5,R=10000)
summary(bootdumpA)
bootdumpA
boot.ci(bootdumpA,conf = 0.95, type = "bca")
Smean3 = bootdumpA$t0
Smean3

#Mean no. of Surveys
#SCELOP#
dA = log(0.05)
fA = log(1-0.1666667)
mnA = dA/fA
mnA

fM2 = log(1-0.3333) #mean number of surveys Model 2#
mnM2 = dM/fM2
mnM2

```

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