# DUPED BY FALSE-NEGATIVE ERRORS: A CASE STUDY WITH THE MEDITERRANEAN GECKO

CALEB A. ALDRIDGE<sup>1,3</sup>, THOMAS P. ROGERS<sup>2</sup>, W. TAYLOR BANKS<sup>2</sup>, AND SCOTT A. RUSH<sup>2</sup>

 <sup>1</sup>Mississippi Cooperative Fish and Wildlife Research Unit, Department of Wildlife, Fisheries and Aquaculture, Mississippi State University, 705 Stone Boulevard, Mississippi State, Mississippi 39762–9690, USA
<sup>2</sup>Department of Wildlife, Fisheries and Aquaculture, Mississippi State University, 705 Stone Boulevard, Mississippi State, Mississippi 39762–9690, USA
<sup>3</sup>Corresponding author, email: caleb.a.aldridge@gmail.com

Abstract.—Understanding habitat associations and organismal activity patterns can help scientists and managers gain insight to the invasive potential of a species; however, false-negative errors are common in detecting species within an area. A false negative error often takes the form of a question: was the species absent or did it just go undetected? We investigated how the assumption of perfect detection influences interpretation of habitat associations and activity patterns of the Mediterranean Gecko, Hemidactylus turcicus (Reptilia: Gekkonidae), which has been introduced to the Southeastern U.S. We conducted nocturnal surveys in Starkville, Mississippi, USA, and detected the Mediterranean Gecko at 17 of 22 sites on at least one occasion. We found that models that do (Single-season Single-species Occupancy Model) and do not (Logistic Regression) account for imperfect detection had a 15% difference in estimates of occupancy and were not dissimilar in the significance of covariates. Inference from our Occupancy Model indicated that well-defined eaves, minutes after sunset, and pedestrian traffic all influence detection probability, but no covariates were associated with Mediterranean Gecko occupancy. In contrast, results from the Logistic Regression model indicated that well-defined eves were of significance to the presence of Mediterranean Gecko. Interpretations of habitat associations and activity patterns can be misleading when imperfect detection goes unaccounted. We hope that more herpetologists take approaches to account for imperfect detection, focusing on sampling and survey methods that can confidently assess the distributional status, habitat associations and activity patterns, and eradication effectiveness of invasive species.

*Key Words.*—activity patterns; detection probability; habitat associations; human disturbance; invasive species; Occupancy Modeling

### INTRODUCTION

The Mediterranean Gecko (Hemidactylus turcicus; Reptilia, Gekkonidae) is a small, nocturnal lizard native to the Mediterranean Basin and Western Asia that was discovered in Key West, Florida, USA, in the early 20th Century (Fowler 1915; Meshaka 2011). Since its introduction, it has spread to urban areas in the southern U.S. (Powell et al. 2016) and is thought to compete with native herpetofauna such as treefrogs (Amphibia: Hylidae) and the Green Anole (Anolis carolinensis; Meshaka et al. 2006; Nelson and Carey 1993) and depress populations of spiders and insects (Gomez-Zlatar et al. 2006; Nelson and Carey 1993; Punzo et al. 2005). Previous studies have sought to characterize habitat associations and activity patterns of the Mediterranean Gecko to gain a better understanding of its invasive potential (Gomez-Zlatar et al. 2006; Meshaka et al. 2006; Nelson and Carey 1993; Williams and McBrayer 2007). It is possible, however, that Mediterranean Geckos go undetected at sites during surveys even when they are present (Nelson and Carey

1993). Indeed, a now large body of literature indicates that false-negative errors in surveys, whereby a species remains undetected at sites that it in fact occupies, is the rule and not the exception (Guillera-Arroita et al. 2014; Kéry 2002; Kéry and Royle 2016; MacKenzie et al. 2017; Mazerolle et al. 2007). From a biogeographic perspective, as was the viewpoint of Nelson and Carey (1993), false-negatives of species occurrence can cause the area and extent of occurrence of a species to be underestimated (Kéry 2002; Rout et al. 2009; Kéry and Royle 2016; MacKenzie et al. 2017).

When modeling habitat associations, and activity patterns, false-negative errors can cause dubious interpretations (Gu and Swihart 2004; Kéry 2008; Mazerolle et al. 2005; Wenger and Freeman 2008). The danger lies in concluding that some pattern exists for the population parameter of interest (e.g., occupancy or abundance) when truthfully the pattern is one of incidence (Kéry 2008; Valenzuela-Sánchez et al. 2019). For instance, Valenzuela-Sánchez et al. (2019) found that the daily microclimatic fluctuations and density of saplings influenced estimates of both the detection and

Copyright © 2021. Caleb A. Aldridge All Rights Reserved.

abundance of the Southern Darwin's Frog (*Rhinoderma darwinii*). However, the sign of the relationship for each response differed between covariates; as microclimatic fluctuation increased detection probability increased and estimated abundance decreased, and vice versa.

Our understanding of the habitat associations and activity patterns of the Mediterranean Gecko has, perhaps, been distorted by imperfect detection (Nelson and Carey 1993). Thus, the aim of our study was to determine how interpretation of habitat associations and activity patterns has been influenced by the assumption of perfect detection. We compared the results of two sampling and modeling approaches, known to give different levels of insight to species-habitat associations. The first approach, and one more common in the literature, used a single-occasion sample design paired with a Logistic Regression, which assumes perfect detection. The second approach used a multipleoccasion sampling design and the Occupancy Model of Kéry (2002), which accounts for imperfect detection. Thus, ours is a case study with the Mediterranean Gecko of how the assumption of perfect detection can mislead habitat associations and activity patterns of herpetofauna, a potentially wide-spread problem in the field of herpetology.

## MATERIALS AND METHODS

Study area and site selection.-We followed sampling guidelines of Nelson and Carey (1993) and White and Husak (2015) for the Mediterranean Gecko, which suggests limiting surveys to the urban center of the largest town in a county (i.e., local province) where old buildings are common. We conducted our surveys in Starkville, Oktibbeha County, Mississippi, USA (33.4638°N, 88.8146°W). We presumed that the Mediterranean Gecko occupied some portion of buildings in the urban center of Starkville as they have been observed on the nearby campus of Mississippi State University (Altig et al. 2016). The urban center of Starkville has a city block design (approximately 0.5 km<sup>2</sup>) with one- to four-story masonry and wood-sided buildings that are used as municipal offices, businesses, restaurants, and residential living spaces.

From pilot sampling, we estimated that we could complete 22 surveys in a single evening (approximately 1900–2200). We designed sampling so that we could complete a survey at each site in a single evening which allowed us to complete surveys at multiple occasions over a relatively short time and meet the closed population assumptions of Occupancy Modeling (see below). We used Google Maps (www.google. com/maps) to draw road vectors in the urban center of Starkville. We then used the sp package (Bivand et al. 2013) in R (R Core Team 2020) to select 22 sites in a stratified sampling design so that sites were nonadjacent, and surveys could be considered independent. For our purposes, sites are defined as a building's wall accessible from public sidewalks (Nelson and Carey 1993; White and Husak 2015).

Sampling design and survey methods.—We design our sampling so as to nest a classical sampling design (i.e., single-occasion; Mazerolle et al. 2007; Mazerolle 2015) within a standard sampling design for occupancy modeling (i.e., multiple-occasions; MacKenzie and Royle 2005). To account for imperfect detection, at least two sampling occasions on a closed population are necessary: a closed population experiences no colonization or extinction at sites within and between sampling occasions (MacKenzie et al. 2017). Additional sampling must be conducted when detection probability drops below 0.8 (Kéry 2002; MacKenzie and Royle 2005), however. We estimated detection probability (0.63) and unbiased occupancy (0.62) from encounter histories in Gomez-Zlatar et al. (2006) to determine the number of sampling occasions needed in our study to detect the target organism on at least one occasion at sites that it truly occupies (Supplemental Information). Referencing the standard design table in MacKenzie and Royle (2005), we determined that three sampling occasions were necessary for a total of 66 surveys (22 sites × three sampling occasions). We conducted surveys on 27 and 30 September 2019 and 2 October 2019 as average low temperature during this time in Starkville (17° C) is within the range conducive to Mediterranean Gecko activity (16°-31° C; Gomez-Zlatar and Moulton 2005). The sequence of sites differed for each sampling occasion, but the first survey of each sampling occasion began approximately 30 min after sunset.

We apply the term habitat *sensu* Morris (1987) as spatial units with a similar suite of environmental variables and distinguishable from other spatial units with different suites of environmental variables, together constituting a set of habitats. Thus, each site was assigned a habitat, constituent environmental variables defined below. We use the term conditions to define the suite of environmental variables that vary from survey to survey (i.e., between sampling occasions) at a site and can affect animal behavior (MacKenzie et al. 2017). We only measured habitat and conditions that previous research had concluded or presumed to be significant indicators of habitat association or influential on activity patterns of the Mediterranean Gecko.

We recorded the time at which surveys began and ended to account for variable activity of the Mediterranean Gecko (Gomez-Zlatar and Moulton 2005; Mateus and Jacinto 1998). For each survey, we systematically searched the surface of walls, going left to right, top to bottom with flashlights to detect geckos (Gomez-Zlatar et al. 2006; White and Husak 2015). If at least one gecko was encountered during a survey, we recorded a 1 (detection) and a 0 (nondetection) otherwise. In defining our areas of search, we evaluated detection probability as a function of time and area searched, metrics defined below. We estimated pedestrian traffic as the number of passersby within 3 m of a site during the time of a survey (i.e., pedestrians using the sidewalk nearest the building wall being searched). We included pedestrian traffic because human disturbance presumably causes individuals to retreat to nearby refugia and reduce its availability for detection (Williams and McBrayer 2007). We recorded artificial lighting as present if there were street lamps or lights on the site (i.e., building wall) or if lights from adjacent buildings, including across the street, directly illuminated the site. Artificial lighting has been reported to positively influence the presence of Mediterranean Geckos as it increases prev availability and the ability of surveyors to detect the Mediterranean Gecko (Meshaka et al. 2006; Williams and McBrayer 2007). During daytime hours of 28 September 2019, we measured the length and height of each building wall sampled and recorded the presence of well-defined eaves ( $\geq 0.3$  m overhang) on buildings as these are thought to provide refuge and points of ambush (Rose and Barbour 1968; Selcer 1986; Nelson and Carey 1993; Williams and McBrayer 2007; White and Husak 2015). Habitat and conditions varied, allowing us to estimate their effects on detection and occupancy (Table 1).

**Statistical analyses.**—To understand how the assumption of perfect detection influences interpretation of habitat associations and activity patterns of the Mediterranean Gecko we compared results from two models (Gorosito et al. 2016; Mazerolle et al. 2005). We fit detection/non-detection data from the first sampling occasion (i.e., classical sampling design) using a Logistic Regression, as is common in the literature for binary response data and assumes perfect detection (Pearce and Ferrier 2000; Gu and Swihart 2004; Guillera-Arroita et al. 2015), to estimate apparent occupancy ( $\psi_a$ ; Guillera-Arroita et al. 2014; MacKenzie et al. 2017). We fit detection/non-detection data from all sampling

occasions (i.e., standard occupancy sampling design) using a Single-species Single-season Occupancy Model (hereafter Occupancy Model), which does not assume perfect detection, to estimate unbiased occupancy ( $\psi$ ) and detection probability (p) simultaneously (Kéry 2008; MacKenzie et al. 2002, 2017). Here, p is defined as the probability of detecting at least one target animal during a survey.

Occupancy Models are essentially two hierarchically linked Logistic Regressions that estimate p given that the target species is available for detection at site iduring survey t and adjusts  $\psi$  using p (MacKenzie et al. 2002, 2017; O'Donnell and Semlitsch 2015; Kéry and Royle 2016). Thus, results of Occupancy Models are reported in two parts, one for the occupancy-portion and one for the detection-portion. Habitats are modeled in the occupancy-portion, but conditions are restricted to the detection-portion. As habitat can affect detection of animals, however, habitat and conditions may be included in the detection-portion of the occupancy model. The major assumptions of Occupancy Models are (1) that  $\psi$  for a site remains constant through the season (sampling period), (2) that  $\psi$  and p are equal across sites or heterogeneity thereof is modeled by habitat and habitat and conditions, respectively, and (3) that detections at sites are independent. Mathematical details of Occupancy Models are beyond the scope of this paper, and we refer readers to Kéry an Royle (2016) and MacKenzie et al. (2017) for more details.

The Logistic Regression was fit using the stats package (R Core Team 2020) and the Occupancy Model using the unmarked package (Fiske and Chandler 2011) in R. We included well-defined eaves, presence of artificial lighting, minutes after sunset, and pedestrian traffic as covariates in the Logistic Regression when estimating  $\psi_{a}$ . Only well-defined eaves and presence of artificial lighting were included in the occupancyportion of the Occupancy Model (i.e., habitat influence on the estimation of  $\psi$ ), while well-defined eaves, presence of artificial lighting, minutes after sunset, and pedestrian traffic were included in the detectionportion (i.e., influence of habitat and conditions on the estimation of p; see Mazerolle 2015 for details on specifying occupancy models in the unmarked

**TABLE 1.** Summary statistics for conditions (i.e., temporal) and habitat types (i.e., spatial) for Mediterranean Geckos (*Hemidactylus turcicus*) found on buildings in Starkville, Mississippi, USA. Conditions varied between surveys and were measured during each; habitat were constant between surveys and measured once. Values in parentheses are for the first sampling occasion. Effort was variable among surveys and was included as an offset. The abbreviation SD = standard deviation.

Covariate	Level	Mean	SD	Present (n)	Absent (n)
Effort (m <sup>2</sup> surveyor <sup>1</sup> )	Conditions	16.71 (15.19)	10.21 (9.67)		
Minutes after sunset	Conditions	90.44 (92.91)	40.58 (42.69)		
Pedestrian traffic (pedestrians minutes <sup>1</sup> )	Conditions	0.44 (0.35)	0.68 (0.49)		
Well-defined eaves	Habitat			14	8
Presence of artificial lighting	Habitat			13	9

package). Effort varied from survey to survey, so we used the area of building walls (length × height, both in meters) divided by minutes searched per person (meters<sup>2</sup> minutes<sup>-1</sup> person<sup>-1</sup>) as an offset covariate in both models (first sample occasion mean = 15.19, standard deviation [SD] = 9.67; all sample occasions mean = 16.71, SD = 10.21). Continuous covariates were scaled to a mean of zero and standard deviation of one and factors were dummy coded prior to analysis. We tested model assumptions for the Logistic Regression using goodness-of-fit statistics and permutation tests (n = 4,999) in the DHARMa package (Hartig 2019). For the Occupancy Model, we tested model assumptions using the MacKenzie-Bailey (2004) goodness-of-fit bootstrap test (n = 4,999). We tested covariates in both models using t-tests and considered covariates influential on the response if their P-value < 0.05. We deciphered the effect of a covariate on a response by holding all other covariates at their mean and varying the covariate of interest; we then plotted effects on the response scale. We calculated Nagelkerke's  $r^2$ , analogous to Pearson's  $r^2$ for Linear Regression, as a measure of model fit using the rcompanion package (Mangiafico 2019) for the Logistic Regression and using the unmarked package (Fiske and Chandler 2011) for the Occupancy Model. We estimated  $\psi$  and  $\psi$  from each model while holding covariates at their mean values. We calculated a 95% confidence interval (CI) for the log-odds of each estimate as

$$logit(X) \pm Z \times logit(S.E.)$$
 (1)

where logit(X) is the log-odds estimate of either  $\psi_a$  or  $\psi$ , Z is the Z-score corresponding to the 95% CI (1.96), and logit (SE) is the log-odds standard error of the log-odds estimate. We then transformed each of the log-odds 95% CI into their proportional form using

$$\frac{e^{logit(95\% CI)}}{1 + e^{logit(95\% CI)}}$$
(2)

where e is Euler's number (approximately 2.71828) and logit (95% CI) corresponds to the log-odds 95% CI estimated using equation 1.

We compared statistical significance of covariates ( $\alpha = 0.05$ ) between the Logistic Regression model and portions of the Occupancy Model. If a covariate was significant in the Logistic Regression model, we interpreted it as influential on  $\psi_a$ . If and only if a covariate was significant in the occupancy-portion of the Occupancy Model, we interpreted it as influential on  $\psi$ . If a covariate was significant in the detectionportion of the Occupancy Model, regardless of whether it was or was not significant in the occupancyportion, we interpreted it as influential on p. If the significance of covariates corresponded between the Logistic Regression model and the occupancy-portion of the Occupancy Model, we considered the models complementary and that the assumption of perfect detection to have little effect on inferences about habitat associations and activity patterns of the Mediterranean Gecko. If significant covariates differed between the Logistic Regression model and the Occupancy Model and there was at least one covariate significant in the detection-portion of the Occupancy Model, then we considered the models contradictory and the assumption of perfect detection invalid.

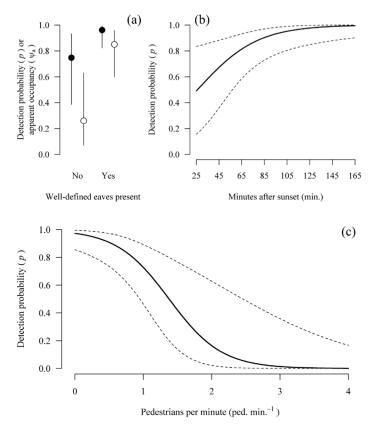
#### RESULTS

The Mediterranean Gecko was encountered at 14 locations during our first sampling occasion, 13 on the second occasion, and 12 on the third occasion (39 of 66 surveys). It was encountered on at least one sampling occasion at 17 of 22 sites. Tests of uniformity (Kolmogorov-Smirnov D = 0.16, P = 0.565) and dispersion (observed dispersion = 1.16, P = 0.174) did not indicate violation of assumptions in the Logistic Regression, so we proceeded with model interpretation. The Logistic Regression indicated that well-defined eaves was the only covariate that was significant (Table 2). Apparent occupancy ( $\psi_a$ ) was estimated to be 0.68 (95% CI = 0.43-0.85) when all covariates were held at their mean value. Apparent occupancy ( $\psi_a$ ) was 0.85 (0.60-0.96) when eaves were present as compared with 0.26 (0.07-0.63) when not present (Fig. 1). Nagelkerke's  $r^2$  for the Logistic Regression model was 0.07.

The MacKenzie-Bailey goodness-of-fit test did not indicate a violation of Occupancy Model fit ( $\hat{c} = 0.72$ ,  $\chi^2 = 2.91$ , P = 0.603, so we proceeded with model interpretation. No habitat types were significant in the occupancy-portion of the Occupancy Model (Table 3). Unbiased occupancy ( $\psi$ ) was estimated to be 0.79 (0.56–0.92) when all variables were held at their mean

**TABLE 2.** Logistic Regression results for apparent occupancy ( $\psi$ a) of Mediterranean Geckos (*Hemidactylus turcicus*) found on buildings in Starkville, Mississippi, USA. Coefficient estimates given in log-odds scale and probability scale (in parentheses). *P* values < 0.05 are indicated in bold and are significant. The abbreviation SE = standard error.

Covariate $(\psi_a)$	Coefficient	SE	t	Р
Intercept	-0.54 (0.37)	1.01	-0.53	0.597
Well-defined eaves	2.82 (0.94)	1.08	2.61	0.009
Presence of artificial lighting	-0.86 (0.30)	1.15	-0.75	0.455
Minutes after sunset	0.34 (0.58)	0.68	0.50	0.614
Pedestrian traffic (pedestrians minutes <sup>-1</sup> )	0.63 (0.65)	0.64	0.98	0.328



**FIGURE 1**. Detection probability and apparent occupancy as a function of presence of well-defined eaves (a), minutes after sunset (b), and pedestrian traffic (c) for Mediterranean Geckos (*Hemidactylus turcicus*) found on buildings in Starkville, Mississippi, USA. Filled circles in subplot a indicate estimates of detection from the detection-portion of the occupancy model while open circles indicate estimates of apparent occupancy from the logistic regression; error bars represent 95% Confidence Interval (CI). Dashed lines represent 95% CI for continuous covariates.

**TABLE 3.** Occupancy Model results for unbiased occupancy ( $\psi$ ) and detection probability (*p*) for Mediterranean Geckos (*Hemidactylus turcicus*) found on buildings in Starkville, Mississippi, USA. Coefficient estimates given in log-odds scale and probability scale (in parentheses). *P*-values < 0.05, indicated in bold, are significant. The abbreviation SE = standard error.

	Coefficient	SE	t	Р
Habitat (ψ)				
Intercept	0.57 (0.63)	1.05	0.55	0.584
Well-defined eaves	1.24 (0.78)	1.08	1.15	0.248
Presence of artificial lighting	-0.04 (0.55)	1.11	-0.03	0.973
Conditions (p)				
Intercept	0.31 (0.75)	1.02	0.30	0.763
Well-defined eaves	2.13 (0.90)	1.02	2.08	0.037
Presence of artificial lighting	1.31 (0.58)	1.06	1.24	0.214
Minutes after sunset	1.51 (0.83)	0.59	2.57	0.010
Pedestrian traffic (pedestrians minutes <sup>-1</sup> )	-1.78 (0.16)	0.57	-3.12	0.002

value. Well-defined eaves, minutes after sunset, and pedestrian traffic, however, were all significant for the detection-portion of the Occupancy Model (Table 3). Detection probability (p) was estimated to be 0.92 (0.75–0.98) when all variables were held at their mean value; p was 0.96 (0.82–0.99) when eaves were present and 0.75 (0.39–0.93) when not present (Fig. 1). Detection probability (p) increased with minutes after sunset but decreased with pedestrian traffic (Fig. 1). Nagelkerke's  $r^2$  for the Occupancy Model was 0.77.

#### DISCUSSION

We investigated the assumption of perfect detection when testing habitat associations and activity patterns of the Mediterranean Gecko. Understanding these relationships can help scientists and managers gain insight to the invasive potential of the Mediterranean Gecko (Christy et al. 2010). Previous work has assumed that the Mediterranean Gecko was detected without error at sites that it occupied. Recent literature, however, suggests this cannot be safely assumed so we compared models that do and do not assume perfect detection. Even when acknowledged, there has been no formal treatment for false-negative errors in surveys for the Mediterranean Gecko (Nelson and Carey 1993). This is concerning as our study indicates that the Mediterranean Gecko was not perfectly detected at all sites that it occupied and suggests that false-negative errors have misled interpretations of its habitat associations and activity patterns.

When examining the statistical significance ( $\alpha = 0.05$ ) of the effects of covariates on occupancy, there was complete incongruence between models that do and do not assume perfect detection. When using a classical sampling design and Logistic Regression,  $\psi_a$  was underestimated (15% difference with  $\psi$ ) and spurious associations between habitat and  $\psi_a$  were present. The Logistic Regression indicated that  $\psi_a$  was influenced by well-defined eaves, while, in truth, well-defined eaves only influenced *p*. Furthermore, activity pattern associations were not significant in the Logistic Regression, differing from both the Occupancy Model and previous literature (Mateus and Jacinto 1998; Williams and McBrayer 2007).

Unlike the Logistic Regression, the Occupancy Model did not indicate that  $\psi$  was influenced by the presence of well-defined eaves. In fact, no covariates were significant in the occupancy-portion of the model suggesting that the Mediterranean Gecko is a generalist whose occupancy within urban areas is limited only by local dispersion (Locey and Stone 2006). There were, however, both habitat and conditions that were influential on p. This suggests that habitat associations and activity patterns found in past studies may need further investigation, but most results in the Occupancy Model support past conclusions. The Occupancy Model indicated that p increases with minutes after sunset (Mateus and Jacinto 1998), decreases with pedestrian traffic (Williams and McBrayer 2007), varies with the presence of well-defined eaves (Nelson and Carey 1993; Williams and McBrayer 2007), and the presence of artificial lighting has little to no effect on p (Meshaka et al. 2006; Williams and McBraver 2007). There are, of course, numerous other factors at various spatial and temporal scales that could influence  $\psi$  and p (e.g., wall color, perch height, prey abundance, and presence of congenerics; Gomez-Zlatar et al. 2006; Meshaka et al. 2006; Williams and McBrayer 2007). Future studies that examine the habitat, macrohabitat, and microhabitat associations and activity patterns should account for imperfect detection, lest false-negative errors mislead investigators.

There are other approaches to account for falsenegative errors. A common approach is to use a Mixed-effects Logistic Regression, which uses multiple-occasion sampling to estimate apparent detection (pa) and adjust  $\psi_a$  by  $p_a$ . Such an approach is powerful when assumptions are met, among which is the assumption that the target organism is known to be present at sites but may not be encountered due to environmental variables and unknown factors (Chen et al. 2009; McIntyre et al. 2020). We fit such a model (Supplemental Information) and found similar results to the Occupancy Model; however, these estimates had greater uncertainty than with the Occupancy Model and it is impossible to disentangle the effects of covariates between the detection process from the state process (Kéry and Royle 2016; MacKenzie et al. 2017). Additionally, we could only use data from sites where the Mediterranean Gecko was detected on at least one occasion to meet the primary assumption. Such an approach can be useful under controlled settings (see Chen et al. 2009), but when surveys have been conducted without this knowledge, it seems pertinent to use models that can accommodate all data to estimate p when  $\psi$  at a site is unknown, i.e., Occupancy Models and, more generally, N-mixture models (MacKenzie et al. 2002, 2017; O'Donnell and Semlitsch 2015; Kéry and Royle 2016).

A final point of interest, sampling designs for Occupancy Modeling can be tweaked so that temporal replication for conditions can be substituted with spatial replication (i.e., sub-sites; Kéry and Royle 2008, 2016). In practice, multiple sites within the largest town within a county level can be used for distributional studies of the Mediterranean Gecko, which is the spatial scale at which these studies have been conducted typically (see Nelson and Carey 1993; Meshaka et al. 2006; White and Husak 2015). Sampling designs would be optimized to save time and travel while preserving replication needed to estimate  $\psi$  and p simultaneously (Kéry and Royle 2008, 2016; Petito et al. 2014). We did such an exercise, using multiple walls as replicates within urban centers of the largest towns in neighboring counties and found that space-for-time substitution was effective and efficient (Supplemental Information). Such designs may be most effective when involving citizenscientists (Altwegg and Nichols 2019), especially as the Mediterranean Gecko and congeners are expected to expand in the U.S. (Weterings and Vetter 2018). Our study is but an example of what we believe is a widespread bias in herpetofaunal-habitat studies (Mazerolle et al. 2005, 2007; Kellner and Swihart 2014). We hope that more herpetologists take approaches to account for imperfect detection, focusing on sampling and survey methods that can confidently assess the distributional status, habitat associations and activity patterns, and eradication effectiveness of invasive species (Mazerolle et al. 2007; Christy et al. 2010; Nafus et al. 2020).

Acknowledgments.—We thank Brian P. Butterfield for reviewing an earlier draft of this manuscript and pointing out errors and omissions. This work was supported by the National Institute of Food and Agriculture, U.S. Department of Agriculture, McIntire-Stennis project under accession number MISZ-082100 and conducted under the Mississippi Department of Wildlife, Fisheries, and Parks Scientific Collecting Permit (#1213193), and an Institutional Animal Care and Use Committee permit from Mississippi State University (21-062).

## LITERATURE CITED

- Altig, R., G.B. Pauly, and R.E. Espinoza. 2016. *Hemidactylus turcicus* (Mediterranean Gecko). Herpetological Review 47:628.
- Altwegg, R., and J. Nichols. 2019. Occupancy models for citizen-science data. Methods in Ecology and Evolution 10:8–21.
- Bivand, R.S., E. Pebesma, and V. Gomez-Rubio. 2013. Applied Spatial Data Analysis with R. 2nd Edition. Springer, New York, New York, USA.
- Chen, G., M. Kéry, J. Zhang, and K. Ma. 2009. Factors affecting detection probability in plant distribution studies. Journal of Ecology 97:1383–1389.
- Christy, M.T., A.A.Y. Adams, G.H. Rodda, J.A. Savidge, and C.L. Tyrrell. 2010. Modelling detection probabilities to evaluate management and control tools for an invasive species. Journal of Applied Ecology 47:106–113.
- Fiske, I., and R. Chandler. 2011. unmarked: an R package for fitting hierarchical models of wildlife occurrence and abundance. Journal of Statistical Software 43:1–23.
- Fowler, H.W. 1915. Cold-blooded vertebrates from Florida, the West Indies, Costa Rica, and eastern Brazil. Proceedings of the Academy of Natural Sciences of Philadelphia 67:244–269.
- Gomez-Zlatar, P., and M.P. Moulton. 2005. Habitat use by the nonindigenous Mediterranean Gecko (*Hemidactylus turcicus*) in north central Florida. Florida Scientist 68:206–214.
- Gomez-Zlatar, P., M.P. Moulton, and R. Franz. 2006. Microhabitat use by introduced *Hemidactylus turcicus* (Mediterranean Gecko) in north central Florida. Southeastern Naturalist 5:425–434.
- Gorosito, I.L., M.M. Bermúdez, R.J. Douglass, and M. Busch. 2016. Evaluation of statistical methods and sampling designs for the assessment of microhabitat selection based on point data. Methods in Ecology and Evolution 7:1316–1324.
- Gu, W., and R.K. Swihart. 2004. Absent or undetected? Effects of non-detection of species occurrence on wildlife-habitat models. Biological Conservation 116:195–203.

- Guillera-Arroita, G., J.J. Lahoz-Monfort, J. Elith, A. Gordon, K. Kujala, P.E. Lentini, M.A. McCarthy, R. Tingley, and B.A. Wintle. 2015. Is my species distribution model fit for purpose? Matching data and models to applications. Global Ecology and Biogeography 24:276–292.
- Guillera-Arroita, G., J.J. Lahoz-Monfort, D.I. MacKenzie, B.A. Wintle, and M.A. McCarthy. 2014. Ignoring imperfect detection in biological surveys is dangerous: a response to 'Fitting and Interpreting Occupancy Models'. PLoS ONE 9:e99571. https:// doi.org/10.1371/journal.pone.0099571.
- Hartig, F. 2019. DHARMa: residual diagnostics for hierarchical (multi-level/mixed) regression models. R package version 0.2.4. https://CRAN.R-project. org/package=DHARMa.
- Kellner, K.F., and R.K. Swihart. 2014. Accounting for imperfect detection in ecology: a quantitative review. PLoS ONE 9:e111436. https://doi.org/10.1371/ journal.pone.0111436.
- Kéry, M. 2002. Inferring the absence of a species a case study of snakes. Journal of Wildlife Management 66:330–338.
- Kéry, M. 2008. Estimating abundance from bird counts: binomial mixture models uncover complex covariate relationships. Auk 125:336–345.
- Kéry, M. and J.A. Royle. 2016. Applied Hierarchical Modeling in Ecology: Analysis of Distribution, Abundance and Species Richness in R and BUGS. Volume 1. Prelude and Static Models. Academic Press, London, UK.
- MacKenzie, D.I., and L.L. Bailey. 2004. Assessing the fit of site-occupancy models. Journal of Agricultural, Biological, and Environmental Statistics 9:300–318.
- MacKenzie, D.I., and J.A. Royle. 2005. Designing occupancy studies: general advice and allocating survey effort. Journal of Applied Ecology 42:1105– 1114.
- MacKenzie, D.I., J.D. Nichols, G.B. Lachman, S. Droege, J.A. Royle, and C.A. Langtimm. 2002. Estimating site occupancy rates when detection probabilities are less than one. Ecology 83:2248–2255.
- MacKenzie, D.I., J.D. Nichols, J.A. Royle, K.H. Pollock, L.L. Bailey, and J.E. Hines. 2017. Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence. 2nd Edition. Academic Press, London, U.K.
- Mangiafico, S. 2019. rcompanion: functions to support extension education program evaluation. R package version 2.3.0. https://CRAN.R-project.org/ package=rcompanion.
- Mateus, O., and J.J. Jacinto. 1998. Activity and habitat of *Hemidactlyus turcicus* (Reptilia, Gekkonidae) in Évora, Portugal. Boletin de Istitudo de Ciencia e

Aldridge et al.—Duped by false-negative errors.

Investigación Juvenil de Aragón 2:37-43.

- Mazerolle, M.J. 2015. Estimating detectability and biological parameters of interest with the use of the R environment. Journal of Herpetology 49:541–559.
- 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.
- Mazerolle, M.J., A. Desrochers, and L. Rochefort. 2005. Landscape characteristics influence pond occupancy by frogs after accounting for detectability. Ecological Applications 15:824–834.
- McIntyre, T., T.L. Majelantle, D.J. Slip, and R.G. Harcourt. 2020. Quantifying imperfect camera-trap detection probabilities: implications for density modelling. Wildlife Research 47:177–185.
- Meshaka, W.E., Jr. 2011. A Runaway Train in the Making: The Exotic Amphibians, Reptiles, Turtles, and Crocodilians of Florida. Monograph 1. Herpetological Conservation and Biology 6:1–101.
- Meshaka, W.E., Jr., S.D. Marshall, J. Boundy, and A.A. Williams. 2006. Status and geographic expansion of the Mediterranean Gecko, *Hemidactylus turcicus*, in Louisiana: implications for the Southeastern United States. Herpetological Conservation and Biology 1:45–50.
- Morris, D.W. 1987. Ecological scale and habitat use. Ecology 68:362–369.
- Nafus, M.G., F.J. Mazzotti, and R.N. Reed. 2020. Estimating detection probability for Burmese Pythons with few detections and zero recaptures. Journal of Herpetology 54:24–30.
- Nelson, D.H., and S.D. Carey. 1993. Range extension of the Mediterranean Gecko (*Hemidactylus turcicus*) along the northeastern Gulf Coast of the United States. Northeast Gulf Science 13:53–58.
- O'Donnell, K.M., and R.D. Semlitsch. 2015. Advancing terrestrial salamander population ecology: the central role of imperfect detection. Journal of Herpetology 49:533–540.
- Pearce, J., and S. Ferrier. 2000. Evaluating the predictive performance of habitat models developed using logistic regression. Ecological Modelling 1333:225–245.

- Petito, M., N. Manceau, P. Geniez, and A. Besnard. 2014. Optimizing occupancy surveys by maximizing detection probability: application to amphibian monitoring in the Mediterranean region. Ecology and Evolution 4:3538–3549.
- Powell, R., R. Conant, and J.T. Collins. 2016. Peterson Field Guide to Reptiles and Amphibians of Eastern and Central North America. 4th Edition. Houghton Mifflin Harcourt, Boston, Massachusetts, USA.
- Punzo, F. 2001. The Mediterranean Gecko, *Hemidactylus turcicus*: life in an urban landscape. Florida Scientist 64:56–66.
- R Core Team. 2015. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project. org.
- Rose, F.L., and C.D. Barbour. 1968. Ecology and reproductive cycles of the introduced gecko, *Hemidactylus turcicus*, in the Southern United States. American Midland Naturalist 79:159–168.
- Selcer, K.W. 1986. Life history of a successful colonizer: the Mediterranean Gecko, *Hemidactylus turcicus*, in Southern Texas. Copeia 1986:956–962.
- Valenzuela-Sánchez, A., B.R. Schmidt, C. Pérez, T. Altamirano, V. Toledo, I. Pérez, S. Teillier, A.A. Cunningham, and C. Soto-Azat. 2019. Assessing habitat quality wen forest attributes have opposing effects on abundance and detectability: a case study on Darwin's frogs. Forest Ecology and Management 432:942–948.
- Wenger, S.J., and M.C. Freeman. 2008. Estimating species occurrence, abundance, and detection probability using zero-inflated distributions. Ecology 89:2953–2959.
- Weterings, R., and K.C. Vetter. 2018. Invasive house geckos (*Hemidactylus* spp.): their current, potential and future distribution. Current Zoology 64:559–573.
- White, J.W., and M.S. Husak. 2015. New county records and range expansion of the Mediterranean Gecko (*Hemidactylus turcicus*) in Southwestern Oklahoma. Southwestern Naturalist 60:99–101.
- Williams, S.C., and L.D. McBrayer. 2007. Selection of microhabitat by the introduced Mediterranean Gecko, *Hemidactylus turcicus*: influence of ambient light and distance to refuge. Southwestern Naturalist 52:578–585.

Supplemental Information: http://www.herpconbio.org/Volume\_16/Issue\_3/Aldridge\_etal\_2021\_Suppl.



**CALEB A. ALDRIDGE** is a Ph.D. candidate at Mississippi State University, Mississippi State, USA, where he studies strategic planning and management of inland fisheries. He received his B.S. in General Biology at the University of North Alabama, Florence, USA (2012), and a M.S. in Biological Sciences from the University of Mississippi, Oxford, USA (2017). His thesis focused on the effect roads have on streamside Plethodontidae counts in a Southeastern USA Plains forest. His areas of interests include developing decision support tools that leverage statistical estimates and expert knowledge to meet conservation objectives, especially in aquatic systems. (Photographed by Caleb Aldridge).



**THOMAS P. ROGERS** is an undergraduate student at Mississippi State University, Mississippi State, USA, where he studies Wildlife, Fisheries and Aquaculture. He previously worked with Bobwhite Quail (*Colinus virginianus*) and is currently working on endangered species research. His research interests include invasive species and human-wildlife conflict. (Photographed by Caleb Aldridge).



W. TAYLOR BANKS is a senior at Mississippi State University, Mississippi State, USA, finishing his Bachelor's degree in Wildlife, Fisheries and Aquaculture. Taylor has assisted with several research projects, which include radio frequency identification, aquatic food web dynamics, and electrofishing surveys. He is also an undergraduate Research Assistant in the water quality lab and fish ecology lab. After graduation, he plans to pursue a Master's degree in fish ecology. (Photographed by Conner Owens).



**SCOTT A. RUSH** is an Associate Professor in the Department of Wildlife, Fisheries and Aquaculture at Mississippi State University, Mississippi State, USA. He received his Ph.D. from the University of Georgia, Athens, USA (2009), where his research focused on indicators of ecosystem properties within the northern Gulf of Mexico tidal marshes. His post-doctoral training, completed at the Great Lakes Institute for Environmental Research at the University of Windsor (Windsor, Ontario, Canada), addressed changes in energy mobility through Great Lakes ecosystems. Now at Mississippi State University, Scott and his students continue to work within an expanding research framework addressing landscape and trophic ecology relative to wildlife populations. Some current work strives to understand the effects of climate change on avian population regulation, and management of ecological communities supporting threatened and endangered species, especially within the context of human-wildlife conflicts. (Photographed by John Trent).