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Predictive traits to the rescue

Climate change poses new challenges to the conservation of species, which at present requires data-hungry models to meaningfully anticipate future threats. Now a study suggests that species traits may offer a simpler way to help predict future extinction risks.

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As biodiversity erosion intensifies worldwide[1,2], threatening our biological heritage, nature management tools are needed more than ever[3]. Unfortunately, the computer models used to assess population declines are data hungry, and data on endangered species — those most in need of modelling — are usually lacking. Writing in *Nature Climate Change*, Pearson and co-authors[4] show a way to sidestep this data disparity by showing that important, and far easier to gather, life-history traits and spatial distribution characteristics may be used as a surrogate for species extinction risks derived from advanced hybrid species range shift and population decline models.

As global climate change is already causing species to move out of their traditional range[5], the preservation of biodiversity requires efficient conservation prioritization strategies[1]. This task is facilitated by the International Union for Conservation of Nature (IUCN) Red List of Threatened Species[2], a system — designed before anthropogenic climate change was seen as a major threat — to determine the threat status of species for policy and planning purposes. This tool, if applied to all taxonomic groups, could serve as an efficient 'barometer of life'[6]. Yet, exhaustively sampling the distribution of all endangered species remains a difficult task[7], especially for highly mobile or cryptic species, and even if this were achieved, future distributions are likely to differ from present ones[8,9]. Predictive models can be used here to complement observations and forecast future distributions[7,10], if made relevant to conservation objectives[3,7]. However, the dynamic models required for population viability and extinction risk analyses[8,9] usually need heavier data input for each target species than simple distribution models[7], hampering their application to many groups of organisms[11]. One remedy for this data limitation is to derive predictive tools for groups of species with similar functions or dynamics instead of individual species, making use of the increasing information available in

trait databases[11], and use them to derive informative biodiversity forecasts to assist conservation planning. A second remedy is proposed by Pearson and co-authors[4], and this is where their findings constitute an important advance.

They show that a set of life-history and spatial traits of endangered species — as already used in the IUCN red list assessments[2] — can be used to predict extinction risks under climate change. They do this by looking for traits that correlate well with model-based predictions of future extinction risks (Fig. 1). The extinction risks are estimated in their study by combining, for each species, two types of model: a first model predicting the spatial distribution of habitat suitability[7], using a range of environmental variables as predictors (such as climate, topography, land use and hydrography); and a second, temporal model simulating population demography and dispersal[8,9], based on the predicted habitat suitability, generic

demographic cycles (life history) and documented or estimated dispersal capacity. This combined spatio-temporal model is finally used to run repeated simulations (including stochasticity, that is, random natural variation) of populations and their interconnections in geographical space and across time to assess trends in population sizes. Extinction risks were calculated with this hybrid modelling approach for six generic life-history types, based on data for 36 species of amphibians and reptiles endemic to the United States. A separate machine-learning modelling approach was then used to look for relationships between the candidate traits, characterizing life-history and distribution characteristics, and the previously predicted extinction risks. They found currently occupied area, population size and generation time to be among the most important factors in their analysis, and further identified interactions between them (for example, extinction risk decreasing in smaller occupied areas with
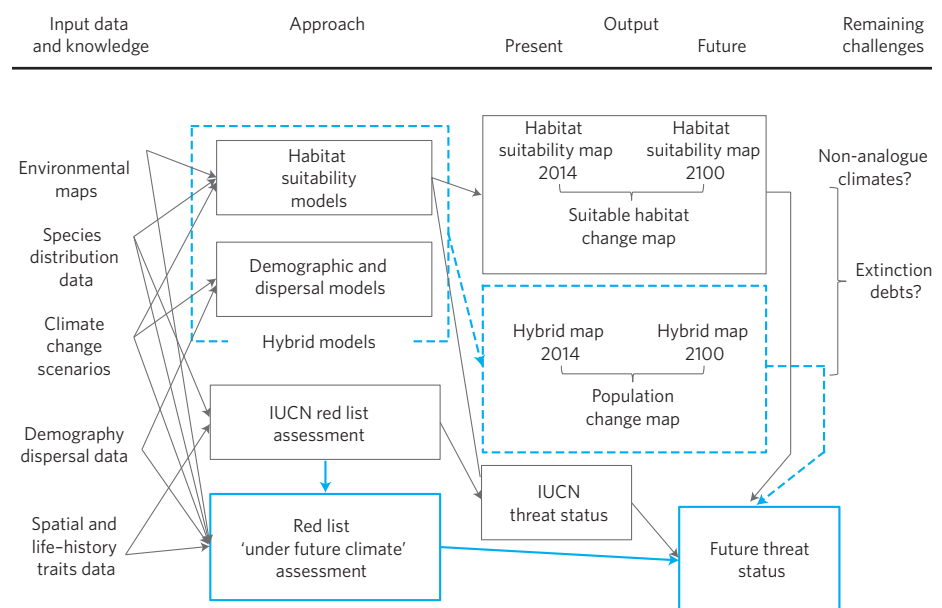

Figure 1 | A schematic representation of the approaches used to identify extinction risk showing some of the data requirements, output products and remaining challenges. The blue solid and dashed lines illustrate the two approaches contrasted by Pearson and co-authors.

increasing generation time) as providing additional predictive power. This suggests that current characteristics of species' range and demography, as well as their interactions, may already provide crucial initial information for classifying species as being at risk of extinction under future climate change.

Such hybrid modelling approaches to estimate extinction risk are recent but not new[8,9]. The novelty in the Pearson et al. study[4] is in using these methods to assess the power of currently available and measurable life-history and spatial traits to predict not only current but also future levels of threats for a range of species. However, they also report that under more severe climate change, "recent trends are less predictive of future trends," suggesting that "previously observed biological impacts of climate change will become less indicative of the future as climate change accelerates". This probably results because, as climate change progresses, more novel climatic conditions appear, in which both model predictions and extrapolation of current knowledge reach a limit[10,11]. An important challenge ahead is thus to explore solutions that can deal with predictions in non-analogue future situations (for example, through experiments or genetic

models)[11]. Future studies should at least report results and predictions for analogue and non-analogue situations separately (Fig. 1), to identify whether changes between predictions made with climate change scenarios of increasing severity are related to the gradual appearance of non-analogue climates. The level of uncertainty around predicted extinction risks, resulting from the repeated simulations, was not reported separately for non-analogue conditions by Pearson and colleagues[4], but may be expected to be greater than for analogue conditions. Another equally important challenge is to make use of the contrast between the spatial habitat suitability component and the temporal demographic and dispersal component of these hybrid models used to estimate extinction risks[9]. For example, simulated persistence of populations in habitats that have become unsuitable after climate change can reveal potentially important extinction debts for some species[8], which may bias extinction estimates at a given time, and may therefore need to be provided when reporting extinction rates across many species.

Although the work of Pearson et al.[4] offers some exciting perspectives as to how life-history and spatial traits may predict future species' threat status under

climate change, some uncertainties remain large and/or are not assessed, and several avenues remain to be explored, including testing with other life-history types, climatic non-analogues and extinction debts (Fig. 1). Given the urgency of biodiversity conservation and the continuous development of IUCN assessments[2] as a barometer of life[6], it is important that research on threat estimations based on traits and models are pursued in parallel.   ❐

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