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Assessing Detection Probability and Survey Frequency for the Threatened Magnificent Broodfrog, *Pseudophryne covacevichae*

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ABSTRACT

Difficulty in detecting species' presence is a common issue when surveying threatened species. This is particularly relevant when target species occur in remote regions, have small populations, are difficult to detect, or sampling effort is limited. This can lead to underestimation of a species' true occurrence, which can be an issue where developments are proposed that could impact populations through habitat loss or fragmentation. We aimed to identify the environmental variables influencing the probability of detecting the magnificent broodfrog (*Pseudophryne covacevichae*), determine environmental triggers for survey initiation and estimate the number of surveys required to provide confidence in the species' true absence at a location. We analysed repeat site survey data from 13 locations where the species was known to occur. Single-season occupancy models identified volumetric soil moisture to be the most influential environmental variable in detection, followed by a combination of volumetric soil moisture and accumulated rainfall in the 5 days prior to a survey. These two variables were used to classify survey conditions into poor, average and excellent, defined by their 5th, 50th and 95th percentiles, to estimate the relationship between survey conditions and survey effort. Cumulative detection probability under 'poor' environmental conditions remained low, with less than 40% cumulative detection probability following six surveys and high uncertainty in posterior distributions. In contrast, under 'average' conditions, detection probability increased to 96% following three surveys, and in 'excellent' conditions, a single survey resulted in 98% probability of detection, and certainty in the posterior distributions increased in both instances. These results demonstrate that targeting surveys under good to optimal environmental conditions can improve detection probability, maximise the efficiency of surveys and reduce the likelihood of false absences.

1 | Introduction

Assessing the impacts of human activities on the distributions and abundances of threatened species is a key feature of legislation aimed at protecting them (Garrard et al. 2015). In Australia, the *Environment Protection and Biodiversity Conservation Act 1999* (EPBC Act) mandates the assessment and approval of any activity anticipated to significantly impact listed threatened species. This necessitates comprehensive environmental impact assessments, which are guided by government policies that dictate their design (Simmonds et al. 2020). Understanding the potential impacts of any development on a species requires knowledge of that species' presence or absence at the location under proposed development.

As species are not perfectly detectable, there is a significant issue associated with certainty in determining the presence or absence at a location (MacKenzie et al. 2002; Gu and Swihart 2004; Wintle et al. 2012). Underlying this uncertainty is the possibility that failure to record a species at a particular site does not necessarily indicate absence (i.e., a true absence). Rather, a record of no occurrence at a given location may result from a species going undetected during a survey period even though it is present (i.e., a false absence) (MacKenzie et al. 2002; Wintle et al. 2012; Garrard et al. 2015). False absences can arise due to insufficient sampling effort (Bridges and Dorcas 2000; de Solla et al. 2005), inabilities of the sampling technique to accurately detect occurrence (Heard et al. 2006), observer inexperience (McClintock et al. 2010; Schmidt et al. 2023), influence of habitat characteristics on detection accuracy (Gu and Swihart 2004), low population abundance (Tanadini and Schmidt 2011) and meteorological effects on the target species, such as rainfall and temperature (Pellet and Schmidt 2005; Saenz et al. 2006; Canessa et al. 2012; Dostine et al. 2013).

Failure to account for variation in detectability has implications for the management of threatened species that exhibit total range extents and habitat distributions that are geographically and/or environmentally limited. The consequences of false absences may lead to incorrect recommendations to developers and governments. This can result in poor outcomes for the species (Gu and Swihart 2004; Heard et al. 2006), including site-level extirpation (Garrard et al. 2015). In many instances, site-level losses would constitute a significant impact for a threatened species (e.g., Neldner et al. 2017). Environmental impact assessments inform decisions on whether the development of potential threatened species' habitats is allowed to proceed, even when the species in question may not have been detected on the site (Garrard et al. 2008). Under this assumption, any legislation aimed at protecting threatened species should ideally be required to address the issue of uncertainty in detection and outline potential measures to avoid high false absence rates during impact assessments (Garrard et al. 2015). Wintle et al. (2012) suggest a solution to this problem is to specify requirements for biological surveys undertaken during impact assessments for a particular species; for example, relating to environmental conditions and/or effort associated with surveys.

Amphibians are the most imperilled vertebrate class globally, with 40% of all species being threatened (Luedtke et al. 2023). Declines in Australian frogs have reflected those documented worldwide. As of 2020, 45 (18.5%) of the 243 currently described frog species are considered threatened (Gillespie et al. 2020), and six are now believed to be extinct (Geyle et al. 2021; Scheele et al. 2023). Imperfect detection is a particular issue for frogs because their detectability is most often determined through calling behaviour, and calling behaviour can be highly dependent on specific environmental conditions (Pellet and Schmidt 2005; Heard et al. 2006; Canessa et al. 2012; Dostine et al. 2013).

In many instances, robust survey designs that consider species' detection probabilities and adequate sampling effort have not been undertaken on Australian frogs (e.g., Heard et al. 2006; Canessa et al. 2012; Dostine et al. 2013). The Australian Government published guidelines for surveying threatened Australian frog species (DEWHA 2010), though many of the protocols listed are generic and not based on methodologies that optimise the detection for a particular species. For species that are rare, occur in remote areas and/or exhibit relatively unpredictable breeding events, generic guidelines may be inadequate. These species require detailed information on the factors that influence calling behaviour and, hence, detection. To improve detection of these frog species, knowledge of specific environmental triggers (e.g., temperature or rainfall) that initiate calling behaviour could be used as a remote indicator to time surveys to maximise detection probability (e.g., Penman et al. 2006).

The magnificent broodfrog (*Pseudophryne covacevichae*) occurs in localised areas on the western margin of the Wet Tropics bioregion of north-east Australia. It is currently known from scattered sites on the south-western Atherton Tablelands and a smaller population in the Paluma Range, 160 km to the south (McDonald 2002; Zozaya and Hoskin 2015). *Pseudophryne covacevichae* exhibits high habitat specificity, being restricted to open eucalypt woodlands on rhyolitic and granitic soils (McDonald 2002, Zozaya and Hoskin 2015) above 700 m elevation (Attexo 2021). Males call primarily during the 'wet season' (approximately December–April), and breeding occurs in shallow ephemeral drainage lines and seepage areas on first- and second-order streams (McDonald 2002). Eggs are laid as terrestrial 'nests' under dense tussock grasses or leaf litter, and after a period of development on land, the eggs hatch and the tadpoles continue development in small pools.

Pseudophryne covacevichae is listed as vulnerable under both the Australian EPBC Act and Queensland's *Nature Conservation Act* (NCA) and endangered on the IUCN red list (IUCN 2021). A primary threat to the species is considered to be habitat loss and degradation (McDonald 2002). Currently, there is concern for the species due to potential broadscale impacts to breeding habitat from windfarm development in some unprotected areas of its small, upland distribution. To meet the Queensland Government renewable energy targets, a series of industrial windfarms are proposed along the western boundary of the Wet Tropics bioregion (Windlab 2021; MFEP 2022; Ark Energy 2024; GEM 2024; Neoen. 2024). The proposed locations for the developments are spatially concordant with known *P. covacevichae* populations and potentially with unknown populations. *Pseudophryne covacevichae* needs to be assessed in development applications, and this relies heavily on reliable assessments of the species occurrence and, equally, absence. An issue is that *P. covacevichae* typically occurs in highly localised areas, at low densities, and exhibits sporadic calling behaviour (Freeman 2001, 2012; McDonald 2002). These factors, coupled with insufficient knowledge of the species distribution and ecology, necessitate a better understanding of calling behaviour and guidelines for detection.

Here we investigated the factors influencing calling activity and thus the detectability of *P. covacevichae*. Based on repeat surveys at known sites, we examined the environmental variables that trigger male calling behaviour. Our aim was to identify variables that can be used to optimise detection of the species, particularly those that could be assessed remotely, and to determine how differing environmental conditions influence detection across repeated surveys.

2 | Methods

2.1 | Study Area

The study was conducted in locations spanning the area encompassed by the two major populations of *P. covacevichae* (Ingram and Corben 1994; McDonald 2002; Zozaya and Hoskin 2015), (Figure 1). There were 11 sites in the south-western Atherton Tablelands region near Ravenshoe and five sites in the Paluma range. The Paluma Range sites were located on the Australian Wildlife Conservancy's Mount Zero-Taravale Wildlife Sanctuary. All sites were chosen based on historic and current occurrence records of *P. covacevichae*, obtained from the Queensland Museum, the Queensland Government Wildnet database (Wildnet 2022), the Australian Wildlife Conservancy and author observations. The habitat at all sites was visually assessed for general suitability prior to surveys taking place, checking for small gullies in open woodland (e.g., Figure 2).

2.2 | Sampling Design

Aural surveys were used to assess *P. covacevichae* presence or absence on each survey. Surveys took place between 14th November 2022 and 27th March 2023. This period encompassed drier (presumably less ideal) conditions at the start of the wet season and wetter (ideal) periods during the wet season. The survey period allows quantification of the effect of surveying during drier versus wetter periods (albeit all in the "wet" season).

As *P. covacevichae* breed on the edge of drainage lines, a 100 m transect was established parallel to the drainage line at each site. Each drainage line was intact and continuous over the full 100 m of the transect (i.e., the entire extent of the transect was not intersected by roads or tracks). Transects were marked by reflective tape at 0 m, 50 m and 100 m to ensure the same path was taken at each survey. Surveys were conducted by two observers, who walked the entire transect slowly and listened for calling *P. covacevichae*. Each survey was performed by the same primary observer (E. Rush), while secondary observers varied. Along each transect, the location of calling individuals was recorded. Because of accessibility and logistic requirements

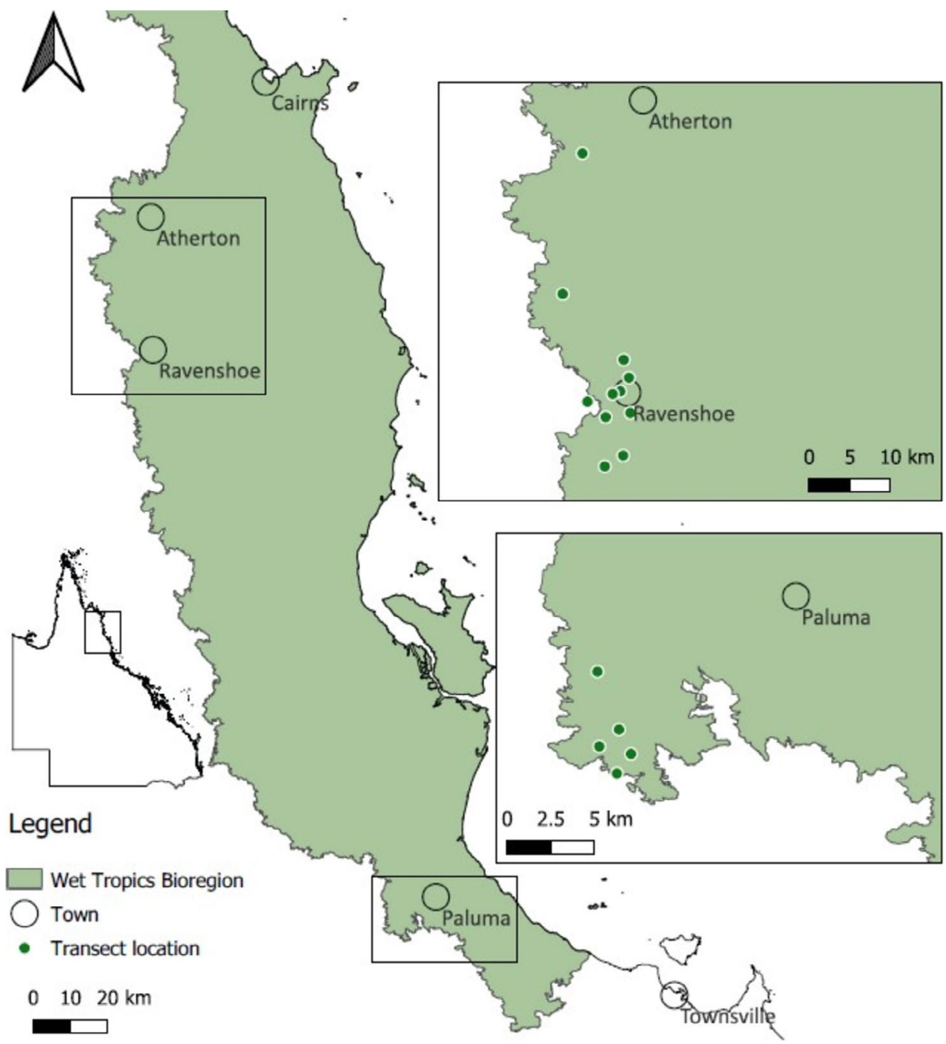

FIGURE 1 | Map of the study area in north Queensland (inset far left). Survey sites located in the Atherton Tablelands region are shown in the inset at the top right and those in the Paluma region in the inset below.

FIGURE 2 | Example of the habitat where aural surveys for *Pseudophryne covacevichae* occurred.

associated with geographically dispersed locations, sites were clustered into groups of three or four sites, and a single cluster was surveyed on the same evening (Canessa et al. 2012). Surveys began at least 40 min after sunset, and all surveys were completed by 23:30. Where possible, the starting time for assessing transects was altered for repeated surveys (i.e., no single site was always the first site surveyed). The duration of a survey varied and was considered complete when the entire transect had been walked and the survey-level variables were recorded. Most sites were surveyed three times over the sampling period. However, due to access issues associated with rainfall, only two repeat survey visits were possible for two of the sites, and only one survey was possible for one of the sites.

2.3 | Survey-Level Variables

At the time of each survey, seven survey-level variables we considered potentially important in determining the calling behaviour of *P. covacevichae* were measured. These variables were: ambient temperature (A), relative humidity (RH), presence of water (W*p*), water temperature (W*t*), volumetric soil water (VSW), total accumulated daily rainfall from the start of the wet season (Racc) and 5 days preceding rainfall (5DR). Ambient temperature (°C) and relative humidity (%) were measured using a Hobo Temperature and Humidity Bluetooth data logger (MX2301A). The presence and amount of water was noted on a categorical scale (i.e., nil, pools, trickle, running, stagnant) and, if water was present, water temperature (°C) was measured using a Hannah pH tester (HI98127). Volumetric soil water (%) (referred to as 'soil moisture') was measured using an ICT Moisture Sensor (MPKit406). This was estimated as the mean of nine measurements: three measurements each taken at three marked points along the transect (0 m, 50 m 100 m). The moisture sensor was inserted into a small, cleared patch of soil (i.e., devoid of grass and leaves) approximately 50–100 cm from the edge of the breeding habitat.

Rainfall data were calculated post-surveys. Data were derived from the Bureau of Meteorology data for weather stations at Ravenshoe (station number 031200) and Paluma (station number 032064). Total accumulated daily rainfall was calculated from the onset of the 2022 wet season (deemed November 1, 2022; (BOM 2023)). It was used to assess detection as a function of wet-season intensity (e.g., total rainfall since the start of the wet season to the survey date). This variable was highly correlated to the number of days since the start of the wet season; hence, it may also be considered as an indicator for the time since the wet season began. The other rainfall variable (5 days preceding rainfall; 5DR) was selected to assess detection probabilities associated with rainfall effects resolved at a shorter temporal scale. This was calculated as the total accumulated daily rainfall in the 5 days prior to a survey (excluding the survey date).

3 | Statistical Analysis

Detection results were compiled into a detection/non-detection matrix. Water temperature (W*t*) was excluded from the analysis because it was sometimes absent at sites and, as such, introduced too many missing values. We began by assessing collinearity between the six remaining survey-level variables by constructing a binomial generalised linear model (GLM) with presence/absence as the response variable and all six survey-level variables as predictor variables. We used the variance inflation factor (VIF) to examine multicollinearity among the predictor variables. Results indicated high collinearity between the presence of water (W*p*) and 5 days preceding rainfall (5DR) (VIF estimates > 3.0). We opted to retain 5DR because of its potential use as a remote trigger for survey initiation, whereas water presence was an arbitrary and irregular on-site measurement. All other variables were retained, leaving five survey-level variables to estimate detection probability.

To examine the influence of the survey-level variables on the probability (p) of detecting *P. covacevichae*, we used single-season occupancy models developed by MacKenzie et al. (2002), using the package Unmarked (version 1.3.2.9) (Fiske and Chandler 2011). Unmarked uses a maximum likelihood approach to estimate the proportion of sites occupied by a species based on presence and absence data, adjusted for detection probabilities less than 1.0 (MacKenzie et al. 2002; Wintle et al. 2012). To meet the assumptions of the model, a site must fit the following criteria: (1) the species occupies the site for the entire duration of sampling; (2) the species is correctly identified; (3) the probability of detecting the species at a site is independent of other sites and (4) the probability of occupancy is constant across sites or a function of the site covariates (MacKenzie et al. 2002). At the completion of surveys, it became apparent that *P. covacevichae* did not occupy two of the sites. This was confirmed by data from bioacoustic recorders that were deployed for a concurrent study. These two sites were removed (one from the Atherton Tablelands and one from Paluma Range). Additionally, the site that was surveyed only once (on the Atherton Tablelands) was also removed, as Unmarked requires at least two survey repetitions per site for inclusion. This reduced the dataset from 16 sites (44 surveys) to 13 sites (37 surveys): nine sites in the Atherton Tablelands region and four in the Paluma Range.

All survey-level variables were standardised (via Z-score transformation). A null model, assuming both constant occupancy and constant detection (i.e., with no predictors) was produced, against which models involving environmental predictors were assessed. Initially, univariate models for each predictor variable were generated. Model performance was then compared to the null model, using Akaike's information criterion (AIC) and ΔAIC. The *p*-value was also assessed for support. Comparing the AIC of a univariate model to the null was used to assess whether the addition of a predictor variable improved model performance while balancing goodness of fit and model complexity. Models with predictor variables returning an AIC value lower than the null were considered potential candidates for explaining the detection of *P. covacevichae*. Models were produced on a logit scale and back-transformed to a probability scale for ease of interpretation.

Detection was then modelled as a function of variables retained from the above process, with occupancy held constant. We constructed models using all possible combinations of the remaining variables and compared their suitability as hypotheses describing detection, using the dredge function in the R package *MuMIn* (Barton 2009), via ΔAIC and Akaike weight (AIC*w*). Models returning ΔAIC values < 2 were considered to have equally significant support (Burnham and Anderson 2002).

The survey-level variables identified as important in determining detection were then integrated into a detection analysis, using a Bayesian framework, examining the relationship between environmental conditions and the probability of correctly identifying occupancy and survey effort (number of surveys). We categorised standardised survey-level variables into 'poor' (5th percentile), 'average' (50th percentile) and 'excellent' (95th percentile) conditions. A single-season occupancy model implemented via the BUGS language (Lunn et al. 2000), with Markov Chain Monte Carlo (MCMC) methods, was then generated. The analysis was conducted within the framework of JAGS (Plummer 2003) via the R package jagsUI (Kellner 2016).

Detection probabilities were derived from the fixed-effect coefficients (betas) of the model output. For each posterior sample, we calculated the logit of detection probability, incorporating both linear and quadratic terms for the retained survey-level variables. The probability of detecting *P. covacevichae* at least once in n surveys (p*) was calculated for each condition using $1—(1—p)^n$, where p represents detection probability (corresponding to the condition) and n is survey number (1–6). This formula accounts for the cumulative nature of detection across multiple surveys and incorporates the uncertainty from posterior distributions in predicted outcomes.

Models were run using three MCMC chains of 30,000 iterations, with a burn-in of 20,000 iterations and a thin rate of 10, yielding 3000 samples from the posterior distributions for each simulated survey number. Vague, uninformative priors were used to initiate the model fitting to ensure preconceived perceptions were not influential in final outcome estimates (Zuur et al. 2012). Model convergence was assessed and confirmed by examining trace plots and Gelman-Rubin diagnostics (Gelman and Rubin 1992; Gelman et al. 1995), which were < 1.1 for all parameters.

All analyses were implemented within the R programming environment, version 4.2.0 (R Core Team 2023).

4 | Results

Calling male *P. covacevichae* were detected in 22 of the 37 surveys and at least once at 11 of the 13 sites. The time to complete a survey ranged from 12 to 28 min, with an average of 17 min. The surveys that occurred in November ($n = 4$), at the start of the wet season, did not detect any frogs. Those surveys had minimal total rainfall accumulation (50 mm), 5 days prior rainfall totals of approximately 10 mm and soil moisture volume of 10% or less.

The results of the univariate models showed that only volumetric soil moisture (VSW) and 5 days preceding rainfall (5DR) were better than the null model in describing the data, based on the evaluation of AIC and ΔAIC (Table 1). Specifically, the model incorporating VSW exhibited the highest support, with an AIC of 42.57 (ΔAIC 0.00) and a *p*-value of 0.01. This was followed by the model that included 5DR alone, which had an AIC of 50.06 (ΔAIC 7.49). The *p*-value associated with this model was slightly higher than 0.05; however, under the information theoretical approach (i.e., AIC), it should still be considered a plausible explanation for the data (Burnham and Anderson 2002). The null model, representing the absence of any predictor variables, yielded an AIC of 51.90 (ΔAIC 9.33), indicating weaker support than VSW and 5DR. In contrast, models incorporating temperature (T), accumulated rainfall (Racc) and relative humidity

TABLE 1 | The null and univariate models used to determine the relative strength of each survey-level variable in the detection probability of *Pseudophryne covacevichae*.

Model	ΔAIC	AIC	Detection coefficient estimate	SE	95% CI	*p*
Ψ(.), *p*(VSW)	0.00	42.57	0.68	0.17	0.34–1.00	0.01
Ψ(.), *p*(5DR)	7.49	50.06	0.70	0.10	0.50–0.89	0.07
Ψ(.), *p*(.)	9.33	51.90	0.69 (intercept)	0.09	0.48–0.83	0.07
Ψ(.), *p*(T)	9.49	52.06	0.68	0.09	0.50–0.86	0.07
Ψ(.), *p*(Racc)	11.02	53.59	0.69	0.09	0.50–0.88	0.17
Ψ(.), *p*(RH)	11.03	53.60	0.68	0.08	0.51–0.84	0.59

Note: Occupancy probability (Ψ) was held constant in all models and detection probability (p) was measured as a function of predictor variables. Values represent detection coefficients only and are on a probability scale. Shaded rows show model fits (AIC), where the inclusion of survey-level variables reduced model AIC below that of the null model.

(RH) showed AIC values larger than the null and ΔAIC exceeding 9.00, indicating the inability of these models to explain the data better than the null. As such, these variables were excluded from further analysis.

TABLE 2 | Comparison of all model combinations, based on the final model, for the evaluation of factors determining *Pseudophryne covacevichae* detection.

Model	ΔAIC	AIC*w*	Log-likelihood	df
Ψ(.), *p*(*VSW*)	0.00	0.65	−18.284	3
Ψ(.), *p*(*VSW* + *5DR*)	1.36	0.33	−17.965	4
Ψ(.), *p*(*5DR*)	7.49	0.02	−22.029	3
Ψ(.), *p*(.)	9.34	0.01	−23.952	2

When both VSW and 5DR were included together in a single model, comparison based on AIC showed the most support for the model that included volumetric soil moisture alone (ΔAIC 0.0, AIC*w* 0.65, Table 2). The second most supported model for detection included both VSW and 5DR, with the ΔAIC suggesting this combination has support as a possible explanation of the data (ΔAIC 1.36, AIC*w* 0.33). These two top models represent a combined relative likelihood (AIC*w*) of ~98%, indicating that variation in detection (i.e., *P. covacevichae* calling) was better explained by VSW or a combination of VSW and 5DR. The model including only 5DR (ΔAIC 7.49, AIC*w* 0.02) and the null model (ΔAIC 9.34, AIC*w* 0.01) had very little support as potential explanations for the data.

The estimate of detection probability with 95% confidence intervals, based on VSW alone, was 0.68 (0.34–1.00). This translates to a steep increase in detection with rising VSW, most pronounced from 20% VSW onward (Figure 3a). As an example,

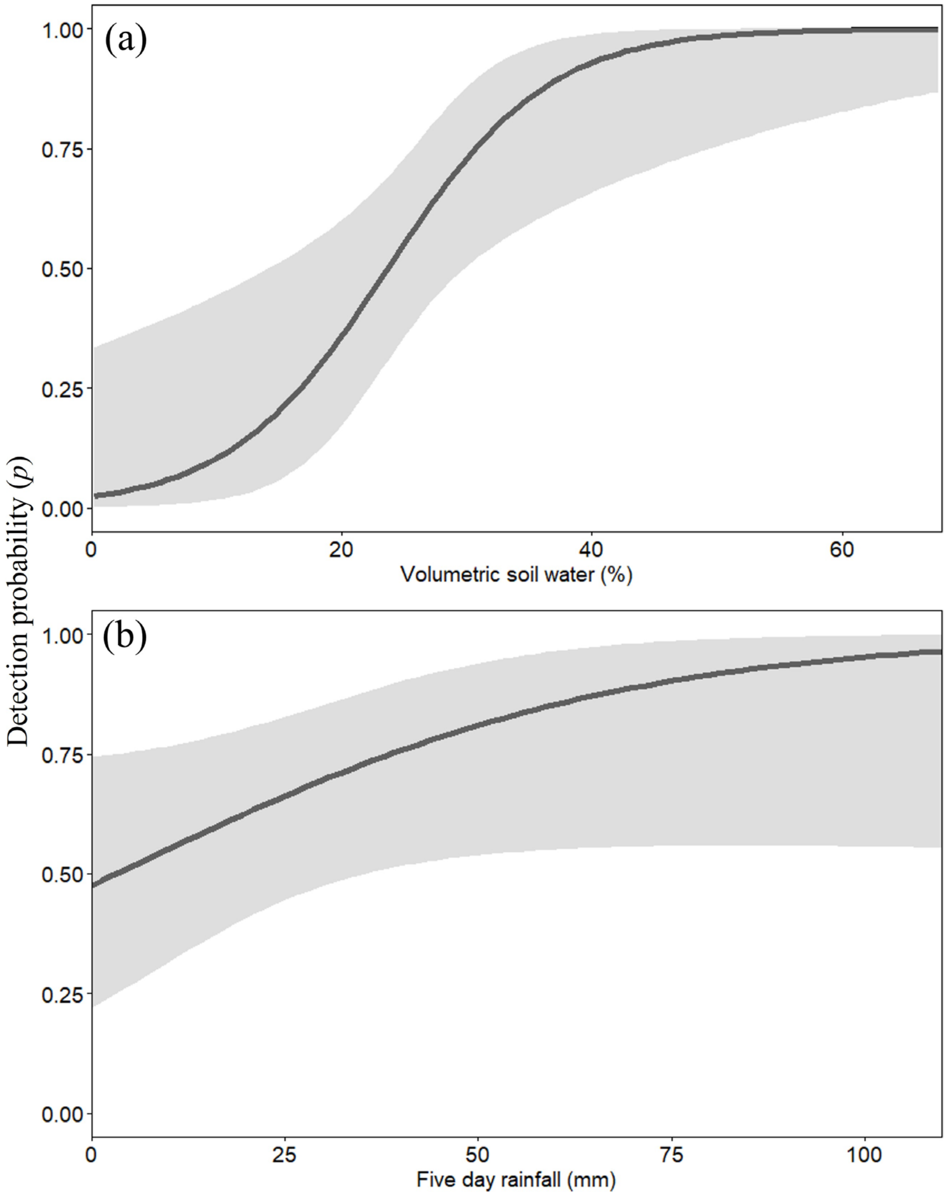

FIGURE 3 | The relationship between the probability of detecting *Pseudophryne covacevichae* when present at a site and survey-level variables: (a) volumetric soil moisture and (b) 5 days preceding rainfall. The light grey ribbon represents 95% confidence intervals.

the estimated probability of detecting *P. covacevichae* at 10% soil moisture was 0.10 (~10%) whereas this had risen to 0.98 (~98%) at 50% soil moisture. Though the relationship was not as strong, 5DR was a contributor to the second most supported model and should be considered when complemented by VSW. The estimate of detection probability based on 5DR alone, with 95% confidence intervals, was 0.70 (0.50–0.89). Detection probability increased marginally with the influence of rising rainfall, peaking at 75 mm until it gradually plateaued (Figure 3b). For example, the estimated probability of detecting *P. covacevichae* was 0.55 (~55%) following 10 mm of rainfall and 0.90 (~90%) following 75 mm of prior rainfall over five days. However, there was no strong differentiation in the confidence intervals associated with this result, and detection probability estimates have the potential to overlap across the rainfall gradient (e.g., 0–100 mm). This is a stark comparison to the VSW model where there is a clear upward trend and confidence intervals associated with the estimates do not overlap.

Refitting VSW and 5DR using MCMC methods allowed for the probability of detecting *P. covacevichae* at least once under poor, average and excellent conditions to be calculated. These conditions corresponded to VSW values of 8.73%, 26.92% and 50.74% (5th, 50th and 95th respectively) and 5DR values of 1.90 mm, 21.00 mm and 92.00 mm (5th, 50th and 95th). Detection probabilities were strongly influenced by the different environmental conditions, with notable variation observed across the simulated cumulative survey effort (Figure 4).

Under excellent conditions (e.g., high values of both VSW and 5DR) detection probabilities were consistently high. For a single survey, the median detection probability was 0.99 (99%) with a narrow range in the posterior distributions, indicating confidence in these predictions. The certainty increased further, reaching 1.0 (100%) in all subsequent surveys. In contrast, under average conditions, a single survey had a median detection probability of 0.66 (66%), though the posterior probabilities varied widely, suggesting uncertainty in this prediction. Following three surveys in average conditions, the detection probability increased to 0.96 (96%) and 60% of all posterior distributions fell above 95%, indicating a substantial increase in certainty. After four surveys, the median detection probability was 98%, and 86% of the posteriors fell above 95%; this certainty increased further in surveys five and six. In contrast, in poor conditions (e.g., low values of VSW and 5DR) the median probability of detection ranged from just 0.07 (7%) in a single survey to 0.37 (37%) after six surveys. The posterior distributions across all six simulated surveys under poor conditions ranged broadly, showing that confidence in detection under these conditions was low.

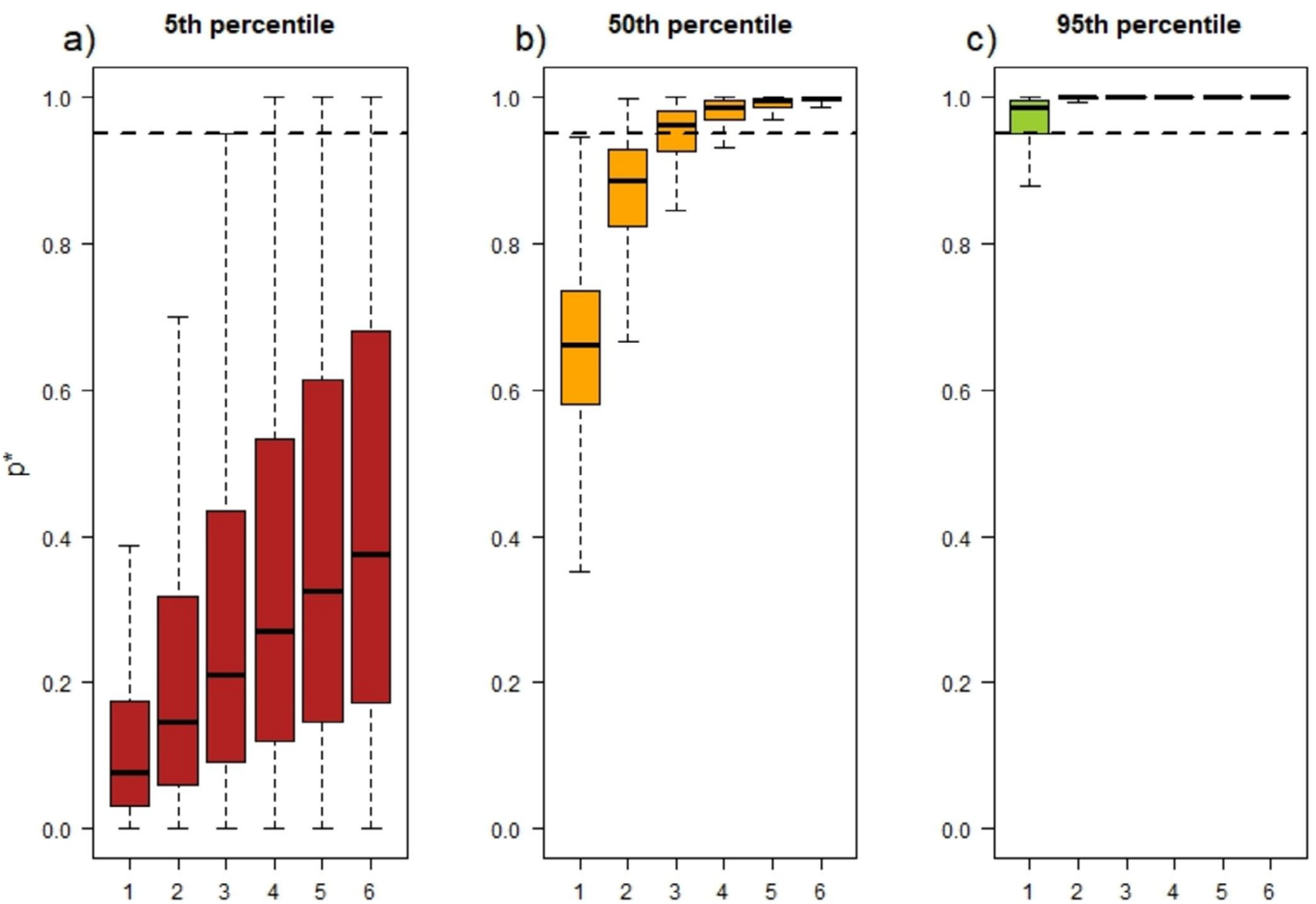

FIGURE 4 | Cumulative probability of detecting *Pseudophryne covacevichae* at least once (p*) over six surveys under 'poor', 'average' and 'excellent' environmental conditions based on soil moisture and 5 days preceding rainfall data: the 5th percentile (panel a), the 50th percentile (panel b) and the 95th percentile (panel c), respectively. The boxplots identify the 10th and 90th percentiles (error bars), the 25th and 75th percentiles (box) and the median concentration (bold line). The dashed line indicates the level where the distribution of posterior probabilities exceeds 0.95 certainty.

5 | Discussion

We investigated the environmental factors influencing *P. covacevichae* detection probability in known populations of north Queensland. Further, we used these variables to estimate the overall probability of detecting *P. covacevichae* over 1–6 surveys, under three environmental scenarios to provide confidence of presence or absence at a site. The results showed that of the survey-level variables, soil moisture was the strongest predictor of calling behaviour. The second strongest predictor was rainfall accumulation in the five days before a survey took place. As would be expected for a semi-terrestrial breeding species like *P. covacevichae*, both these variables had a positive influence on detection probability. These results suggest that survey timing is critical for optimising detection rates for *P. covacevichae*. In addition to the timing of surveys, we demonstrated the influence soil moisture and preceding rainfall conditions can have on the number of surveys (i.e., survey effort) required to confidently determine the species' true absence at a location. Confidence in detecting the species can be increased by surveying under excellent or average conditions where one to three surveys, respectively, would provide above 95% confidence in detection probability. Our results emphasise the importance of robust survey protocols that are targeted specifically to a species to better estimate their presence or absence. This is particularly important for species with restricted distributions, low abundance or irregular calling patterns, where single surveys may fail to detect them.

Higher soil moisture increased the detectability of *P. covacevichae*, suggesting that soil moisture serves as a cue for reproduction. This corroborates with the breeding biology of other *Pseudophryne* species (Pengilley 1966; Woodruff 1976; Bradford and Seymour 1988; Byrne 2008), including Bibron's toadlets (*Pseudophryne bibronii*) which produce advertisement calls at a greater rate when occupying wetter nests and actively select wetter substrates for nest sites (Mitchell 2001; O'Brien et al. 2020). This is due to the frogs' permeable egg capsules requiring moisture for successful embryonic development and to avoid desiccation (Bradford and Seymour 1988; Mitchell 2002; Andrewartha et al. 2008). Drier soils have detrimental effects on *Pseudophryne* hatchlings, leading to smaller-sized metamorphs, diminished survival rates and overall increased risk of desiccation (Pengilley 1966; Bradford and Seymour 1988; Eads et al. 2012). Given that *P. covacevichae* eggs require an ~11 days development period on land (Anstis 2017), it is reasonable to conclude that soil moisture would be the most influential proximate variable in their calling behaviour and thus detectability.

Likewise, rainfall plays a pivotal role in the reproductive strategy of semi-terrestrial anurans like *Pseudophryne*, as they depend on consistent precipitation throughout the breeding season to moisten soil, inundate terrestrial nests and provide the standing water necessary for subsequent tadpole development (Pengilley 1966). In our study, *P. covacevichae* was not detected during surveys that occurred in November. This result reflects the timing of surveys early in the wet season when sufficient rain to sustain soil moisture and support reproduction had not yet occurred. A caveat associated with the use of this rainfall data is that BOM data provides coarse estimates of rainfall that may not accurately reflect the local rainfall for the survey sites. Ideally, more localised rainfall data would be used to calculate these estimates.

The association between rainfall in the days leading to a survey and *P. covacevichae* detectability is consistent with previous research showing the positive influence of rainfall on *Pseudophryne* calling and breeding (Pengilley 1971; White 1993; Terry 2022). Some *Pseudophryne* species are obligate seasonal breeders and others, like the red-crowned toadlet (*Pseudophryne australis*), exhibit opportunistic breeding, where they call and deposit eggs year-round in response to sufficient rainfall (Thumm and Mahony 2002). Though *P. covacevichae* has a fairly predictable breeding season when rainfall occurs in Spring and Summer, they appear to exhibit opportunistic breeding at other times of the year if sufficient rainfall has occurred (E. Rush personal observation 2023). Our results demonstrate a 76% detection probability of *P. covacevichae* following 40 mm of rainfall in the preceding five days, compared to only 20% following 10 mm. However, this relationship should be interpreted in conjunction with soil moisture. The influence of 40 mm of rainfall outside of the wet season, when soil moisture is typically lower, is unlikely to yield the same influence on *P. covacevichae* detection.

Conversely, ambient temperature and relative humidity were not found to have a significant influence on *P. covacevichae* calling behaviour, aligning with observations of *P. australis*, which calls between a temperature range of 5°C–30°C (NSW NPWS 2001). Similarly, total rainfall accumulation showed no discernible impact on the probability of detecting *P. covacevichae*. This was unexpected, considering rainfall accumulation would presumably reflect the overall soil moisture levels in the region. A more comprehensive investigation into the influence of rainfall accumulation (and consequently, days since the onset of the wet season) that included event magnitudes and frequencies would be beneficial in elucidating its impact and facilitating predictions regarding the optimal timing of surveys.

While soil moisture was the strongest predictor of *P. covacevichae* detection, it is not a standard measure in most field surveys and requires specialised equipment and on-site visits. We suggest rainfall is the easiest measure to efficiently synchronise surveys to enhance detection predictions. Our results suggest that rainfall in the five days prior can be a co-predictor of detection when associated with soil moisture (refer Table 2); however, the use of this variable alone requires further refinement to ensure its accuracy as a remote trigger to initiate surveys. Additionally, investigating the influence of very high rainfall on detection probability would be valuable, as prolonged inundation of the narrow drainage lines appears to initially reduce *P. covacevichae* calling activity (E. Rush observation, 2023), potentially due to the calling sites being temporarily underwater. We attempted to capture this in the presence and volume of water on site, but its correlation with 5 days prior rainfall meant it could not be analysed.

We found that cumulative detection probability was highly influenced by soil moisture and 5 days prior rainfall, with substantial differences observed under lower versus average to higher values of the two variables. Under poor conditions, marked by low soil moisture and prior rainfall, confidence in detection would be unreliable, with less than 40% probability after six surveys. In contrast, three surveys in average conditions would ensure 95% confidence of the species absence at a location. This result is in line with the survey protocols for Australia's threatened frogs that recommend four repeat surveys for *P. covacevichae* during the wet season (DEWHA 2010). A primary limitation to our analysis is the dynamic nature of the tropical wet season, where environmental conditions can fluctuate daily and will change vastly through the breeding season of *P. covacevichae*. Conditions will rarely align with our simulated data; however, understanding how variation in these survey-level variables influences detection probability will provide a useful guide in planning survey efforts and, importantly, provide a framework for determining the appropriate number of repeat surveys to confidently determine true absence.

At two of our sites, *P. covacevichae* were not detected during the surveys, but they were heard calling at these sites either outside of the transect or outside of the recorded survey period (e.g., while walking toward the site) on at least one of the three surveys. Their non-detection during the time of the survey, within the transect, exemplifies how unpredictable the species calling activity can be, specifically during drier conditions. Considering the irregular calling behaviour of *P. covacevichae*, coupled with high habitat specificity and low abundance, relying solely on single surveys to determine occupancy, particularly in suboptimal environmental conditions, is likely to greatly underestimate the species' presence in a location.

While populations of *P. covacevichae* do occur on protected tenure (Nature Refuge and National Park), particularly those in the south, the majority of known populations occur in unprotected tenure (e.g., private land, State Forest and Forest Reserve). The prospect of widespread industrial development in north Queensland (DEC 2023; GEM 2024) raises questions about habitat alteration in unprotected areas within the range of this species and others. Though the effects of new infrastructure developments on *P. covacevichae* populations are unknown, in other related species, including *P. australis*, they have impacted habitat quality through direct habitat loss, fragmentation, sedimentation and hydrological changes (Thumm and Mahony 1999; Stauber 2006; Cummins et al. 2019). Hence, infrastructure developments are considered a potential threat to *P. covacevichae*.

Our results aid in improving the likelihood of detection for *P. covacevichae* by indicating the environmental conditions in which to conduct surveys as well as providing more certainty around the number of surveys required to infer true presence or absence. Additionally, our results postulate that the total rainfall during the previous five days increases detection probability when paired with high soil moisture levels resulting from the ongoing wet season, suggesting a potential remote trigger for survey initiation. As such, we recommend surveys for *P. covacevichae* correspond with extended rainfall activity over the wet season, the timing of which can vary annually, to ensure soil moisture is elevated and following five days of consistent rainfall at or above 40 mm. Importantly, environmental conditions at the time of surveying should be considered where an absence is recorded, and where necessary, additional surveys should be conducted to provide confidence that the species is truly absent and not simply undetected.

Author Contributions

Emily Rose Rush: conceptualization, data curation, formal analysis, funding acquisition, methodology, project administration, writing – original draft, writing – review and editing. **Conrad J. Hoskin:** conceptualization, funding acquisition, methodology, supervision, writing – review and editing. **Will Edwards:** conceptualization, formal analysis, methodology, supervision, writing – original draft, writing – review and editing.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Andrewartha, S. J., N. J. Mitchell, and P. B. Frappell. 2008. "Phenotypic Differences in Terrestrial Frog Embryos: Effect of Water Potential and Phase." *Journal of Experimental Biology* 211: 3800–3807.

Anstis, M. 2017. *Tadpoles and Frogs of Australia*. New Holland Publishers Pty Limited.

Ark Energy. 2024. *Wooroora Station Wind Farm*. https://arkenergy.com.au/wind/wooroora-station-wind-farm/ [Accessed 02/04/2024].

Attexo. 2021. *MNES Assessment Report Chalumbin Wind Farm Project*, edited by N. O'donnell. Prepared for Epuron Projects Pty Ltd.

Barton, K. 2009. MuMIn: Multi-Model Inference. http://r-forge.r-project.org/projects/mumin/.

BOM. 2023. *Northern Rainfall Onset*. Australian Government. http://www.bom.gov.au/climate/rainfall-onset/#tabs=About-the-rainfall-onset [Accessed].

Bradford, D. F., and R. S. Seymour. 1988. "Influence of Water Potential on Growth and Survival of the Embryo, and Gas Conductance of the Egg, in a Terrestrial Breeding Frog, Pseudophryne Bibroni." *Physiological Zoology* 61: 470–474.

Bridges, A. S., and M. E. Dorcas. 2000. "Temporal Variation in Anuran Calling Behavior: Implications for Surveys and Monitoring Programs." *Copeia* 2000: 587–592.

Burnham, K., and D. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*. Springer.

Byrne, P. G. 2008. "Strategic Male Calling Behavior in an Australian Terrestrial Toadlet (*Pseudophryne bibronii*)." *Copeia* 2008: 57–63.

Canessa, S., G. W. Heard, K. M. Parris, and M. A. McCarthy. 2012. "Integrating Variability in Detection Probabilities When Designing Wildlife Surveys: A Case Study of Amphibians From South-Eastern Australia." *Biodiversity and Conservation* 21: 729–744.

Cummins, D., W. J. Kennington, T. Rudin-Bitterli, and N. J. Mitchell. 2019. "A Genome-Wide Search for Local Adaptation in a Terrestrial-Breeding Frog Reveals Vulnerability to Climate Change." *Global Change Biology* 25: 3151–3162.

de Solla, S. R., L. J. Shirose, K. J. Fernie, G. C. Barrett, C. S. Brousseau, and C. A. Bishop. 2005. "Effect of Sampling Effort and Species Detectability on Volunteer Based Anuran Monitoring Programs." *Biological Conservation* 121: 585–594.

DEC. 2023. *Queensland's Renewable Energy Target*. Queensland Government. Available. https://www.epw.qld.gov.au/about/initiatives/renewable-energy-targets#:~:text=The%20Queensland%20renewable%20energy%20target,exceeds%2050%25%20of%20Queensland's%20consumption [Accessed 19/02/2023].

DEWHA. 2010. "Survey Guidelines for Australia's Threatened Frogs." In *Department of the Environment*, edited by W. Heritage and The Arts. Australian Government.

Dostine, P. L., S. J. Reynolds, A. D. Griffiths, and G. R. Gillespie. 2013. "Factors Influencing Detection Probabilities of Frogs in the Monsoonal Tropics of Northern Australia: Implications for the Design of Monitoring Studies." *Wildlife Research* 40: 393–402.

Eads, A. R., N. J. Mitchell, and J. P. Evans. 2012. "Patterns of Genetic Variation in Desiccation Tolerance in Embryos of the Terrestrial-Breeding Frog, *Pseudophryne guentheri*." *Evolution* 66: 2865–2877.

Fiske, I., and R. Chandler. 2011. "Unmarked: An R Package for Fitting Hierarchical Models of Wildlife Occurrence and Abundance." *Journal of Statistical Software* 43: 1–23.

Freeman, A. 2001. *Monitoring of the Magnificent Broodfrog, December 2000 to March 2001*. Queensland Parks and Wildlife Service.

Freeman, A. 2012. *A Monitoring Survey Report and Plan for the Magnificent Broodfrog (Pseudophyrne Covacevichae)*, edited by Unit T.S. Department of Environment and Resource Management.

Garrard, G. E., S. A. Bekessy, M. A. McCARTHY, and B. A. Wintle. 2008. "When Have We Looked Hard Enough? A Novel Method for Setting Minimum Survey Effort Protocols for Flora Surveys." *Austral Ecology* 33: 986–998.

Garrard, G. E., S. A. Bekessy, M. A. McCarthy, and B. A. Wintle. 2015. "Incorporating Detectability of Threatened Species Into Environmental Impact Assessment." *Conservation Biology* 29: 216–225.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin. 1995. *Bayesian data analysis*. Chapman and Hall/CRC.

Gelman, A., and D. B. Rubin. 1992. "Inference From Iterative Simulation Using Multiple Sequences." *Statistical Science* 7: 457–472.

GEM. 2024. *Global Wind Power Tracker*. Global Energy Monitor. https://globalenergymonitor.org/projects/global-wind-power-tracker/ Accessed 03/04/2024.

Geyle, H. M., C. J. Hoskin, D. S. Bower, et al. 2021. "Red Hot Frogs: Identifying the Australian Frogs Most at Risk of Extinction." *Pacific Conservation Biology* 28: 211–223.

Gillespie, G. R., J. D. Roberts, D. Hunter, et al. 2020. "Status and Priority Conservation Actions for Australian Frog Species." *Biological Conservation* 247: 108543.

Gu, W., and R. K. Swihart. 2004. "Absent or Undetected? Effects of Non-detection of Species Occurrence on Wildlife–Habitat Models." *Biological Conservation* 116: 195–203.

Heard, G. W., P. Robertson, and M. P. Scroggie. 2006. "Assessing Detection Probabilities for the Endangered Growling Grass Frog (*Litoria raniformis*) in Southern Victoria." *Wildlife Research* 33: 557–564.

Ingram, G., and C. Corben. 1994. "Two New Species of Broodfrogs (*Pseudophryne*) From Queensland." *Memoirs of the Queensland Museum* 37: 267–272.

IUCN. 2021. "Magnificent Broodfrog, *Pseudophryne covacevichae*." *IUCN Red List of Threatened Species* 2022: eT41048A78437322. https://doi.org/10.2305/IUCN.UK.2022-2.RLTS.T41048A78437322.en [Accessed 18/01/2024].

Kellner, K. 2016. *jagsUI: A Wrapper Around 'Rjags' to Streamline 'JAGS' Analyses*. https://github.com/kenkellner/jagsUI [Accessed 08/02/2024].

Luedtke, J. A., J. Chanson, K. Neam, et al. 2023. "Ongoing Declines for the World's Amphibians in the Face of Emerging Threats." *Nature* 622: 308–314.

Lunn, D. J., A. Thomas, N. Best, and D. Spiegelhalter. 2000. "WinBUGS-a Bayesian Modelling Framework: Concepts, Structure, and Extensibility." *Statistics and Computing* 10: 325–337.

MacKenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew Royle, and C. A. Langtimm. 2002. "Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One." *Ecology* 83: 2248–2255.

McClintock, B. T., L. L. Bailey, K. H. Pollock, and T. R. Simons. 2010. "Unmodeled Observation Error Induces Bias When Inferring Patterns and Dynamics of Species Occurrence via Aural Detections." *Ecology* 91: 2446–2454.

McDonald, K. R. 2002. *Recovery Plan for the Magnificent Broodfrog Pseudophryne Covacevichae 2000–2004*. Environmental Protection Agency.

MFEP. 2022. *Mt Fox Site Detail*. https://www.mtfoxenergypark.com.au/home/project-details [Accessed 22/03/2023].

Mitchell, N. J. 2001. "Males Call More From Wetter Nests: Effects of Substrate Water Potential on Reproductive Behaviours of Terrestrial Toadlets." *Proceedings of the Royal Society of London. Series B: Biological Sciences* 268: 87–93.

Mitchell, N. J. 2002. "Low Tolerance of Embryonic Desiccation in the Terrestrial Nesting Frog *Bryobatrachus nimbus* (Anura: Myobatrachinae)." *Copeia* 2002: 364–373.

Neldner, V., M. Laidlaw, K. R. McDonald, et al. 2017. *Scientific Review of the Impacts of Land Clearing on Threatened Species in Queensland*. Department of Science, Information Technology and Innovation Brisbane.

Neoen. 2024. *Clean Energy for Queensland*. https://kabangreenpowerhub.com.au/ [Accessed 02/03/2024].

NSW NPWS. 2001. *Environmental Impact Assessment Guideline: Red-crowned Toadlet*. Service, NSW National Parks & Wildlife Service.

O'Brien, D. M., A. J. Silla, and P. G. Byrne. 2020. "Nest Site Selection in a Terrestrial Breeding Frog: Interrelationships Between Nest Moisture, pH and Male Advertisement." *Animal Behaviour* 169: 57–64.

Pellet, J. M., and B. R. Schmidt. 2005. "Monitoring Distributions Using Call Surveys: Estimating Site Occupancy, Detection Probabilities and Inferring Absence." *Biological Conservation* 123: 27–35.

Pengilley, R. 1971. "Calling and Associated Behaviour of Some Species of Pseudophryne (Anura: Leptodactylidae)." *Journal of Zoology* 163: 73–92.

Pengilley, R. K. 1966. *The Biology of Species of the Genus Pseudophryne (Anura: Leptodactylidae)*. Australian National University.

Penman, T. D., F. L. Lemckert, and M. J. Mahony. 2006. "Meteorological Effects on the Activity of the Giant Burrowing Frog (*Heleioporus australiacus*) in South-Eastern Australia." *Wildlife Research* 33: 35–40.

Plummer, M. 2003. "JAGS: A Program for Analysis of Bayesian Graphical Models Using Gibbs Sampling." In Proceedings of the 3rd International Workshop on Distributed Statistical Computing, 124, no. 125: 1–10.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna Austria.

Saenz, D., L. A. Fitzgerald, K. A. Baum, and R. N. Conner. 2006. "Abiotic Correlates of Anuran Calling Phenology: The Importance of Rain, Temperature, and Season." *Herpetological Monographs* 20: 64–82.

Scheele, B. C., G. W. Heard, M. Cardillo, et al. 2023. "An Invasive Pathogen Drives Directional Niche Contractions in Amphibians." *Nature Ecology & Evolution* 7: 1682–1692.

Schmidt, B. R., S. S. Cruickshank, C. Bühler, and A. Bergamini. 2023. "Observers Are a Key Source of Detection Heterogeneity and Biased Occupancy Estimates in Species Monitoring." *Biological Conservation* 283: 110102.

Simmonds, J. S., A. E. Reside, Z. Stone, J. C. Walsh, M. S. Ward, and M. Maron. 2020. "Vulnerable Species and Ecosystems Are Falling Through the Cracks of Environmental Impact Assessments." *Conservation Letters* 13: e12694.

Stauber, A. 2006. Habitat requirements and habitat use of the red-crowned Toadlet Pseudophryne australis and the giant burrowing frog *Heleioporus australiacus* in the Sydney basin.

Tanadini, L. G., and B. R. Schmidt. 2011. "Population Size Influences Amphibian Detection Probability: Implications for Biodiversity Monitoring Programs." *PLoS One* 6: e28244.

Terry, W. 2022. "A Note on the Calling Behaviour of Brown Toadlet, *Pseudophryne bibronii*, at a Site in Central Victoria." *Australian Zoologist* 42: 733–737.

Thumm, K., and M. Mahony. 1999. "Loss and Degradation of Red-Crowned Toadlet Habitat in the Sydney Region." *Declines and Disappearances of Australian Frogs*: 99–108.

Thumm, K., and M. Mahony. 2002. "Evidence for Continuous Iteroparity in a Temperate-Zone Frog, the Red-Crowned Toadlet, *Pseudophryne australis* (Anura: Myobatrachidae)." *Australian Journal of Zoology* 50: 151–167.

White, A. 1993. "Ecological and Behavioural Observations on Populations of the Toadlets Pseudophryne Coriacea and *Pseudophryne bibronii* on the Central Coast of New South Wales." In *Herpetology in Australia: A Diverse Discipline (ed. D. Lunney & D. Ayers)*: 139–149.

Wildnet. 2022. Wildnet database. https://www.qld.gov.au/environment/plants-animals/species-information/wildnet [Accessed].

Windlab. 2021. *Upper Burdekin Wind Farm*. https://www.windlab.com/our-projects/upper-burdekin-wind-farm/ [Accessed 22/03/2023].

Wintle, B. A., T. V. Walshe, K. M. Parris, and M. A. McCarthy. 2012. "Designing Occupancy Surveys and Interpreting Non-detection When Observations Are Imperfect." *Diversity and Distributions* 18: 417–424.

Woodruff, D. S. 1976. "Courtship, Reproductive Rates, and Mating System in Three Australian Pseudophryne (Amphibia, Anura, Leptodactylidae)." *Journal of Herpetology* 10: 313–318.

Zozaya, S. M., and C. J. Hoskin. 2015. "A Significant Range Extension for the Magnificent Broodfrog '*Pseudophryne covacevichae*', With Comments on Similarity With '*P. major*', and Additional Data on the Distribution of '*Uperoleia altissima*'." *Australian Zoologist* 37: 365–368.

Zuur, A. F., A. A. Saveliev, and E. N. Ieno. 2012. Zero inflated models and generalized linear mixed models with R.