Dealing with model errors while calibrating crop models: A Bayesian perspective

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Process-based crop models are a mathematical representation of our knowledge about biophysical processes that describe plant growth and interactions with the environment. These models serve as useful tools for predicting the impact of climate change on crop production or assessing the fate of agrochemicals in the environment. To ensure robust predictions, models are usually calibrated to observations. While uncertainties in observations are usually taken into account, other sources of uncertainty such as those in model inputs, equations, parameters, etc. also need to be quantified. This is especially important when model predictions guide adaptation and mitigation strategies. Bayesian inference is suitable for this purpose since it enables the accounting of different uncertainties, while also incorporating prior knowledge. Thus, Bayesian methods are used for model calibration to improve system-representation and therefore enhance prediction quality. However, this does not always occur due to the presence of model errors. These errors are a result of incomplete knowledge or simplifying assumptions made to reduce model complexity and computational costs. We investigated the problems in calibrating such imperfect crop models using Bayesian inference with commonly used simple statistical assumptions about errors. Then, we tested two other Bayesian approaches that could address these problems.

We first tested the commonly applied simple Bayesian approach to calibrate a process-based phenology model to observations of silage maize. In this approach, model parameters and their uncertainty were estimated while accounting for observation uncertainty, but ignoring model errors. We found that as the model was calibrated to increasing amounts of observation data, the uncertainty in the model parameters reduced as expected. However, the prediction quality of the calibrated model did not always improve. This was attributed to the presence of model errors that was ignored during calibration. As a potential solution, we calibrated the model using Bayesian multi-level modelling (BMM) which could account for model errors. Furthermore, we also accounted for the hierarchical structure of cultivars nested within maize ripening groups, thus simultaneously obtaining model parameter estimates for the species, ripening groups and cultivars. Applying this approach improved the model's calibration quality and further aided in identifying possible model deficits related to temperature effects in the post-flowering phase of development and soil moisture. As a second potential solution, an alternative calibration strategy was tested which accounted for model errors by relaxing the strict statistical assumptions in classical Bayesian inference. This approach resulted in conservative but more reliable predictions than the commonly used approach, except when the prediction target represented an average behaviour of all calibration data.

Our results showed that Bayesian methods with representative error assumptions led to improved model performance and a more realistic quantification of uncertainties. This could facilitate the effective application of process-based crop models in predictions.