

EDITORIAL COMMENTARY

# Editorial commentary on ‘Patterns and uncertainties of species’ range shifts under climate change’

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The need for anticipating and mitigating the potential effects of climate change on biodiversity has triggered the development of predictive tools to provide quantitative scenarios to guide decision making (Pereira *et al.*, 2010). Notably, the recently established ‘Intergovernmental Platform on Biodiversity and Ecosystem Services’ (IPBES) will rely on these predictive tools. Between 1990 and 2000, statistical models that relate species occurrences to climatic variables were developed to predict species ranges and to forecast potential changes under the strong assumption that the detected relationships between the species of interest and the selected climatic variables will hold into the future (reviewed in Guisan & Thuiller, 2005). Since then, a variety of statistical approaches have been proposed and compared (see Thuiller, 2014). In the early 2000s, with the rise of statistical software such as Splus, SAS or later R, several algorithms became available to ecologists to propose species range change scenarios based on the IPCC climate models and SRES scenarios (Nakicenovic & Swart, 2000). Generalized linear models, generalized additive models, regression trees, genetic algorithms or artificial neural networks were used increasingly to assess the potential impacts of climate change on biodiversity. During this period, I stumbled upon the issue that although different algorithms are likely to give the same answer under current (calibration) conditions, they tended to drastically diverge when they were used to predict species ranges under future climate. This was published with Global Change Biology under this article ‘Patterns and uncertainties of species’ range shifts under climate change’ (Thuiller, 2004). Although 10 years later, I find this result relatively obvious, at the time I was amazed that seemingly subtle differences between algorithms could actually lead to sharp divergences when projecting into the future. A species could indeed be predicted committed to extinction with one algorithm, and under range expansion with another. Since then, substantial progress has been made toward understanding why such strong discrepancies could occur (e.g. collinearity, complex interactions between variables or incomplete climatic niche estimations) and several

analyses have confirmed this result (Lawler *et al.*, 2006; Pearson *et al.*, 2006).

How to deal with variability from different initial conditions, algorithms, parameterization, and bounding conditions is still an open question in ecology and other fields of science (Araújo & New, 2007). As reviewed in Araújo & New (2007), an ensemble of forecasts is one of the most accepted ways to account for projection variability since it relies on multiple projections across sets of initial conditions, algorithms (e.g. generalized linear models or boosted regression trees), parameters (e.g. quadratic vs. polynomial terms, number of regression trees in a random forest), and bounding conditions (e.g. different climate models). Although ensemble forecasting was a relatively well-accepted approach in other fields such as economics or climatology, it was relatively unknown in ecology in the early 2000s and did not emerge as a plausible alternative to single initial data algorithms until 2004 (Thuiller, 2004) and 2007 (Araújo & New, 2007). The major advantage of combining a set of forecasts is to give a probability distribution per pixel as opposed to a single crude value. This allows for extraction of average predictions as well as confidence intervals given varying input data, algorithms, parameterization, and bounding conditions. Still, although such an approach is now a common practice (Marmion *et al.*, 2009), ensemble forecasts are often used as a single forecast by extracting an average or a weighted average based on different evaluation techniques, without considering the variability behind those averages and without considering which metric to use for scoring the different projections. If forecasts have to be used in conservation planning or to be used guiding tools for decision making, they should present not only the main trend but also the variability around this trend.

## References

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