12. Guidelines for Threatening Processes

As discussed in an earlier section (2.3), the criteria aim to detect symptoms of endangerment rather than causes (see also Mace *et al.* 2008). Consequently, they are applicable to any threatening process that results in symptoms such as population decline, small population sizes, and small geographic distributions. A taxon may be classified as threatened even if a threatening process cannot be identified. Regardless of the nature of threats, assessments must follow IUCN (2001, 2012b) and these guidelines to ensure valid application of the criteria. However, different threats, especially new or poorly understood processes such as global climate change may require further guidance in the application of definitions and criteria.

The purpose of this section is to provide such specific guidance. In this version, we focus on global climate change; future versions will provide further guidance on how the criteria may be interpreted to assess taxa affected by other threats. It is important to note that the guidance in this section is not an alternative to previous sections.

One aspect of a Red List assessment involves listing the major threats in the required documentation, as described in IUCN (2001, 2012b; Annex 3), using a standard classification scheme available at www.iucnredlist.org/technical-documents/classification-schemes. The guidance given here does not relate to this process; instead the focus is on the application of the Red List Categories and Criteria.

12.1 Global climate change

There has been concern that the Red List Criteria may not be adequate for assessing species threatened with climate change. This is because many species that are projected to undergo substantial range contractions in the future have short generation lengths. Consequently, there are concerns that the assessment time frames are too short for the inferred population declines to trigger the relevant IUCN Red List Criteria, which consider declines over a three-generation period (see section 12.1.1). However, recent studies show that the IUCN Red List Criteria can identify species vulnerable to extinction due to climate change. In a study involving North American reptiles and amphibians, Pearson *et al.* (2014) showed that extinction risk due to climate change can be predicted by information available now, such as current occupied area and population size, much of which is used in the IUCN Red List Criteria.

Stanton *et al.* (2015) defined "warning time" as the time between when a species is first identified as threatened and when it goes extinct, assuming no conservation action. Using the same species and climate projections as Pearson *et al.* (2014), they showed that IUCN Red List Criteria can identify species that would go extinct because of climate change without conservation action, and can do so with decades of warning time. In an independent study, Keith *et al.* (2014) reached the same conclusion for a short-lived Australian amphibian. Although these studies show the ability of the IUCN Red List Criteria to identify species vulnerable to extinction because of climate change, they also show that warning times may be short in data-poor situations, and if conservation action is started only when a species is listed at the highest IUCN threat category (Critically Endangered). Therefore, there is a need to develop further guidance for using the IUCN Red List system, especially in data-poor situations and for timely policy responses to exploit the maximum warning time available for species on extinction trajectories in response to changes in climate. As new research increases understanding of the impacts of climate change on species, the results will be used to improve these guidelines. Below, guidance is provided on a number of relevant issues, based on research available in 2015.

12.1.1 Time horizons

An important issue in the application of the criteria to species impacted by climate change concerns the time horizons over which the assessments are made.

The time horizons used in the criteria serve several purposes. First, the generation time is used as a surrogate for turnover rates within populations and as a biologically relevant scaling factor that corrects for the variation in rates at which different taxa survive and reproduce. Second, the time horizon is set to a minimum of 10 years because measuring changes over shorter time periods is difficult and does not reflect time scales for human interventions. Third, the time horizon is set to a maximum of 100 years into the future, because of the uncertainties in predicting population sizes for a long time from the present day (Mace *et al*. 2008).

The global climate is projected to continue to change for several centuries (IPCC 2013; Chapter 12). The effects on biological systems will certainly continue for a long time. Thus, for many species, especially short-lived ones, Red List assessments are based on time horizons much shorter than the long periods over which we now expect the world's climate and its effect on species will change. This by itself may not make climate change fundamentally different: other threats, such as habitat loss may also continue for a long time.

However, the nature of change in biological systems caused by climate change is thought to be different than changes caused by other threats. Thuiller *et al*. (2005), for example, argued that, "the recognized time scales for assigning species IUCN Red List Categories are not suited to evaluating the consequences of slow-acting but persistent threats," suggesting that the projected climate change impacts are thought to be of a more deterministic nature than other threats. In addition, some amount of climate change-related impact is irreversible (already committed) because of the lag between greenhouse gas emissions and climate change (and subsequent biological change).

While stochastic events (catastrophic fires, ENSO events, etc.) that contribute to the variability and hence the risk of extinction of populations clearly operate at different time scales than climate change, there are other processes that also are slow-acting and persistent. For example, it is debatable whether threats such as habitat loss and fragmentation are any less persistent or any more uncertain than climate change. Although climate change may be persistent, the predictions are also very uncertain. For example, IPCC (2013) makes most of its predictions only until 2100 because general climate models tend to produce very different outputs towards the end of the 21st century.

The criteria recognize that some threats may be irreversible (as explicitly noted in criterion A). For example, in many cases, habitat loss brought about by urban sprawl is not reversible. Various threats may involve time lags similar to that of climate change. For example, human populations have a momentum, and thus there is often a lag between a change in the human population growth rate and resulting changes in human pressures on natural systems.

Thus, the assessment of species with short generation times is not fundamentally different under climate change and under other threats. Although short-lived species may not be listed under criterion A initially, if they are affected by climate change they will be listed (likely under criteria B or C) as their ranges and populations change as a response to climate change. They can also be listed under criterion E (see below).

In summary, many of the issues related to time horizons are not specific to global climate change. Although future versions of this document may provide further guidance on this issue, for the time being, the horizons for each of the criteria should continue to be applied as they are currently specified, regardless of the nature of the threatening factor, including global climate change.

12.1.2 *Suggested steps for applying the criteria under climate change*

There are a number of challenges in applying the criteria to species impacted by global climate change, which have resulted in several misapplications of the criteria. A common mistake is making arbitrary changes to thresholds or time horizons specified in the IUCN Red List Criteria (see Akçakaya *et al.* 2006 for examples and details). An important characteristic of the Red List is that threat categories are comparable across taxonomic groups. For this important standard to be maintained, it is essential that the thresholds and time periods used in the criteria are not altered (see section 12.1.1).

To assess species that might be impacted by climate change, the following steps are recommended (Figure 12.1), as available data and information about the species permit.

1. Assessors are encouraged to think systematically through the potential mechanisms of the impact of climate change on the species (see section 12.1.3 below). The identification of likely mechanisms of impact will help with defining key variables used in Red List assessments in the context of climate change. This diagnostic process may be aided by development of diagrammatic models.

2. Assessors should identify and estimate or infer the values of all the parameters in the Red List criteria relevant to the mechanisms of taxon change under climate change identified in Step 1. These parameters include "very restricted distribution" and "plausibility and immediacy of threat" (section 12.1.4), "number of locations" (12.1.5), "severely fragmented populations" (12.1.6), "extreme fluctuations" (12.1.7), "continuing decline" (12.1.8), and "population reductions" (12.1.8). Inferences about such variables can lead to listing under criteria A, B, D2 or C2 (Figure 12.1).

3. To incorporate future climate impacts on species more explicitly, assessors are encouraged to make inferences about the magnitude of future population reduction (criteria A3 and A4) and whether continuing decline (criteria B and C2) will occur due to climate change (see section 12.1.8). Such inferences can be aided by developing models of (a) bioclimatic habitat or (b) population dynamics (see sections 12.1.9, 12.1.10, and 12.1.12). The identification of likely mechanisms of impact will also help with developing such models. The output of such models can lead to listings under criteria A, C1 or E (Figure 12.1).

4. Finally, the results of the bioclimatic models can be used to determine the spatial structure of stochastic population models, which are then used to estimate probability of extinction for assessment under criterion E (discussed in detail in section 12.1.11). This allows assessors to explicitly incorporate effects of future habitat shifts and habitat fragmentation, future increases in climate variability (hence in extreme fluctuations), and dispersal limitations and barriers. The output of such models can lead to listings under criteria A or E (Figure 12.1). However, this approach requires substantial amounts of demographic information that may not be available for most species.

Assessors should first complete Steps 1 and 2, and then complete as many of the remaining steps as the available data and expertise allow. In the following sections, we discuss mechanisms of

impact of climate change, applications of various definitions and criteria, and use of different types of models for estimating population reductions and continuing declines. Although we discuss particular criteria in this section, this does not mean that these are the only applicable ones. As with any other threat, the taxon should be assessed against all the criteria as available data permit.
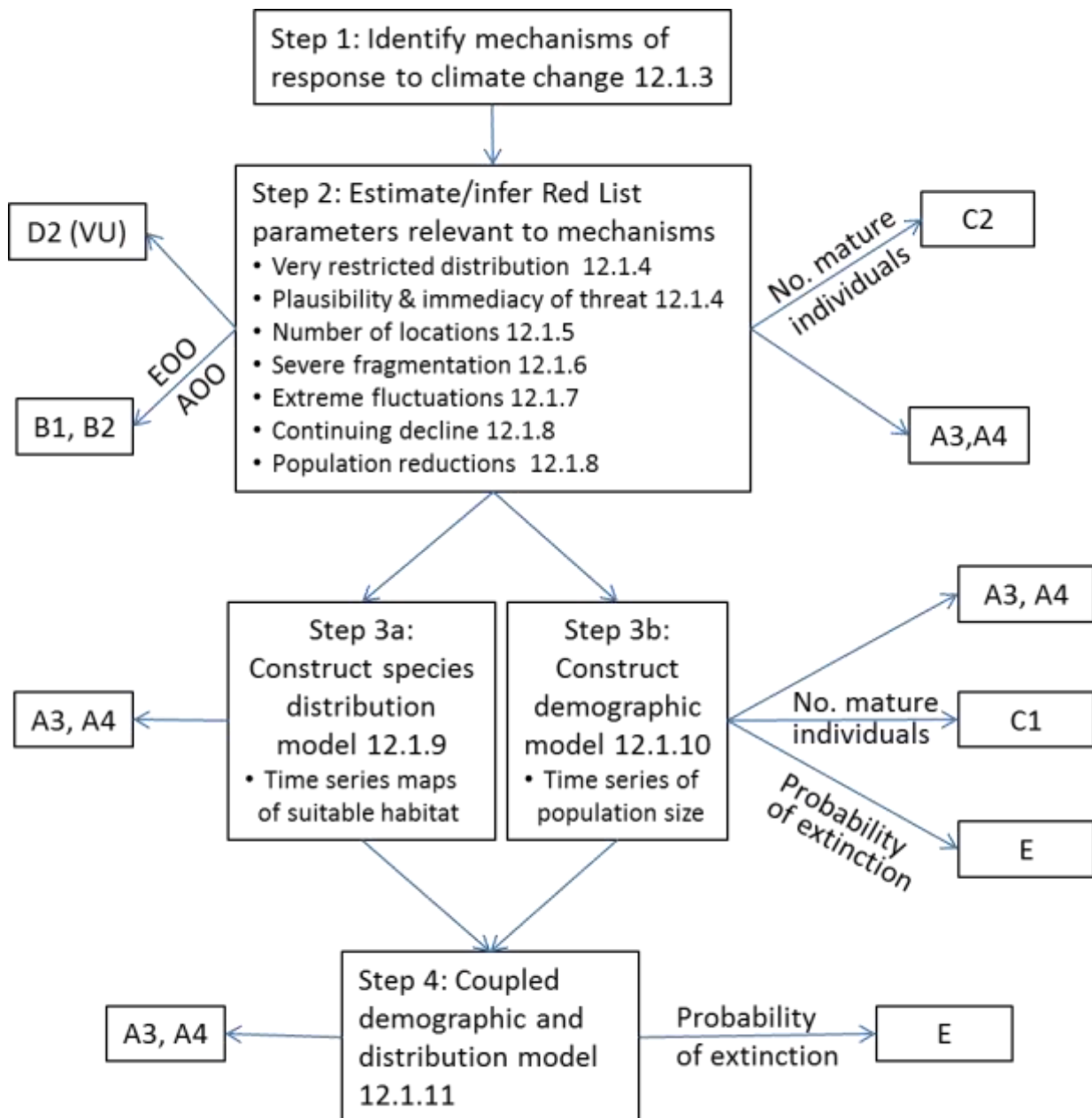

Figure 12.1. Protocol for assessing extinction risks under climate change using the IUCN Red List Criteria for threatened species (IUCN 2001). Letters and numbers in marginal boxes refer to respective Red List Criteria. Numbers within central boxes refer to relevant sections of text in these Guidelines. Any assessment must address all plausible threats (not just climate change), and should also evaluate eligibility for listing under criteria A1, A2 and D1 (not shown).

12.1.3 Mechanisms

Climate change can affect populations via many mechanisms; thinking about how this will occur for given taxa can clarify the parameters and criteria relevant for a Red List assessment. Relevant parameters for assessments under climate change include "very restricted distribution", "plausibility & immediacy of threat", "number of locations", "severe fragmentation", "continuing decline", "extreme fluctuations", and "population reductions". The relevant criteria for future effects of climate change include A3, A4, B1, B2, C1, C2, D2 (VU), and E (Figure 12.1).

The effects of climate change on taxa are analysed quantitatively through two main groups of symptoms: changes in the taxon's distribution and changes in the demography of the taxon which is then included in population models. While range changes have been the most studied symptom of species decline due to climate change (Pearson *et al.* 2002), changes in demography can also lead to reductions in population abundance even when species distributions are projected to increase under climate change. This is because births, deaths, emigration and immigration drive population dynamics and these are demographic factors not necessarily directly linked to habitat and range size (Thuiller *et al.* 2014). Demographic factors that could be affected by climate change include vital rates (e.g., survival, growth, fecundity, and dispersal), species interactions, phenology, population responses to disturbance, and deposition and production of calcareous structures and tissues (e.g., in corals) (Foden *et al.* 2013). Hence, when considering population declines driven by climate change, it is important to consider the main mechanisms by which this is likely to occur as this will highlight the most appropriate criteria for assessment under this threat.

Changes in habitat can occur under climate change because climate is a predictor of habitat suitability for many taxa. Changes in precipitation and temperature across space can shift, fragment, contract or increase species ranges, leading to changes in EOO and AOO and the degree of fragmentation. The ability of a population to track shifts or increases in suitable habitat will depend on its dispersal capabilities (Foden *et al.* 2013). However, changes in climatic variables can also expose organisms to conditions outside their range of physical tolerance, resulting in reduced survival and fecundity, leading to reductions in population size (Deutsch *et al.* 2008). In the case of corals, increased ocean temperatures or changes in pH can reduce or prevent development of calcareous tissues, thus reducing survival and growth rates. Increased temperatures can change predator-prey relationships, or food webs, by altering organisms' behaviour such as movement and exposure times, with potential ramifications to both the predator and prey or consumer and resource (Gilman *et al.* 2010). Phenology, or the timing of life-cycle processes, can shift by climate change such that a mismatch occurs between, say, the timing of flowering and the presence of pollinators (Memmott *et al.* 2007). And changes in the intensity and frequency of environmental events, such as fire, drought, or floods can reduce populations that have evolved under a different regime (Dale *et al*. 2001). For example, obligate seeding plants that rely on seedbanks for post-fire seed regeneration will undergo population declines if fire frequency is increased, because fewer seeds will be added to seedbanks between successive fires.

12.1.4 Very restricted distribution and plausibility and immediacy of threat (VU D2)

Taxa that have very restricted distributions and become susceptible under climate change to a threat that is plausible and liable to cause the entire population to rapidly become Critically Endangered or even Extinct in the Wild will be eligible for listing as Vulnerable under criterion D2. However, classification under criterion D2 is only permissible if the effects of climate change

are such that the taxon is capable of becoming Critically Endangered or Extinct in a very short time period after the effects of the threat become apparent.

Application of this criterion requires only knowledge of the species' distribution and an understanding of the severity and immediacy of impacts of a plausible threat. For example, a sessile terrestrial organism that is susceptible to salt would qualify for listing as VU D2 if it had a very restricted distribution in a coastal location that is projected to become more exposed to salt water or saltspray as a consequence of projected rises in sea-level and/or increased frequency of coastal storms. More detailed examples are given below.

Example 1. A species that currently does not meet the area thresholds under criterion B may be classified as VU D2 if bioclimate models (see section 12.1.12) predict that a range reduction could correspond to a population reduction of 80% or more (and other information indicates that there are few locations; see above). In this case, the start of the decline may not occur soon, but the decline is plausible, and once it begins it is expected to cause a population reduction in a very short period of time (e.g., within one to two generations or 10 years) so that the species will be classified as CR A3c, so it now meets VU D2.

Example 2. A species of coral currently has restricted area of occupancy (less than 20 km^2) but does not satisfy the criteria for classification under criterion B. Climate change models predict increases in ocean temperatures, greater than the typical seasonal variation, across the entire range of the species. This temperature increase is expected to cause coral bleaching such that the area of occupancy will be reduced to less than 10 km^2 within 10 years of the start of bleaching. It is highly uncertain when the temperature increase or the onset of the bleaching will occur, but there is a reasonable chance that it will occur in the future. Once the bleaching starts, the species will meet CR B2ab within a short time, so it now meets VU D2.

Example 3. A small mammal with an AOO >500 km^2 occurs in a single location (see example of Species 3 in section 12.1.5) where it is dependent on snow cover (for insulation and predator avoidance during the winter). Climate change is expected to increase the probability of a series of years with no or inadequate snow cover. If this occurs, the species is expected to decline by 80% or more within 1–2 generations due to mortality from exposure and predation. Although having a number of years with no snow cover is a stochastic process and cannot be exactly predicted, in this case the climate models indicate that it is a plausible event. The species meets VU D2 because this plausible event, once it occurs, will cause the species to be listed as CR.

Example 4. A species has AOO <20 km^2, but is not declining or under any specific threat or experiencing extreme fluctuations. It is expected that future climate change will affect this species, but the effects are expected to cause gradual and slow decline, which will not trigger any criteria for CR or cause extinction within three generations. Thus, this species does not meet VU D2.

Example 5. A fish species known only from a single oceanic archipelago, where it occurs from 1 to 30 m depth. It lives in small recesses on slopes and walls of rocky reefs. In this region, localized declines, including the complete loss of at least one other endemic fish species, have occurred after strong El Niño-Southern Oscillation (ENSO) events that result in shallow waters that are too warm and nutrient poor for extended periods of time. The frequency and duration of ENSO events in this region appears to be increasing. Given the restricted distribution of the species and its specialized shallow water habitat, oceanographic environmental changes, such as those associated

with future ENSO events, may cause the extinction of this species in a short period of time (as has happened for a similar species). Thus, it meets VU D2.

12.1.5 Definition of "Location" under climate change (B1, B2, D2)

Using the number of locations in Red List assessments requires the most serious plausible threat(s) to be identified (see section 12.1.3). In some cases, the most serious plausible threat will be climate change, but it may not be correct to assume that species threatened by climate change occupy a single location. In general, it is not possible to identify climate change as the main threat (for purposes of defining locations) without knowing something about how the effects of climate change are likely to be played out through the proximate causes or direct threats. For most species susceptible to climate change, climate change itself (e.g., increasing temperatures or changes in precipitation) is not the direct threat. Rather, the process through which climate change is expected to affect species involves a large variety of threats or proximate causes—such as changes in fire frequency, hydrology, species interactions, habitat suitability, diseases—that affect the species vital rates (these proximate causes can be inferred using knowledge of species ecology and predicted changes in relevant climatic variables). Thus, even when the ultimate cause of endangerment is climate change, the locations occupied by a species should be defined (and counted) in terms of these direct threats. Climate change should only be used to define the number of locations when it is the direct threat (e.g., where survival rates are reduced by thermal stress and are likely to be the principal direct cause of population declines or when suitable habitat is reduced due to changes in temperature and precipitation).

In some cases, climate change may threaten different parts of a species' range through different proximate factors, or not affect some parts at all (for example, part of the range may be expanding). In such cases, the most serious plausible threats should be used to define locations in different parts of the species range in accordance with section 4.11 (options a–d).

Examples of estimating the number of locations for species susceptible to climate change:

Species 1 is restricted to a single climatic zone affected by severe storms that cause episodes of high mortality. The frequency of severe storms in the region is projected to increase by at least 20% over the next 100 years. A single severe storm is unlikely to affect the entire range of the species, but two severe storms could cover the entire range. The species is correctly estimated to occur at two locations based on severe storms as the proximate threat (the minimum number of independent storms that could affect its entire range). It would be incorrect to interpret the species as occupying a single location based on the single climatic zone occupied in which severe storm frequency is projected to increase.

Species 2 is restricted to three coastal freshwater wetlands potentially affected by saltwater incursion associated with sea level rise. Two of the wetlands occur on the same floodplain, one at a low-lying site 0.5 metres above sea level, and another perched on the upper floodplain five metres above sea level. The third wetland also occurs at five metres above sea level, but in another region where there is a very large inter-tidal range. Sea level is projected to rise, on average by 1.0 metre by year 2100. The low-lying wetland will certainly be affected by sea level rise. The nearby perched wetland is very unlikely to be affected by sea level rise. The third wetland could be affected by saltwater incursion during extreme spring tides under projected future climate, but this is uncertain. Incursion by saltwater is the most serious plausible threat at the low-lying (first) site and the distant (third) site with the high inter-tidal range. These two sites could be interpreted as a single location if they are both threatened by the same regional sea-level rise. However, if sea level rise could lead to different outcomes at the two sites they could be interpreted as two separate

locations. For example, the same amount of sea level rise may inundate the first wetland but only sporadically affect the third wetland, causing different types of impacts at the two wetlands (total habitat loss in one and temporary population reduction in the other). If the independence of threat outcomes at the two wetlands is uncertain, then a bounded estimate of [1-2] locations is appropriate (see section 3). The second wetland is very unlikely to be affected by sea level rise, and hence the most serious plausible threat for this wetland is not sea level rise. If this site is subject to other threats, the most serious plausible one will govern how many locations are represented at that site. For example, if the entire wetland is threatened by polluted runoff, then it should be counted as a single location and the total number of locations for the species is [2-3]. Alternatively, if the second wetland is not threatened, then the number of subpopulations at that site could be used as a proxy or the number of locations may not be applicable to the assessment of the species (i.e., the subcriteria for number of locations cannot be met, see section 4.11).

Species 3 is restricted to the highest altitudes of two mountain ranges separated by a plain of 100 km. The two mountain ranges have a seasonal cover of winter snow that extends above a similar threshold altitude (1,800 m above sea level), although the summits of their mountains are at different elevations. Seasonal snow cover affects breeding success by providing insulation during cold winters. The extent of snow cover is projected to decline stochastically over the next 30 years. The most serious plausible threat is the risk of a year in which there will be very low or no winter snow cover, which causes an episode of very high mortality in the species population. The chance of this occurring in the same year on both mountain ranges is about 30%, based on correlation of minimum snow extent over previous years. Despite their geographic separation, the two mountain ranges are interpreted as a single location for the species because they may be affected by the same 'low-snow cover' event.

12.1.6 Severe fragmentation (B1, B2, and C2)

If a taxon is not currently severely fragmented (see section 4.8), this cannot be used to meet the severe fragmentation subcriteria (e.g., criterion B1a) even if there is evidence to infer that it may become so under future climates. However, projected future fragmentation can be used to infer continuing decline, if certain conditions are met. Continuing decline is recent, current or projected future decline (see section 4.6). Severe fragmentation can for some species lead to local extinctions of subpopulations inhabiting the smallest habitat fragments. If the population density and the projected distribution of fragments justify a prediction of increasing rate of local extinctions in the near future, this may be used to infer continuing future decline in population size.

The same conditions may also allow inferring population reduction under criterion A3, but this requires a quantitative prediction. Suppose that a bioclimatic model (see section 12.1.12) predicts that EOO of a taxon will decline by 20% in the next three generations due to climate change. Assuming that the population reduction will be at least as large as the EOO reduction (but see section 12.1.8), this can be used to infer a 20% population reduction, but would not by itself meet the VU threshold for A3. However, suppose that a population dynamic model predicts that populations smaller than a certain size have 50% risk of extinction. If the bioclimatic model also predicts that 40% of the population will be in fragments that support populations of this size or smaller, then we can infer that the population will undergo a further 20% reduction due to increased local extinction of smaller populations. Combined with the 20% reduction due to range contraction, this result can be used to infer a total of 40% population reduction, listing the species as VU A3.

12.1.7 *Extreme fluctuations (B1, B2, and C2)*

One of the predictions of many climate models is an increase in the frequency of extreme weather events (such as droughts, heat waves, etc.). This may increase population fluctuations to extreme levels (see section 4.7). If a taxon is not currently experiencing extreme fluctuations, but is predicted to do so in the future as a result of climate change, this prediction cannot be used to meet the extreme fluctuation subcriteria (e.g., B1c). However, a projected future increase in population fluctuations can be used to infer continuing decline, if certain conditions are met. Continuing decline is recent, current or projected future decline (see section 4.6). Extreme fluctuations can for some species lead to an increase in rate of local extinctions of subpopulations (especially if combined with severe fragmentation; see above). If the population sizes and the projected increase in fluctuations justify a prediction of increasing rate of local extinctions in the near future, this may be used to infer continuing future decline in population size.

A prediction of future extreme fluctuations can also contribute to a VU D2 listing if projected local extinctions could cause it to meet the criteria for CR in a very short period of time (see above).

12.1.8 *Inferring population reduction and continuing decline (A3, A4, B1, B2, C2)*

Criteria A3 and A4 may be applied if a population reduction of a given magnitude may be inferred from relevant evidence. Unless there are quantitative models enabling projections of suitable habitat or population size under future climates, the evidence base will be indirect or circumstantial (section 3.1). For example, if there is evidence of a strong relationship between temperature and survival or temperature and breeding success, and there are projections of future temperatures that suggest that they will rise rapidly enough to reduce the number of mature individuals by at least 30% within the next 10 years or three generations, whichever is longer, then this information may be used to apply criterion A3. Similar inferences may be used to infer the direction of trends in the number of mature individuals, which may be used to infer continuing declines under criteria B1, B2 and C2.

12.1.9 *Inferring reductions from bioclimatic models (A3, A4)*

Bioclimate envelope models (or bioclimate models) are often used to predict changes in a taxon's range as defined by climatic variables. Such models are also known as species distribution models (SDM) or ecological niche models (ENM) that use climatic variables as predictor variables (see section 12.1.12 for detailed guidance on developing these models). The results of bioclimate envelope models will be a series of habitat suitability maps. In order to infer population reduction (for use in criteria A3 or A4) from these maps, it is necessary to calculate the expected population size from the current map and from the map for the time step that corresponds to three generations in the future. If climate data are not available for the year that corresponds to three generations in the future, it should be created by interpolation from the available layers.

Even if the current population size of the taxon is known, the same method of estimation should be used for both the "current" and the "future" maps. This is because the quantity of interest is the proportional change in population size, and using the same methods removes some of the effects of the assumptions involved in making this conversion from habitat suitability (HS) to population size.

The relationship between population reduction and habitat loss may not be linear (see section 5.8). However, in the absence of more specific information, it is an allowable assumption. With this assumption, the conversion from habitat suitability to population size will involve summing all

the HS values in each map, and calculating the proportional change in three generations. One important correction to this calculation is to use a threshold value of HS, to exclude from calculation of proportional reduction any areas that are unlikely to support a population because of low suitability. Another correction that should be made is to exclude patches that are too small to support a viable subpopulation (because of demographic stochasticity or Allee effects), or too isolated to be colonized by dispersers from occupied patches. Note that these corrections require species-specific information, and must be made separately for each taxon.

For species with limited dispersal ability, it is important to examine the overlap between successive habitat maps, projected at 1-generation intervals. The degree of overlap between each successive pair of habitat maps determines the relationship between habitat loss and population reduction. If there is little overlap, population reduction is likely to be larger than the projected habitat loss.

Other types of correlative analyses of population size or density as a function of environmental factors can also be used to infer population reductions. For example, the 2015 assessment of the Polar Bear (*Ursus maritimus*) used statistical relationships between sea ice and population size, combined with projected future decrease in sea ice, to calculate the range of plausible future 3-generation population reduction amounts (Wiig *et al.* 2015).

Projected change in habitat can also be used to infer continuing decline in habitat quality (e.g., criterion B1b(iii)).

12.1.10 Inferring reductions from demographic change

As noted in section 12.1.3, climate change may lead to population reductions or continuing declines through a range of demographic mechanisms. Understanding these can help to project the direction and rate of population response. The tools that are used to inform these projections will depend on the mechanism of response. In this section we briefly review the principal mechanisms, alert assessors to appropriate means of inference and suggest suitable tools to inform projection.

Some mechanisms are based on a direct ecophysiological relationship between a climate variable and one or more vital rates of the population. For example, in some taxa quantified relationships exist between fecundity and particular temperature variables for which projections can be derived from the outputs of Global Circulation Models (e.g., Kearney and Porter 2009). Other vital rates including survival, growth and dispersal may be affected. A range of plausible scenarios can be constructed from uncertainty in both the species response and the climate projection to estimate plausible bounds of population reduction. This method of projection will usually involve some assumptions about rates of adaptation to new environmental conditions (Hoffmann and Sgrò 2011). In some cases, there may be sufficient data to use demographic models for this purpose.

Some mechanisms involve a relationship between calcification rates and ocean acidity for organisms with calcified body parts (e.g., corals, molluscs) (Orr *et al.* 2005). Hence projections of ocean acidification (with characterisation of uncertainty in trends) should permit inferences about the continuing declines (criteria B and C) and projections of population reduction over required time frames (criterion A). Again, this should be based on defensible assumptions about rates of adaptation and should generate bounded estimates to represent the uncertainty in the projections.

A wide range of taxa have life history processes and vital rates that respond to regimes of fire, flood or storms, and hence may undergo population reductions depending on how disturbance regimes respond to climate change. It is possible to generate projections for indices of change in the frequency, intensity and season of such disturbance events from Global Circulation Models (e.g., Milly *et al.* 2002, Clarke *et al.* 2012, Zhao *et al.* 2015). Such projections, in combination with models of the species responses to the disturbance should support inferences about continuing declines and bounded estimates of population reduction over required time frames. Changes in the frequency of heat waves and other extreme weather events could be treated in a similar manner where they are key drivers of declines.

A fourth mechanism of response to climate change involves changes to species interactions. These are challenging to predict, but it may be plausible to project the direction of change, as a basis for inferring continuing declines, if the mechanisms are reasonably well understood. Examples include population changes of a target species inferred from projected increases in the area of spatial overlap between the habitat of the target taxon with those of its competitors, predators or disease vectors. Another example involves continuing declines inferred from phenological decoupling of mutualistic or facilitation interactions, or conversely phenological changes that result in increased exposure to competitors, predators or diseases.

Quantitative estimates of population reduction may be derived for many of these estimates using stochastic population models (e.g., Akçakaya *et al.* 2004). The parameterisation of these models may be adjusted to reflect projected trends in vital rates under a range of future climate scenarios based on regionally skilled Global Circulation Models (see section 12.1.12 for guidance on the selection of these). All applications of such models should justify the parameter settings and selection of scenarios used in projection. Recent developments allow the coupling of stochastic demographic models to species distribution models projected to produce a time series of habitat suitability maps under future climate scenarios (e.g., Keith *et al.* 2008). Alternative modelling approaches are developing to achieve similar goals (e.g., Cabral *et al.* 2013). These not only allow projections of future population reductions for assessment of criteria A3 and A4, but may produce estimates of extinction risk over required time frames for assessment under criterion E (see section 12.1.11).

12.1.11 Estimating extinction risk quantitatively with coupled habitat and population models (E)

Because of its time horizon for VU of 100 years (regardless of generation time), criterion E can be used to list species with short generation times that are predicted to be threatened by climate change. However, the difficulties with using criterion E (see section 9) are increased when climate change is the main threat, because of the need to take into account multiple types of stochastic and deterministic changes in the taxon's environment, demography and habitat that are caused or exacerbated by climate change.

New approaches that link outputs of global circulation models (GCMs, or climate models) to species habitat models and metapopulation models can be used to estimate risks of extinction (Keith *et al*. 2008, Anderson *et al*. 2009, Brook *et al*. 2009, Cabral *et al*. 2013) when adequate data are available for developing both bioclimate models (see section 12.1.12) and population models (see section 9). Preliminary findings from these studies showed that extinction risks under climate change are subject to complex dependencies between species life history, distribution patterns and landscape processes (Keith *et al*. 2008).

It is very important not to ignore other threats, which may interact with, or supersede, climate change impacts when predicting species vulnerability to climate change. Approaches that focus

on climate change alone may therefore lead to underestimation of extinction risks (Brook *et al*. 2009).

12.1.12 Using bioclimate models

Some of the guidance in the preceding sections refers to variables that may be calculated from outputs of bioclimate envelope models (or, bioclimate models). Such models are also known as species distribution models (SDM) or ecological niche models (ENM) that use climatic variables as predictor variables. This section will summarize methodological guidance in the use of these models for the purposes of Red List assessments. It is important to note that the use of these models is not necessary for all assessments of species threatened with climate change. Future versions of this document may include guidelines for other types of predictive modelling (such as eco-physiological models) that may be useful for Red List assessments.

Bioclimate envelope models have been widely applied to explore potential impacts of climate change on species distributions (for reviews of this field see: Guisan and Zimmerman 2000, Guisan and Thuiller 2005, Heikkinen *et al*. 2006, Franklin 2010, Peterson *et al*. 2011; for a practical introduction see Pearson 2007). These models commonly utilize associations between environmental variables and known species' occurrence records to identify climatic conditions within which populations can be maintained. The spatial distribution that is suitable for the species in the future can then be estimated under future climate scenarios. Advantages and disadvantages of this modelling approach have been widely debated in the literature, and multiple uncertainties make it essential that the model outputs are carefully interpreted (Pearson and Dawson 2003, Hampe 2004, Araújo and Guisan 2006, Thuiller *et al*. 2008).

Bioclimate envelope models may provide useful information for Red Listing by identifying species that are more or less likely to experience contractions in the area of suitable climate space in the future and by estimating the degree to which potential distributions in the future might overlap with current observed distributions. The guidelines here are intended as a list of methodological issues that must be carefully considered in applications of these models for red listing under climate change. It is important that methodologies are well justified within the context of any particular study, and with respect to the biology of the taxon being assessed. Assessments that rely on bioclimate models will be reviewed by the Standards and Petitions Committee (SPC), so sufficient detail must be provided to allow the SPC to determine if the model follows these guidelines.

Results of bioclimatic envelope models can be used in various ways to help with species assessments under the Red List Categories and Criteria. These uses include inferring population reduction under criterion A3 and continuing decline (see section 12.1.9), linking bioclimate and demographic models for criteria E (section 12.1.11), inferring continuing decline from projected increases in fragmentation (see section 12.1.6), and projecting plausible threats for use in criterion D2 (see section 12.1.4). Although the interpretation of the results from these models for Red List assessments relies on a number of assumptions, they do allow a tentative solution to the problem of incorporating the long-term impacts of climate change. A number of alternative modelling approaches are being developed to explore the relationship between climate change and species endangerment (see section 12.1.11), which will allow more comprehensive guidelines for assessing the risk of extinction due to climate change.

Quality of species occurrence data

Bioclimate envelope models rely on observed occurrence records for characterizing species limits of tolerance to climate predictors so it is essential that these data are of good quality. Confidence in the accuracy of georeferencing and species identifications of occurrence records should be high. It is important that georeferencing of occurrence records is accurate to a degree that is relevant to the resolution of the environmental variables (e.g., accuracy should be within a few tens of metres if the resolution of analysis is 1 km^2). Ideally, occurrence records should be associated with vouchered specimens and/or should have been identified by experts in the taxonomic group of interest. Data extracted from distributed databases (e.g., GBIF, HerpNET) should be carefully checked for accuracy, coverage and sampling intensity prior to use.

Occurrence data sampled from the whole range of the species should be included when calibrating bioclimate models, even in the case of regional assessments. Excluding occurrences from outside the region of interest reduces the model's ability for getting information on the full 'climate envelope' of the species. If, for instance, the current environmental conditions of a set of occurrence points in an area outside the region correspond to future projected conditions in some part of the region, then excluding those points from the model decreases the model's ability to correctly predict areas within the region that may become suitable in the future.

Selection of environmental predictor variables

Predictor variables need to be carefully selected. It is important to select variables that are expected to exert direct influence on the distributions of species (e.g., minimum temperature of the coldest month, maximum temperature of the warmest month, spring precipitation) through known eco-physiological mechanisms, and avoid indirect variables (e.g., altitude, topographic heterogeneity) (e.g., Guisan and Zimermann 2000). Variables such as elevation, latitude or longitude may serve as useful proxies for current climatic conditions but they hinder the accuracy of future predictions, because the relationships between these and climatic variables may change in the future. In particular, including elevation in the model is likely to result in the underestimation of the projected effects of future climate change. Often, there are several candidate variables for modelling the distributions of species, but they tend to be correlated amongst each other. When this is the case, it is often advisable to investigate the correlation amongst them and select a reduced number of uncorrelated variables (to avoid problems of co-linearity; Araújo and Guisan 2006). One possible approach is to use Principal Components Analysis (PCA) to identify a reduced number of significant axes and then select a sub-set of ecologically meaningful variables that are associated with each one of the significant axis. Note that the number of predictor variables should not exceed the number of species occurrence records that are used. As a general rule, no more than one predictor variable for every five observations should be used. Some methods (e.g., Maxent, Phillips *et al*. 2006; Boosted Regression Trees, Elith *et al*. 2008) select a parsimonious number of variables automatically in which case the above rule would not apply. One reason to aim for parsimony in variable selection is to avoid overfitting of the models, thus increasing generality.

Land-use masks

In addition to the climatic predictor variables, current and future land-use also constrains the distribution of species. This is especially crucial for species whose bioclimatic envelope is predicted to shift through human-dominated landscapes. Assessments that rely on climate data alone are prone to over-predict areas of suitable habitat because climate may be suitable, but land cover may be unsuitable (Pearson *et al*. 2004). A land use map can be used as a mask to exclude such unsuitable areas from current and projected habitat. However, if land-use and climatic

variables are likely to interact, then the land-use variables should be included in the model together with the climatic variables, rather than used as a mask (Stanton *et al.* 2012).

Choosing an appropriate spatial resolution

Bioclimatic models have been fitted with data of varying resolutions, for instance ranging from 1 ha cells in Switzerland (Randin *et al.* 2009), to 2 degree latitude-longitude cells at a global level. There is commonly a trade-off between the geographical extent of the study area and the resolution of the data: studies across large areas are likely to use data at coarser resolutions than studies across smaller regions. Similarly, it is often necessary to use data at finer resolution when modelling the bioclimate envelope of restricted range species, whereas wide-ranging species may be effectively modelled using data at coarser resolutions. Also, when modelling species across regions with low spatial heterogeneity (e.g., flat terrain), coarser resolution data are less of a problem than when models are used across areas of high heterogeneity (e.g., rugged terrain). It is important to bear in mind, however, that analyses at coarse resolutions may not account for microclimates that may be important for species persistence (Pearson *et al.* 2006, Trivedi *et al.* 2008, Randin *et al.* 2009).

Model selection

A large number of bioclimatic modelling techniques exist, and it has been shown that agreements between predicted and observed distributions are often greater with models allowing complex response curves (e.g., Elith *et al.* 2006). There is an ongoing debate as to whether more complex models are more adequate for modelling species ranges under climate change (Araújo and Rahbek 2006), so it is difficult at this point to provide unequivocal guidelines with respect to the choice of the modelling techniques. However, it is important that assessments of species range changes are based on established methodologies that have been used and verified by several independent research groups.

Assessing the robustness of model projections

Studies have shown that projections from alternative models can be so variable as to compromise assessment of whether species potential distributions should contract or expand for any given climate scenario (e.g., Araújo *et al.* 2005, Araújo *et al.* 2006, Pearson *et al.* 2006). Assessments of the temporal trends in the sizes of species potential distributions should, therefore, include an assessment of the robustness of the projections by comparing results of a range of bioclimatic modelling techniques. We suggest that at least three modelling techniques should be compared and be as independent as possible with regards to how they link the response and the predictor variables (e.g., GAM and GLM are conceptually similar and tend to produce similar results). Various strategies may be employed in cases when models forecast inconsistent trends. One such strategy is to investigate the cause of the discrepancies. Typically, this would involve investigation of the species response curves obtained with each one of the methods, evaluating if there is any clear error, and then selecting the projections by the method producing more reasonable results. This approach is useful for species with well-known ecologies where expert judgements can be made and contrasted with the model outputs. The downside of the approach is that it involves subjective judgement that may yield non-repeatable results. An alternative strategy is to run ensembles of forecasts using a number of established approaches and then combine the individual model projections through consensus methodologies (for a review see Araújo and New 2007). The disadvantage here is that potentially significant ecological knowledge is not being used.

Background/pseudo-absence in the species distribution data

Species distribution data may be either presence-only (i.e., records of localities where the species has been observed) or presence/absence (i.e., records of presence and absence of the species at sampled localities). Alternative modelling approaches have been developed to deal with each of these cases. Some approaches that use presence-only data also utilize 'background' (e.g., Maxent, Phillips *et al*. 2006) or 'pseudo-absence' (e.g., Elith *et al*. 2006) data. In these cases, model results are sensitive to the extent of the study region from which background or pseudo-absence samples are taken. It is therefore important to select an appropriate study region. In general, background and pseudo-absence records should not be selected from areas where the species is absent due to non-climatic factors, such as dispersal limitation or inter-species competition (because such records provide a false-negative signal that will lead to poorer characterization of the species' climatic requirements; Anderson and Raza 2010). Where possible, selection of the extent of the study region should therefore take into account factors including the dispersal capacity of the species and distributions of competitors.

Capturing entire species ranges and avoiding model extrapolation

It is necessary to include occurrence records from throughout the species range in order to avoid artificially truncating response curves when modelling the species' niche (Elith and Graham 2009, Thuiller *et al*. 2004). For example, models based on data from only one country within a multi-national species range will generally be unacceptable. It is possible that response curves could be adequately characterized using part of the range provided that excluded localities do not represent parts of the niche that are represented by other occurrence records, but such cases must be well justified. Caution must also be exercised when extrapolating model results under future climate scenarios (i.e., extrapolating in environmental space beyond the range of data used to build the model; Pearson *et al*. 2006). Extrapolation should be avoided where possible (e.g., Pearson *et al*. 2002), or else the behaviour of the model (i.e., the shape of response curves when extrapolating) should be known and well justified.

Model testing

Testing model performance is an important step in any modelling exercise. Multiple tests have been employed to assess the performance bioclimate envelope models (e.g., AUC, Kappa, TSS; Fielding and Bell 1997), but it is important to note that testing of bioclimate models remains problematic for at least three reasons. First, models aim to predict the distribution of potentially suitable climates, yet data against which this can be tested are not available (use of species absence records is unsatisfactory because predictions of 'presence' in areas that are climatically suitable but unoccupied for non-climatic reasons will be classified as model 'errors') (Peterson *et al*. 2011). Second, performance of the models is usually inflated because studies use data for training the models that are not independent from the data used for testing them (Araújo *et al*. 2005). Finally, projections are made for events that have not yet occurred, so any attempts to test the models must focus on examination of the internal consistency of the models rather than their predictive accuracy (Araújo and Guisan 2006). So, although standard testing methodologies are an important part of model building, it should be noted that the predictive skill of the bioclimatic models under climate change remains untested.

Using appropriate metrics of species range changes

Bioclimate models may be useful to assess trends in the availability of suitable climate conditions for species. There are two possible measures that are likely to be useful. One is based on combining probabilities or suitability indices from the models, and the second is based on

measuring the potential area occupied by the species after transforming probabilities (or suitabilities) into estimates of presence and absence. To make such a transformation, it is necessary to use thresholds (see, for example, Liu *et al*. 2005). For instance, use of the lowest presence threshold (e.g., Pearson *et al*. 2007) may be justified in cases with few occurrence records, but balancing sensitivity and specificity may be more appropriate when a larger number of presence/absence records are available. Sensitivity of conclusions to the selection of alternative methods for defining thresholds should be examined. However, it should be noted that the measures of change in climate suitability that are relevant to red listing are relative measures (of proportional change in time) and these are, in principle, robust to alternative methods for defining thresholds. The absolute areas (of range or potential habitat) should not be used as part of assessments of species extinction risk under climate change because estimates of change from bioclimate models are very sensitive to the thresholds used. Note that thresholds may also be used when converting habitat suitability to population size (see section 12.1.9).

Future emission scenarios

Climate models are based upon socio-economic scenarios. Each of these scenarios makes different assumptions about future greenhouse gas emissions, land-use and other driving forces. Assumptions about future technological and economic developments are built into families of 'storylines', each of which describing alternative pathways for the future because there is no theoretical basis for long-term socio-economic forecasting. The IPCC Fifth Assessment Report (AR5) projected changes in the climate system using a set of scenarios called Representative Concentration Pathways (RCPs). In order to account for uncertainty in predictions of future climate change, studies should explore a range of plausible scenarios of climate change (e.g., the RCP8.5 and RCP4.5 scenarios in IPCC 2013), and the broader the range of scenarios considered the better. The set of scenarios selected should be justified. Furthermore, as emission scenarios are revised in future, the relevant red list assessments based on them should be revised.

13. References

Akçakaya, H.R. 2000. Population viability analyses with demographically and spatially structured models. *Ecological Bulletins* 48: 23–38.

Akçakaya, H.R. 2002. Estimating the variance of survival rates and fecundities. *Animal Conservation* 5: 333–336.

Akçakaya, H.R. and Raphael, M.G. 1998. Assessing human impact despite uncertainty: viability of the northern spotted owl metapopulation in the northwestern USA. *Biodiversity and Conservation* 7: 875–894.

Akçakaya H.R. and Sjögren-Gulve, P. 2000. Population viability analysis in conservation planning: an overview. *Ecological Bulletins* 48: 9–21.

Akçakaya, H.R., Ferson, S., Burgman, M.A., Keith, D.A., Mace, G.M. and Todd, C.A. 2000. Making consistent IUCN classifications under uncertainty. *Conservation Biology* 14: 1001–1013.

Akçakaya H.R, Burgman M.A., Kindvall O., Wood C.C., Sjogren-Gulve P., Hatfield J.S. and McCarthy M.A. 2004. '*Species Conservation and Management: case studies*.' Oxford University Press, Oxford.

Akçakaya, H.R., Butchart, S.H.M., Mace, G.M., Stuart, S.N. and Hilton-Taylor, C. 2006. Use and misuse of the IUCN Red List Criteria in projecting climate change impacts on biodiversity. *Global Change Biology* 12: 2037–2043.

Akçakaya, H.R., Keith, D.A., Burgman, M., Butchart, S.H.M., Hoffmann, M., Regan, H.M., Harrison, I., and Boakes, E. 2017. Inferring extinctions III: A cost-benefit framework for listing extinct species. *Biological Conservation* 214: 336–342.

Akçakaya, H.R., Hochkirch, A., Bried, J.T., van Grunsven, R.H.A., Simaika, J.P., De Knijf, G. and Henriques, S. 2021. Calculating population reductions of invertebrate species for IUCN Red List assessments. *Journal of Insect Conservation* 25: 377–382.

Anderson, B., Akçakaya, H.R., Araújo, M., Fordham, D., Martinez-Meyer, E., Thuiller, W. and Brook, B.W. 2009. Dynamics of range margins for metapopulations under climate change. *Proceedings of the Royal Society B* 276: 1415–1420.

Anderson, R.P. and Raza, A. 2010. The effect of the extent of the study region on GIS models of species geographic distributions and estimates of niche evolution: preliminary tests with montane rodents (genus *Nephelomys*) in Venezuela. *Journal of Biogeography* 37: 1378–1393.

Araújo, M.B. and Guisan, A. 2006. Five (or so) challenges for species distribution modelling. *Journal of Biogeography* 33: 1677–1688.

Araújo, M.B. and New, M. 2007. Ensemble forecasting of species distributions. *Trends in Ecology and Evolution* 22: 42–47.

Araújo, M.B., Pearson, R.G., Thuiller, W. and Erhard, M. 2005. Validation of species-climate impact models under climate change. *Global Change Biology* 11: 1504–1513.

Araújo, M.B., Whittaker, R.J., Ladle, R.J. and Erhard, M. 2005. Reducing uncertainty in extinction risk from climate change. *Global Ecology and Biogeography* 14: 529–538.

Bird, J.P., Martin, R., Akçakaya, H.R., Gilroy, J., Burfield, I.J., Garnett, S.T., Symes, A., Taylor, J., Şekercioğlu, Ç.H. and Butchart, S.H.M. 2020. Generation lengths of the world's birds and their implications for extinction risk. *Conservation Biology* 34: 1252–1261.

BirdLife International. 2004. Threatened birds of the world 2004. CD-ROM. BirdLife International, Cambridge, UK.

Boyce, M.S. 1992. Population viability analysis. *Annual Review of Ecology and Systematics* 23: 481–506.

Brook, B.W., Akçakaya, H.R., Keith, D.A., Mace, G.M., Pearson, R.G. and Araújo, M.B. 2009. Integrating bioclimate with population models to improve forecasts of species extinctions under climate change. *Biology Letters* 5: 723–725.

Brook, B.W., O'Grady, J.J., Chapman, A.P., Burgman, M.A., Akçakaya, H.R. and Frankham, R. 2000. Predictive accuracy of population viability analysis in conservation biology. *Nature* 404: 385–387.

Brooks, T.M., Pimm, S.L., Akçakaya, H.R., Buchanan, G.M., Butchart, S.H.M., Foden, W., Hilton-Taylor, C., Hoffmann, M., Jenkins, C.N., Joppa, L., Li, B.V., Menon, V., Ocampo-Peñuela, N. and Rondinini, C. 2019. Utility of Area of Habitat for the IUCN Red List. *Trends in Ecology and Evolution.* 34: 977–986. DOI: 10.1016/j.tree.2019.06.009.

Burgman, M.A. and Fox, J.C. 2003. Bias in species range estimates from minimum convex polygons: implications for conservation and options for improved planning. *Animal Conservation* 6: 19–28.

Burgman, M.A., Keith, D.A. and Walshe, T.V. 1999. Uncertainty in comparative risk analysis of threatened Australian plant species. *Risk Analysis* 19: 585–598.

Burgman, M.A., Ferson, S. and Akçakaya, H.R. 1993. *Risk Assessment in Conservation Biology*. Chapman and Hall, London.

Bustamante, M.R. 2002. Monitoreos de poblaciones de anuros en los Andes de Ecuador, con énfasis en el estudio poblacional de las especies del Bosque protector Cashca Totoras (Provincia Bolívar). Tesis de Licenciatura, Pontificia Universidad católica del Ecuador.

Butchart, S.H.M. and Bird, J. 2009. Data Deficient birds on the IUCN Red List: what don't we know and why does it matter? *Biological Conservation* 143: 239–247.

Butchart, S.H.M., Stattersfield, A.J. and Brooks, T.M. 2006. Going or gone: defining 'Possibly Extinct' species to give a truer picture of recent extinctions. *Bulletin of the British Ornithologists Club* 126A: 7–24.

Butchart, S.H.M., Lowe, S., Martin, R.W., Symes, A., Westrip, J.R.S. and Wheatley, H. 2018. Which bird species have gone extinct? A novel quantitative classification approach. *Biological Conservation* 227: 9–18.

Cabral, J.S., Jeltsch, F, Thuiller, W., Higgins, S., Midgley, G.F., Rebelo, A.G., Rouget, M. and Schurr, F.M. 2013. Impacts of past habitat loss and future climate change on the range dynamics of South African Proteaceae. *Diversity and Distributions* 19: 363–376.

Cardoso, P., Borges, P.A., Triantis, K.A., Ferrández, M.A. and Martín, J.L. 2011. Adapting the IUCN red list criteria for invertebrates. *Biological Conservation* 144: 2432–2440.

Clarke, H., Lucas, C. and Smith, P. 2012. Changes in Australian fire weather between 1973 and 2010. *International Journal of Climatology* 33(4): 931–944, DOI: 10.1002/joc.3480.

Coleman, F.C., Koenig, C.C. and Collins, L.A. 1996. Reproductive styles of shallow-water groupers (Pisces: Serranidae) in the eastern Gulf of Mexico and the consequences of fishing spawning aggregations. *Environmental Biology of Fishes* 47: 129–141.

Collar, N.J. 1998. Extinction by assumption; or, the Romeo Error on Cebu. *Oryx* 32: 239–244.

Collen, B., Dulvy, N.K., Gaston, K.J., Gärdenfors, U., Keith, D.A., Punt, A.E., Regan, H.M., Böhm, M., Hedges, S., Seddon, M., Butchart, S.H.M., Hilton-Taylor, C., Hoffmann, M., Bachman, S.P. and Akçakaya, H.R. 2016. Clarifying misconceptions of extinction risk assessment with the IUCN Red List. *Biology Letters* 12: 20150843.

Dale, V.H., Joyce, L.A., McNulty, S., Neilson, R.P., Ayres, M.P., Flannigan, M.D., Hanson, P.J., Irland, L.C., Lugo, A.E., Peterson, C.J., Simberloff, D., Swanson, F.J., Stocks, B.J. and Wotton, B.M. 2001. Climate change and forest disturbances. *BioScience* 51(9): 723–734.

DeAngelis, D.L. and Diaz, S.G. 2019. Decision-making in agent-based modeling: a current review and future prospectus. *Frontiers in Ecology and Evolution* 6: DOI: 10.3389/fevo.2018.00237.

Dennis, B., Munholland, P.L. and Scott, J.M. 1991. Estimation of growth and extinction parameters for endangered species. *Ecological Monographs* 61: 115–143.

Deutsch, C.A., Tewksbury, J.J., Huey, R.B., Sheldon, K.S., Ghalambor, C.K., Haak, D.C. and Martin, P.R., 2008. Impacts of climate warming on terrestrial ectotherms across latitude. *PNAS* 105(18): 6668–6672.

Dutson, G.C.L., Magsalay, P.M. and Timmins, R.J. 1993. The rediscovery of the Cebu Flowerpecker *Dicaeum quadricolor*, with notes on other forest birds on Cebu, Philippines. *Bird Conservation International* 3: 235–243.

Elith, J. and Graham, C.H. 2009. Do they / How do they / WHY do they differ? - on finding reasons for differing performances of species distribution models. *Ecography* 32: 66–77.

Elith, J., Graham, C. and the NCEAS species distribution modeling group. 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography* 29: 129–151.

Elith, J., Leathwick, J.R. and Hastie, T. 2008. A working guide to boosted regression trees. *Journal of Animal Ecology* 77: 802–813.

Ferson, S., Root, W. and Kuhn, R. 1998. *RAMAS Risk Calc: Risk Assessment with Uncertain Numbers*. Applied Biomathematics, Setauket, New York.

Fielding, A.H. and Bell, J.F. 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24: 38–49.

Foden, W.B., Butchart, S.H.M., Stuart, S.N., Vié, J.-C., Akçakaya, H.R., Angulo, A., DeVantier, L.M., Gutsche, A., Turak, E., Cao, L., Donner, S.D., Katariya, V., Bernard, R., Holland, R.A., Hughes, A.F., O'Hanlon, S.E., Garnett, S.T., Şekercioğlu, Ç.H. and Mace, G.M. 2013. Identifying the

world's most climate change vulnerable species: a systematic trait-based assessment of all birds, amphibians and corals. *PLoS ONE* 8(6): e65427. DOI:10.1371/journal.pone.0065427.

Franklin, J. 2010. *Mapping Species Distributions: Spatial Inference and Prediction.* Cambridge University Press, UK.

Gärdenfors, U. 2000. Population viability analysis in the classification of threatened species: problems and potentials. *Ecological Bulletins* 48: 181–190.

Gärdenfors, U., Hilton-Taylor, C., Mace, G.M. and Rodríguez, J.P. 2001. The application of IUCN Red List Criteria at regional levels. *Conservation Biology* 15: 1206–1212.

Gaston, K. J. 1996. The multiple forms of the interspecific abundance-distribution relationship. *Oikos* 76: 211–220.

Gilman, S.E., Urban, M.C., Tewksbury, J., Gilchrist, G.W. and Holt, R.D. 2010. A framework for community interactions under climate change. *Trends in Ecology and Evolution* 25(6): 325–331.

Gould, W.R. and Nichols, J.D. 1998. Estimation of temporal variability of survival in animal populations. *Ecology* 79: 2531–2538.

Guisan, A. and Zimmerman, N. 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135: 147–186.

Guisan, A. and Thuiller, W. 2005. Predicting species distribution: Offering more than simple habitat models. *Ecology Letters* 8: 993–1009.

Hallingbäck, T., Hodgetts, N., Raeymaekers, G., Schumacker, R., Sérgio, C., Söderström, L., Stewart, N. and Váòa, J. 2000. Guidelines for Application of the 1994 IUCN Red List Categories of Threats to Bryophytes. Appendix 1 in: T. Hallingbäck and N. Hodgetts (compilers) *Mosses, Liverworts, and Hornworts. Status survey and Conservation Action Plan for Bryophytes.* IUCN SSC Bryophyte Specialist Group. IUCN, Gland, Switzerland and Cambridge, U.K.

Hampe, A. 2004. Bioclimatic models: what they detect and what they hide. *Global Ecology and Biogeography* 11: 469–471.

He, F. and Gaston, K.J. 2000. Estimating species abundance from occurrence. *The American Naturalist* 156: 553–559.

Heikkinen, R.K., Luoto, M., Araújo, M.B., Virkkala, R., Thuiller, W. and Sykes, M.T. 2006. Methods and uncertainties in bioclimatic modelling under climate change. *Progress in Physical Geography* 30: 751–777.

Hobday, A.J., Tenger, M.J. and Hakker, P.L. 2001. Over-exploitation of a broadcast spawning marine invertebrate: decline of the white abalone. Reviews in Fish Biology and Fisheries 10: 493–514.

Hoffmann, A.A. and Sgrò, C.M. 2011. Climate change and evolutionary adaptation. *Nature* 470: 479–485.

IPCC. 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. Downloaded from http://ipcc.ch/report/ar5/wg1/ (14 Jan 2016).

IUCN. 1994. *IUCN Red List Categories*. IUCN Species Survival Commission. IUCN, Gland, Switzerland and Cambridge, U.K.

IUCN. 1998. *Guidelines for Re-introductions*. Prepared by the IUCN SSC Re-introduction Specialist Group. IUCN, Gland, Switzerland and Cambridge, U.K.

IUCN. 2001. *IUCN Red List Categories and Criteria: Version 3.1*. IUCN Species Survival Commission. IUCN, Gland, Switzerland and Cambridge, U.K.

IUCN. 2003. *Guidelines for Application of IUCN Criteria at Regional Levels. Version 3.0*. IUCN Species Survival Commission. IUCN, Gland, Switzerland and Cambridge, UK.

IUCN. 2012a. *Guidelines for Application of IUCN Red List Criteria at Regional and National Levels: Version 4.0.* IUCN, Gland, Switzerland and Cambridge, UK. Available at www.iucnredlist.org/technical-documents/categories-and-criteria

IUCN. 2012b. *IUCN Red List Categories and Criteria: Version 3.1. Second edition.* IUCN, Gland, Switzerland and Cambridge, UK. Available at www.iucnredlist.org/technical-documents/categories-and-criteria

IUCN. 2021. *IUCN Green Status of Species: A global standard for measuring species recovery and assessing conservation impact.* Version 2.0. Gland, Switzerland: IUCN. Available at https://www.iucnredlist.org/resources/green-status-assessment-materials

Juniper, T. 2003. *Spix's Macaw: the Race to Save the World's Rarest Bird.* Fourth Estate, London.

Kearney M. and Porter W. 2009. Mechanistic niche modelling: combining physiological and spatial data to predict species' ranges. *Ecology Letters* 12: 334–350.

Keith, D.A. 1998. An evaluation and modification of World Conservation Union Red List criteria for classification of extinction risk in vascular plants. *Conservation Biology* 12: 1076–1090.

Keith, D., Akçakaya, H.R., Butchart, S.H.M., Collen, B., Dulvy, N.K., Holmes, E.E., Hutchings, J.A., Keinath, D., Schwartz, M.K., Shelton, A.O. and Waples, R.S. 2015. Temporal correlations in population trends: conservation implications from time-series analysis of diverse animal taxa. *Biological Conservation* 192: 247–257.

Keith, D.A., Auld, T.D., Ooi, M.K.J. and Mackenzie, B.D.E. 2000. Sensitivity analyses of decision rules in World Conservation Union (IUCN) Red List criteria using Australian plants. *Biological Conservation* 94: 311–319.

Keith, D., McCarthy, M.A., Regan, H., Regan, T., Bowles, C., Drill, C., Craig, C., Pellow, B., Burgman, M.A., Master, L.L., Ruckelshaus, M., Mackenzie, B., Andelman, S.J. and Wade, P.R. 2004. Protocols for listing threatened species can forecast extinction. *Ecology Letters* 7: 1101–1108.

Keith, D.A, Akçakaya, H.R., Thuiller, W., Midgley, G.F., Pearson, R.G., Phillips, S.J., Regan, H.M., Araújo, M.B. and Rebelo, A.G. 2008. Predicting extinction risks under climate change: coupling stochastic population models with dynamic bioclimatic habitat models. *Biology Letters* 4: 560–563.

Keith, D.A., Mahony, M., Hines, H., Elith, J., Regan, T.J., Baumgartner, J.B., Hunter, D., Heard, G.W., Mitchell, N.J., Parris, K.M., Penman, T., Scheele, B.E.N., Simpson, C.C., Tingley, R., Tracy, C.R., West, M. and Akçakaya, H.R. 2014. Detecting extinction risk from climate change by IUCN Red List Criteria. *Conservation Biology* 28: 810–819.

Keith, D.A., Butchart, S.H.M., Regan, H.M., Harrison, I., Akçakaya, H.R., Solow, A.R. and Burgman, M.A. 2017. Inferring extinctions I: A structured method using information on threats. *Biological Conservation* 214: 320–327.

Keith, D.A., Akçakaya, H.R. and Murray, N.J. 2018. Scaling range sizes to threats for robust predictions of risks to biodiversity. *Conservation Biology* 32: 322–332. DOI: 10.1111/cobi.12988.

Kindvall, O. 2000. Comparative precision of three spatially realistic simulation models of metapopulation dynamics. *Ecological Bulletins* 48: 101–110.

Kunin, W.E. 1998. Extrapolating species abundance across spatial scales. *Science* 281: 1513–1515.

Lacy, R.C. 2000. Considering threats to the viability of small populations with individual-based models. *Ecological Bulletins* 48: 39–51.

Lam, J.T.L. 2009. Shortened Nassau Grouper spawning ban. *Society for the Conservation of Reef Fish Aggregations Newsletter* 13: 4.

Lande, R., Engen, S. and Saether, B.-E. 2003. *Stochastic population dynamics in ecology and evolution.* Oxford University Press, Oxford, UK.

Liu, C., Berry P.M., Dawson T.P. and Pearson, R.G. 2005. Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* 28: 385–393.

Mace, G.M. and Lande, R. 1991. Assessing extinction threats: toward a reevaluation of IUCN threatened species categories. *Conservation Biology* 5: 148–157.

Mace, G.M., Collar, N.J., Gaston, K.J., Hilton-Taylor, C., Akçakaya, H.R., Leader-Williams, N., Milner-Gulland, E.J. and Stuart, S.N. 2008. Quantification of extinction risk: IUCN's system for classifying threatened species. *Conservation Biology* 22: 1424–1442.

Mackenzie, D.I., Nichols, J.D., Royle, J., Pollock, K.H., Bailey, L.L. and Hines, J. 2017. *Occupancy Estimation and Modeling: Inferring Patterns and Dynamics of Species Occurrence*. Second Edition. Academic Press.

Magsalay, P., Brooks, T., Dutson, G. and Timmins, R. 1995. Extinction and conservation on Cebu. *Nature* 373: 294.

McCarthy, M.A., Possingham, H.P., Day, J.R. and Tyre, A.J. 2001. Testing the accuracy of population viability analysis. *Conservation Biology* 15: 1030–1038.

Memmott, J., Craze, P.G., Waser, N.M. and Price, M.V. 2007. Global warming and the disruption of plant–pollinator interactions. *Ecology Letters* 10: 710–717.

Miller R.M., Rodríguez, J.P., Aniskowicz-Fowler, T., Bambaradeniya, C., Boles, R., Eaton, M.A., Gärdenfors, U., Keller, V., Molur, S., Walker, S. and Pollock, C. 2007. National threatened species listing based on IUCN criteria and regional guidelines: Current status and future perspectives. *Conservation Biology* 21: 684–696.

Milly, P.C.D., Wetherald, R.T., Dunne, K.A. and Delworth, T.L. 2002. Increasing risk of great floods in a changing climate. *Nature* 415: 514–517.

Ocampo-Peñuela, N., Jenkins, C.N., Vijay, V., Li, B.V. and Pimm, S.L. 2016. Incorporating explicit geospatial data shows more species at risk of extinction than the current Red List. *Science Advances* 2: e1601367.

Orr, J.C., Fabry, V.J., Aumont, O., Bopp, L., Doney, S.C., Feely, R.A., Gnanadesikan, A., Gruber, N., Ishida, A., Joos, F., Key, R.M., Lindsay, K., Maier-Reimer, E., Matear, R., Monfray, P., Mouchet, A., Najjar, R.G., Plattner, G.K., Rodgers, K.B., Sabine, C.L., Sarmiento, J.L., Schlitzer, R., Slater, R.D., Totterdell, R.J., Weirig, M.F., Yamanaka, Y. and Yoo, A. 2005. Anthropogenic ocean acidification over the twenty-first century and its impact on calcifying organisms. *Nature* 437: 681–686.

Ostro, L.E.T., Young, T.P., Silver, S.C. and Koontz, F.W. 1999. A geographic information system method for estimating home range size. *Journal of Wildlife Management* 63: 748–755.

Pacifici, M., Santini, L., Di Marco, M., Baisero, D., Francucci, L., Grottolo Marasini, G., Visconti, P., and Rondinini, C. 2013. Generation length for mammals. *Nature Conservation* 5: 87–94.

Pearson, R.G. 2006. Climate change and the migration capacity of species. *Trends in Ecology and Evolution* 21: 111–113.

Pearson, R.G. 2007. Species Distribution Modeling for Conservation Educators and Practitioners. *Lessons in Conservation* 3: 54–89. Available at: https://www.amnh.org/content/download/141368/2285424/file/LinC3_SpeciesDistModeling.pdf.

Pearson, R.G. and Dawson, T.P. 2003. Predicting the impacts of climate change on the distribution of species: Are bioclimate envelope models useful? *Global Ecology and Biogeography* 12: 361–371.

Pearson, R.G., Raxworthy, C.J., Nakamura, M. and Peterson, A.T. 2007. Predicting species' distributions from small numbers of occurrence records: a test case using cryptic geckos in Madagascar. *Journal of Biogeography* 34: 102–117.

Pearson, R.G., Dawson, T.P., Berry, P.M. and Harrison, P.A. 2002. Species: A spatial evaluation of climate impact on the envelope of species. *Ecological Modelling* 154: 289–300.

Pearson, R.G., Thuiller, W., Araújo, M.B., Martinez, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T. and Lees, D. 2006. Model-based uncertainty in species' range prediction. *Journal of Biogeography* 33: 1704–1711.

Pearson, R.G., Stanton, J.C., Shoemaker, K.T., Aiello-Lammens, M.E., Ersts, P.J., Horning, N., Fordham, D.A., Raxworthy, C.J., Ryu, H., McNees, J. and Akçakaya, H.R. 2014. Life history and spatial traits predict extinction risk due to climate change. *Nature Climate Change* 4: 217–221.

Peterson, A.T., Soberón, J., Pearson, R.G., Anderson, R.P., Martínez-Meyer, E., Nakamura, M. and Araújo, M.B. 2011. *Ecological Niches and Geographical Distributions: A Modeling Perspective.* Princeton University Press, Princeton, New Jersey.

Phillips, S.J., Anderson, R.P. and Schapire, R.E. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231–259.

Porszt, E.J., Peterman, R.M., Dulvy, N.K., Cooper, A.B. and Irvine, J.R. 2012. Reliability of indicators of decline in abundance. *Conservation Biology* 26: 894–904.

Pratt, T.K., Fancy, S.G. and Ralph, C.J. 2001. 'Akiapola'au (*Hemignathus munroi*) and Nukupu'u (*Hemignathus lucidus*). In: A. Poole and F. Gill (eds) *The Birds of North America*, no. 600. The Birds of North America, Philadelphia, PA.

Randin, C.F., Engler, R., Normand, S., Zappa, M., Zimmermann, N.E., Pearman, P.B., Vittoz, P., Thuiller, W. and Guisan, A. 2009: Climate change and plant distribution: local models predict high-elevation persistence. *Global Change Biology* 15: 1557–1569.

Redford, K.H., Amato, G., Baillie, J., Beldomenico, P., Bennett, E.L., Clum, N., Cook, R., Fonseca, G., Hedges, S., Launay, F., Lieberman, S., Mace, G.M., Murayama, A., Putnam, A., Robinson, J.G., Rosenbaum, H., Sanderson, E.W. Stuart, S.N., Thomas, P. and Thorbjarnarson, J. 2011. What does it mean to successfully conserve a (vertebrate) species? *BioScience* 61: 39–48.

Reynolds, M.H. and Snetsinger, J.J. 2001. The Hawaii rare bird search 1994–1996. *Studies in Avian Biology* 22: 133–143.

Rodríguez, J.P. 2002. Range contraction in declining North American bird populations. *Ecological Applications* 12: 238–248.

Sadovy, Y. and Cheung, W.L. 2003. Near extinction of a highly fecund fish: the one that nearly got away. *Fish and Fisheries* 4: 86–99.

Sadovy, Y. and Domeier, M. 2005. Are aggregation-fisheries sustainable? Reef fish fisheries as a case study. *Coral Reefs* 24: 254–262.

Sethi, S.A., Branch, T.A. and Watson, R. 2010. Global fishery development patterns are driven by profit but not trophic level. *PNAS* 207: 12163–12167.

Shoo, L.P., Williams, S.E. and Hero, J.-M. 2005. Climate warming and the rainforest birds of the Australian wet tropics: using abundance data as a sensitive predictor of change in total population size. *Biological Conservation* 125: 335–343.

Sjögren-Gulve, P. and Hanski, I. 2000. Metapopulation viability analysis using occupancy model. *Ecological Bulletins* 48: 53–71.

Stanton, J.C. 2014. Present-day risk assessment would have predicted the extinction of the passenger pigeon (*Ectopistes migratorius*). *Biological. Conservation.* 180: 11–20.

Stanton, J.C., Pearson, R.G., Horning, N, Ersts, P. and Akçakaya, H.R. 2012. Combining static and dynamic variables in species distribution models under climate change. *Methods in Ecology and Evolution* 3: 349–357.

Stanton, J.C., Shoemaker, K.T., Pearson, R.G. and Akçakaya, H.R. 2015. Warning times for species extinctions due to climate change. *Global Change Biology* 20(3): 1066–1077.

Stoner, A.W., Davis, M.H. and Booker, C.J. 2012. Negative consequences of Allee effect are compounded by fishing pressure: comparison of Queen Conch reproduction in fishing grounds and a marine protected area. *Bulletin of Marine Science* 88(1): 89–104.

Thompson, C.J., Koshkina, V., Burgman, M.A., Butchart, S.H.M. and Stone, L. 2017. Inferring extinctions II: a practical, iterative model based on records and surveys. *Biological Conservation* 214: 328–335.

Thuiller, W., Brotons, L., Araújo, M.B. and Lavorel, S. 2004. Effects of restricting environmental range of data to project current and future species distributions. *Ecography* 27: 165–172.

Thuiller, W., Münkemüller, T., Schiffers, K.H., Georges, D., Dullinger, S., Eckhart, V.M., Edwards Jr, T.C., Gravel, D., Kunstler, G., Merow, C., Moore, K., Piedallu, C., Vissault, S., Zhao, M., Tuleya, R.E., Bender, M., Vecchi, G.A., Villarini, G., Chavas, D. 2015. Global Projections of Intense Tropical Cyclone Activity for the Late Twenty-First Century from Dynamical Downscaling of CMIP5/RCP4.5 Scenarios. *Journal of Climate* 28: 7203–7224.

Trivedi, M.R., Berry, P.M., Morecroft, M.D. and Dawson, T.P. 2008. Spatial scale affects bioclimate model projections of climate change impacts on mountain plants. *Global Change Biology* 14: 1089–1103.

White, G.C., Franklin, A.B. and Shenk, T.M. 2002. Estimating parameters of PVA models from data on marked animals. In: S.R. Beissingerand and D.R. Mccullough (eds) *Population Viability Analysis*, pages 169–190. University of Chicago Press, Chicago.

Wiig, Ø., Amstrup, S., Atwood, T., Laidre, K., Lunn, N., Obbard, M., Regehr, E. and Thiemann, G. 2015. *Ursus maritimus*. *The IUCN Red List of Threatened Species* 2015: e.T22823A14871490. http://dx.doi.org/10.2305/IUCN.UK.2015-4.RLTS.T22823A14871490.en

Wilhelm, S.I., Rail, J.-F., Regular, P.M., Gjerdrum, C. and Robertson, G.J. 2016. Large-scale changes in abundance of breeding Herring Gulls (*Larus argentatus*) and Great Black-Backed Gulls (*Larus marinus*) relative to reduced fishing activities in southeastern Canada. *Waterbirds* 39: 136–142, 137.

Zimmermann, N.E., Zurell, D. and Schurr, F.M. 2014. Does probability of occurrence relate to population dynamics? *Ecography* 37(12): 1155–1166.