Abstract: Analysts usually construct a model and then act as though it correctly represents the state of the world. This understates the uncertainty associated with the model’s predictions, because it fails to express the analyst’s uncertainty that the model itself might be in error. Several approaches have been proposed to account for model uncertainty within a probabilistic assessment, including what-if studies, stochastic mixtures, Bayesian model averaging, generalized method of moments, probability bounds analysis, robust Bayes analyses, and imprecise probabilities. Although each approach has advantages that make it attractive in some situations, each also has serious limitations. For example, several approaches require the analyst to explicitly enumerate all the possible competing models. This might sometimes be reasonable, but the uncertainty will often be more profound and there might be possible models of which the analyst is not even aware. Although Bayesian model averaging and stochastic mixture strategies are considered by many to be the state of the art in accounting for model uncertainty in probabilistic assessments, numerical examples show that both approaches actually tend to erase model uncertainty rather than truly propagate it through calculations. In contrast, probability bounds analysis, robust Bayes methods, and imprecise probability methods can be used even if the possible models cannot be explicitly enumerated and, moreover, they do not average away the uncertainty but propagate it fully through calculations. In the context of risk analysis and uncertainty modeling, it is often possible to project uncertainty about X (which may be aleatory, epistemic or both) through a function f to characterize the uncertainty about Y = f(X) even though f itself has not been precisely characterized. Although the general strategies for quantitatively expressing and projecting model uncertainty though mathematical calculations seem either dubious or quite crude, there are a variety of special cases where methods to handle model uncertainty are rather well developed and available solutions are both comprehensive and subtle.

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