Bayesian inverse modeling for quantitative precipitation estimation

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Abstract

A key element of numerical weather prediction is quantitative precipitation estimation. Nowadays a diversity of measurements is available, including polarimetric radar and rain gauges. We focus on the different polarimetric radar observables like horizontal and vertical reflectivity Z_H and Z_V, cross-correlation coefficient ρ_{HV} or specific differential phase K_{DP}, which can be seen as observations of the drop size distribution (DSD) in the scan. How can we derive knowledge from observations of the polarimetric variables about the underlying DSD in a systematic way? What is the role of uncertainties caused by observation error, model error or numerical simulations?

A major point of this work is to estimate the parameters of a two-parameter exponential DSD, $N(D) = N_0 \exp(\Lambda D)$, from the data, a classic case of an inverse problem. This task is challenging given the nature of inverse problems, where many parameter values may be consistent with the few and error-prone observations we have of the underlying continuous process. To solve the problem, we adopt a Bayesian framework, which is especially promising for grasping the uncertainties. In this context we characterize the uncertainty of the parameters as probability distributions. We find that an important part of the model is the error model, which goes into the formulation of the data likelihood.

Our inverse problem is investigated in a simulated environment (SE) using the COSMO-DE numerical weather prediction model. A 3D forward operator simulates polarimetric X-band radar measurements of the radar beam given the state of the atmosphere, in particular the DSD. The advantage of the SE is that we know the parameters we want to estimate. Thus building the inverse model into this SE gives us the opportunity of verifying our results against the COSMO-simulated DSD-values (which are mostly unknown in the real world). We implement Markov Chain Monte Carlo methods to sample from the posterior. From the estimated DSD we are then able to predict precipitation parameters of interest, including rain rate.

Our final goal is a spatially variable model, where we will use multivariate Gaussian processes to model the DSD parameters N_0 and Λ.