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Communicating uncertainties in earth sciences in view of user needs

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Uncertainties are inevitable in all results obtained in the earth sciences, regardless whether these are based on field observations, experimental research or predictive modelling. When informing decision and policy makers or stakeholders, it is important that these uncertainties are also communicated. In communicating results, it important to apply a ”Progressive Disclosure of Information (PDI)” from non-technical information through more specialised information, according to the user needs. Generalized information is generally directed towards non-scientific audiences and intended for policy advice. Decision makers have to be aware of the implications of the uncertainty associated with results, so that they can account for it in their decisions. Detailed information on the uncertainties is generally intended for scientific audiences to give insight in underlying approaches and results.

When communicating uncertainties, it is important to distinguish between scientific results that allow presentation in terms of probabilistic measures of uncertainty and more intrinsic uncertainties and errors that cannot be expressed in mathematical terms. Examples of earth science research that allow probabilistic measures of uncertainty, involving sophisticated statistical methods, are uncertainties in spatial and/or temporal variations in results of:

• Observations, such as soil properties measured at sampling locations. In this case, the interpolation uncertainty, caused by a lack of data collected in space, can be quantified by e.g. kriging standard deviation maps or animations of conditional simulations.

• Experimental measurements, comparing impacts of treatments at different sites and/or under different conditions. In this case, an indication of the average and range in measured responses to treatments can be obtained from a meta-analysis, summarizing experimental findings between replicates and across studies, sites, ecosystems, etc.

• Model predictions due to uncertain model parameters (parametric variability). These uncertainties can be quantified by uncertainty propagation methods such as Monte Carlo simulation methods.

Examples of intrinsic uncertainties that generally cannot be expressed in mathematical terms are errors or biases in:

• Results of experiments and observations due to inadequate sampling and errors in analyzing data in the laboratory and even in data reporting.

• Results of (laboratory) experiments that are limited to a specific domain or performed under circumstances that differ from field circumstances.

• Model structure, due to lack of knowledge of the underlying processes. Structural uncertainty, which may cause model inadequacy/ bias, is inherent in model approaches since models are approximations of reality.

Intrinsic uncertainties often occur in an emerging field where ongoing new findings, either experiments or field observations of new model findings, challenge earlier work. In this context, climate scientists working within the IPCC have adopted a lexicon to communicate confidence in their findings, ranging from ”very high", "high", "medium", "low" and "very low" confidence. In fact, there are also statistical methods to gain insight in uncertainties in model predictions due to model assumptions (i.e. model structural error). Examples are comparing model results with independent observations or a systematic intercomparison of predictions from multiple models. In the latter case, Bayesian model averaging techniques can be used, in which each model considered gets an assigned prior probability of being the ‘true’ model. This approach works well with statistical (regression) models, but extension to physically-based models is cumbersome. An alternative is the use of state-space models in which structural errors are represent as (additive) noise terms.

In this presentation, we focus on approaches that are relevant at the science – policy interface, including

multiple scientific disciplines and policy makers with different subject areas. Approaches to communicate uncertainties in results of observations or model predictions are discussed, distinguishing results that include probabilistic measures of uncertainty and more intrinsic uncertainties. Examples concentrate on uncertainties in nitrogen (N) related environmental issues, including:

• Spatio-temporal trends in atmospheric N deposition, in view of the policy question whether there is a declining or increasing trend.

• Carbon response to N inputs to terrestrial ecosystems, based on meta-analysis of N addition experiments and other approaches, in view of the policy relevance of N emission control.

• Calculated spatial variations in the emissions of nitrous-oxide and ammonia, in view of the need of emission policies at different spatial scales.

• Calculated N emissions and losses by model intercomparisons, in view of the policy need to apply no-regret decisions with respect to the control of those emissions.