

Stop ignoring map uncertainty in biodiversity science and conservation policy

To the Editor — Halting the unprecedented loss of biodiversity is one of humanity's greatest challenges^{1,2}. Area-based management frameworks, such as national parks or marine protected areas, are a popular tool to combat threats to biodiversity but require comprehensive information on the spatial distribution of biodiversity to properly instigate. Recent advances in observation technologies, data sharing and modelling techniques mean that comprehensive predictive maps of the distribution of species, populations, assemblages and bioregions can now be readily produced. However, despite ongoing discussion about the need to address uncertainty in species and biodiversity distribution modelling^{3–8}, and the effect that ignoring uncertainty may have on evaluating risk (and ultimately on conservation outcomes), the uncertainty of predictions is still inadequately communicated by the research community.

In a Web of Science search, we found 96% (895 of 929) of papers published in 2020 that map biodiversity patterns did not present any kind of uncertainty map alongside their mapped predictions of species, species assemblages or biological indices such as species richness (search term: TS = (“species distribution model*” OR “habitat suitability”); see Supplementary Information and Supplementary Data for more details on the literature search). Even in cases in which a single species or species richness was modelled directly — arguably the simplest forms of spatial prediction — 96% (824 of 857) of studies published in 2020 did not present any uncertainty map in the main article.

Uncertainty forms an integral part of any prediction. Uncertainty maps can highlight where data deficiencies exist and where management decisions need to be more precautionary, help to identify the most suitable locations for protected areas (Fig. 1) and pinpoint where changes in biodiversity might be easiest to detect or detected earliest (in other words, areas with high certainty in the predictions that are strongly related to the underlying predictor variables). The absence of uncertainty information can therefore lead to a substantial misdirection of important but limited conservation resources.

Uncertainties in biodiversity predictions can originate from a wide range of sources⁹.

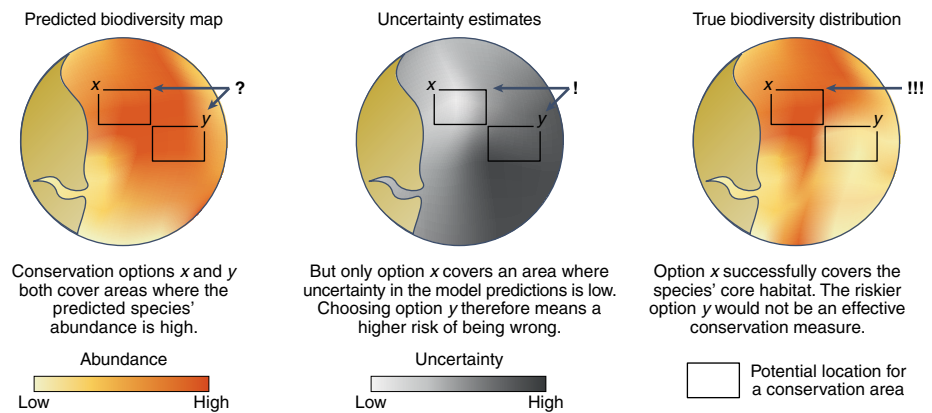


Fig. 1 | The importance of prediction uncertainty for avoiding poor conservation outcomes. For simplicity we illustrate an example of a single target unit (such as a species, population or specific species assemblage), but the same underlying concept also applies to multiple species and communities. The left panel shows a prediction in which uncertainties are not yet addressed; here both conservation options x and y seem similarly effective. By contrast, the middle panel highlights where the model is most certain that the prediction is correct, helping to identify conservation option x as the preferred option if the aim is to conserve core habitat; exclamation mark highlights the marked difference between the options. The right panel shows what the true (but unknown) distribution could look like; exclamation marks highlight the ‘best’ option.

Natural fluctuations in populations, sampling bias, uncertainty in environmental predictor variables, weak relationships between environmental predictors and biodiversity distributions, choice of modelling framework and the setup of individual models can all contribute to uncertainty in the final biodiversity prediction. Although it is challenging to address or quantify all sources of uncertainty (particularly capturing uncertainty of environmental variables¹⁰), all steps should be taken to minimize the influence of uncertainty — primarily by choosing methods that are suitable for the data and the question^{3,9}.

For many commonly used distribution modelling techniques, it is relatively simple to generate and map prediction uncertainties of a particular model. The standard error and confidence intervals of point predictions are a typical output from most statistical model-based methods (for example, generalized linear models); confidence intervals can be generated using various bootstrap techniques for many methods that do not produce uncertainty as a standard output (for example, boosted regression trees); and credible intervals can

be calculated from Bayesian approaches (for example, Bayesian hierarchical models). Although uncertainty is usually lost upon assembling multiple predicted single-species distributions, recent advances in multispecies generalized linear models mean uncertainty can now also be directly calculated for species assemblages and other biodiversity predictions¹¹. Given that many methods already routinely calculate uncertainty, we suggest that if an approach lacks the ability to quantify uncertainty, this is sufficient reason to seek alternative methods.

Meaningful maps of prediction uncertainty are critical for interpreting biodiversity predictions. Ideally, the uncertainty map directly relates to the biodiversity prediction and is not presented in the form of an unrelated ranking or scale. Uncertainty maps can be reported as a separate map alongside the predictive map (as shown in Fig. 1), and software tools also exist to present both uncertainty and the prediction in the same graphic (for example, ref. ¹²). Presenting uncertainty maps is comparable to presenting standard deviations alongside mean values or showing error bars on bar plots. Without addressing

uncertainty, biodiversity predictions cannot be considered scientific undertakings.

Knowledge about natural systems is always imperfect, and thus any management decision involves an underlying risk that needs to be understood. Decision frameworks for managing risk and incorporating uncertainty in conservation planning exist¹³, and uncertainty and risk are regularly quantified in fisheries and in population assessments of threatened species. However, examples of situations in which uncertainty and risk are quantified and used for spatial conservation decisions are rare (for example, ref. ¹⁴) — which is perhaps not surprising, given that uncertainty maps are essentially ignored in biodiversity science. Without addressing uncertainty, decision-makers risk mismanaging our most valuable and irreplaceable natural assets. Useful predictive models clearly communicate uncertainty and predict key natural values of interest. These can be monitored directly and can considerably assist decision-makers to set unambiguous biodiversity targets for which they can then be held accountable.

Uncertainty needs to be embraced for the fundamental part it plays in highlighting where model and data deficiencies exist and in improving the likelihood of positive conservation outcomes. A critical step is that editors, reviewers and authors for

scientific journals ensure that published biodiversity maps are accompanied by maps of prediction uncertainty. This should be up-front in the same way that other figures with mean values are required to display uncertainty metrics for meaningful interpretation. Likewise, policy developers, policy analysts and managers should insist that they are provided with predictive maps and their uncertainty surfaces to help to maximize the impact of conservation action and resources. □

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Published online: 12 May 2022

<https://doi.org/10.1038/s41559-022-01778-z>

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Author contributions

J.J., P.K.D., N.A.H. and C.R.J. developed the initial manuscript outline. J.J. conceived and performed the literature review and analysed the data. J.J., S.N.C.W., P.K.D., S.D.F., N.A.H., M.H. and C.R.J. wrote and edited the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1038/s41559-022-01778-z>.

Peer review information *Nature Ecology & Evolution* thanks the anonymous reviewers for their contribution to the peer review of this work.