ROCKY MOUNTAIN AMPHIBIAN PROJECT: DATA MIGRATION AND 3-YEAR TREND ANALYSIS FOR AMPHIBIANS ON THE MEDICINE BOW-ROUTT NATIONAL FORESTS

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Introduction

Amphibians are declining worldwide and currently are considered one of the most threatened vertebrate classes in the world (Stuart et al. 2004, Hof et al. 2011). Forty-one percent of all amphibian species are threatened with extinction or are already extinct (Pimm et al. 2014). Despite this evidence, efforts to monitor, study, and conserve amphibian biodiversity are notoriously underfunded relative to other vertebrates (Gratwicke et al. 2012).

Known threats to Rocky Mountain amphibians include diseases (e.g. chytrid fungus), pesticides, herbicides, pollutants, introduced predators, UV radiation, and habitat loss and fragmentation. Altered water availability, water temperatures, and hydroperiods due to recent pine beetle outbreaks and climate change could further impact amphibian biodiversity. Wetland desiccation and shortened hydroperiods resulting from reduced snowpack and increased evapotranspiration due to climate change (MacCracken et al. 2003, Brooks 2004, Barnett et al. 2005, Mote 2005, McMenamin et al. 2008, Brooks 2009) pose numerous potential direct and indirect effects on amphibians in the Rocky Mountain region (for reviews see Blaustine et al. 2010, Li et al. 2013). More concerning is that these threats may work synergistically against amphibian populations (Salice 2012). Effects of pine beetle outbreaks on hydrology are complex and poorly understood (Pugh and Gordon 2013), but are known to alter snow accumulation, snowmelt patterns, and water quality (Edburg et al. 2012, Pugh and Small 2012).

Despite global declines and numerous complex threats to amphibians, resource managers have struggled to find affordable yet effective long-term monitoring methods. In 2012, the Wyoming Natural Diversity Database (WYNDD), Wyoming Game and Fish Department (WGFD), U.S. Forest Service (USFS), and Colorado Natural Heritage Program (CNHP) initiated an occupancy-based amphibian monitoring study design developed by the USGS Amphibian Research and Monitoring Initiative (ARMI) (Corn et al. 2005). This monitoring approach has been used successfully in several national parks. An occupancy-based approach to monitoring is less data intensive than traditional abundance-based approaches and, particularly for difficult to detect species like amphibians, can result in more robust estimates. Thus, an occupancy-based approach to monitoring amphibians can provide a more economical means of obtaining robust estimates of occupancy trends over large landscapes and multiple years.

Based on pilot study results, we designed and began implementation of standardized amphibian monitoring at 33 locations in the Medicine Bow and Routt National Forests (MBRNF) in southern Wyoming and northern Colorado. The monitoring effort, now known as the Rocky Mountain Amphibian Project (RMAP; www.toadtrackers.org), was expanded to 36 locations in the Bridger-Teton National Forest (BTNF) in western Wyoming in 2014. Support from the University of Wyoming Biodiversity Institute (BI) in 2013 helped to ensure the sustainability of this long-term monitoring effort by involving trained citizen scientists to augment surveys conducted by agency biologists and biological technicians. RMAP now has the tools necessary to train citizen scientists and agency biologists to conduct standardized surveys, coordinate survey efforts across all collaborators, and supply surveyors with basic supplies needed to complete surveys. By spreading survey effort across all partners, RMAP has collected annual monitoring data for amphibians on the MBRNF since 2012.

Although preliminary estimates of amphibian occupancy have been provided annually for the Medicine Bow National Forest (MB) and Routt National Forest (RT) separately, analyses across the full

MBRNF study area have been precluded by data storage issues. Initially, the MB (Wyoming) and the RT (Colorado) each stored data in separate database for ease of data entry and management. With additional funding from the BI, a centralized online-accessible database and data entry system was completed by the UW Wyoming Geographic Information Science Center (WYGISC) in the fall of 2015. Following completion of the centralized database, existing data from the different RMAP databases needed to be vetted, formatted, and migrated into the new central database before analyses of population trends across the entire project area could be conducted. Thus, the purpose of this project was to migrate all MBRNF data into the new database and assess amphibian occupancy across the full MBRNF study area for the first time.

Goals and Objectives

The goal of this project was to consolidate RMAP data from both the MB and RT in to the new centralized database to facilitate amphibian occupancy trend analyses across the full MBRNF study area.

Specific Objectives

1. Vet, format, and migrate existing RMAP data from surveys on the RT into the online-accessible geodatabase developed by UW-WYNDD and WYGISC. This included migrating catchment data and associated site shapefiles collected and developed by the RT and CNHP.
2. Use occupancy modeling to estimate the probability of detecting a species during a survey and occupancy trends of amphibian species from 2012-2014 on the MBRNF.
3. Provide the MBRNF with the data analysis, occupancy trends on key species, and a report concerning amphibians on the MBRNF.

Methods

Study Area

RMAP currently encompasses the Medicine Bow and Routt National Forests in southern Wyoming and northern Colorado and the Bridger-Teton National Forest in western Wyoming. Lodgepole pines (*Pinus contorta*) in the MBRNF have been heavily impacted by mountain pine beetle outbreaks. Survey catchments in the MBRNF occur in amphibian habitat within lodgepole pine, mixed conifer, and subalpine forest types. Amphibian habitat in the study area includes wet meadows, bogs, beaver ponds, springs, and backwaters or slow moving areas along mountain streams. Five amphibian species are known to occur on the MBRNF and include the Western (Boreal) Toad (*Anaxyrus boreas*), Boreal Chorus Frog (*Pseudacris maculata*), Northern Leopard Frog (*Lithobates pipiens*), Wood Frog (*Lithobates sylvaticus*), and Tiger Salamander (*Ambystoma mavortium*).

Study Design

Standardized long-term amphibian monitoring is critical to understanding and obtaining defensible population trends. The RMAP study design incorporates USGS ARMI guidelines for their mid-level occupancy-based modeling approach (Corn et al. 2005) and methods closely resemble those used by

Yellowstone and Grand Teton National Parks (Bennets et al. 2013). Thus, our data are compatible with other monitoring datasets for montane amphibians in the Rocky Mountain region.

The primary sampling unit consists of all aquatic sites within a designated survey area (hereafter catchment). A site is defined as a unique aquatic feature (wetland, pond, wet meadow, bog, stream reach, etc.) within a catchment. Surveying multiple sites within a catchment not only increases the likelihood of detecting a species if it is present in the catchment, but also accommodates annual variability in the persistence of wetlands and/or the use of a specific wetland by amphibians.

We used occupancy modeling results from our pilot study and related projects (Estes-Zumpf et al. 2012, Estes-Zumpf et al. 2014) to inform the number and size of survey catchments to monitor within the MBRNF. We used stratified sampling to identify survey catchments in potential amphibian habitat across the study area. To select catchments more likely to contain amphibian breeding habitat, we restricted selection to areas containing a high proportion of wetland edge habitat. The selection process was weighted based on ease of access from roads and trails and was stratified across 3 elevation classes. Lastly, we stratified sampling by USFS ranger district on each forest unit. We then digitized at least 4 survey sites encompassing all presumed amphibian habitat within each catchment. We used ArcGIS (ESRI Inc., Redlands, CA) to conduct all habitat analyses.

Because 2012 was the first year of standardized surveys at catchments identified through the catchment selection process, survey locations had to be field-validated to assess presence of amphibian habitat. Following 2012 surveys, catchments were reevaluated and the number of sites within each catchment was adjusted to ensure all sites in a given catchment could be visited within one work day. In some cases, catchments were deemed to not contain adequate potential amphibian habitat (no slow moving or standing water present) and were dropped from the monitoring program and replaced with a backup catchment identified during the initial catchement selection process. Occupancy modeling analyses were conducted only on data from the final suite of catchments and sites. Thus, data for 2012 were missing from catchments substituted for catchments dropped after 2012. As such, results from 2012 should be viewed with caution because that year does not accurately represent the full suite of catchments and sites surveyed from 2013 onward.

Amphibian surveys followed standardized protocols designed to accommodate estimation of species detection probabilities. Surveys were conducted during the breeding season (mid-May to early August depending on elevation and annual weather conditions) when species were most detectable. Surveyors were provided survey packets consisting of 1) a catchment overview sheet (with basic information, directions, and maps) and 2) site-specific datasheets (1 for each site in the catchment) prepopulated with site and catchment name, relevant navigation and recommended photo points and a site map on the back. Visual encounter surveys were conducted either independently by each of 2 observers (dual-observer method) or collectively by a group of surveyors (team method). We recorded evidence of breeding as well as the number of any adults and juveniles of each species at each site. Detailed explanations of the study design, site selection, and survey protocols can be found at www.toadtrackers.org and in associated project reports (Estes-Zumpf et al. 2012, Estes-Zumpf et al. 2014).

A subset of amphibians detected each year were swabbed for chytrid fungus (*Batrachochytrium dendrobatidis; Bd*) following procedures outlined by Livo (2004). Bd samples were sent to a lab for PCR testing. All survey and sampling gear were decontaminated between drainages and between isolated sites within drainages to prevent the spread of Bd among sample locations.

Statistical Methods

Multi-scale occupancy modeling

The primary objective of analyses was to estimate occupancy probability for each year (2012, 2013 and 2014), while controlling for detection probability (ρ), for each amphibian species. Single-season, multi-scale occupancy models were used to estimate the probability of detection and occupancy for each amphibian species separately (MacKenzie et al. 2006, Nichols et al. 2008, Pavlacky et al. 2012). Multi-scale occupancy models enabled the estimation of occupancy at two spatial scales within a single modeling framework: catchment occupancy (Ψ; broad scale) and occupancy of sites within catchments (Θ; fine scale). Broad scale occupancy (Ψ) is simply the probability that a catchment is occupied; however, fine scale occupancy (Θ) is the probability of a site being occupied given that the catchment is occupied. In other words, Θ is conditional on the catchment 1st being occupied (Nichols et al. 2008, Pavlacky et al. 2012). Additionally, the multi-scale model accounts for lack of independence among sites within catchments, resulting in reliable error estimates (Nichols et al. 2008, Pavlacky et al. 2012). Model selection was conducted with Akaike's Information Criterion corrected for small sample sizes (AIC_c), and ΔAIC_c and AIC_c weight were used to compare the relative support for each model (Burnham and Anderson 2002). To minimize the effects of multicollinearity between predictors within a model, we used a cut-off of two for the variance inflation factor. We used a multistage modeling approach (Doherty et al. 2012), which enabled the comparison of a suite of predictor variables (Table 1):

> Stage1: occupancy parameters (catchment and site) were held as complex (global) models while all possible additive combinations of detection predictors, excluding $temp^2$ and *veg*, competed (Table 1). $temp^2$ and *veg* were included as univariate predictors because otherwise the size of models and number of predictor combinations would have been intractable. If $temp^2$ and/or *veg* were significant, the top model was assessed post-hoc with and without the addition of $temp^2$ and/or *veg*, and the higher ranked model was retained.
>
> Stage 2: detection was held as the top model from Stage 1 while different occupancy (catchment and site) models competed (Table 1).
>
> Stage 3: the top Stage 2 model that included a year term for both catchment and site occupancy was used to estimate occupancy by year for both spatial scales. Thus, occupancy was estimated by year regardless of whether the top Stage 2 model contained a year term for occupancy parameters.

For all species, models that did not converge were removed at each stage; thus, although the same suite of predictors was used for each species, not all predictors converged for all species, resulting in different model sets. When comparing nested models with AIC it is important to account for highly ranked models with uninformative predictors which are "carried" by informative predictors (Burnham and Anderson 2002, Arnold 2010). Models with uninformative predictors take AIC model weight that would otherwise go towards higher ranked models, and thus skew model set interpretation. We considered models to be uninformative if a nested model with one less predictor differed in deviance by ≤1 and was within 0 to ~3.5 $\Delta \mathrm{AIC}_c$, suggesting that the larger model did not improve model fit relative to the smaller, nested model (see Appendix 1 for an example; Burnham and Anderson 2002, Arnold 2010). Models with uninformative predictors were presented in model sets to facilitate interpretation; however, these models were excluded when calculating AIC_c weights. The effect of a predictor was considered statistically significant if the 95% confidence interval (CI) for the beta estimate did not overlap zero.

Results

Data vetting, formatting, and migration

We worked with the RT and CNHP to vet and format data from 2012-2014 previously housed in a database at CNHP. The size and complexity of some catchments had prohibited survey of all sites during each visit. Thus, we worked together to reduce the number of sites within a catchment when necessary so that future surveyors could feasibly survey all sites each visit. To maximize use of data collected, we first dropped from the monitoring program sites within a catchment that were rarely if ever surveyed since the start of the program. Data from sites that were dropped were not used in occupancy analyses. We also worked with the RT and CNHP to upload catchment and site GIS shapefiles into the new central geodatabase. All survey and species data collected are now linked to the relevant site and catchment feature class polygons. This will aid greatly in reducing data entry error and querying data from specific survey locations. The final suite of established monitoring locations on the MBRNF used for occupancy analyses consisted of 164 wetland sites (MB = 90; RT = 74) across 33 catchments (MB = 18; RT = 15) (Figure 1). Most sites in most catchments were surveyed annually; however, forest fires, weather, and other stochastic events occasional prevented a catchment or a site within a catchment from being surveyed in some years.

Boreal chorus frog

The top two detection probability models for Boreal Chorus Frog from Stage 1 comprised 61% of model weights and both included a significant negative quadratic effect of air temperature (beta = -0.006, 95% CI = -0.011, -0.001; Figure 3; Appendix 2 Table 1). Detection probability also increased with site area in the top detection model (Figure 3; beta = 0.038, 95% CI = 0.001, 0.075).

Probability of occupancy for both catchments and sites was constant and did not vary across years at either spatial scale; however, site occupancy (Θ) was more variable between years than catchment occupancy (Ψ) (Figure 2a**,** Appendix 2 Table 2). Boreal Chorus Frog was the most common species in the MBRNF, with a probability of catchment occupancy of 0.706 (95% CI = 0.599, 0.793) and a probability of site occupancy of 0.626 (95% CI = 0.561, 0.687; Appendix 2 Table 2).

Northern leopard frog

Northern Leopard Frog detection increased as air temperature increased and as site area decreased. The top detection probability model from Stage 1 had 73% of model weights and included a significant negative effect of site area (beta = -0.952, 95% CI = -1.385, -0.519; Appendix 3 Table 1) and a significant positive effect of air temperature (beta = 0.142, 95% CI = 0.008, 0.275) on detection probability. Detection probability also varied by year (Figure 4). Probability of detecting Northern Leopard Frogs was higher in 2012 and 2014 than in 2013.

Northern Leopard Frog occupancy did not vary significantly across years at the catchment level (Figure 2b). The top two NLF occupancy models were closely ranked and comprised 76% of model weights (Appendix 3 Table 2). In both top models, catchment occupancy for Northern Leopard Frogs decreased with increasing elevation (Ψ beta = -0.004, 95% CI = -0.007, -0.001; Figure 4). Probability of site occupancy was constant in the top model (0.815, 95% CI = 0.663, 0.908), but there was a non-significant year effect in the second- ranked model (Appendix 3 table 2; Figure 2b).

Wood frog

The probability of detecting Wood Frogs was higher later in the breeding season and increased with air temperature and site area. The top detection probability model from Stage 1 had 55% of model weights (Appendix 4 Table 1) and included significant positive effects of Julian date (beta = 0.056, 95% CI = 0.025, 0.086), air temperature (beta = 0.087, 95% CI = 0.014, 0.159), and site area (beta = 0.099, 95% CI = 0.032, 0.166) on detection (Figure 5). Probably of detection was lower for citizen scientists than biologists (beta = -1.236, 95% CI = -2.140, -0.332); however, the effect of surveyor type needs to be interpreted with caution since it is likely confounded with other factors such as year and sample size because citizen scientists only began conducting surveys in 2014. Detection probability in 2013 was significantly higher than 2014, but did not vary significantly for any other year comparisons (Figure 5).

Wood Frog occupancy did not vary significantly by year at either the catchment or site scale (Figure 2c). The top two occupancy models were closely ranked and comprised 63% of model weights (Appendix 4 Table 2). In the top model, catchment and site occupancy were both constant; catchment occupancy was 0.28 (95% CI = 0.19, 0.38) and site occupancy was 0.64 (95 % CI = 0.52, 0.74). In the second ranked model, site area had a positive but non-significant effect on site occupancy (beta = 0.073, 95% CI = -0.050, 0.197).

Boreal toad

The top two detection models for Boreal Toads from Stage 1 were closely ranked and comprised 53% of model weights (Appendix 5 Table 1). Detection was constant in the top model (detection probability = 0.603, 95% CI = 0.483, 0.712), whereas, air temperature had a non-significant positive effect on detection in the 2nd ranked model (beta = 0.084, 95% CI = -0.024, 0.192).

Boreal Toad occupancy was low across the MBRNF. The top two occupancy models from Stage 2 were similarly ranked and comprised 73% of model weights (Appendix 5 Table 2). In the top model, catchment occupancy was constant (occupancy probability = 0.111, 95% CI = 0.055, 0.211) and site occupancy varied with year (Figure 2d). In the second ranked model, site occupancy still varied with year, however, elevation had a non-significant positive effect on catchment occupancy (beta = 0.002, 95% CI = -0.001, 0.005). Catchment occupancy did not vary significantly by year (Figure 2d).

Tiger salamander

Due to infrequent tiger salamander detections during surveys, detection probability models in Stage 1 only converged when occupancy parameters (Ψ and Θ) were held as constant (intercept only) models. The top detection model from Stage 1 had 55% of model weights (Appendix 6 Table 1) and detection probability increased significantly with air temperature (beta = 0.101, 95 % CI = 0.010, 0.192) and varied by year (Figure 6). Detection in 2012 was significantly higher than 2014, but did not vary significantly for any other year comparisons (Figure 6).

Tiger Salamander occupancy did not vary significantly by year at either the catchment or site scale (Figure 2e). The top two occupancy models from Stage 2 comprised 56% of model weights (Appendix 6 Table 2). Catchment and site occupancy were both constant in the top model: catchment occupancy = 0.389 (95% CI = 0.198, 0.622) and site occupancy = 0.242 (95% CI = 0.121, 0.425). Catchment occupancy was also constant in the second ranked model, however, there was a non-significant negative effect of site area on site occupancy (beta = -0.068, 95% CI = -0.207, 0.071). No model converged that included a year effect for both catchment and site occupancy; however, models did converge that allowed catchment but not site occupancy to vary by year and, alternatively, site but not catchment occupancy to vary by year (Appendix 6 Table 2; Figure 2e).

Chytrid fungus(Bd)

Since the onset of this monitoring program, Bd has been detected at 12 of 18 catchments sampled (Table 2) and in 4 of 5 amphibian species (Table 3) on the MB. Bd has not yet been detected in Tiger Salamanders sampled during RMAP surveys on the MB, however, this could be due to the low number of salamanders sampled since 2012 (Table 3). The MB4_Fall Creek catchment, a known Boreal Toad breeding site, continues to test negative Bd as of 2016 (Table 2) and is the only known Bd-free Boreal Toad breeding site on the MB. Although Bd has been sampled across RT catchments since 2012, those results are not included in this report.

Discussion

This project was essential to consolidating all existing data collected on the MBRNF into the new online-accessible RMAP database and enabling amphibian occupancy analyses to be conducted across the full MBRNF study area for the first time. Overall, we found no evidence of a change in catchment occupancy for the first three years of amphibian monitoring on the MBRNF (2012-2014) for any of the five species in the study area. Although occupancy estimates appear to vary by year for Boreal Toads and Tiger Salamanders (Figure 1), results for these species should be viewed with caution due to the low number of detections and/or difficulty in detecting these species when present, resulting in extremely large confidence intervals around estimates. Data collected from additional years of standardized amphibian monitoring should help to improve confidence around estimates of detection and occupancy for these and other species.

In general, Boreal Chorus Frogs and Tiger Salamanders were the most common species detected across the MBRNF, occupying 71% and 39% of catchments, respectively in any given year from 2012-

2014. Because the probability of detecting Tiger Salamanders when present was low relative to other species, occupancy modeling results suggest that the species is more common across the MBRNF than estimated by naïve occupancy rates (naïve $\Psi = 27\%$), which fail to correct for difficulty in detecting this species using traditional VES survey techniques. Boreal Toads were the least common species detected, followed closely by Northern Leopard Frogs, which were primarily found at lower elevation sites on the MBRNF.

Because the primary focus of this analysis was to look at trends in occupancy over time, we did not include a full suite of habitat variables that could influence amphibian occupancy, such as presence of fish and type of water body or wetland surveyed. However, the influence of habitat characteristics on presence of a species can be assessed in future analyses with the data now available. Furthermore, University of Wyoming graduate student Andy Gygli has been collecting data at RMAP catchments for two years and will be assessing habitat characteristics that influence breeding at a site by different species. Results from this analysis will be available as part of his Master's thesis.

Air temperature was found to influence the probability of detecting Boreal Chorus Frogs, Wood Frogs, and Tiger Salamanders. This is likely because amphibians are ectotherms and increase daily activity as the surrounding habitat warms. Although the probability of detecting Wood Frogs and Tiger Salamanders continued to increase as temperature increased, Boreal Chorus Frogs increased in detection until about $18^{o}C$ ($\sim 64^{o}F$), after which detection decreased. This decrease in detection at higher air temperatures may result from Boreal Chorus Frogs seeking shade or other thermal refuges to reduce water loss. Detection probability also varied by year for several species, though the reason for this is not apparent. Annual variation in detection might be due to differences in vegetative cover across years, or because average survey conditions (such as temperature or timing of surveys as measured by Julian Date) differed across years. Because we did not test for an interaction between year and either temperature or Julian date in this analysis, we are unable to assess how these might have changed across years.

Although we modeled the effect of surveyor type (citizen scientist vs. biologist/biological technician) on detection probability, results should not be interpreted as a comparison between citizen scientists and biologists. Surveyor effect was included to improve estimates of detection probability by correcting for bias, if present, due to type of surveyor. The number of catchments surveyed by biologists greatly exceeded that of citizen scientists because citizen scientists were not involved in RMAP surveys until 2014. The unequal sample sizes prevent a rigorous comparison of performance between citizen scientists and biologist. However, we are in the process of assessing the performance of these two surveyor groups over two years (2014 & 2015) using data from 125 sites visited by both groups in the same season.

The primary goal of this work was to consolidate RMAP data across the MBRNF and assess amphibian occupancy for the whole MBRNF study area for the first 3 years of standardized monitoring surveys (2012-2014). WGFD is currently in the process of analyzing the full 5 years of RMAP data collected across the MBRNF (2012-2016) and 3 years of data collected on the BTNF (2014-2016). Results of this larger analysis will allow us to evaluate the ability of RMAP to effectively track amphibian occupancy as well as breeding over time. Assessing evidence of breeding over time is an important aspect of amphibian monitoring because presence of individuals at a site does not necessarily indicate successful breeding. For longer-lived species such as Boreal Toads, a site can continue to be “occupied” by a few older adults even though no recruitment is occurring.

RMAP represents one of the first attempts to conduct standardized amphibian monitoring across a regional spatial scale and multiple jurisdictional boundaries. The North American Amphibian Monitoring Program (NAAMP; https://www.pwrc.usgs.gov/NAAMP/) has done this in the eastern United States using road-based nocturnal calling surveys. Although NAAMP has been successful and may be suitable for lower elevations in Wyoming, road-based amphibian calling surveys are not a feasible alternative for monitoring montane amphibians in the Rocky Mountain region. Thus, RMAP contributes critical information on trends in occupancy of montane amphibians outside of national parks in the Rocky Mountains.

With support from the MBRNF and BI, RMAP now has the resources to train people from diverse backgrounds to conduct standardized amphibian surveys, coordinate survey efforts across multiple mountain ranges in two states, and compile data into a central database accessible by all collaborators. With continued monitoring through RMAP, resource managers will be able to regularly assess the status of amphibian in their region, use available data to conduct more in-depth analyses to investigate habitat relationships and potential impacts from stressors such as wetland desiccation and disease, and demonstrate a concerted effort to managing amphibians in light of demonstrated global and local declines.

The value of long-term monitoring data for amphibians cannot be overemphasized. Natural variation in amphibian abundance is typical, especially in arid regions where water availability is driven by annual weather conditions. This variation makes assessing actual trends in amphibian populations difficult unless assessed over longer time periods. While the need for long-term monitoring is typically recognized and supported for other taxa such as birds and big game, establishing and maintaining monitoring for amphibians remains a challenge. With the resources now available to the Rocky Mountain region through RMAP, we hope that amphibian monitoring will not only continue, but also expand.

Literature Cited

Arnold, T. W. 2010. Uninformative parameters and model selection using Akaike's information criterion. Journal of Wildlife Management 74:1175–1178.

Barnett, T.P., J.C. Adam, and D.P. Lettenmaier. 2005. Potential impacts of a warming climate on water availability in snow-dominated regions. Nature 438:303–309.

Bennetts, R., S. Corn, R. Daley, W.R. Gould, C. Jean, D. A. Patla, C. R. Peterson, and A. Ray. 2013. Cooperative amphibian monitoring protocol for the Greater Yellowstone Network: Narrative, version 1.0. Natural Resource Report NPS/GRYN/NRR—2013/654. National Park Service, Fort Collins, Colorado.

Blaustein, A.R., S.C. Walls, B.A. Bancroft, J.J. Lawler, C.L. Searle, and S.S. Gervasi. 2010. Direct and indirect effects of climate change on amphibian populations. Diversity. (2): 281-313.

Brooks, R.T. 2009. Potential impacts of global climate change on the hydrology and ecology of ephemeral freshwater systems of the forests of the northeastern United States. Clim. Change 95:469-483.

Brooks, R.T. 2004. Weather-related effects on woodland vernal pool hydrology and hydroperiod. Wetlands 24:104-114.

Burnham, K. P., and D. R. Anderson. 2002. Model selection and multimodel inference. 2nd edition. Springer, New York.

Ceradini, J. P., and A. D. Chalfoun. 2017. When perception reflects reality: Non-native grass invasion alters small mammal risk landscapes and survival. Ecology and Evolution. In Press.

Corn, P.S., M.J. Adams, W.A. Battaglin, A.L. Gallant, D.L. James, M. Knutson, C.A. Langtimm, and J.R. Sauer. 2005. Amphibian Research and Monitoring Initiative – Concepts and implementation. U.S. Geological Survey Scientific Investigations Report 2005-5015.

Doherty, P. F., G. C. White, and K. P. Burnham. 2012. Comparison of model building and selection strategies. Journal of Ornithology 152:317–323.

Edburg, S.L; J.A. Hicke, P.D. Brooks, E.G. Pendall, B.E. Ewers, U. Norton, D. Gochis, E.D. Gutmann, A..J.H. Meddens. 2012. Cascading impacts of bark beetle-caused tree mortality on coupled biogeophysical and biogeochemical processes. Frontiers in Ecology and the Environment 10(8).

Estes-Zumpf, W.A., A. Bowe, D. Keinath and J. Siemers. 2012. Monitoring amphibian population responses to a changing environment: Final study design for long-term monitoring of amphibians on the Medicine Bow and Routt National Forests. Prepared for the Medicine Bow and Routt National Forests and the Thunder Basin National Grassland by the Wyoming Natural Diversity Database, Laramie, WY.

Estes-Zumpf, W.A., D. Keinath, and A. Bowe. 2012. Monitoring amphibian population responses to a changing environment: Power analysis based on 2011 pilot study. Prepared for the Medicine Bow and Routt National Forests and the Thunder Basin National Grassland by the Wyoming Natural Diversity Database, Laramie, WY.

Estes-Zumpf, W., Z. Walker, and D. Keinath. 2014. Western amphibian monitoring initiative State Wildlife Grant final completion report. Prepared for the Wyoming Game and Fish Department Fish Division by the Wyoming Natural Diversity Database, Laramie, Wyoming.

Gratwicke, B., T.E. Lovejoy, and D.E. Wildt. 2012. Will amphibians croak under the Endangered Species Act? Bioscience 62:197-202.

Hof, C., M.B. Araújo, W. Jetz, and C. Rahbek. 2011. Additive threats from pathogens, climate and land-use change for global amphibian diversity. Nature 480:516-519.

Li, Y., J.M. Cohen, and J.R. Rohr. 2013. Review and synthesis of the effects of climate change on amphibians. Integrative Zoology, 8:145–161.

Livo, L.J. 2004. Methods for obtaining Batrachochytrium dendrobatidis (Bd) samples for PCR testing. Department of Integrative Physiology, University of Colorado, Boulder, Colorado.

MacCracken, M.C., E.J. Barron, D.R. Easterling, B.S. Felzer, and T.R. Karl. 2003. Climate change scenarios for the U.S. National Assessment. American Meteorological Society 84:1711–1723.

MacKenzie, D. I., J. D. Nichols, A. J. Royle, K. H. Pollock, L. L. Bailey, and J. E. Hines. 2006. Occupancy estimation and modeling: inferring patterns and dynamics of species occurrence. Elsevier Inc., Burlington, MA.

McMenamin, S.K., E.A. Hadly, and C.K. Wright. 2008. Climatic change and wetland desiccation cause amphibian decline in Yellowstone National Park. Proceedings of the National Academy of Sciences 105:16988-16993.

Mote, P.W., A.F. Hamlet, M.P. Clark, and D.P. Lettenmaier. 2005. Declining mountain snowpack in western North America. Bulletin of the American Meteorological Society 86:39-49.

Nichols, J. D., L. L. Bailey, O. J. F. Allan, N. W. Talancy, E. H. C. Grant, A. T. Gilbert, E. M. Annand, T. P. Husband, and J. E. Hines. 2008. Multi-scale occupancy estimation and modelling using multiple detection methods. Journal of Applied Ecology 45:1321–1329.

Pavlacky, D. J. C., J. A. Blakesley, G. C. White, D. J. Hanni, and P. M. Lukacs. 2012. Hierarchical multi-scale occupancy estimation for monitoring wildlife populations. Journal of Wildlife Management. 76:154–162.

Pimm, S.L, C.N. Jenkins, R. Abell, T.M. Brooks, J.L. Gittleman, L.N. Joppa, P.H. Raven, C.M. Roberts, J.O. Sexton. 2014. The biodiversity of species and their rates of extinction, distribution, and protection. Science 344:1246752

Pugh, E. and Small, E. 2012. The impact of pine beetle infestation on snow accumulation and melt in the headwaters of the Colorado River. Ecohydrol., 5:467–477

Pugh, E. and Gordon, E. (2013), A conceptual model of water yield effects from beetle-induced tree death in snow-dominated lodgepole pine forests. Hydrol. Process., 27: 2048–2060

Salice, C.J. 2012. Multiple stressors and amphibians: Contributions of adverse health effects and altered hydroperiod to population decline and extinction. Journal of Herpetology 46:675-681

Stuart, S.N., J.S. Chanson, N.A. Cox, B.E. Young, A.S.L. Rodrigues, D.L. Fischman, and R.W. Waller. 2004. Status and Trends of Amphibian Declines and Extinctions Worldwide. Science 306:1783-1786.

Table 1. Predictor variables used to model detection probability (p), catchment occupancy (Ψ) and site occupancy (Θ) for all amphibian species. Catchment scale predictors had one value per catchment, thus all sites within a catchment had the same predictor value. Site scale predictors had one value per site, thus each catchment had multiple values. Catchment and site predictors may or may not vary by year. Survey scale predictors were estimated separately for each survey for each site, thus each site had multiple predictor values. "Y" and "N" under Detection, Catchment and Site indicate whether the predictor was used to model that parameter (Y) or not (N).

Predictor	Scale	Detection	Catchment	Site	Description
constant	NA	Y	Y	Y	Constant (intercept only)
year	Catchment	Y	Y	Y	Survey year (2012, 2013 or 2014)
elev	Catchment	N	Y	N	Average catchment elevation (m)
area	Site	Y	N	Y	Area (ha) of each site in catchment
jdate	Survey	Y	N	N	Julian date (Day-of-year)
temp	Survey	Y	N	N	Air temperature (^{o}C)
temp^2	Survey	Y	N	N	Quadratic effect of air temperature (^{o}C)
veg	Survey	Y	N	N	Percent shoreline with emergent vegetation[1]
surveyor	Survey	Y	N	N	Survey was conducted by a citizen scientist (1) or a biologist (0)

[1] Percent of shoreline with emergent vegetation was assigned one of 5 categories: 0%, 1-25%, 25-50%, 50-75%, 75-100%.

Table 2. Presence of amphibian chytrid fungus (Bd) at 18 catchments on the Medicine Bow National Forest. Bd swabs were collected from amphibians from 2012-2016. Red frogs indicate at least one sample tested positive for Bd at a catchment in a given year. Grey frogs indicate that no samples tested positive for Bd. Sample sizes and species sampled varied each year.

Catchment	2012	2013	2014	2015	2016
MB_RP		🟥		🟥	
MB1	🟥	⬛	🟥	🟥	🟥
MB10	⬛	🟥	🟥	🟥	⬛
MB11		⬛	⬛	⬛	
MB12	⬛	⬛	🟥	🟥	
MB13		⬛	⬛	🟥	⬛
MB14		⬛	⬛	🟥	🟥
MB16		🟥		🟥	
MB17					⬛
MB18				⬛	
MB19			🟥		
MB2	⬛	🟥	⬛	🟥	🟥
MB21		⬛		🟥	
MB3	⬛	🟥	⬛	🟥	🟥
MB4		⬛	⬛	⬛	⬛
MB5			⬛		
MB6		⬛	⬛	⬛	
MB7b		🟥	🟥	🟥	🟥

Table 3. Presence of amphibian chytrid fungus (Bd) in 5 amphibian species from 2012-2016 across 18 catchments on the Medicine Bow National Forest. Red frogs indicate at least one sample tested positive for Bd at a catchment in a given year. Grey frogs indicate that no samples tested positive for Bd. Sample sizes and species sampled varied each year.

Catchment	Boreal Toad	Boreal Chorus Frog	Northern Leopard Frog	Wood Frog	Tiger Salamander
MB_RP	🟥	▨		🟥	
MB1		🟥		🟥	
MB10		🟥		🟥	
MB11		▨		▨	
MB12		🟥		🟥	
MB13		🟥	▨		
MB14		🟥			
MB16		🟥			▨
MB17		▨			
MB18			▨		
MB19		🟥			
MB2			🟥		
MB21		🟥			
MB3			🟥		
MB4	▨				
MB5		▨		▨	
MB6				▨	
MB7b				🟥	

Table 4. Amphibian species found at monitoring catchments on the Medicine Bow-Routt National Forests in Wyoming and Colorado from 2012-2014. Species include Boreal Chorus Frog (BCF), Northern Leopard Frog (NLF), Wood Frog (WF), Boreal Toad (BT), and Tiger Salamander (TS). Naïve occupancy estimates reflect the number of catchments where a species was detected divided by the total number of survey catchments (n=33) and are not corrected for imperfect species detection.

Catchment Name	**BCF**	**NLF**	**WF**	**BT**	**TS**
WYOMING					
MB_Ryan Park	YES	-	YES	YES	-
MB1_Hanging Ponds	YES	-	YES	-	-
MB10_Cecil Ponds	YES	-	YES	YES	-
MB11_Fish Crk Park	YES	-	YES	-	-
MB12_Willow Park	YES	-	YES	-	-
MB13_Sand Lake Bench	YES	-	-	-	-
MB14_S. Fork Ponds	YES	-	-	-	-
MB16_Fletcher Peak	YES	-	-	-	YES
MB17_Battle Creek	YES	-	-	-	-
MB18_Sandstone Crk	YES	-	-	-	-
MB19_Round Mtn	YES	-	-	-	-
MB2_Crow Crk Ponds	YES	YES	-	-	YES
MB21_Hog Park	YES	-	YES	-	-
MB3_Lodgepole Crk	-	YES	-	-	-
MB4_Fall Crk	YES	-	-	YES	-
MB5_Squaw Crk	YES	-	YES	-	-
MB6_Muddy Crk	-	-	YES	-	-
MB7b_Devils Gate	-	-	YES	-	-
COLORADO					
RT1_Big Crk Lakes-North	YES	-	YES	-	-
RT10_Summit Lake-North	YES	-	-	-	-
RT11_Muddy Creek	YES	-	-	-	YES
RT15_Carter Creek	YES	-	YES	-	YES
RT16_Morrison Creek	-	-	-	YES	-
RT17_Gore Creek	YES	-	-	-	-
RT18_Beaver Creek	-	-	-	-	YES
RT19_Allen Basin	YES	-	-	-	YES
RT2_Big Crk Lakes-South	-	YES	YES	-	-
RT20_Mandall Lakes	-	-	-	-	-
RT4_Lone Pine Creek	YES	-	-	-	YES
RT5_Summit Lake-South	YES	-	-	-	YES
RT7_Grouse Mountain	YES	-	-	-	-
RT8_Bear's Ears	YES	YES	-	-	YES
RT9_First Creek	YES	YES	-	-	-
Total number of occupied catchments	26	5	12	4	9
Naïve Occupancy 2012-2014	**0.79**	**0.15**	**0.36**	**0.12**	**0.27**

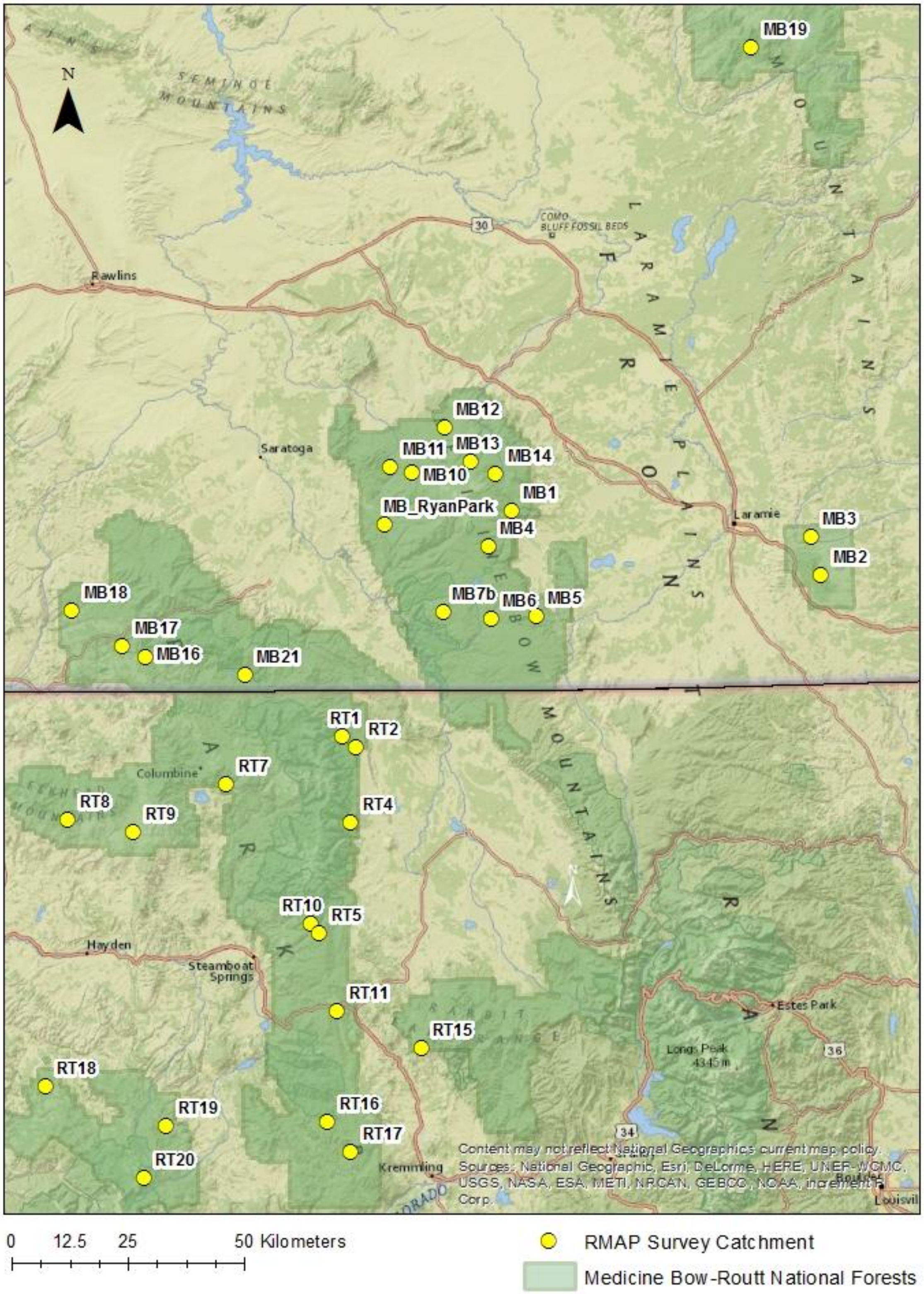

Figure 1. Location of Rocky Mountain Amphibian Project (RMAP) monitoring catchments (n=33) on the Medicine Bow and Routt National Forests in southern Wyoming and northern Colorado.

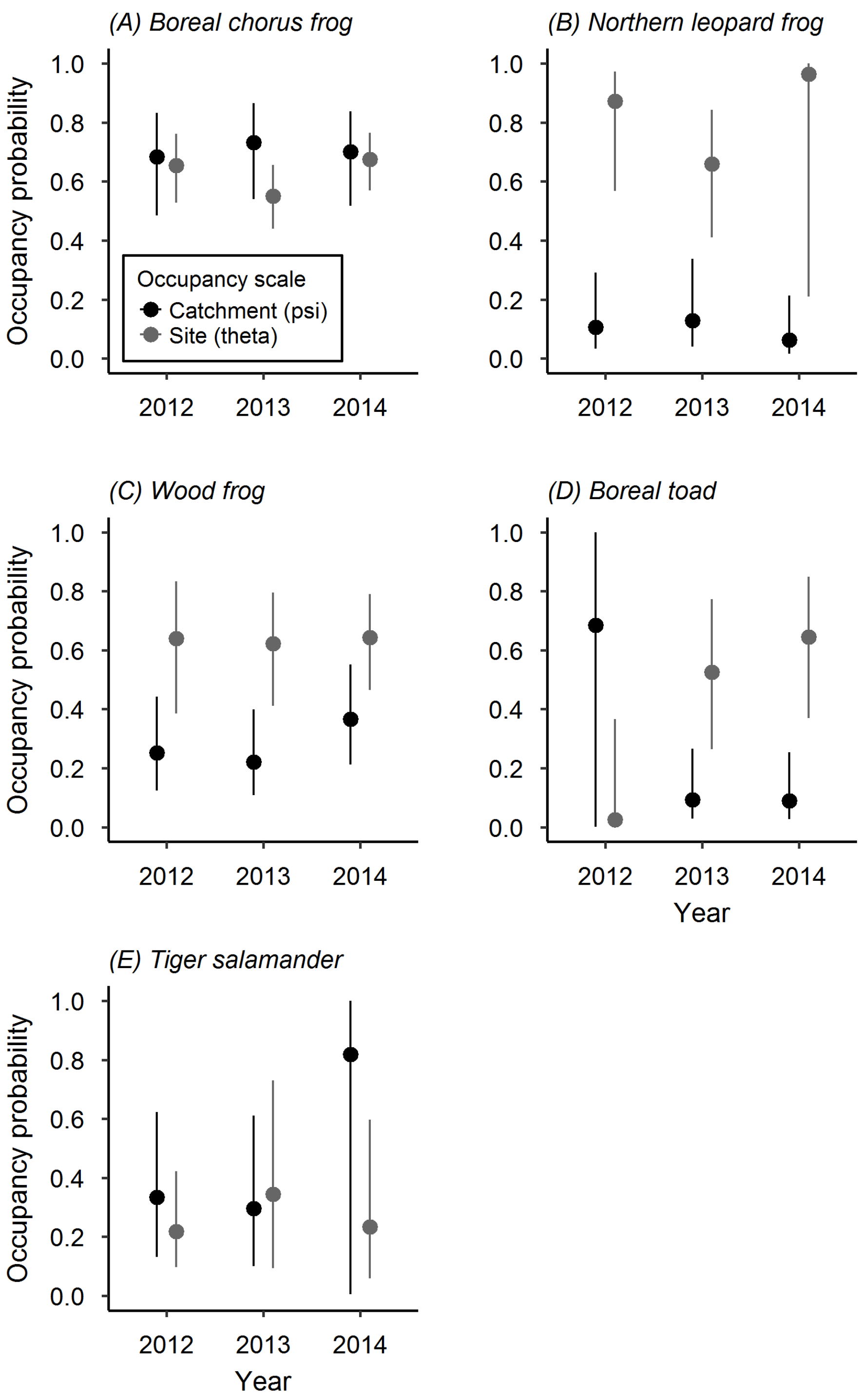

Figure 2. Occupancy probability predicted from the top model for each species that contained a year term for catchment and site occupancy. For tiger salamanders, separate models were used to predict catchment and site occupancy by year because a model with a year term for both spatial scales did not converge. Any other occupancy predictors in the model were held at their mean for prediction. Points represent mean estimates and error bars are 95% confidence intervals.

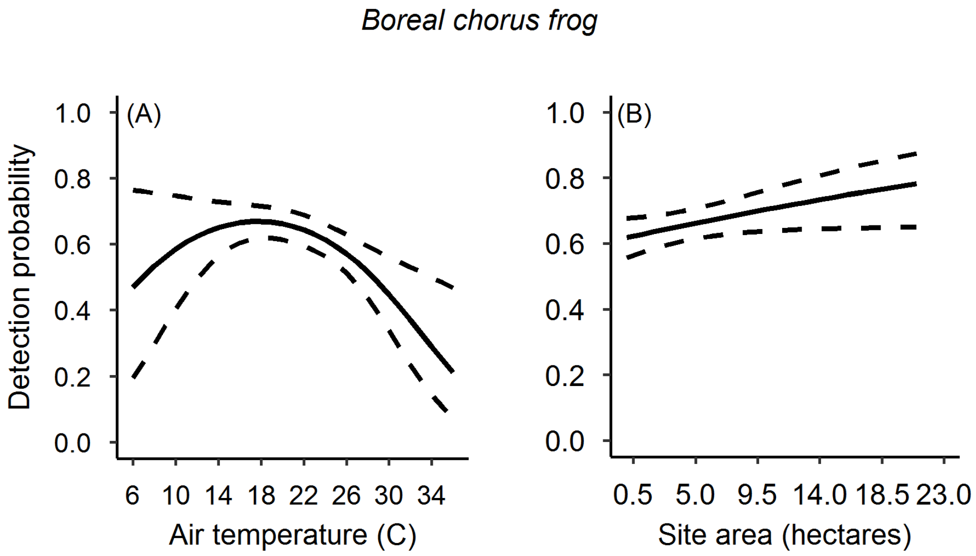

Figure 3. Predicted detection probability from the top model for the boreal chorus frog while holding the other predictor at its mean. Solid and dotted lines are the predicted mean and 95% confidence intervals, respectively.

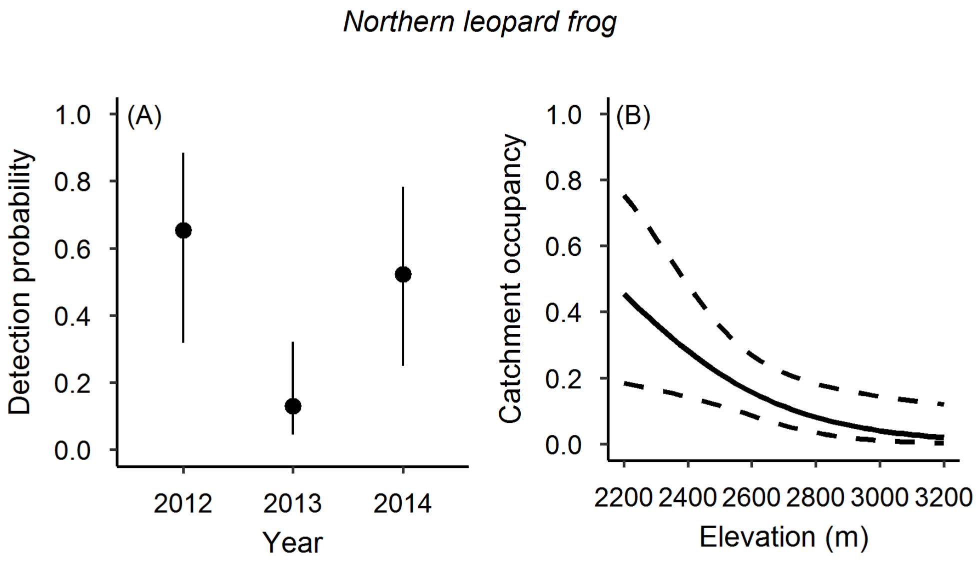

Figure 4. Predicted detection (A) and catchment occupancy (B) probability from the top model for the northern leopard frog while holding other predictors at their mean. Points (A) and the solid line (B) are predicted means, and error bars (A) and dotted lines (B) are predicted 95% confidence intervals.

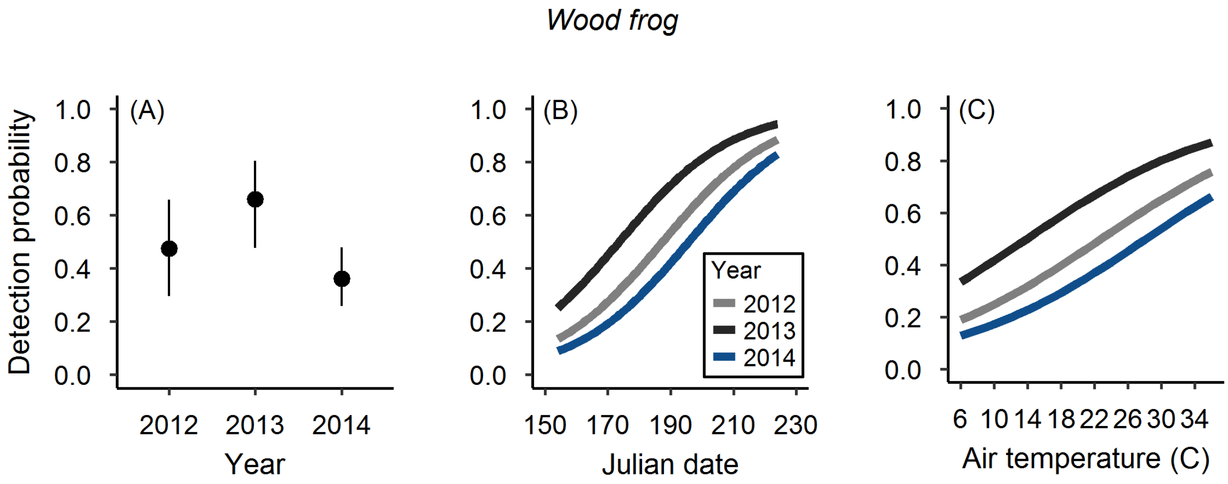

Figure 5. Predicted detection probability from the top model for the wood frog while holding other predictors at their mean. Points and error bars (A) represent predicted means and 95% confidence intervals, respectively. Lines (B and C) represent predicted means by year and confidence intervals are not shown.

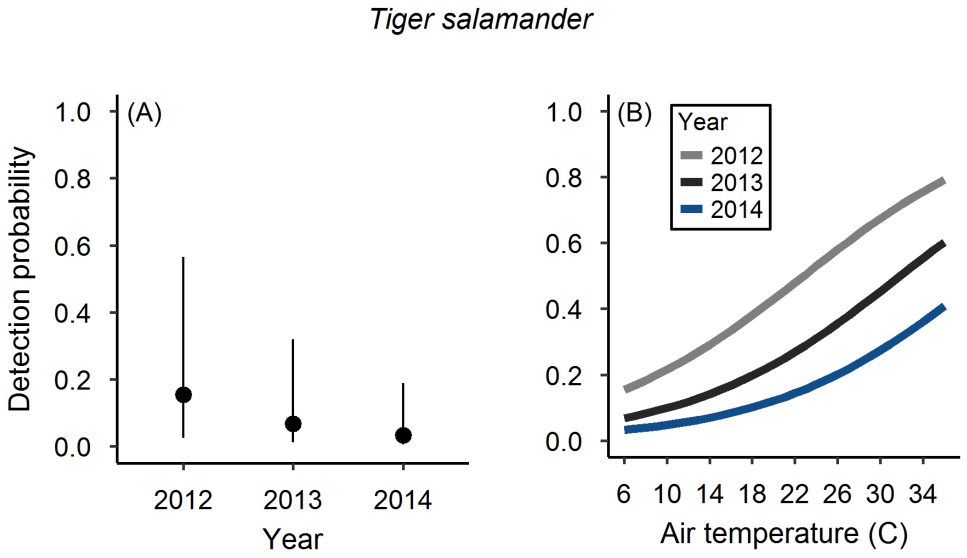

Figure 6. Predicted detection probability from the top model for the tiger salamander while holding other predictors at their mean. Points and error bars (A) represent predicted means and 95% confidence intervals, respectively. Lines (B) represent predicted means by year and confidence intervals are not shown.

Appendix 1: Understanding AIC and uninformative predictors

Arnold 2010 (1175): "…AIC…is defined as -2logL(θ||y) + 2K, where logL(θ||y) is the maximized log-likelihood of the model parameters given the data and K is the number of estimable parameters (Burnham and Anderson 2002:61). For any well-supported approximating model, it is possible to add any single parameter and achieve a new model that is ≤2 AIC units from the well-supported model, because even if the additional parameter has no explanatory ability whatsoever (i.e., log-likelihood is unchanged), AIC will only increase by 2 due to the 1-unit increase in K." AIC_c is corrected for small sample sizes and may apply a parameter penalty larger than 2 depending on the value of *n/K*. Thus, the same consideration applies to AIC_c but the model with an uninformative predictor (or parameter) may be slightly more than 2 AIC units away from the nested, informative model. Although Arnold 2010, and Burnham and Anderson 2002, refer to log-likelihood or negative log-likelihood (NLL) in the discussion of uninformative predictors, the deviance values in our occupancy models are identical to NLL; thus, the ΔAICc and deviance values can be used to identify models with uninformative predictors.

Deviance or NLL can be considered a relative measure of model fit, with lower values indicating better fit. We would thus expect the addition of an informative predictor to reduce deviance relative to the same model excluding that predictor. In A1 Table 1, the 2nd ranked model, *temp + jdate*, seems fairly competitive since it is approximately 2 ΔAIC from the top model (models below 2 ΔAIC are commonly considered to be competitive, Burnham and Anderson 2002). However, *jdate* is an uninformative predictor being "carried" by an informative predictor, *temp*, thus making the model appear competitive. The difference in deviance between the top two models is very small (0.11), i.e., the addition of *jdate* is not improving model fit relative to the simpler model with only *temp*. Thus, the AIC weight that is attributed to *temp + jdate* should instead go towards the top model. After accounting for the uninformative predictor, it is obvious that there is one clear top model, *temp*, as shown in A1 Table 2. Additionally, when many nested models are compared (e.g., Appendices 2-6), AIC weight may be "stolen" from higher ranked models by many different uninformative models, resulting in a substantial cumulative reduction in model weight for the informative models. This can result in a very misleading model set if the uninformative predictor effect is not understood or corrected.

A1 Table 3 is provided as an example of how AIC and deviance values change with the addition of an informative predictor, *year*. Model fit, as measured by deviance, for *temp + year* reduced (or improved) by 7.25 compared to the *temp* model, and by 5.02 compared to the *year* model. Additionally, *temp + year* was ranked above the simpler *temp* and *year* only models, indicating that it explained substantial additional variation in occupancy and overcame the penalty for the additional predictor.

A1 Table 1. Subset of tiger salamander detection probability models, from a multi-scale occupancy analysis, used as an example uninformative predictor model set. For all models, occupancy parameters (Ψ and Θ) were constant (intercept only). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} -$ minimum AIC_c, *w* = AIC_c model weight.

Model	*K*	AICc	ΔAICc	*w*	Deviance
temp	4	316.64	0.00	0.73	308.19
temp + jdate	5	318.76	2.12	0.25	308.08
jdate	4	323.88	7.24	0.02	315.43

A1 Table 2. Subset of tiger salamander detection probability models, from a multi-scale occupancy analysis, used as an example uninformative predictor model set. For all models, occupancy parameters (Ψ and Θ) were constant (intercept only). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} -$ minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
temp	4	316.64	0.00	0.97	308.19
temp + jdate	5	318.76	2.12	NA	308.08
jdate	4	323.88	7.24	0.03	315.43

A1 Table 3. Subset of tiger salamander detection probability models, from a multi-scale occupancy analysis, used as an example informative predictor model set. For all models, occupancy parameters (Ψ and Θ) were constant (intercept only). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} -$ minimum AIC_c, *w* = AIC_c model weight.

Model	*K*	AICc	ΔAICc	*w*	Deviance
temp + year	6	313.90	0.00	0.66	300.94
temp	4	316.64	2.74	0.17	308.19
year	5	316.64	2.74	0.17	305.96

Appendix 2: Boreal chorus frog model sets

A2 Table 1. Stage 1 boreal chorus frog multi-scale occupancy model set used to find the best model for detection probability (p). Occupancy parameters, Ψ and Θ, were held as complex (global) models while different detection models competed (35 models). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci}$ – minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
area + temp + $temp^2$	16	1376.72	0.00	0.40	1337.66
temp + $temp^2$	15	1377.98	1.26	0.21	1341.83
area + temp	15	1378.58	1.86	0.16	1342.43
temp	14	1380.29	3.57	0.07	1346.97
area + jdate + temp	16	1380.40	3.67	0.06	1341.33
area + surveyor + temp	16	1381.11	4.39	NA	1342.05
area	14	1381.76	5.04	0.03	1348.44
jdate + temp	15	1382.61	5.89	NA	1346.46
surveyor + temp	15	1382.73	6.01	NA	1346.58
area + surveyor + jdate + temp	17	1383.24	6.52	NA	1341.18
area + jdate	15	1383.36	6.64	0.01	1347.21
area + temp + year	17	1383.71	6.99	NA	1341.66
constant	13	1383.86	7.14	0.01	1353.31
area + surveyor	15	1384.04	7.32	NA	1347.89
area + jdate + temp + year	18	1385.12	8.40	0.01	1340.00
surveyor + jdate + temp	16	1385.30	8.58	0.01	1346.23
temp + year	16	1385.38	8.66	0.01	1346.32
area + surveyor + temp + year	18	1385.91	9.19	0.00	1340.79
area + surveyor + jdate	16	1386.02	9.30	0.00	1346.96
jdate	14	1386.03	9.31	0.00	1352.72
surveyor	14	1386.04	9.32	0.00	1352.72
area + year	16	1386.38	9.66	0.00	1347.32
area + jdate + year	17	1387.46	10.74	0.00	1345.41
surveyor + temp + year	17	1387.52	10.80	0.00	1345.47
jdate + temp + year	17	1387.54	10.82	0.00	1345.49
area + surveyor + jdate + temp + year	19	1387.73	11.01	0.00	1339.46
area + surveyor + year	17	1388.14	11.42	0.00	1346.08
year	15	1388.45	11.73	0.00	1352.30
surveyor + jdate	15	1388.50	11.78	0.00	1352.35

area + surveyor + jdate + year	18	1389.73	13.01	0.00	1344.61
surveyor + jdate + temp + year	18	1389.99	13.27	0.00	1344.87
surveyor + year	16	1390.11	13.39	0.00	1351.04
jdate + year	16	1390.37	13.65	0.00	1351.31
surveyor + jdate + year	17	1392.41	15.69	0.00	1350.36
veg	17	1393.65	16.93	0.00	1351.60

A2 Table 2. Stage 2 boreal chorus frog multi-scale occupancy model set used to find the best model for occupancy parameters, Ψ and Θ (16 models). For all models, detection probability (p) was held as the top model from stage 1: p(area + temp + temp^2). K = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci}$ – minimum AIC_c, w = AIC_c model weight. NA under w represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating w. The model in bold was used to estimate occupancy by year for both spatial scales.

Ψ model	Θ model	K	AICc	ΔAICc	w	Deviance
constant	constant	6	1356.04	0.00	0.40	1343.07
constant	year	8	1357.80	1.76	0.16	1340.11
elev	constant	7	1358.22	2.18	0.13	1342.92
constant	area	7	1358.29	2.25	0.13	1342.99
elev	year	9	1360.07	4.03	0.05	1339.93
constant	year + area	9	1360.08	4.04	NA	1339.94
elev	area	8	1360.52	4.48	0.04	1342.82
year	constant	8	1360.71	4.67	0.04	1343.02
elev	year + area	10	1362.41	6.37	NA	1339.76
year	**year**	**10**	**1362.60**	**6.56**	**0.01**	**1339.95**
year + elev	constant	9	1363.00	6.96	NA	1342.86
year	area	9	1363.07	7.03	0.01	1342.93
year + elev	year	11	1364.98	8.94	0.00	1339.76
year	year + area	11	1365.00	8.96	0.00	1339.78
year + elev	area	10	1365.41	9.37	0.00	1342.76
year + elev	year + area	12	1367.43	11.39	0.00	1339.58

Appendix 3: Northern leopard frog model sets

A3 Table 1. Stage 1 northern leopard frog multi-scale occupancy model set used to find the best model for detection probability (p). Occupancy parameters, Ψ and Θ, were held as complex (global) models while different detection models competed (11 models). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} -$ minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
area + temp + year	17	243.90	0.00	0.73	201.85
area + year	16	245.85	1.95	0.27	206.78
area + jdate + temp + year	18	246.40	2.50	NA	201.28
area + jdate + year	17	248.79	4.89	NA	206.74
year	15	265.30	21.40	0.00	229.15
temp + year	16	266.67	22.77	0.00	227.60
jdate + year	16	268.12	24.22	0.00	229.05
jdate + temp + year	17	269.65	25.75	0.00	227.60
constant	13	271.99	28.09	0.00	241.44
temp	14	274.17	30.27	0.00	240.85
temp + $temp^2$	15	276.79	32.88	0.00	240.63

A3 Table 2. Stage 2 northern leopard frog multi-scale occupancy model set used to find the best model for occupancy parameters, Ψ and Θ (16 models). For all models, detection probability (p) was held as the top model from stage 1: p(area + temp + year). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci}$ – minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*. The model in bold was used to estimate occupancy by year for both spatial scales.

Ψ model	Θ model	*K*	AICc	ΔAICc	*w*	Deviance
elev	constant	8	230.68	0.00	0.45	212.99
elev	year	10	231.39	0.70	0.32	208.73
elev	area	9	232.93	2.24	0.15	212.78
elev	year + area	11	233.75	3.07	NA	208.53
year + elev	constant	10	234.93	4.24	NA	212.28
year + elev	**year**	**12**	**235.73**	**5.05**	**NA**	**207.88**
constant	constant	7	236.06	5.38	0.03	220.76
constant	year	9	236.54	5.86	0.02	216.40
year + elev	area	11	237.29	6.60	NA	212.07
constant	area	8	238.19	7.51	0.01	220.50
year + elev	year + area	13	238.28	7.59	0.01	207.73
constant	year + area	10	238.82	8.14	0.01	216.17
year	constant	9	240.37	9.69	0.00	220.23
year	year	11	240.97	10.29	0.00	215.75
year	area	10	242.61	11.93	0.00	219.96
year	year + area	12	243.41	12.72	0.00	215.56

Appendix 4: Wood frog model sets

A4 Table 1. Stage 1 wood frog multi-scale occupancy model set used to find the best model for detection probability (p). Occupancy parameters, Ψ and Θ, were held as complex (global) models while different detection models competed (34 models). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} -$ minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
area + surveyor + jdate + temp + year	19	578.97	0.00	0.55	530.70
area + surveyor + jdate + year	18	581.33	2.36	0.17	536.21
area + surveyor + jdate + temp	17	582.39	3.42	0.10	540.34
area + jdate + temp + year	18	583.44	4.47	0.06	538.32
area + surveyor + jdate	16	584.09	5.12	0.04	545.03
area + jdate + year	17	584.90	5.93	0.03	542.85
surveyor + jdate + temp + year	18	586.62	7.64	0.01	541.50
area + temp + year	17	587.62	8.65	0.01	545.57
surveyor + jdate + year	17	587.92	8.95	0.01	545.87
area + year	16	588.37	9.40	0.01	549.31
area + surveyor + temp + year	18	589.46	10.48	0.00	544.34
area + surveyor + temp	16	589.74	10.77	0.00	550.68
area + surveyor	15	590.21	11.23	0.00	554.05
area + surveyor + year	17	590.28	11.30	0.00	548.22
surveyor + jdate + temp	16	590.96	11.98	0.00	551.89
area + temp	15	591.08	12.11	0.00	554.93
area + jdate + temp	16	591.31	12.34	0.00	552.25
jdate + temp + year	17	591.54	12.57	0.00	549.49
area	14	591.69	12.72	0.00	558.38
jdate + year	16	591.88	12.91	0.00	552.82
surveyor + jdate	15	591.97	12.99	0.00	555.81
area + jdate	15	592.46	13.49	0.00	556.31
year	15	597.85	18.88	0.00	561.70
temp + year	16	597.95	18.98	0.00	558.89
surveyor + temp + year	17	599.89	20.91	0.00	557.83
surveyor + year	16	599.90	20.92	0.00	560.83
surveyor	14	600.40	21.42	0.00	567.08
surveyor + temp	15	600.43	21.45	0.00	564.27
jdate + temp	15	601.16	22.18	0.00	565.00
jdate	14	601.46	22.48	0.00	568.14

constant	13	601.89	22.92	0.00	571.34
temp	14	601.98	23.00	0.00	568.66
temp + $temp^2$	15	604.81	25.84	0.00	568.66
veg	17	611.40	32.42	0.00	569.35

A4 Table 2. Stage 2 wood frog multi-scale occupancy model set used to find the best model for occupancy parameters, Ψ and Θ (16 models). For all models, detection probability (p) was held as the top model from stage 1: p(area + surveyor + jdate + temp + year). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci} –$ minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*. The model in bold was used to estimate occupancy by year for both spatial scales.

Ψ model	Θ model	*K*	AICc	ΔAICc	*w*	Deviance
constant	constant	9	554.85	0.00	0.38	534.70
constant	area	10	555.71	0.86	0.25	533.06
elev	constant	10	557.35	2.51	0.11	534.70
year	constant	11	558.21	3.37	0.07	532.99
elev	area	11	558.28	3.43	0.07	533.06
year	area	12	559.19	4.34	0.04	531.33
constant	year	11	559.86	5.01	0.03	534.64
constant	year + area	12	560.79	5.95	0.02	532.94
year + elev	constant	12	560.84	5.99	NA	532.99
year + elev	area	13	561.88	7.03	NA	531.33
elev	year	12	562.49	7.64	0.01	534.64
elev	year + area	13	563.49	8.64	0.01	532.94
year	**year**	**13**	**563.52**	**8.67**	**0.01**	**532.97**
year	year + area	14	564.59	9.74	0.00	531.27
year + elev	year	14	566.28	11.43	0.00	532.96
year + elev	year + area	15	567.42	12.58	0.00	531.27

Appendix 5: Boreal toad model sets

A5 Table 1. Stage 1 boreal toad multi-scale occupancy model set used to find the best model for detection probability (p). Occupancy parameters, Ψ and Θ, were held as complex (global) models while different detection models competed (33 models). *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci}$ – minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
constant	11	226.99	0.00	0.27	201.78
temp	12	227.17	0.18	0.25	199.32
surveyor	12	229.07	2.07	0.10	201.22
jdate	12	229.08	2.08	0.10	201.23
surveyor + temp	13	229.41	2.41	NA	198.86
temp + temp2	13	229.45	2.45	NA	198.90
area	12	229.62	2.62	0.07	201.77
area + temp	13	229.84	2.84	NA	199.29
jdate + temp	13	229.86	2.87	NA	199.31
temp + year	14	230.38	3.39	0.05	197.07
jdate + year	14	230.66	3.66	0.04	197.34
surveyor + jdate	13	231.47	4.47	NA	200.92
year	13	231.64	4.65	0.03	201.09
area + surveyor	13	231.73	4.74	NA	201.18
area + jdate	13	231.77	4.78	NA	201.22
surveyor + temp + year	15	231.92	4.92	0.02	195.76
jdate + temp + year	15	231.98	4.98	0.02	195.83
area + surveyor + temp	14	232.08	5.08	NA	198.76
surveyor + jdate + temp	14	232.15	5.16	NA	198.84
area + jdate + temp	14	232.60	5.60	NA	199.28
surveyor + jdate + year	15	232.73	5.74	NA	196.58
area + temp + year	15	233.18	6.19	NA	197.03
surveyor + year	14	233.21	6.21	0.01	199.89
area + jdate + year	15	233.31	6.31	NA	197.15
surveyor + jdate + temp + year	16	233.91	6.92	NA	194.85
area + surveyor + jdate	14	234.22	7.22	NA	200.90
area + year	14	234.36	7.36	NA	201.04
area + jdate + temp + year	16	234.61	7.62	0.01	195.55
area + surveyor + temp + year	16	234.63	7.64	0.01	195.57

area + surveyor + jdate + temp	15	234.89	7.89	0.01	198.73
area + surveyor + jdate + year	16	235.35	8.35	0.00	196.28
area + surveyor + year	15	235.88	8.88	0.00	199.72
area + surveyor + jdate + temp + year	17	236.42	9.43	0.00	194.37

A5 Table 2. Stage 2 boreal toad multi-scale occupancy model set used to find the best model for occupancy parameters, Ψ and Θ (14 models). For all models, detection probability (p) was held as the top model from stage 1: p(constant). *K* = number of parameters, AIC$_c$ = Akaike's Information Criterion corrected for small sample sizes, ΔAIC$_c$ = AIC$_{ci}$ – minimum AIC$_c$, *w* = AIC$_c$ model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*. The model in bold was used to estimate occupancy by year for both spatial scales.

Ψ model	Θ model	*K*	AICc	ΔAICc	*w*	Deviance
constant	year	5	218.48	0.00	0.42	207.80
elev	year	6	219.10	0.62	0.31	206.14
constant	year + area	6	220.68	2.20	NA	207.71
elev	year + area	7	221.36	2.88	NA	206.06
constant	constant	3	221.84	3.36	0.08	215.57
elev	constant	4	222.35	3.87	0.06	213.90
year + elev	**year**	**8**	**222.42**	**3.94**	**0.06**	**204.73**
constant	area	4	223.95	5.47	0.03	215.50
elev	area	5	224.52	6.04	0.02	213.84
year + elev	year + area	9	224.75	6.27	NA	204.60
year	constant	5	226.14	7.66	0.01	215.46
year + elev	constant	6	226.75	8.27	0.01	213.78
year	area	6	228.36	9.88	0.00	215.39
year + elev	area	7	229.02	10.54	0.00	213.72

Appendix 6: Tiger salamander model sets

A6 Table 1. Stage 1 tiger salamander multi-scale occupancy model set used to find the best model for detection probability (p). Occupancy parameters, Ψ and Θ, were held as constant (intercept only) models while different detection models competed (33 models). Detection models did not converge when more complicated occupancy models were used. *K* = number of parameters, AIC_c = Akaike's Information Criterion corrected for small sample sizes, $\Delta AIC_c = AIC_{ci}$ – minimum AIC_c, *w* = AIC_c model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*.

Model	*K*	AICc	ΔAICc	*w*	Deviance
temp + year	6	313.90	0.00	0.55	300.94
area + temp + year	7	315.66	1.76	NA	300.36
surveyor + temp + year	7	315.97	2.07	NA	300.67
jdate + temp + year	7	316.22	2.32	NA	300.92
temp	4	316.64	2.74	0.14	308.19
year	5	316.64	2.74	0.14	305.96
area + year	6	317.04	3.14	0.11	304.07
area + surveyor + temp + year	8	317.85	3.95	NA	300.16
area + jdate + temp + year	8	318.05	4.15	NA	300.36
surveyor + jdate + temp + year	8	318.34	4.44	NA	300.65
area + temp	5	318.38	4.48	NA	307.70
surveyor + year	6	318.57	4.67	NA	305.60
jdate + temp	5	318.76	4.86	NA	308.08
jdate + year	6	318.83	4.93	NA	305.86
temp + $temp^2$	5	318.84	4.94	NA	308.16
surveyor + temp	5	318.86	4.96	NA	308.18
area + surveyor + year	7	319.14	5.24	NA	303.84
area + jdate + year	7	319.38	5.47	NA	304.07
area + surveyor + jdate + temp + year	9	320.30	6.40	NA	300.16
area + jdate + temp	6	320.62	6.72	NA	307.65
area + surveyor + temp	6	320.66	6.76	NA	307.69
surveyor + jdate + year	7	320.76	6.86	NA	305.46
surveyor + jdate + temp	6	321.02	7.11	NA	308.05
area + surveyor + jdate + year	8	321.53	7.63	0.01	303.83
constant	3	321.93	8.03	0.01	315.66
area	4	322.09	8.19	0.01	313.64
area + surveyor + jdate + temp	7	322.95	9.05	0.01	307.65
jdate	4	323.88	9.98	0.00	315.43

surveyor	4	324.00	10.10	0.00	315.56
area + surveyor	5	324.29	10.39	0.00	313.61
area + jdate	5	324.30	10.40	0.00	313.62
surveyor + jdate	5	325.98	12.08	0.00	315.29
area + surveyor + jdate	6	326.55	12.65	0.00	313.58

A6 Table 2. Stage 2 tiger salamander multi-scale occupancy model set used to find the best model for occupancy parameters, Ψ and Θ (12 models). For all models, detection probability (p) was held as the top model from stage 1: p(temp + year). *K* = number of parameters, AIC$_c$ = Akaike's Information Criterion corrected for small sample sizes, ΔAIC$_c$ = AIC$_{ci}$ – minimum AIC$_c$, *w* = AIC$_c$ model weight. NA under *w* represents a model with an uninformative predictor. Uninformative predictors were assessed within seven ΔAICc and models with uninformative predictors were excluded when calculating *w*. Models in bold were used to estimate catchment (Ψ) and site (Θ) occupancy by year, respectively.

Ψ model	Θ model	*K*	AICc	ΔAICc	*w*	Deviance
constant	constant	6	313.90	0.00	0.37	300.94
constant	area	7	315.25	1.35	0.19	299.94
elev	constant	7	315.98	2.08	0.13	300.68
year	**constant**	**8**	**316.32**	**2.42**	**0.11**	**298.63**
elev	area	8	317.36	3.46	0.07	299.67
year	area	9	317.78	3.88	0.05	297.64
constant	**year**	**8**	**318.00**	**4.10**	**0.05**	**300.31**
year + elev	constant	9	318.51	4.61	NA	298.37
constant	year + area	9	319.40	5.50	NA	299.26
year + elev	area	10	320.01	6.11	NA	297.36
elev	year	9	320.21	6.31	0.02	300.07
elev	year + area	10	321.66	7.76	0.01	299.01