SOUTHEAST REGIONAL AND STATE TRENDS IN ANURAN OCCUPANCY FROM CALLING SURVEY DATA (2001–2013) FROM THE NORTH AMERICAN AMPHIBIAN MONITORING PROGRAM

OSWALDO C. VILLENA^{1, 3}, J. ANDREW ROYLE¹, LINDA A. WEIR¹, TASHA M. FOREMAN¹, KIMBERLY D. GAZENSKI¹, AND EVAN H. CAMPBELL GRANT²

¹US Geological Survey, Patuxent Wildlife Research Center, 12100 Beech Forest Road, Laurel, Maryland 20708, USA ²US Geological Survey, Patuxent Wildlife Research Center, Silvio O Conte Anadromous Fish Laboratory, 1 Migratory Way, Turners Falls, Massachusetts 01376, USA

³Corresponding author, e-mail: oswaldo.villena@gmail.com

Abstract.—We present the first regional trends in anuran occupancy for eight states of the southeastern United States, based on 13 y (2001–2013) of North American Amphibian Monitoring Program (NAAMP) data. The NAAMP is a long-term monitoring program in which observers collect anuran calling observation data at fixed locations along random roadside routes. We assessed occupancy trends for 14 species. We found weak evidence for a general regional pattern of decline in calling anurans within breeding habitats along roads in the southeastern USA over the last 13 y. Two species had positive regional trends with 95% posterior intervals that did not include zero (*Hyla cinerea* and *Pseudacris crucifer*). Five other species also showed an increasing trend, while eight species showed a declining trend, although 95% posterior intervals for 107 species/state combinations. Of these, 14 showed a significant decline and 12 showed a significant increase in occupancy (i.e., credible intervals did not include zero for these 26 trends).

Key Words.-amphibians; calling survey; NAAMP; occupancy modeling; occupancy trends

INTRODUCTION

Declining amphibian populations are being observed worldwide, resulting in range reductions and extinctions of some species (Stuart et al. 2004; Walls et al. 2011). In the United States even common species are declining (Adams et al. 2013). Declines in amphibian populations had been reported by the scientific community as early as the 1960s, though early reports were based primarily on anecdotal evidence (Bragg 1960; Gibbs et al. 1971; Blaustein and Wake 1990; Phillips 1994). In 1994, at the Indiana Dunes meeting of the Declining Amphibian Population Task Force (DAPTF), a network of scientists and conservationists concluded that a statistically defensible program, which could be applied at the state, regional, and continental scale, was needed to monitor amphibian populations in North America (Weir and Mossman 2005). In response to this need, the North American Amphibian Monitoring Program (NAAMP) partnership was formed in 1997, and NAAMP partners adopted a standardized data collection method in 2001 (Weir and Mossman 2005).

The NAAMP is a collaborative effort among state natural resource agencies, academics, nonprofit organizations, and the US Geological Survey (USGS). The USGS provides central coordination and database management, while state partners recruit and train volunteers to conduct calling surveys following the

NAAMP unified protocol (Weir and Mossman 2005). NAAMP surveys are conducted in 23 states that are mainly located east of the Mississippi River or bordering its western bank. The NAAMP surveys rely solely on the detection of calling anurans, where observers listen for anuran vocalizations and identify species by their unique calls. Observers report calling activity for each species heard during a five minute listening period (Weir and Mossman 2005). State and regional trends were previously reported from the northeastern region of the United States using NAAMP data (Weir et al. 2005, 2009, 2014), but other regions have not been assessed. For this paper, our objective is to estimate trends of anuran species for the southeastern region of the United States as a whole, as well as separately for the eight states within the region.

MATERIALS AND METHODS

North American Amphibian Monitoring Program surveys are conducted along random roadside routes; each route is composed of 10 locations (sites or stops) spaced ≥ 0.8 km apart where observers identify species by their breeding vocalizations (Weir and Mossman 2005). At each site, observers listen for 5 min and record the species they detected using a calling index to rate the level of calling activity from one to three, where one indicates individuals calling with no overlap, two

TABLE 1.	Number of	of surve	eys conduc	cted an	d numbe	r of si	tes sur	veyed j	per yea	r for a	amphibi	ians in	each	state in	the sout	heastern	United	States.
Surveys in	Georgia,	North (Carolina, S	South C	Carolina,	and T	enness	see did	not sta	rt unti	1 after 2	2001, a	and in	Florida	surveys	were no	t condu	icted in
2001 or 20	07–2009.																	

	Number of		Survey Year											
State	Surveys	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Florida	308	-	230	230	190	90	20	-	-	-	180	160	152	130
Georgia	459	-	-	-	-	-	-	-	200	330	350	310	350	240
Louisiana	547	270	240	250	270	260	120	100	110	130	150	130	80	80
Mississippi	219	60	80	40	90	60	40	60	80	160	100	60	70	40
North Carolina	856	-	-	-	-	-	210	470	490	430	450	370	430	360
South Carolina	555	-	-	-	-	-	-	-	320	350	280	280	290	290
Tennessee	251	-	-	-	60	230	110	70	40	30	50	60	110	110
Virginia	389	160	220	160	120	130	70	110	90	90	110	100	100	50
Total	3,584													

indicates individuals calling with some calls overlapping, and three indicates a full chorus of indistinguishable individuals (Weir and Mossman 2005). In addition to species data, observers record environmental data that can be used as covariates during analysis (e.g., air temperature and time of the survey). Beginning in 2006, observers were required to pass an online frog call identification quiz (Available from http://www.pwrc.usgs.gov/frogquiz [Accessed 20 August 2014]). Data from observers who did not pass the quiz were not used for analysis.

We used NAAMP calling survey data from eight states of the southeastern United States: Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia (Fig. 1), with 10 years of data on average per state, 2001–2013 (Table 1). Across this region, data were collected on 375 routes.



FIGURE 1. The eight southeastern states of the USA where NAAMP surveys were conducted (gray): Florida, Georgia, Louisiana, Mississispipi, North Carolina, South Carolina, Tennessee, and Virginia.

Occasionally a site or whole route had to be discontinued (e.g., safety issue). In this data set there are 3,765 unique sites. Of these, 15 sites were discontinued and replaced with new sites, so at any given time a route had 10 sites.

In the 13-y period examined here, observers conducted 3,584 surveys. Because each route had 10 listening sites, this would result in 35,840 site visits if all 10 sites were visited in every survey. Occasionally observers did not survey a site (e.g., road block, weather deterioration), so the actual number of site visits was 35,630. Observers usually report the air temperature for all 10 sites, but for various reasons did not report air temperature for 19.5% of the 35,630 site visits in this analysis. This value is higher than the 3% reported in the northeast analysis (Weir et al. 2014) primarily because the NAAMP unified protocol only requires air temperature to be recorded at the start and end of the survey for Gulf Coast states, as air temperature tends not to vary as much in this region over the course of an evening (Weir and Mossman 2005). To replace any null temperature values, we calculated the average air temperature for the associated route survey using the reported temperatures by the observer from the remaining route sites that night.

Sunset time varies by date and location. We used R (Available from http://www.r-project.org [Accessed 21August 2014]), an open source statistical software, with its maptools package (Available from http://cran.r-project.org/web/packages/maptools/index.html [Accessed 21 August 2014]) to calculate sunset time, using the survey date and the start point of the route, adjusted for daylight savings time when necessary. Observers reported the time the survey started and ended for the route, and optionally reported start time at each site. Observers reported the start time in 76% of site visits, otherwise we estimated the site visit time based on the other times provided by the observer (24% of site visits).



FIGURE 2. Southeastern distributions of 11 species with limited distributions. Black shading indicates areas considered within the range of each species. Range maps similar to those in Conant and Collins (1998) were created by modifying USGS National Amphibian Atlas (County level distribution maps. Available from http://www.pwrc.usgs.gov/naa [Accessed 22 August 2014]).

We converted site visit start times into minutes after sunset (site visit start time - sunset time). Although observers were instructed to start surveys 30 min after sunset or later, some site visits occurred prior to sunset (< 1% of site visits).

Although observers detected 42 species, we considered only the 14 species observed at $\geq 25\%$ of our survey sites in our analysis, as fewer detections result in larger credible intervals (Walls et al. 2011). We considered all routes to be within the range of three species with widespread distribution in the southeast: *Gastrophryne carolinensis* (Eastern Narrow-mouthed Toad), *Lithobates catesbeianus* (American Bullfrog), and *L. sphenocephalus* (Southern Leopard Frog). For species with more limited distributions, we considered sites to be within a range of a species if any portion of the route fell within generalized species range maps (Fig. 2). We used only routes within the range in analyses for the remaining 11 species: *Anaxyrus americanus*

(American Toad), Acris crepitans (Northern Cricket Frog), Anaxyrus fowleri (Fowler's Toad), Acris gryllus (Southern Cricket Frog), Anaxyrus terrestris (Southern Toad), Hyla avivoca (Bird-voiced Tree Frog), H. chrysoscelis (Cope's Gray Tree Frog), H. cinerea (American Green Tree Frog), H. gratiosa (Barking Tree Frog), H. squirella (Squirrel Tree Frog), and Pseudacris crucifer (Spring Peeper).

Statistical model.—Whereas observers report species heard using a 1–3 index to abundance, for modeling purposes, we converted the data to detection/nondetection format; such that for observations at site *i* during survey *j*, if a species is detected at site *i* on survey *j*, it takes a value of 1; when a species is not detected at site *i* on survey *j*, it takes a value of 0 (Kéry and Schaub 2012). We modeled detection probability and site occupancy using multi-season occupancy models (MacKenzie et al. 2002; MacKenzie et al. 2003; MacKenzie et al. 2006), implemented using a Bayesian analysis framework (Royle and Kéry 2007; Kéry 2010, p. 237-274; Kéry and Schaub 2012, p. 436) in JAGS (Available from http://mcmc-jags.sourceforge.net/ [Accessed 22 July 2016]). We modeled each species independently. Covariates can be included on both detection and occupancy probabilities, and are typically modeled using the logit link function (Kéry 2010; Kéry and Schaub 2012; Weir et al. 2014). We used time of the survey, day-of-year, air temperature, latitude, and the interaction of latitude and day-of-year as covariates on detection probability in our model because these variables have been found to influence detection probability at the site level (Weir et al. 2005, 2009).

To evaluate these factors, we considered logit models of the form:

$$\operatorname{logit}(p[i, j, t]) = \beta_{\circ} + \sum_{k=1}^{K} \beta_{k} \cdot u_{k[i, j, t]}$$

where $\mathcal{U}_{k[i,j,t]}$ is the value of (detection) covariate k = 1, 2, ..., K for the observation collected at site *i* (a specific route/stop combination) and sampling occasion *j* within year *t*.

Because sampling occurred over 13 y, we accommodated explicit occupancy dynamics that allowed the occupancy status of sites (z[i,t] = 1 if site *i* is occupied in year *t* and 0 otherwise) to change from occupied to unoccupied and vice versa. The full model as described by MacKenzie et al. (2003) and Royle and Kéry (2007) accommodates both local extinction (the complement of local survival) and colonization parameters according to a Markovian model:

$$z[i,t] \sim Bernoulli(\psi[i,t])$$

With

$$\psi[i,t] = \phi(z[i,t-1]) + \gamma (1 - z[i,t-1])$$

where Φ is the Local Survival Probability, the probability that a previously occupied site (i.e., at time *t*-1) remains occupied at time *t*, and γ is the Colonization Probability; i.e., the probability that a site unoccupied at time *t*-1 becomes occupied at time *t*. In practice, Φ and γ may both be year-specific. In our analysis, we wanted to allow geographic specificity in the occupancy dynamics parameters (at the level of the state), in which case a fully parameterized model would involve 96 Φ parameters. To achieve a more economical model parameterization, we assumed only state-specific values

of the parameters, and we adopted the autologistic formulation of the model described by Royle and Dorazio (2008, p. 311) in which Ψ [*i*,*t*] is modeled on the logit-scale according to:

 $logit(\psi[i,t]) = a0(U.S.state[i]) + a1(U.S.state[i]) * z[i,t-1]$

where, under this parameterization, the local survival rate for US state *s* is $logit^{-1}(a0[s] + a1[s])$ and the local colonization rate for US state *s* is $logit^{-1}(a0[s])$.

Trend estimation.—To characterize USA state-level trends, we computed N[s,t] = the number of occupied sites, by summing the true latent occupancy state (z(i,t)) for all sites within each US state *s*, and for each year *t*. This was converted to proportion of occupied sites by dividing by the number of sites within the species expected range in each geographic state. We define this time-series of N[s,t] values to be the Trajectory (note: the term trend is usually used in the context of a scalar summary of change over time).

We summarized this Trajectory using a linear leastsquares fit (Weir et al. 2009) to the posterior samples of the trajectory N[s,t] for t = 1,2,...,13. We refer to the slope of the least-squares fit as the trend. This calculation was done by post-processing the Markov Chain Monte Carlo (MCMC) output in R (the R script is provided in Supplemental Information 1) using the R function lsfit(). For each state, we report both the set of estimated N[s,t] values and the trend (the linear fit; see results). If the 95% posterior confidence interval for the least-squares trend did not include zero, then we conclude a positive or negative trend in occupancy.

To calculate the regional trend, we computed the sum of N[*s*,*t*] over all the geographic states, creating the regional trajectory N[*t*] = Σ_s N[*s*,*t*]. The regional trend was computed by a least-squares fit to the time-series of N[*t*] values. We computed the percentage annual change from these summary results using two methods. For method 1, we used the slope from the linear trend model divided by the intercept of the model so that the trend is expressed as a percentage of the initial occupancy rate. For method 2, we computed the geometric mean rate of change following Link and Sauer (1998). This summary is:

% annual change =
$$\left(\frac{N[13]}{N[1]}\right)^{\frac{1}{12}}$$

Model fitting.—We used the package JAGS to fit the models for each species adopting code from Kéry and Schaub (2012, p. 436). We used the R statistical software, and the jagsUI package (Available from: https://cran.r-project.org/web/packages/jagsUI/index.html [Accessed 22 December 2016]) to carry out MCMC

TABLE 2. Posterior summaries (posterior mean and 2.5 and 97.5 percentiles) of regional occupancy trends (slope of the least-squares fit) for 14
anuran species. Slope represents change in probability of site occupancy per year. In bold are the two species for which the 95% credible
intervals did not include zero. We computed the annual percentage change (%CPY) based on the estimated trend relative to the intercept under
the linear trend model, and also using the geometric mean rate of change following Link and Sauer (1998). Species names are abbreviated in the
table as follows: Anaxyrus americanus (Aame), Acris crepitans (Acre), Anaxyrus fowleri (Afow), Acris gryllus (Agry), Anaxyrus terrestris
(Ater), Gastrophryne carolinensis (Gcar), Hyla avivoca (Havi), H. chrysoscelis (Hchr), H. cinerea (Hcin), H. gratiosa (Hgra), H. squirella
(Hsqu), Lithobates catesbeianus (Lcat), L. sphenocephalus (Lsph), and Pseudacris crucifer (Pcru).

Species Code	Slope	2.5%	97.5%	%CPY-Linear	%CPY-Geometric
Aame	-0.0016	-0.0164	0.0114	-0.5582	-1.4389
Acre	-0.0039	-0.0106	0.0037	-1.3702	-1.8013
Afow	0.0011	-0.0071	0.0101	0.2543	0.1587
Agry	-0.0033	-0.0176	0.0088	-0.7851	-1.0152
Ater	-0.0104	-0.0252	0.0070	-1.8954	-2.7264
Gcar	-0.0051	-0.0227	0.0076	-1.4091	-1.8384
Havi	-0.0065	-0.0234	0.0075	-1.9011	-2.5671
Hchr	0.0017	-0.0057	0.0114	0.2949	0.1868
Hcin	0.0123	0.0046	0.0217	2.2309	2.3382
Hgra	0.0005	-0.0147	0.0188	0.1386	-0.5737
Hsqu	-0.0020	-0.0168	0.0162	-0.3784	-0.5309
Lcat	-0.0049	-0.0212	0.0072	-1.1536	-1.1723
Lsph	0.0030	-0.0076	0.0118	0.7153	1.0708
Pcru	0.0101	0.0001	0.0196	1.3772	1.7089
			Average	-0.3171	-0.5858

MCMC using JAGS (see Supplemental Information 1 for R script). We obtained posterior samples from three Markov chains run for 10,000 iterations with a burn-in phase of 2,000 iterations, initiated with random starting values. For *H. chrysoscelis* and *G. carolinensis* we used 20,000 iterations to improve convergence. We assessed convergence of the model parameters using the R-hat statistic (Brooks and Gelman 1998) for the monitored values of N[*s*,*t*]. The average R-hat values (averaged over N[*s*,*t*] values) was 1.05 for all species, which indicated satisfactory convergence of the Markov chains. We used the model indicator variable approach of Kuo and Mallick (1998; see also Royle and Dorazio 2008,



FIGURE 3. Regional trend graphs for two species that show increasing regional trends, with 95% posterior intervals did not include zero. The black line is the estimated occupancy rate, while the dashed line is the observed occupancy. Species names are abbreviated as follows: *Hyla cinerea* (Hcin) and *Pseudraris crucifer* (Pcru).

p.109) to identify the best model for each species and to calculate the associated posterior probabilities for each model. These posterior probabilities can be used to estimate model-averaged annual occupancy by state or across the region, providing an overall estimate of (model-averaged) trend which incorporates uncertainty as to the exact form of the covariate detection model. We report the top 10 models for each species in Supplemental Information 2 to demonstrate the uncertainty in finding the best covariate model to explain detection probability.

RESULTS

We analyzed southeastern regional occupancy trends for 14 species (Table 2). The average linear trend for the region for all species was -0.32% per year and the average rate of change (geometric mean) of our regional trends for all species was -0.59% per year (both values represent change in probability of occupancy at sampled sites). Two species (H. cinerea, and P. crucifer) showed increasing trends with 95 % posterior interval did not include zero (Fig. 3). Four other species (A. fowleri, H. chrysoscelis, H. gratiosa, and L. sphenocephalus) also suggested increases (i.e., positive slope), although 95 % posterior interval includes zero. Data for the remaining eight species (A. americanus, A. crepitans, A. gryllus, A. terrestris, G. carolinensis, H. avivoca, H. squirella, and L. catesbeianus) suggested declines (i.e., negative slope for probability of site occurrence over time); the 95%



FIGURE 4. Regional trend graphs for 12 species that show increasing and declining regional trends, with 95% posterior intervals that included zero. The black line is the estimated occupancy rate, while the dashed line is the observed occupancy. Species names are abbreviated as follows: *Anaxyrus americanus* (Aame), *Acris crepitans* (Acre), *Anaxyrus fowleri* (Afow), *Acris gryllus* (Agry), *Anaxyrus terrestris* (Ater), *Gastrophryne carolinensis* (Gcar), *Hyla avivoca* (Havi), *H. chrysoscelis* (Hchr), *H. gratiosa* (Hgra), *H. squirella* (Hsqu), *Lithobates catesbeianus* (Lcat), and *L. sphenocephalus* (Lsph).

posterior intervals included zero in these eight cases (Fig. 4; Table 2).

We also determined occupancy trends for each state independently (Table 3). We assessed trends for 107 species/state combinations. Of these, 14 species/state combinations showed a declining trend in occupancy and 12 species/state combinations showed an increasing occupancy trend (posterior credible intervals did not include zero for any of the 26 trends; Table 3, Appendix). State-level trends for Florida showed five species were increasing in occupancy (*A. gryllus*, *H.*

chrysoscelis, H. gratiosa, L. sphenocephalus, and P. crucifer), and one species was declining in occupancy (H. cinerea). In Georgia, one species was increasing in occupancy (A. fowleri). In Louisiana, one species was increasing in occupancy (A. fowleri), and one species was declining in occupancy (A. terrestris). In Mississippi, four species were declining in occupancy (A. crepitans, A. gryllus, A. terrestris, and L. catesbeianus), and one species was increasing in occupancy (H. avivoca). In North Carolina, two species were declining in occupancy (A. fowleri, and H.

TABLE 3. Posterior summaries (posterior mean and 2.5 and 97.5 percentiles) of occupancy trends for species/state combinations. Slope represents change in probability of site occupancy per year. In bold are the 27 species/state combinations for which the 95% credible interval of the trend did not include zero. NA indicates states outside of the species range. Species names are abbreviated as follows: *Anaxyrus americanus* (Aame), *Acris crepitans* (Acre), *Anaxyrus fowleri* (Afow), *Acris gryllus* (Agry), *Anaxyrus terrestris* (Ater), *Gastrophryne carolinensis* (Gcar), *Hyla avivoca* (Havi), *H. chrysoscelis* (Hchr), *H. cinerea* (Hcin), *H. gratiosa* (Hgra), *H. squirella* (Hsqu), *Lithobates catesbeianus* (Lcat), *L. sphenocephalus* (Lsph), *Pseudacris crucifer* (Pcru). States are abbreviated as: Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), and Virginia (VA).

Species		FL			GA			LA			MS	
Code	Slope	2.50%	97.50%	Slope	2.50%	97.50%	Slope	2.50%	97.50%	Slope	2.50%	97.50%
Aame	NA	NA	NA	-0.0014	-0.0362	0.0142	-0.0165	-0.0354	0.0003	0.0026	-0.0037	0.0091
Acre	-0.0144	-0.0328	0.0007	0.0169	-0.0022	0.0263	-0.0065	-0.0145	0.0011	-0.0138	-0.0217	-0.0070
Afow	0.0074	-0.0254	0.0397	0.0324	0.0003	0.0517	0.0279	0.0126	0.0420	-0.0120	-0.0237	0.0020
Agry	0.0182	0.0076	0.0288	-0.0101	-0.0512	0.0217	0.0046	-0.0176	0.0252	-0.0337	-0.0454	-0.0210
Ater	0.0077	-0.0161	0.0261	-0.0131	-0.0402	0.0256	-0.0335	-0.0445	-0.0176	-0.0378	-0.0485	-0.0241
Gcar	0.0120	-0.0141	0.0299	-0.0004	-0.0459	0.0378	-0.0110	-0.0306	0.0029	-0.0092	-0.0363	0.0133
Havi	0.0042	-0.0093	0.0175	-0.0183	-0.0636	0.0168	0.0038	-0.0065	0.0138	0.0161	0.0042	0.0270
Hchr	0.0356	0.0201	0.0512	0.0017	-0.0231	0.0534	0.0065	-0.0039	0.0166	0.0034	-0.0087	0.0151
Hcin	-0.0120	-0.0205	-0.0030	-0.0002	-0.0282	0.0510	0.0007	-0.0073	0.0086	0.0021	-0.0062	0.0127
Hgra	0.0537	0.0402	0.0663	-0.0048	-0.0384	0.0231	0.0022	-0.0152	0.0127	-0.0067	-0.0233	0.0114
Hsqu	-0.0107	-0.0260	0.0143	-0.0074	-0.0539	0.0267	0.0066	-0.0129	0.0232	0.0162	-0.0150	0.0356
Lcat	0.0031	-0.0081	0.0087	-0.0087	-0.0400	0.0431	0.0061	-0.0044	0.0156	-0.0277	-0.0412	-0.0113
Lsph	0.0148	0.0002	0.0309	0.0240	-0.0269	0.0422	-0.0036	-0.0111	0.0037	-0.0162	-0.0390	0.0045
Pcru	0.0414	0.0294	0.0528	0.0316	-0.0053	0.0654	-0.0047	-0.0103	0.0009	0.0031	-0.0032	0.0135
		NC			SC			TN			VA	
	Slope	2.50%	97.50%	Slope	2.50%	97.50%	Slope	2.50%	97.50%	Slope	2.50%	97.50%
Aame	-0.0027	-0.0037	0.0244	0.0382	0.0005	0.0791	-0.0011	-0.0331	0.0032	0.0024	-0.0101	0.0189
Acre	-0.0034	-0.0170	0.0092	-0.0301	-0.0562	0.0130	0.0039	-0.0180	0.0259	-0.0001	-0.0058	0.0056
Afow	-0.0221	-0.0428	-0.0007	0.0165	-0.0122	0.0298	-0.0190	-0.0428	0.0020	-0.0018	-0.0124	0.0091
Agry	-0.0021	-0.0503	0.0251	0.0107	-0.0445	0.0303	-0.0394	-0.0709	0.0222	-0.0522	-0.0678	-0.0316
Ater	-0.0141	-0.0437	0.0213	-0.0079	-0.0280	0.0434	NA	NA	NA	-0.0264	-0.0388	-0.0104
Gcar	-0.0178	-0.0563	0.0228	0.0081	-0.0396	0.0400	-0.0171	-0.0537	0.0113	-0.0008	-0.0057	0.0023
Havi	NA	NA	NA	-0.0178	-0.0533	0.0025	-0.0458	-0.0677	-0.0054	NA	NA	NA
Hchr	-0.0299	-0.0364	-0.0165	0.0495	0.0153	0.0617	-0.0118	-0.0332	0.0173	0.0002	-0.0074	0.0083
Hcin	0.0470	0.0319	0.0559	0.0455	0.0293	0.0544	-0.0246	-0.0572	0.0075	-0.0003	-0.0182	0.0171
Hgra	-0.0319	-0.0637	0.0198	-0.0128	-0.0358	0.0185	-0.0247	-0.0649	0.0250	0.0125	-0.0220	0.0403
Hsqu	-0.0148	-0.0468	0.0486	0.0215	-0.0158	0.0597	NA	NA	NA	-0.0002	-0.0198	0.0160
Lcat	-0.0041	-0.0417	0.0264	0.0030	-0.0373	0.0216	-0.0127	-0.0434	0.0226	-0.0117	-0.0191	-0.0040
Lsph	0.0143	-0.0001	0.0332	-0.0039	-0.0391	0.0238	-0.0472	-0.0606	-0.0247	-0.0053	-0.0136	0.0026
Pcru	-0.0002	-0.0109	0.0148	0.0255	-0.0085	0.0606	-0.0208	-0.0285	-0.0102	0.0010	-0.0032	0.0051

chrysoscelis), and one species was increasing in occupancy (H. cinerea). In South Carolina, three species were increasing in occupancy (A. americanus, H. chrysoscelis, and H. cinerea). In Tennessee, three species were declining in occupancy (H. avivoca, L. sphenocephalus, and P. crucifer); in Virginia, three species were declining in occupancy (A. gryllus, A. terrestris, and L. catesbeianus). Two species (G. carolinensis, and H. squirella) did not show trends in any state in the southeastern region (where posterior credible intervals did not include zero).

DISCUSSION

Based on the regional average linear trend and the regional average rate of change, we found that the probability of occurrence for calling anurans within breeding habitats along roads in the southeast declined over the last 13 y. Of the 14 species we examined for the southeastern region, only two showed a significant increasing trends at the regional level (i.e., credible intervals did not include zero) while the other 12 regional trends, four suggesting increases and eight suggesting declines, had credible intervals include zero. When considering trends for all 107 species/state

combinations, 14 showed a significant declining trend in occupancy (i.e., 95% posterior intervals did not include zero) while 12 showed an increasing trend. Overall, the rate and support for regional declining occupancy trends in the southeast was much smaller than that found in the northeast (Weir et al. 2014).

Of the 14 species we examined, eight were also examined in the Weir et al. (2014) northeast analysis: A. americanus, A. crepitans, A. fowleri, H. cinerea, L. catesbeianus, L. sphenocephalus, P. crucifer, and H. chrysoscelis (H. chrysoscelis was analyzed as a complex with H. versicolor in the northeast analysis). Of the 16 species/state combinations showing decline in the southeast, five species (A. crepitans, A. fowleri, L. catesbeianus, L. sphenocephalus, and P. crucifer) had shown a decline in several northeastern states (Weir et al. 2014): A. crepitans in Maryland and Virginia; A. fowleri in Maryland; L. catesbeianus in Maine, Maryland, Massachusetts, New Hampshire, and Virginia; L. sphenocephalus in New Jersey and Virginia; and P. crucifer in Maine and Pennsylvania (Weir et al. 2014).

Virginia was included in the northeastern USA analysis (Weir et al. 2014) as well as presented here for the southeastern region. Positive species/state trends with credible intervals not including zero were not detected in Virginia for any species included in either analysis. Four of the seven species included in both the northeast and southeast analyses, A. americanus, A. fowleri, H. cinerea, and P. crucifer, did not show any state trends for Virginia in either regional analysis (all credible intervals included zero) and one species, L. catesbeianus, showed a state decline for Virginia in both regional analyses with credible intervals not including The other two species, A. crepitans, and L. zero. sphenocephalus, showed a state decline in the northeast analysis of Virginia (Weir et al. 2014), but the negative trends of the species have credible intervals including zero in the southeast analysis. This slight change is potentially explained by increased observations of A. crepitans and L. sphenocephalus along Virginia NAAMP routes during 2012 and 2013, two years that were not included in the northeast analysis.

The International Union for Conservation of Nature and Natural Resources (IUCN) lists every species in our study as Least Concern/Not Red-listed (meaning that they are not globally threatened or endangered), but our results suggest that at the state level there is evidence of species declines. Our results are further supported by recent work on amphibian populations within (mainly) protected areas in the United States, where Adams et al. (2013) found a 2.7 % decline in annual occupancy for species categorized as Least Concern by the IUCN, with Red-listed species (i.e., those categorized as endangered, vulnerable, and near threatened globally) showing a decline of 11.6%. In addition, Walls et al. (2011) found

that 12 species (A. crepitans, A. fowleri, G. carolinensis, H. chrysoscelis, H. cinerea, H. squirella, Incilius nebulifer, L. catesbeianus, L. clamitans, L. sphenocephalus, P. crucifer, and Pseudacris fouquettei) showed declines in the lower Mississippi Alluvial Valley of Louisiana using 5 y of data collected under NAAMP protocol, which is in agreement with the study of Stuart et al. (2004) that suggested that 31.7% of the United States species were declining.

Our work suggests that some species thought to be relatively common and not in need of conservation attention, as rated by IUCN (Available from http://www.iucnredlist.org/ [Accessed 28 August 2014]) and NatureServe, may be in decline in some southeastern states. NatureServe (Available from http://www.nature serve.org/ [Accessed 29 August 2014]) categorizes A. crepitans, A. gryllus, A. terrestris, G. carolinensis, H. cinerea, H. squirella and L. sphenocephalus as Apparently Secure in Virginia. Also, NatureServe considers H. gratiosa between Vulnerable and Apparently Secure in Louisiana, North Carolina, and Tennessee. The other species that show declining trends in our analysis at the state level for the southeastern region are considered as secure species by NatureServe.

Data in this study are from a long-term monitoring program, which could provide valuable information to conservation and management programs in the southeastern region because most monitoring studies in this region have been of short duration and small coverage (Walls 2014). Short-term monitoring programs may lack statistical power and could lead to misleading conclusions (Reed and Blaustein 1995). Walls (2014) also mentioned that Mississippi has the lowest number of amphibian monitoring studies in the southern region. In our present study the state of Mississippi shows the highest number of species with a declining trend of occupancy (*A. crepitans, A. gryllus, A. terrestris,* and *L. catesbeianus*).

Our analysis accommodated the probability that a species was present during a survey but went undetected (false negative errors). We used a statistical model that estimates the parameters of the dynamic occupancy model, survival and colonization, separately from the parameter for the observation process, detection probability. This model uses repeated surveys within sample locations during the period of closure, during which the occupancy state of a site must be constant (i.e., the site is either occupied or unoccupied throughout the period of sampling). Not accounting for imperfect detection will lead to biased estimates of all estimated quantities, where occupancy may be estimated too low and probabilities of extinction, colonization, and turnover may be estimated too high (Kéry and Schaub 2012). Field experiments simulating calling surveys have found that in addition to false negatives, observers may make the error of identifying a call as belonging to

both singing birds (Simons et al. 2007) and calling frogs (McClintock et al. 2010; Miller et al. 2012).

We did not fit models of false positive errors because such models are sensitive to other sources of heterogeneity in detection probability (Royle and Link 2006) absent specific information about the false positive error rate (Miller et al. 2012). Even though our analysis did not account for false positive errors, it is presumed that omitting data associated with failed or absent Frog-Ouiz scores helps to reduce the occurrence of false positives in the dataset. Future analyses of NAAMP data may use Frog-Quiz data to directly estimate both false positive and negative rates, as less sensitive statistical models for these detection processes are an active area of research (Miller et al. 2012; Chambert et al. 2015). We report state and regional occupancy trends using a 13-y data set from southeastern NAAMP states for 14 anuran species. With continuing data collection in these and other participating states, NAAMP will be able to provide the conservation community with much needed information on the status of frogs and toads.

Acknowledgments.--We extend thanks to all NAAMP observers and state coordinators for their time and effort, which makes the NAAMP survey possible. Any use of product or firm names is for descriptive purposes only and does not imply endorsement by the federal government. This is contribution number 537 of the Amphibian Research and Monitoring Initiative (ARMI) of the US Geological Survey.

LITERATURE CITED

- Adams, M.J., D.A. Miller, E. Muths, P.S. Corn, E.H. Grant, L.L. Bailey, G.M. Fellers, R.N. Fisher, W.J. Sadinski, H. Waddle, et al. 2013. Trends in amphibian occupancy in the United States. PLoS ONE, 8:1-5. http://dx.doi.org/10.1371/journal.pone.0064347
- Blaustein, A.R., and D.B. Wake. 1990. Declining amphibian populations: a global phenomenon. Trends in Ecology & Evolution 5:203-204.
- Bragg, A.N. 1960. Population fluctuation in the amphibian fauna of Cleveland County, Oklahoma during the past twenty-five years. The Southwestern Naturalist 5:165-169.
- Brooks, S.P., and A. Gelman. 1998. Alternative methods for monitoring convergence of iterative simulations. Journal of Computational and Graphical Statistics 7:434-455.
- Chambert, T., D.A. Miller, and J.D. Nichols. 2015. Modeling false positive detections in species occurrence data under different study designs. Ecology 96:332-339.

- a species that is not present (false positive errors), for Gibbs, E.L., G.W. Nace, and M.B. Emmons. 1971. The live frog is almost dead. BioScience 21:1027–1034.
 - Kéry, M. 2010. Introduction to WINBUGS for Ecologist: A Bayesian Approach to Regression, ANOVA, Mixed Models and Related Analyses. Academic Press, Amsterdam, Netherlands.
 - Kéry, M., and M. Schaub. 2012. Bayesian Population Analysis Using WinBUGS: A Hierarchical Perspective. Academic Press, Amsterdam, Netherlands.
 - Kuo, L., and B. Mallick. 1998. Variable selection for regression models. Sankhya B 60:65-81.
 - Link W.A., and J.R. Sauer. 1998. Estimating population change from count data: application to the North American Breeding Bird Survey. Ecological Applications 8:258–268.
 - MacKenzie, D.I., J.D. Nichols, J.E. Hines, M.G. Knutson, and A.B. Franklin. 2003. Estimating site occupancy, colonization, and local extinction when a species is detected imperfectly. Ecology 84:2200-2207.
 - 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. 2006. Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence. Academic Press, San Diego, California, USA.
 - McClintock, B.T., L.L. Bailey, K.H. Pollock, and T.R. Simons. 2010. Experimental investigation of observation error in anuran call surveys. Journal of Wildlife Management 74:1882–1893.
 - Miller, D.A., L.A. Weir, B.T. McClintock, E.H.C. Grant, L.L. Bailey, and T.R. Simons. 2012. Experimental investigation of false positive errors in auditory species occurrence surveys. Ecological Applications 22:1665-1674.
 - Phillips, K. 1994. Tracking the Vanishing Frogs: An Ecological Mystery. St. Martin's Press, New York, New York, USA.
 - Reed, J.M., and A.R. Blaustein. 1995. Assessment of "nondeclining" amphibian populations using power analysis. Conservation Biology 9:1299-1300.
 - Royle, J.A., and R.M. Dorazio. 2008. Hierarchical Modeling and Inference in Ecology: The Analysis of Data from Populations, Metapopulations and Communities. Academic Press, San Diego, California, USA.
 - Royle, J.A., and M. Kéry. 2007. A Bayesian state-space formulation of dynamic occupancy models. Ecology 88:1813-1823.

- Royle, J.A., and W.A. Link. 2006. Generalized site occupancy models allowing for false positive and false negative errors. Ecology 87:835–841.
- Simons, T.R., M.W. Alldredge, K.H. Pollock, and J.M. Wettroth. 2007. Experimental analysis of the auditory detection process on avian point counts. Auk 124:986–999.
- Stuart, S.N., J.S. Chanson, N.A. Cox, B.E. Young, A.S. Rodriguez, D.L. Fischman, and R.W. Waller. 2004. Status and trends of amphibian declines and extinctions worldwide. Science 306:1783–1786.
- Walls, S.C. 2014. Identifying monitoring gaps for amphibian populations in a North American biodiversity hotspot, the southeastern USA. Biodiversity and Conservation 23:3341–3357.
- Walls, S.C., J.H. Waddle, and R.M. Dorazio. 2011. Estimating dynamics in an anuran assemblage from Louisiana, USA. Journal of Wildlife Management 75: 751–761.
- Weir, L.A., and M.J. Mossman. 2005. North American Amphibian Monitoring Program (NAAMP). Pp. 307– 313 *In* Amphibian Declines: Conservation Status of

United States Amphibians. Lannoo, M. (Ed.). University of California Press, Berkeley, California, USA.

- Weir, L.A., J.A. Royle, P. Nanjappa, and R.A. Jung. 2005. Modeling anuran detection and site occupancy on North American Amphibian Monitoring Program (NAAMP) routes in Maryland. Journal of Herpetology 39:627-639.
- Weir, L.A., I.J. Fiske, and J.A. Royle. 2009. Trends in anuran occupancy from northeastern states of the North American Amphibian Monitoring Program. Herpetological Conservation and Biology 4:389–402.
- Weir, L.A., J.A. Royle, K.D. Gazenski, and O. Villena. 2014. Northeast regional and state trends in anuran occupancy from calling survey data (2001–2011) from the North American Amphibian Monitoring Program. Herpetological Conservation and Biology 9:223–245.
- Weir, L.A., J.A. Royle, P. Nanjappa, and R.E. Jung. 2005. Modeling anuran detection and site occupancy on North American Amphibian Monitoring Program (NAAMP) routes in Maryland. Journal of Herpetology 39:627–639.



OSWALDO VILLENA is a Student Contractor for the US Geological Survey Patuxent Wildlife Research Center where he is working for the North Amphibian Monitoring Program. In 2010, he received a M.S. in Environmental Sciences from Towson University, Maryland, USA. Currently he is in his last year of his Ph.D. work in the Marine Estuarine & Environmental Science Program at the University of Maryland College Park, USA. His research is focused on population and community ecology, and ecotoxicology. (Photographed by Randy Barker).



ANDY ROYLE is a Research Statistician with US Geological Survey (USGS) Patuxent Wildlife Research Center engaged in the development of statistical methods and analytic tools for animal demographic modeling, statistical inference, and sampling wildlife populations and communities. Andy is a co-author of Hierarchical Modeling and Inference in Ecology, as well as numerous scientific papers. He has been with USGS since 2004. Previously he worked as a statistician (1998–2004) for the US Fish and Wildlife Service in the Migratory Bird Management Office and as a Visiting Scientist in the Geophysical Statistics (1996) from North Carolina State University and a B.S. in Fisheries and Wildlife (1990) from Michigan State University. (Photographed by Andy Royle).



LINDA WEIR is a Branch Chief at US Geological Survey (USGS) Patuxent Wildlife Research Center in Laurel, Maryland, USA. In her previous position, she served as the USGS Coordinator of the North American Amphibian Monitoring Program. Linda received her Bachelor's degree in Zoology from the State University of New York, College at Oswego (SUNY Oswego), USA, and her Master's degree in Sustainable Development and Conservation Biology from the University of Maryland, USA. Linda is also co-author of North American Amphibians: Diversity and Distribution. (Photographed by Christa Deacy-Quinn).

Herpetological Conservation and Biology





TASHA FOREMAN is a Wildlife Biologist contracted to the US Geological Survey (USGS) Patuxent Wildlife Research Center. She started as a Field Technician with the Northeast Amphibian Research and Monitoring Initiative (ARMI) research team in 2013 and currently acts as the Assistant National Coordinator for its North American Amphibian Monitoring Program (NAAMP). Tasha received her B.S. in Natural Resource Ecology and Management at Oklahoma State University in 2008 and her M.S. in Biology at Howard University in 2013. Her thesis was a case study focused on determining the successional status of a restored forested wetland in Maryland by comparing the initial post-restoration herpetofaunal community and habitat types to those found 15 years later. Current research interests include supporting herpetofaunal conservation and management via public education and involvement. (Photographed by Andrew Dietrich).

KIMBERLY GAZENSKI is graduate student at the University of Maryland, College Park, USA, in the Sustainable Development and Conservation Biology program. In 2011, she received a B.S. in Integrated Science and Technology concentrating in Environment and Biosystems from James Madison University, Virginia, USA. After graduating, Kimberly worked as both a student contractor and as an IAP contractor at the Patuxent Wildlife Research Center of the US Geological Survey until 2014. During this time she helped manage route maps for the NAAMP Program, and worked on various project using R for spatial and statistical analyses. More recently, she was a Certification Assistant for the Wildlife Habitat Council. She also worked as the Landscape Conservation and Climate Change Intern for Defenders of Wildlife where she used GIS to validate NatureServe's Climate Change Vulnerability Index. (Photographed by Kimberly Gazenski).



EVAN GRANT is a Research Wildlife Biologist with the US Geological Survey (USGS) Patuxent Wildlife Research Center, where he directs the northeast region of the Amphibian Research and Monitoring Initiative (ARMI) program and is now also the Coordinator of the NAAMP program. He has published more than 40 articles related to amphibian populations. He has been with USGS since 2003. He received a Ph.D. (2009) from University of Maryland College Park and a B.S. (2001) in Natural Resources from Cornell University. (Photographed by Pam Toschik).

Villena et al.—Anuran occupancy trends in the Southeastern United States.

APPENDIX. Occupancy trend graphs for 26 species/state combinations with significant trends. The black line is posterior mean of least squares trend. The box plots depict the posterior distribution of occupied sites for each year. The three horizontal lines of the box plots represent quartiles (25%, 50%, and 75% of the distribution), the smaller horizontal lines are 2.5% and 97.5%, and circles are extreme values. Species names are abbreviated as follows: *Anaxyrus americanus* (Aame), *Acris crepitans* (Acre), *Anaxyrus fowleri* (Afow), *Acris gryllus* (Agry), *Anaxyrus terrestris* (Ater), *Hyla avivoca* (Havi), *H. chrysoscelis* (Hchr), *H. cinerea* (Hcin), *H. gratiosa* (Hgra), *Lithobates catesbeianus* (Lcat), *L. sphenocephalus* (Lsph), *Pseudacris crucifer* (Pcru). States are abbreviated as: Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), and Virginia (VA).





SUPPLEMENTAL INFORMATION 1.

R/JAGS script used to model Spring peeper (*Hyla gratiosa*) frog data. Script for model selection is not included in the code.

###SE NAAMP Analysis for Southern Cricket Frog###

```
library(jagsUI)
library(plyr)
setwd("C:\\Users\\....")
# MCMC settings
ni <- 12000
nt <- 1
nb <- 2000
nc <- 3
#path for datafiles
pathname<- "C:\\Users\\....."
#read in species data
spec<- "Pcru"
y.orig<-read.table(paste(pathname, spec, ".csv", sep=""),
            na.strings=c("NULL","NA"), sep=",", header=TRUE)
dim(y.orig)
y<-y.orig
y<- y[,3:119]
y<- as.matrix(y)
#read in state data
spec<- "routes_states"
state<-read.table(paste(pathname, spec, ".csv", sep=""),</pre>
           na.strings=c("NULL","NA"), sep=",", header=TRUE)
dim(state)
state<-state[.3]</pre>
state<-as.numeric(factor(state))</pre>
#read in range data
spec<- "RoutesInSE_Query"
speciesrange<- read.table(paste(pathname, spec, ".csv", sep=""),
                 na.strings=c(" "),sep=",", header=TRUE)
#routenumber<- speciesrange[,1]</pre>
isna<- is.na(speciesrange[2:16])
speciesnum<- ifelse(isna == TRUE, 0, 1)
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
speciesrange<- speciesrange[-2]</pre>
```

speciesrange<- speciesrange[-2]</pre> speciesrange<- speciesrange[-2]</pre> speciesrange<- speciesrange[-2]</pre> speciesrange<- speciesrange[-2]</pre> speciesrange<- speciesrange[-2]</pre> speciesrange<- cbind(speciesrange, speciesnum)</pre> y.route<- y.orig[,1:2] y.route<- y.route[-2] speciesrange<-merge(speciesrange, y.route,by=intersect(names(speciesrange), names(y.route))) names(speciesrange) sum(speciesrange\$Pcru) speciesrange<- speciesrange\$Pcru sum(speciesrange) rangesites<- sum(speciesrange, na.rm=TRUE) #read in Julian date data spec<- "juliandate" julian<- read.table(paste(pathname, spec, ".csv", sep=""), na.strings=c("NULL","NA"),sep=",",header=TRUE) dim(julian) juldate<- julian[,3:119] juldate<- as.matrix(juldate) #read in air temperature data spec<- "airtemp" airtemp<- read.table(paste(pathname, spec, ".csv", sep=""), na.strings=c("NULL","NA"),sep=",",header=TRUE) dim(airtemp) airtemp<- airtemp[,3:119] airtemp<- as.matrix(airtemp)</pre> #read in minutes after sunset data spec<- "MinAfterSunset" minutes<- read.table(paste(pathname, spec, ".csv", sep=""), na.strings=c("NULL","NA"),sep=",",header=TRUE) dim(minutes) minutes<- minutes[,3:119] minutes<- as.matrix(minutes)</pre> #read in startpoints coordinates spec<- "Startpoints" startpoints<- read.table(paste(pathname, spec, ".csv", sep=""), na.strings=c("NULL","NA"),sep=",",header=TRUE) dim(startpoints) #join based on routenumber startcoords<-join(y.orig, startpoints, by=intersect(names(y.orig), names(startpoints))) dim(startcoords) #subset lat lons lat<- startcoords[,120] head(lat)

```
nsite < -dim(y)[1]
ncol < -dim(y)[2]
#create datelat covariate
datelat<- array(NA, dim=c(nsite,ncol))
date2lat<- array(NA, dim=c(nsite,ncol))
for(i in 1:nsite){
for(v in 1:ncol){
  datelat[i,v] <- juldate[i,v]*lat[i]
  date2lat[i,v]<- juldate[i,v]*juldate[i,v]*lat[i]</pre>
 }}
#standardize data
mean.lat<-mean(lat, na.rm=TRUE)
sd.lat<-sd(lat)
lat<-(lat-mean.lat)/sd.lat
min.l <- min(lat)
max.l <- max(lat)
mean.min<-mean(minutes, na.rm=TRUE)
sd.min<-sd(minutes[!is.na(minutes)])</pre>
minutes<-(minutes-mean.min)/sd.min
dim(minutes)
min.m <- min(minutes, na.rm=TRUE)</pre>
max.m <- max(minutes, na.rm=TRUE)
mean.date<- mean(juldate, na.rm=TRUE)
sd.date<- sd(juldate[!is.na(juldate)])</pre>
date<-(juldate-mean.date)/sd.date
min.d <- min(date, na.rm=TRUE)
max.d <- max(date, na.rm=TRUE)
mean.temp<-mean(airtemp, na.rm=TRUE)</pre>
sd.temp<- sd(airtemp[!is.na(airtemp)])</pre>
airtemp<-(airtemp-mean.temp)/sd.temp
min.a <- min(airtemp, na.rm=TRUE)
max.a <- max(airtemp, na.rm=TRUE)
mean.datelat<-mean(datelat, na.rm=TRUE)
sd.datelat<- sd(datelat[!is.na(datelat)])</pre>
datelat<- (datelat-mean.datelat)/sd.datelat
min.dl <- min(datelat, na.rm=TRUE)
max.dl <- max(datelat, na.rm=TRUE)
mean.date2lat<-mean(date2lat, na.rm=TRUE)
sd.date2lat<- sd(date2lat[!is.na(date2lat)])</pre>
date2lat<- (date2lat-mean.date2lat)/sd.date2lat
min.d2l <- min(date2lat, na.rm=TRUE)
max.d2l <- max(date2lat, na.rm=TRUE)
nyear<-13
nstate<-8
nrep<-9
Zst<-matrix(rbinom(nyear*nsite,1,0.5),ncol=nyear,nrow=nsite)
```

##3D matrix for species and covariate data
y->ytmp
y=array(dim=c(nsite,nrep,nyear))

for(t in 1:nyear){
 y[,,t]=ytmp[,((t-1)*nrep+(1:nrep))]
}

date <- array(date, dim=c(nsite,nrep,nyear))
airtemp <- array(airtemp, dim=c(nsite,nrep,nyear))
minutes <- array(minutes,dim=c(nsite,nrep,nyear))
datelat <- array(datelat, dim=c(nsite,nrep,nyear))
date2lat <- array(date2lat, dim=c(nsite,nrep,nyear))</pre>

```
#to make sure all covariates have the same # of NA's
airtemp[is.na(date) != is.na(airtemp)] <- 0
minutes[is.na(date) != is.na(minutes)] <- 0</pre>
```

#check # of NA's
#Species should ALWAYs have more NA's due to skipped stops
sum(is.na(y))
sum(is.na(date))
sum(is.na(airtemp))
sum(is.na(minutes))

```
#create table of number of reps for each route for each year
nanum<-ifelse(is.na(y) == TRUE, 0, 1)
X2001<- rowSums(nanum[,,1])
X2003<- rowSums(nanum[,,2])
X2003<- rowSums(nanum[,,3])
X2004<- rowSums(nanum[,,4])
X2005<- rowSums(nanum[,,5])
X2006<- rowSums(nanum[,,6])
X2007<- rowSums(nanum[,,7])
X2008<- rowSums(nanum[,,7])
X2009<- rowSums(nanum[,,9])
X2010<- rowSums(nanum[,,10])
X2011<- rowSums(nanum[,,11])
X2012<- rowSums(nanum[,,12])
X2013<- rowSums(nanum[,,13])</pre>
```

```
nrep<- matrix(c(X2001,X2002,X2003,X2004,X2005,X2006,X2007,X2008,X2009,X2010,X2011,X2012,X2013), ncol=nyear,nrow=dim(y)[1])
```

#Remove out of range observations
y.zst<- apply(y, c(1,3),sum,na.rm=TRUE)</pre>

withdata<- apply(y.zst,1,sum)>0

y.zst[withdata & speciesrange==0,]<- 0 y[withdata & speciesrange==0,,]<- 0

sum(speciesrange[apply(y.zst,1,sum)>0]==0)
plot(startcoords[,c("Lon","Lat")])
points(startcoords[,c("Lon","Lat")][speciesrange==1,],pch=20)

points(startcoords[apply(y.zst,1,sum)>0 & speciesrange==0,c("Lon","Lat")],pch=20,col="red")

```
pst<-rep(0,nyear)
data <- list ("y","nsite","nrep","nyear","state","date","airtemp","minutes","lat","speciesrange","datelat","date2lat")
```

```
Zst<- matrix(0,nrow=nrow(y.zst),ncol=ncol(y.zst))
Zst[y.zst>0]<-1
sum(Zst)
```

```
#inital values
inits <- function()
list (p0=runif(nyear, 0.2, 0.5),z=Zst,
     a1=matrix(rnorm(nyear-1),nrow=8,ncol=(nyear-1),byrow=TRUE), #3),
     a2=0,a3=0,a4=0,a5=0,a6=0,a7=0,beta.d=0,beta.a=0,beta.m=0,beta.d2=0,
     beta.a2=0,beta.m2=0,beta.l=0,beta.l2=0, beta.datelat=0, beta.date2lat=0)
#creating model file
sink("occ-cov_limiteddatelat.txt")
cat("
  model {
  #psi~dunif(0,1)
  for(t in 1:nyear){
                         #3){
  p0[t] \sim dunif(0,1)
  logitp[t] <- log(p0[t]/(1-p0[t]))
  \# \text{ logitp}[t] \sim \text{dnorm}(0,1)
  }
  \#p[4] \sim dunif(0,1)
  beta.d ~ dnorm(0, .1)
  beta.a ~ dnorm(0, .1)
  beta.m ~ dnorm(0, .1)
  beta.d2 ~ dnorm(0,.1)
  beta.a2 ~ dnorm(0,.1)
  beta.m2 ~ dnorm(0,.1)
  beta.1 ~ dnorm(0,.1)
  beta.l2 ~ dnorm(0,.1)
  beta.datelat ~ dnorm(0,.1)
  beta.date2lat ~ dnorm(0,.1)
  for(s in 1:8){
  a0[s] \sim dnorm(0,.1)
  logitpsi[s] \sim dnorm(0,.1)
  logit(psi[s])<-logitpsi[s]</pre>
  for(t in 1:(nyear-1)){ #3){
  # a0[s,t] \sim dnorm(0,.1)
  a1[s,t]~dnorm(0,.1)
  #intcol[s,t] <- a0[s,t]
  # intsurv[s,t]<-a0[s,t]+a1[s,t]
  }
  }
  a2~dnorm(0,.1)
  a3~dnorm(0,.1)
  a4~dnorm(0,.1)
```

```
a5~dnorm(0,.1)
  a6 \sim dnorm(0, 1)
  a7~dnorm(0,.1)
  for(i in 1:nsite){
  bleen[i]<- psi[state[i]]*speciesrange[i]
  z[i,1]~dbern(bleen[i])
  for(t in 2:nyear){
  logit(muZ[i,t]) <- a0[state[i]] + a1[state[i],1]*z[i,t-1]
  muZ2[i,t]<- muZ[i,t]*speciesrange[i]
  z[i,t]~dbern(muZ2[i,t])
  }
  }
  for (t in 1:nyear){
  for(i in 1:nsite){
  \# Py[i,t] <- z[i,t] *p[t]
  for(j in 1:(nrep[i,t])){
  logit(p[i,j,t]) < logitp[t] + beta.d*date[i,j,t] + beta.a*airtemp[i,j,t] + beta.m*minutes[i,j,t]
  + beta.m2*pow(minutes[i,j,t],2) + beta.a2*pow(airtemp[i,j,t],2) + beta.d2*pow(date[i,j,t],2)
  + beta.l*lat[i] + beta.l2*pow(lat[i],2)+ beta.datelat*date[i,j,t]*lat[i] + beta.date2lat*pow(date[i,j,t],2)*lat[i]
  Py[i,j,t] <- z[i,t] * p[i,j,t]
  y[i,j,t] \sim dbern(Py[i,j,t])
                                  }
  }
  }
  for(i in 1:nsite){
  for(s in 1:8)
  X[i,s]<-equals(state[i],s)
  }
  }
  for(s in 1:8)
  for (t in 1:nyear){
  N[s,t] \le inprod(z[,t],X[,s])
  }
  }
  , fill = TRUE)
sink()
#Parameters monitored
parameters <- c("logitp","a0","a1","a2","a3","a4","a5","a6","a7","beta.d","beta.a",
          "beta.m","N","beta.d2","beta.a2","beta.m2","beta.l","beta.l2","beta.datelat","beta.date2lat")
outdatlat_Pcru <- jags(data, inits, parameters, "occ-cov_limiteddatelat.txt", n.thin=nt,
```

n.chains=nc, n.burnin=nb, n.iter=ni, parallel=TRUE)

dput(outdatlat_Pcru,"backup.txt")
dput(outdatlat_Pcru\$sims.list,"simslist.txt")

SUPPLEMENTAL INFORMATION 2. Top ten detection probability models (in terms of posterior probability) for each of the 14 species are reported below. These variables include Julian date, air temperature, minutes after sunset, latitude, date-latitude interaction, and the quadratic versions of each (denoted by superscript). A value of one in the table indicates that the variable is in the model, and a value of zero indicates it is not. Species names are abbreviated in the table as follows: Anaxyrus americanus (Aame), Acris crepitans (Acre), Anaxyrus fowleri (Afow), Acris gryllus (Agry), Anaxyrus terrestris (Ater), Gastrophryne carolinensis (Gcar), Hyla avivoca (Havi), H. chrysoscelis (Hchr), H. cinerea (Hcin), H. gratiosa (Hgra), H. squirella (Hsqu), Lithobates catesbeianus (Lcat), L. sphenocephalus (Lsph), Pseudacris crucifer (Pcru).

Species code	Date	Date ²	Airtemp	Airtemp ²	Minutes	Minutes ²	Latitude	Latitude ²	Date-Lat	Date-Lat ²	Posterior Probability
	0	0	0	0	0	0	0	0	0	0	0.1106
	0	0	1	1	0	0	1	1	0	0	0.0319
	0	0	1	1	0	0	0	0	0	0	0.0316
	0	1	1	1	1	0	1	1	0	0	0.0285
Aame	0	0	0	0	0	0	1	1	0	0	0.0233
1 44110	0	1	0	0	1	0	1	1	0	0	0.0213
	1	0	0	0	0	0	0	0	0	0	0.0210
	0	0	0	0	0	0	1	0	0	0	0.0204
	0	1	1	0	1	0	1	1	0	0	0.0152
	0	0	1	1	0	0	1	0	0	0	0.0144
	1	1	0	0	1	1	1	0	0	1	0.4023
	1	1	0	0	1	1	1	0	1	1	0.2027
	1	1	0	0	1	1	1	1	0	1	0.1389
Acre	1	1	0	0	1	1	1	1	1	1	0.1067
	1	1	1	0	1	1	1	1	1	1	0.0374
Tiere	1	1	1	0	1	1	1	1	0	1	0.0361
	1	1	1	0	1	1	1	0	0	1	0.0204
	1	1	1	1	1	1	1	1	0	1	0.0186
	1	1	1	1	1	1	1	1	1	1	0.0125
	1	1	1	0	1	1	1	0	1	1	0.0114
	1	1	1	1	1	1	1	1	0	1	0.9381
	1	1	1	1	1	1	1	1	1	1	0.0619
Afow											
	0	0	0	0	0	0	0	0	0	0	0.1661
	0	1	0	0	0	0	0	0	0	0	0.0781
Agry	1	0	0	0	0	0	0	0	0	0	0.0738
	0	0	0	0	0	0	1	0	0	0	0.0457
	1	0	0	0	0	1	0	0	0	0	0.0424

	0	1	0	0	1	0	0	0	0	0	0.0327
	0	1	0	0	0	0	1	0	0	0	0.0267
	0	0	1	0	0	0	0	0	0	0	0.0244
	1	1	0	0	0	0	0	0	0	0	0.0244
	1	1	0	0	0	1	0	0	0	0	0.0217
	0	0	0	0	0	0	0	0	0	0	0.0688
	0	1	0	0	0	0	0	0	0	0	0.0418
	1	0	0	0	0	0	0	0	0	0	0.0413
Ater	0	1	0	0	1	0	0	0	0	0	0.0370
	1	0	0	0	0	1	0	0	0	0	0.0338
	0	0	1	0	0	0	0	0	0	0	0.0255
	0	0	1	1	0	0	0	0	0	0	0.0247
	0	0	0	0	0	0	1	0	0	0	0.0221
	0	0	0	0	0	0	1	1	0	0	0.0199
	1	1	0	0	0	0	0	0	0	0	0.0194
	1	1	0	0	1	1	1	1	1	1	0.9491
	1	1	1	0	1	1	1	1	1	1	0.0465
	1	1	1	1	1	1	1	1	1	1	0.0044
Gcar											
	1	0	0	0	0	1	0	0	0	0	0.1098
	0	0	0	0	0	0	0	0	0	0	0.1046
	1	1	0	0	0	1	0	0	0	0	0.0830
	0	1	0	0	0	0	0	0	0	0	0.0750
Havi	1	1	0	0	1	1	0	0	0	0	0.0580
	0	1	0	0	1	0	0	0	0	0	0.0407
	1	1	1	1	1	1	0	0	0	0	0.0220
	1	0	0	0	0	0	0	0	0	0	0.0213
	1	1	1	1	0	1	0	0	0	0	0.0189
	1	0	1	1	0	1	0	0	0	0	0.0179
	1	1	1	1	1	1	1	1	1	0	0.3381
	1	1	1	1	1	1	1	1	0	1	0.2186
	1	1	1	1	1	1	1	1	0	0	0.2185
Hchr	1	1	1	1	1	1	1	0	0	1	0.1181
	1	1	1	1	1	1	1	0	0	0	0.0720
	1	1	1	1	1	1	1	0	1	0	0.0160
	1	1	1	1	1	1	1	1	1	1	0.0148

	1	1	1	1	1	1	1	0	1	1	0.0039
	1	1	1	0	1	1	1	1	1	0	0.0001
	1	1	1	1	1	1	0	0	0	0	0.2925
	1	1	0	0	1	1	0	0	0	0	0.1358
	1	1	0	0	0	1	0	0	0	0	0.0772
	1	1	1	1	1	1	1	0	0	0	0.0534
Hain	1	1	1	1	1	0	0	0	0	0	0.0459
псш	1	1	1	1	0	1	0	0	0	0	0.0405
	1	0	0	0	0	1	0	0	0	0	0.0400
	1	1	0	0	1	1	1	0	0	0	0.0393
	1	1	0	0	0	0	0	0	0	0	0.0331
	1	0	0	0	0	0	0	0	0	0	0.0313
	0	0	0	0	0	0	0	0	0	0	0.0709
	0	1	0	0	0	0	0	0	0	0	0.0430
	1	0	0	0	0	0	0	0	0	0	0.0383
	0	0	1	0	0	0	0	0	0	0	0.0336
	1	0	0	0	0	1	0	0	0	0	0.0328
Hgra	0	1	0	0	1	0	0	0	0	0	0.0313
	0	0	1	1	0	0	0	0	0	0	0.0284
	0	0	0	0	0	0	1	0	0	0	0.0213
	0	0	0	0	0	0	1	1	0	0	0.0200
	0	1	1	1	0	0	0	0	0	0	0.0189
	0	0	0	0	0	0	0	0	0	0	0.0658
	0	1	1	1	1	0	0	0	0	0	0.0445
	0	1	0	0	1	0	0	0	0	0	0.0429
	1	0	0	0	0	1	0	0	0	0	0.0417
	0	0	1	0	0	0	0	0	0	0	0.0388
Hsqu	1	0	0	0	0	0	0	0	0	0	0.0382
	0	0	1	1	0	0	0	0	0	0	0.0363
	0	1	0	1	0	0	0	0	0	0	0.0356
	0	1	1	0	1	0	0	0	0	0	0.0331
	1	1	1	1	1	1	0	0	0	0	0.0331
	1	1	1	1	1	1	0	0	0	0	0.0273
	1	1	1	0	1	1	1	0	0	1	0.4579
	1	1	1	0	1	1	1	0	1	0	0.2801
	1	1	1	0	1	1	1	U	1	1	0.2353
Leat	1	1	1	0	1	1	1	1	0	1	0.0097
Loui	1	1	1	U	1	1	1	1	1	0	0.0053
	1	1	1	0	1	1	1	l	1	1	0.0052
	1	1	1	1	1	1	1	0	0	1	0.0029
	1	1	1	1	1	1	1	0	1	0	0.0018
	1	1	1	1	1	1	1	0	1	1	0.0015

	1	1	1	1	1	1	1	1	0	1	0.0002
	1	1	1	1	1	1	1	1	1	0	0.9737
	1	1	1	1	1	1	1	1	1	1	0.0263
Lsph											
Ĩ											
	1	1	0	0	1	1	1	0	1	1	0.5581
	1	1	0	0	1	1	1	1	1	1	0.3092
	1	1	0	0	1	1	1	0	0	1	0.1046
	1	1	0	0	1	1	1	0	1	0	0.0164
Pcru	1	1	0	0	1	1	1	0	0	0	0.0052
	1	1	1	0	1	1	1	0	1	1	0.0031
	1	1	1	0	1	1	1	1	1	1	0.0012
	1	1	0	0	1	1	1	1	0	1	0.0011
	1	1	0	0	1	1	1	1	1	0	0.0006
	1	1	1	0	1	1	1	0	0	1	0.0006