Editorial

Robust risk assessments require probabilistic approaches

"Deterministic risk assessment" versus "probabilistic risk assessment" is a common dichotomy in environmental risk assessment. For someone more familiar with risk calculation than with ecotoxicology jargon, the former term may sound like an oxymoron: "risk" involves chance and uncertainty, while "deterministic" means the absence of randomness. Conversely, "probabilistic risk assessment" can sound like a pleonasm, since risk assessment by definition should involve probabilities for quantification of uncertainty. These viewpoints are not new: methods for probabilistic risk assessment of chemicals have been proposed, developed, and debated for more than 20 years (e.g., Jager et al., 2001; Maertens et al., 2022; Verdonck et al., 2003). Nevertheless, simpler methods for risk characterization such as single-value risk scores still seem to be favored, for example, for regulatory risk assessment. There may be several reasons for this, including a lack of training in statistical methodology and inertia in regulatory systems. The conventional traditions of the past can therefore be barriers to effective management of the future, where climate change will be increasingly important.

Global climate change is affecting the impacts of chemicals on ecosystems in multiple ways, such as changes in chemical use, emission, transport, fate and exposure, as well as sensitivities of species and ecological communities. This fact was thoroughly documented by a series of papers from a SETAC Pellston workshop in 2011 (Stahl et al., 2013), followed by a call for better integration of climate change science in environmental risk assessments (Landis et al., 2014). The 6th Assessment Report of the Intergovernmental Panel on Climate Change states with high confidence: ecosystem damage by pollutants, together with habitat fragmentation and unsustainable use of natural resources, will increase ecosystem vulnerability to climate change globally, even within protected areas (SPM.B.2.2) (IPCC, 2022). Nevertheless, the potential influence of climate change is often ignored in assessments of chemical pollution and risk (e.g., EEA, 2018). It still takes more effort to look beyond the silos of each field, particularly as guidance on incorporating the outcomes of climate modeling into environmental risk assessment does not yet exist. Consequently, there are few examples of environmental risk assessment of chemical stressors that integrate future climate scenarios, climate model projections, and regional downscaling with sufficient robustness.

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This current gap between risk assessment approaches and climate modeling was the topic of a SETAC Pellston workshop held in Norway in June 2022. Experts from a range of disciplines, including climate modeling, hydrology, environmental chemistry, biology, and ecotoxicology, were brought together on a small island in the Oslo fjord for four days to collaborate on case studies from North America, Europe, and Australia. While the development of a framework illustrated by these case studies is still in progress, a few lessons learned and key messages can already be presented here.

> *"Bayesian networks can lower the threshold for scientists to get started with probabilistic modeling of chemical exposure and effects under climate change scenarios, and to quantitatively express their confidence in the risk characterization."*

1. Climate model ensembles: Using only one or a few alternative climate models for a given region is useless because the stochastic variations of any individual climate model can be of similar magnitude as regional climate change (Deser et al., 2012). An ensemble with more than 100 global climate models is ideal, and 30 should be regarded as a minimum. The outcome should be labeled projections rather than predictions, representing a range of plausible outcomes, given a specific socioeconomic development scenario for the future.
2. Robust climate information: Projected values of climatic variables, such as temperature and precipitation, must be aggregated and transformed into climate information that can be used as predictor variables for chemical exposure and effect characterization. A robust format is a probability distribution function represented by statistical parameters, such as mean and standard deviation.
3. Regional downscaling: Parameters defining the statistical properties of local climate variables can be estimated by means of downscaling. Different approaches exist, for example, dynamical and empirical-statistical downscaling; these are based on different assumptions and have different strengths and weaknesses (World Climate Research Program CORDEX). Therefore, combining these approaches, rather than selecting one of them, will further lead to more robust results.
4. Integration: Incorporation of such climate information into environmental risk assessment will require a fully probabilistic methodology to represent the combination of future climate conditions, chemical exposures, and environmental effects.

The outcomes of probabilistic assessments are often presented in terms of uncertainty. This may give the reader the impression that probabilistic risk assessments are more uncertain than their deterministic counterparts. In fact, the opposite is true: single-value risk scores hide the underlying uncertainties and portray only a projection of multivariate processes into a point estimate. Shifting the focus from uncertainty to confidence, both in teaching and in dissemination, could help promote the acceptance of probabilistic assessments.

A robust framework for integrating climate information into risk assessment will still pose many challenges, both conceptually and computationally. In our experience, Bayesian networks—a type of probabilistic graphical models—have been proven to be a suitable tool for this purpose (Moe et al., 2021). The graphical layout is helpful for the development of conceptual models with a causal structure, while the mathematical components (probability distributions) can represent our best knowledge of and confidence in states and processes, throughout the model. While other methods can allow for more advanced modeling of uncertainty and higher precision of predictions, a major strength of Bayesian networks is the user-friendly graphical interface. This tool can lower the threshold for scientists to get started with probabilistic modeling of chemical exposure and effects under climate change scenarios, and to quantitatively express their confidence in the risk characterization.

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