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How soon can the IUCN Red List criteria of Threatened Species detect risks posed by climate change?

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Abstract: *Anthropogenic climate change is a key threat to global biodiversity. To inform strategic actions aimed at conserving biodiversity as the climate changes, conservation planners need early warning about the relative risks faced by different species. The IUCN Red List criteria for Threatened Species is widely acknowledged as useful risk assessment tool for informing conservation under constraints imposed by limited data. However, doubts have been expressed about the ability of the Red List criteria to detect risks imposed by potentially slow-acting threats such as climate change, particularly because criteria addressing rates of population decline are assessed over time scales as short as 10 years. We used spatially explicit stochastic* *population models coupled with dynamic species distribution models projected to future climates to ask how long before extinction a species would become eligible for listing as threatened based on the Red List criteria. In this study, we focussed on a short-lived frog species (*Assa darlingtoni*) chosen specifically to represent potential weaknesses in the criteria to allow detailed consideration of the analytical issues and to develop an approach for wider application. The results suggest that the criteria are more sensitive to climate change than previously anticipated, with lead times between initial listing in a threatened category and predicted extinction varying between 40 and 80 years, depending on data availability. We attribute this sensitivity primarily to the ensemble properties of the criteria, which assess contrasting symptoms of extinction risk. Nevertheless, we recommend that the robustness of the criteria warrants further investigation across species with contrasting life-histories and patterns of decline. The adequacy of these lead times for early warning depends on practicalities of environmental policy and management, bureaucratic or political inertia and the anticipated species response times to adaptation and mitigation actions.*

Key words: extinction risk, IUCN Red List, climate change, amphibian, frog, population model, species distribution model, risk assessment

Word count: 6208

Introduction

Anthropogenic climate change is one of the major global threats to biodiversity, with more than a million terrestrial species potentially 'committed to extinction' by mid-century (Thomas et al. 2004; Parry et al. 2007; Hannah 2012). Accurate predictions of the risks of such losses are vital to motivate and inform effective remedial actions at global and local scales, and to focus specific efforts on species and locations that would benefit most. For these reasons, species at significant risk of extinction as a result of climate change ought to be included on listings of threatened species (Westoby & Burgman 2006).

The IUCN Red List of Threatened Species (e.g. Vie et al. 2009) is widely recognised as an authoritative and reliable global listing in which species are assigned to categories representing different levels of extinction risk (IUCN 2001; Mace et al. 2008). The Red List is based on five quantitative assessment criteria, derived from population theory, that are used to assign species to any of three different threat categories (Critically Endangered, Endangered or Vulnerable) or else an appropriate category for taxa not identified as threatened (Extinct in the Wild, Near Threatened, Least Concern or Data Deficient) (IUCN 2001). Empirical evaluations have shown that the Red List protocol is consistent and predicts extinction risk accurately (e.g. Keith et al. 2004).

Climate change has been identified as a threat to a relatively small fraction of species currently listed as threatened in Australia (Westoby & Burgman 2006) and globally (Vie et al. 2009), yet distribution modelling (Thomas et al. 2004; Hof et al. 2011) and trait analyses (Foden et al. 2013) suggest that more taxa are at risk. For example, one-quarter of the world's bird and amphibian taxa and half of all coral taxa were found to possess traits that make them susceptible to climate change, but these taxa are not currently listed as threatened (Foden et al. 2013). There could be several explanations for this discrepancy. Firstly, many taxa that are potentially susceptible to climate change may presently appear safe from extinction due to limited exposure to climate change or lagged responses (Foden et al. 2013). Secondly, assessors may be reluctant to consider climate change as a threat to specific taxa due to high levels of uncertainty about both the magnitude of future climate change and its ecological effects (Westoby & Burgman 2006). Thirdly, climate change may act in concert with other, more readily identified threats (Hof et a. 2012). Finally, the Red List criteria may not be well suited to detection of climate change threats (Hannah 2012).

One of the Red List's most important roles is as an 'early-warning' system that identifies species at most immediate risk to inform priorities for conservation action (Vie et al. 2009). To perform this role effectively, the Red List criteria should identify species at risk of extinction with some lead time in advance of the expected extinction event, irrespective of its cause. The Red List criteria assess declines over time horizons that are scaled by generation length to account for the fact that long-lived species are at greater risk of extinction when exposed to elevated annual mortality rates than short-lived species (Mace et al. 2008). Many vertebrate and invertebrate species that have generation lengths less than seven years are therefore assessed over time horizons of 10 - 20 years.

In contrast, the majority of studies assessing potential impacts of climate change on species are based on projections that range from 50 to 100 years into the future (Cameron 2012). This has led to concerns that the Red List criteria are 'poorly suited to assessing threats such as climate change, which happen now but have effects years or decades in the future' (Hannah 2012). Thomas et al. (2004) suggest that the Red List criteria assess declines using time scales that ‘are not suited to evaluate the consequences of slow-acting but persistent threats.’ In essence, for many taxa (especially those with short generation lengths), the assessment time frames within the Red List criteria may be too short for climate related declines to be apparent, even though past greenhouse gas emissions have already determined the fate of the species in the absence of timely remedial action (Akçakaya et al. 2006).

Several studies have used methods based on the IUCN Red List criteria to identify species threatened by climate change (reviewed by Akçakaya et al. 2006; also Levinsky et al. 2007; Thuiller et al. 2008). These studies apply only some of the Red List criteria (typically only criterion A, which addresses population reduction) and involve modifications to the time horizons and/or the thresholds of decline. As Akçakaya et al. (2006) point out, these arbitrary modifications make the criteria less consistent across different symptoms of extinction risk and across different taxonomic groups, and consequently make the criteria less capable of identifying the species at greatest risk of extinction.

Despite the concerns and speculations about the performance of the Red List criteria for assessing extinction risks under climate change, we could find no empirical risk assessments that directly address the issue. To inform the debate and demonstrate how the problem may be investigated, we present a detailed assessment of extinction risk using all five IUCN Red List criteria. Specifically, we ask how soon the Red List criteria identify a species as threatened by climate change, and which criteria are crucial for early detection of risk. We chose a short-lived amphibian species for which climate change appears to be the major current threat. To carry out the risk assessment, we used a coupled modelling approach capable of addressing species life history and habitat responses to projected climate scenarios (Keith et al. 2008; Fordham et al. 2012).

Methods

Study species

Frogs are an extinction-prone group worldwide (Houlahan et al. 2000; Stuart et al. 2004) and thought to be particularly susceptible to future climatic changes (Pounds et al. 2006). Our study species, *Assa darlingtoni* Loveridge 1933 (the hip-pocket frog), family Myobatrachidae, occurs between the Conondale Range (26°42'S) and the Dorrigo Plateau (30°20'S) in cool moist rainforest or eucalypt forest within several disjunct montane areas of the coastal escarpment, mostly above 600 m, in central eastern Australia. Its females lay 8 to 18 relatively large eggs in leaf litter, with the tadpoles emerging after a short period of embryonic development and wriggling into lateral pouches of the adult male which cares for them for about 40 days before emergence as subadults (Tyler 1985, Ehmann and Swann 1985). Breeding occurs in the spring and summer months, usually after moderate to heavy rainfall. Males call from secreted positions under leaf litter. Dispersal appears to be very localised, with few animals likely to move more than a few hundred metres through the leaf litter.

Climate change is the most serious plausible threat to the persistence of *A. darlingtoni,* given that it is restricted to cool moist montane habitats that are projected to warm over the coming decades. Although the species range may have previously been reduced by forest clearing and logging, almost all of its remaining distribution is protected from further habitat loss within conservation reserves. The species co-occurs with several stream-dependent frogs whose decline is attributed to disease caused by chytrid fungus. Few individuals of *A. darlingtoni* have been tested for susceptibility to the disease, but its populations are apparently not declining. Its limited reliance on water bodies may limit exposure to chytrid, although some species with similar life histories are known to be susceptible (Bell et al. 2004). In this study, we did not model the effects of chytrid on the persistence of *A. darlingtoni*. Other threats to the species are localised, including timber extraction, roading, weed invasion, grazing and frequent burning (http://www.environment.nsw.gov.au/threatenedSpeciesApp/profile.aspx?id=10070, downloaded 26/3/2013). *Assa darlingtoni* is currently classified as Least Concern on the global Red List (Table 1) 'in view of its wide distribution, presumed large population, and because it is unlikely to be declining fast enough to qualify for listing in a more threatened category' (Hero et al. 2004).

Assessment

We assessed the status of *A. darlingtoni* using IUCN Red List categories and criteria (IUCN 2001). The five criteria assess: A) population reductions over 10 years or three generations, whichever is longer; B) geographic range size in combination with severe fragmentation, number of locations, continuing declines and extreme fluctuations; C) population size in combination with continuing declines, population structure and extreme fluctuations; D) population size and range size in isolation of other factors;

and E) quantitative estimates of extinction risk. The criteria were interpreted in accordance with IUCN guidelines (IUCN 2011).

Although the available data permit a limited assessment of current status, they were insufficient for comprehensive assessments of the criteria at multiple temporal reference points. We therefore used a population model to estimate all the variables required for Red List assessment. The model was constructed and parameterised from available data and expert knowledge (see below). We incorporated uncertainty by constructing fuzzy estimates of population variables comprising best estimates (mean of all simulations) with plausible upper and lower bounds drawn from the 5th and 95th percentiles of the model output (Akçakaya et al. 2000). We used RAMAS Red List (Akçakaya et al. 2007) to calculate the risk categories from the fuzzy estimates. To examine the robustness of assessment outcomes to missing data, we re-assessed the overall status after excluding the criterion that returned the highest category of risk (Keith et al. 2000).

In implementing Red List assessments, RAMAS Red List allows users to specify their attitude to risk and uncertainty by setting values to represent their risk tolerance and dispute tolerance (Akçakaya et al. 2000). Values of risk tolerance range from 0 (an extremely risk-averse precautionary attitude to risk and uncertainty), to a 1 (an extremely risk-prone evidentiary attitude). For all assessments, we set risk tolerance to 0.45, representing a slightly more precautionary attitude than the balance of evidence, consistent with IUCN's (2001) recommendation that assessors take a 'precautionary but realistic' attitude to risk and uncertainty. Values of dispute tolerance range from 0 for inclusion of all estimates to 1 for inclusion of only the consensus estimates (in this case the best estimate). For all assessments, we set dispute tolerance at 0.5, excluding the most extreme estimates of each variable (Akçakaya et al. 2000, 2007).

Predictive modelling

Species distribution model

Locality data were assembled from survey records and specimens held by the NSW Office of Environment and Heritage, the Queensland Environmental Protection Authority, and the Australian and Queensland Museums. All records were checked by experts (HH, MM) to remove erroneous and unreliable records. The 758 reliable records were then randomly thinned so that each location was separated by a minimum distance of 1.5 km to reduce spatial dependence and survey bias. A further seven records were discarded because they were located at sites outside the mapped area of native forest, on which this species is wholly dependent. This is likely to have resulted from small positional inaccuracies rather than forest loss after the species was recorded. Remaining records were transposed onto a 9 arc-second (approximately 285 m) grid, producing a final data set for modelling that included 127 presence records. A set of 9100 background sample points (Phillips et al. 2006) was generated on the same 285 m grid from within a region defined by four bioregions (South Eastern Queensland, NSW North Coast, New England, and Nandewar), and two subregions (the Banana-Auburn Ranges and Eastern Darling Downs) within the Brigalow Belt South bioregion (IBRA7, http://www.environment.gov.au/parks/nrs/science/bioregion-framework/ibra/index.html#ibra). Background sites were only taken from sites with native vegetation. The use of bioregions was intended to constrain the absence records to ecologically plausible regions of species occurrence under present day or future climatic conditions, thereby sharpening the predictions of suitable habitat.

A set of environmental data layers (9 arc-second grid cells) was selected by experts (HH, MM) as potential predictors of suitable habitat for *A. darlingtoni* (Table 2). A series of alternative Species Distribution Models (SDMs) with different subsets of predictors was fitted using a Maximum Entropy algorithm, MAXENT (Phillips et al. 2006), which performed well in comparative tests with other methods (Elith et al. 2006). The models were constructed using hinge features with a regularisation multiplier of 1.5 to create reasonably smooth responses that would extrapolate in a biologically realistic manner (Elith et al. 2010). Model outputs were evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC) for the training points used in model fitting and subjective review by experts familiar with the species habitat and distribution (HH, MM). The most suitable model included seven predictors (Table 2) and was masked to exclude cleared land.

Future projections

The predicted distribution of *A. darlingtoni* was projected into the future using changes in the climatic variables included in the SDM (Table 2). Changes in climatic variables were projected using four Global Circulation Models (GCMs; IPCC 2007) found to perform well for temperature and rainfall anomalies in eastern Australia (Suppiah et al. 2007): CSIRO-Mk3; GDFL-CM2; MPMP-ECHAM5; and UKMO-HADCM3. Two greenhouse gas emission scenarios were used from each model (A1FI and A2), of which A1FI has a larger temperature increase that most closely resembles the realised trajectory (Peters et al. 2013). In addition to projecting models to baseline (1990) conditions, projections were generated for years 2030, 2050, 2070 and 2100. Projected distributions were then generated for each year between 2000 and 2099 by linear interpolation (Keith et al. 2008).

Demographic model

A spatially explicit, stochastic matrix population model based on annual time steps was constructed in RAMAS Metapop v5 (Akçakaya & Root 2005). Three life history stages were recognised in the model: tadpoles; juveniles; and adults. Only females were modelled, because we assumed that the availability of males (which can care for multiple clutches) did not limit population growth. Mean rates of survival and fecundity were estimated from literature (Ehmann and Swann 1985) and the authors' unpublished data and expert knowledge on small terrestrial ectothermic vertebrates (Table 3). Mean observed clutch sizes (range 8 to 18, mean = 13 eggs) were doubled to estimate annual fecundity because females are capable of depositing two clutches in a season.

In the absence of a population census time series, the mean rates were assumed to vary year to year due to environmental stochasticity, with small coefficients of variation (Table 3) reflecting the relatively stable conditions on the rainforest floor and assuming that adult survival was less sensitive to environmental stochasticity than other life history processes. The environmental stochasticity of all vital rates was modelled using a lognormal distribution. Variation in survival and fecundity were assumed to be correlated within populations acccording to a distance function derived from annual rainfall data from stations in the region (Fordham et al. 2012). Demographic stochasticity was incorporated using a binomial distribution for survival and a Poisson distribution for fecundity (see Akcakaya & Root 2005).

Density dependence in *A. darlingtoni* was represented by a ceiling model (Akçakaya & Root 2005) because the species has a short generation length and lacks territorial behaviour and strong aggressive interactions between individuals. Thus, if the carrying capacity was exceeded, the size of a population was adjusted to the carrying capacity, in the subsequent year. The carrying capacity of each population was estimated from the habitat suitability values predicted by the SDM (Keith et al. 2008).

Populations were defined spatially as 10 × 10 km grid cells to enable computationally practical modelling of dispersal between adjacent cells in the landscape and to average local variations in habitat suitability. Dispersal rates were estimated by experts familiar with movement of *A. darlingtoni* in the field (MM, HH), assuming that only juveniles move, and only between adjacent cells, mostly over distances less than 100 m. Based on the geometry of the grid, we estimated that the annual probability of a juvenile dispersing to a neighbouring cell was 0.002.

Model integration

The SDM and population model were coupled using the procedure described by Keith et al. (2008). Modelled 285 m cells with habitat suitability values less than the fifth percentile of values at training points (0.082) were assumed to be unsuitable and set to zero. These 285 m cells were then aggregated into a 9975 m (c. 10 km) grid, in which each cell was defined as a population unit for modelling purposes. Based on call data for males recorded in the field, and field sampling of leaf litter indicating a 1:1 sex ratio (M. Mahony, unpubl. data), optimal habitat was estimated to be capable of supporting 160 adult female frogs per hectare (1300 per 285 m cell, aggregating to 1,592,500 per 9975 m cell). The carrying capacity of each population was therefore estimated as *ths**1300, where *ths* is the sum of habitat suitability values within respective 9975 m cells. A second threshold based on the first percentile of summed habitat suitability (29.7) was applied to exclude 9975 m cells with a very small and potentially diffuse area of suitable habitat. The remaining 9975 m cells were designated as individual 'populations'.

For each population we calculated trends in carrying capacity under climate change using the projections of the SDM from each combination of GCM and emission scenario. These trends were incorporated into the model simulations. Nine model scenarios were run, including the eight GCM-emission combinations and a stable climate scenario, in which carrying capacities of all populations were held constant. The simulations were run over 1000 replicates of 100 annual time steps (2000 – 2099). Mean estimates of extinction risk and population size (the number of adult females) and their standard deviations, and the spatial configuration of populations for each time step were extracted from the model output to calculate the variables required for assessing the IUCN Red List criteria. Assessments were made every 20 years from 2010 to 2090.

Results

The current total population of *A. darlingtoni* was estimated to include approximately 1.7 million mature females. The population remained stable for 100 years when modelled under a stable climate (Fig. 1). Under all modelled future climate change scenarios, however, the population remained stable only until about 2040-2050, with subsequent declines projected to occur at different rates for different combinations of GCM and emission scenario. Under the most severe projection (CSIRO-Mk3 A1FI), the species had become Extinct in the Wild by 2095 (Fig. 1). In other projections, the species remained extant, but total population size had been reduced by between 39% (GDFL-CM2 A2 scenario) and 96% (CSIRO-Mk3 A2 scenario) over the 100-year period (Fig. 1).

According to the Red List criteria, *A. darlingtoni* would become eligible for listing as a threatened species as early as 2010 or as late as 2050, depending on the pattern of decline in the population and distribution projected under different GCMs and emission scenarios (Table 4). In contrast, under a stable climate scenario, the status of the species remained as Least Concern throughout the twenty-first century. The species qualified for listing in 2010 in only one projection (CSIRO-Mk3 A1FI). In all eight combinations of GCM and emission scenario, early eligibility for listing was dependent on criterion E and/or B, with both criteria supporting the first listing in two of the eight cases (Table 4). The estimates of extinction risk over 100 years (required to assess the Vulnerable category under criterion E) were uncertain in the assessments carried out for years later than 2010 because projections were only available to 2100. Hence we used the shape of the population trajectory to estimate whether extinction was a plausible outcome over 100-year time frames ending in 2110, 2130, 2150, 2170 and 2190. The plausible bounds of these assessment outcomes always included the Least Concern category, recognising the uncertainty of an extinction outcome. Criterion B and, to a lesser extent criterion A, had an influence on the overall status of the species in the second half of the century, and often over-rode criterion E by 2070 or 2090 (Table 4). Criteria C and D did not determine the overall status of *A. darlingtonii* in any of the assessments (Table 4).

In later years, the Red List assessments became more robust because the overall status was generally supported by more criteria and more subcriteria than in early years (Table 4). Consequently, the overall status always remained threatened when data for the highest-risk criterion were omitted from assessments carried out in 2070 and 2090, but was reduced to Least Concern for some combinations of GCM and emission scenario when data for the highest-risk criterion were omitted from assessments carried out in 2030 and 2050.

Discussion

Early detection of extinction risks under climate change

Despite short time frames for assessing population declines, our results for *A. darlingtoni* suggest that, for some species with short life cycles, the IUCN Red List criteria may be more sensitive to extinction risks posed by climate change than anticipated. Under the most extreme modelled scenario in which extinction occurred in 100% of simulations by 2095, *A. darlingtoni* first qualified under criterion A (population decline) for listing as threatened (Vulnerable category) in 2050. Under the four least severe scenarios, *A. darlingtoni* did not qualify for listing as threatened under criterion A at any time during the twenty-first century and the risk of extinction by 2100 was estimated to be zero. Risks could not be quantified beyond 2100, the shapes of population trajectories suggest that species persistence could be certain for several decades into the twenty-second century.

More importantly, criterion A was not the only criterion that identified when *A. darlingtoni* was at appreciable risk of extinction. In most cases, *A. darlingtoni* qualified for threatened status under criteria B (distribution size) and/or E (quantitative estimates of extinction risk) before it met criterion A, and the overall outcome of assessments never relied upon criterion A alone. Under the most severe scenario, the species was assessed as Vulnerable under criterion E as early as 2010 and, by the time it qualified as Vulnerable under criterion A in 2050, it also qualified at that level under criterion B. Hence the Red List criteria identified the species as being at risk of extinction 85 years before it actually went extinct and 40 years before it met criterion A. Under criterion A alone, the species qualified for listing 45 years before its modelled extinction. For all other modelled climate change scenarios, *A. darlingtoni* qualified for threatened listing at least 80 years prior to its inferred date of extinction based on the shape of its population trajectory in the late twenty-first century.

It is noteworthy that the time frames for assessing criterion E (10 years or 3 generations, 20 years or five generations and 100 years, respectively for CR, EN and VU) are longer than those for criterion A (10 years or 3 generations for all threat categories), and that criterion B does not specify explicit time frames (only qualitative evidence of a continuing decline). These differences between individual criteria underpin their ensemble properties and buffer against extreme sensitivity of risk assessment outcomes to short generation lengths.

By indicating that *A. darlingtoni* is likely to qualify for threatened status 40-80 years before it goes extinct (depending on which criteria are assessable), our results suggest that that the Red List criteria perform reasonably well as an early-warning system for conservation planners and managers. How much lead time an 'early-warning' system should give depends on the practicalities of environmental policy and management, bureaucratic or political inertia and the anticipated species response times to various actions. This mix of factors suggests a need for a minimum of several decades warning between initial listing and extinction with longer lead times required if a desire for greater certainty or socio-economic costs motivated a delay in action until Endangered or Critically Endangered listing. The long lags associated with climate change mitigation and some adaptation measures underscores the need for early action..

Limitations of analysis

In this paper we examined only a single species chosen specifically to represent an identified potential weakness in the Red List criteria, namely the short time frame for assessing future declines relative to the expected time scale of climate change impacts. Our focus on *A. darlingtoni*, with contrasting population trajectories under different future climates, permitted a detailed examination of the assessment processes and development of an analytical approach. This approach will be useful for evaluating the sensitivity of the Red List criteria to climate change impacts on a larger group of species with more diverse life histories. Additional studies of short-lived species with different temporal patterns of decline, and of longer-lived species with different climate-life history dependencies would further advance understanding of how the Red List criteria perform as an early warning system for climate change impacts.

We assumed that our study species would not show any appreciable evolutionary response to climate change that may influence its future persistence. This assumption warrants further exploration because species with short generation lengths, such as *A. darlingtonii*, might experience mutation and natural selection at rates that are rapid enough to enhance fitness under changing climates (Hoffmann and Sgro 2011). Phenotypic or behavioural plasticity may also influence *in situ* persistence of populations under a changing climate. Although our capacity to predict which short-lived species might undergo evolutionary responses to climate change is currently limited, such effects have been demonstrated in a range of short-lived species (Skelley et al. 2007; Franks and Hoffmann 2012). We expect evolutionary responses to delay the time at which listing in a threatened category is triggered, as well as the time to eventual extinction. This is unlikely to result in shorter warning times, and hence our conclusions should be conservative whether not evolutionary responses occur. Species with long generation times, however, may be more sensitive to climate change because genomic change is less likely to keep pace with climate change.

For analytical economy, we used averaged estimates of population size and distribution (with confidence intervals) across 1000 simulations for the variables addressed by the criteria. In reality, each of the 1000 replicates represents an alternative future scenario that could be assessed individually against the criteria. Averaging may have under-estimated the trends in some scenarios. The risk assessment outcomes from averaged estimates may approximate modal or median assessments based on individual trajectories, but this remains to be tested.

Although we incorporated uncertainty into our analysis by implementing fuzzy calculations on best estimates with upper and lower bounds for all input variables (Akçakaya et al. 2000), our assessments are likely to have underestimated the uncertainty relative to real-world assessments. This is because our simulated population trajectories did not incorporate observer error, which is likely to be a significant source of uncertainty in real-world estimates of population sizes based on field surveys (Burgman et al. 1999; Regan et al. 2002). Furthermore, although we incorporated model uncertainty by using projections based on multiple GCMs, we ignored other components of model uncertainty, such as in the demographic model and SDM. For example, biophysical models may project different distributions to those produced by correlative SDMs (Kearney & Porter 2009). More realistic levels of uncertainty could be achieved by i) using simulations based on several plausible demographic models and SDMs; and ii) adding a random error to modelled estimates to simulate field sampling (Zurell et a. 2010).

Factors influencing performance of Red List criteria under climate change

Several factors potentially influence the performance of the Red List criteria for species threatened by climate change. Firstly, in our analysis the earliest detection of threat was reliant upon a single criterion. Often this was criterion E, which is more likely to detect extinction risks than are other criteria (McLean & Wilson 2011), but is typically more data-demanding and time-consuming to assess. When criterion E was not evaluated, several simulations showed that a taxon could remain listed as Least Concern for several decades despite being at appreciable (>10%) risk of extinction within a century. This could be problematic when data are insufficient to support a quantitative analysis of extinction risk. Indeed, few of the currently Red-Listed taxa have been assessed for criterion E (IUCN 2011). This may sometimes be due to limited expertise or time to construct appropriate models, rather than a lack of data. *Assa darlingtoni*, for example, had not previously been assessed under criterion E, even though sufficient data were available.

Risk assessments for later in the twenty-first century were shown to be robust to missing data. Nevertheless, our results reinforce IUCN's recommendation that 'each taxon should be evaluated against all the criteria' (IUCN 2001, p5). In some cases this may require engaging additional expertise or resources to support assessments. Our study showed that the models necessary to assess criterion E also have the capacity to produce bounded estimates of population size, distribution area and their trends, enabling more comprehensive assessments of criteria A - D than otherwise possible.

Secondly, optimal performance of the Red List categories and criteria relies on correct interpretation of the criteria and supporting concepts. Our risk assessments closely followed the current guidelines to derive quantitative estimates of the required variables over the appropriate time frames and spatial scales (IUCN 2011). We also incorporated uncertainty into the calculations to determine the range of plausible risk assessment outcomes. Akçakaya et al. (2006) noted that several assessments of extinction risk under climate change used modified or incomplete versions of the criteria. This may affect the performance and consistency of the criteria and their ability to estimate relative risks.

Thirdly, to inform proactive policy and management as climate change and its impacts unfold, an early warning system relies upon monitoring of species populations and distributions to support regular risk assessments (Butchart et al. 2010). Responsive management would likely require more frequent assessments than are currently implemented. The most recent global Red List assessment for *A. darlingtoni* was conducted a decade ago (Hero et al. 2004).

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Table 1. Current status of *Assa darlingtoni* in different geographic domains.

Domain	List	Status	Source
Global	IUCN Red List of threatened species	Least Concern	http://www.iucnredlist.org/details/full/41130/0, downloaded 14/1/2013
National	Australian *Environment Protection and Biodiversity Conservation Act 1992*	Not listed	http://www.environment.gov.au/cgi-bin/sprat/public/publicthreatenedlist.pl?wanted=fauna, downloaded 14/1/2013
State	Queensland *Nature Conservation Act 1992*	Near Threatened	http://www.ehp.qld.gov.au/wildlife/threatened-species/near-threatened/near_threatened_animals.html, downloaded 14/1/2013
State	NSW *Threatened Species Conservation Act 1995*	Vulnerable	http://www.environment.nsw.gov.au/threatenedspeciesapp/profile.aspx?id=10070, downloaded 14/1/2013

Table 2. Environmental variables used as predictors of suitable habitat for *Assa darlingtoni*. Six (x) of the predictors were included in the best model, while a substrate mask (+) was applied to exclude predicted suitable habitat from coastal sands.

Predictor layer	Source	Best model
Annual mean temperature	BioClim v6.0	x
Mean diurnal temperature range	BioClim v6.0	x
Temperature seasonality	BioClim v6.0	
Annual mean moisture index	BioClim v6.0	
Mean moisture index of the lowest quarter	BioClim v6.0	x
Maximum topographic wetness index		x
Slope		x
Substrate mask (excluding coastal sands)	Keith (2011) with additions for SE Qld	+
Native vegetation (present/absent)	Keith (2011) with additions for SE Qld	x

Table 3. Estimated vital rates (and coefficients of variation) for the matrix population model for *A. darlingtoni*.

	Tadpole	Juvenile	Adult
Tadpole	0	0	5(2%)
Juvenile	0.6(2%)	0	0
Adult	0	0.2(2%)	0.4(1%)

Table 4. IUCN Red List status of *Assa darlingtoni* assessed for present day (2010) and four future dates under a stable climate and using projections from four different Global Circulation Models (bold) and two emission scenarios. Status is based on best estimate with plausible bounds in parentheses. The criteria determining the overall status are listed (in parentheses if the best estimate matches overall status, but plausible bounds span lower categories of risk). Omission shows the overall status if data were omitted for the criterion supporting the highest status.

	A1FI scenario			A2 scenario		
Year	Status	Criteria	Omission	Status	Criteria	Omission
Stable climate						
2010	LC(LC-LC)	-	LC			
2030	LC(LC-LC)	-	LC			
2050	LC(LC-LC)	-	LC			
2070	LC(LC-LC)	-	LC			
2090	LC(LC-LC)	-	LC			
CSIRO-Mk3						
2010	VU(VU-VU)	E	LC	LC(LC-LC)	-	LC
2030	VU(VU-VU)	E	LC	VU(VU-VU)	B1,B2,E	VU
2050	VU(VU-EN)	(A2),B2,E	VU	EN(EN-EN)	B1	VU
2070	EN(EN-EN)	B1,B2	VU	EN(EN-EN)	B1,B2	VU
2090	CR(CR-CR)	A3,A4,B1,B2,E	CR	CR(CR-CR)	A3,A4	EN
GDFL-CM2						
2010	LC(LC-LC)	-	LC	LC(LC-LC)	-	LC
2030	LC(LC-LC)	-	LC	LC(LC-LC)	-	LC
2050	VU(VU-VU)	B1	LC	VU(VU-VU)	B1	LC
2070	EN(VU-EN)	B1	VU	VU(VU-VU)	B1,B2,E	VU
2090	EN(EN-EN)	B1	VU	EN(EN-EN)	B1	VU
MPMP-ECHAM5						
2010	LC(LC-LC)	-	LC	LC(LC-LC)	-	LC
2030	VU(LC-VU)	E	LC	VU(LC-VU)	E	LC
2050	EN(EN-EN)	B1	VU	VU(VU-EN)	B1,B2,E	VU
2070	EN(EN-EN)	B1,B2	VU	EN(EN-EN)	B1	VU
2090	EN(EN-EN)	A2,A3,B1,B2,E	EN	EN(EN-EN)	B1,B2	EN
UKMO-HADCM3						
2010	LC(LC-LC)	-	LC	LC(LC-LC)	-	LC
2030	VU(LC-VU)	B1,E	VU	VU(LC-VU)	E	LC
2050	EN(VU-EN)	B1	VU	VU(VU-VU)	B1,B2,E	VU
2070	EN(EN-EN)	B1,B2	EN	EN(EN-EN)	B1	VU
2090	EN(EN-EN)	B1,B2,E	EN	EN(EN-VU)	B1,B2	EN

Figure 1. Population trajectories- of *Assa darlingtoni* under alternative future climate projections: (a) stable climate and CSIRO Mk3; (b) MPMP-ECHAM5; (c) UKMO-HADCM3; and (d) GDFL-CM2. Population size expressed as percentage of initial number of mature females.