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Preparations for non-linear filtering on convective scales.

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Atmospheric data assimilation on convective scales faces considerable challenges. A non-hydrostatic Numerical Weather Prediction model describing the evolution of the atmosphere on convective scales may exhibit highly non-linear behavior due to inherently three-dimensional dynamics and phase changes in atmospheric moisture. Such a model is also spatially high-dimensional, where apart from the grid resolution the dimensionality of the model is determined by a minimum domain size requirement, which is related to predictability. In practice non-hydrostatic models operate on a limited area domain and boundary conditions need to be specified. These boundaries, obtained from a donor model, may create imbalances not representing a model state. If the domain is small these imbalances can saturate the analysis leading to a subsequent loss of predictability. Another challenge lies in the assimilation of observations. Currently there are only few (remote sensing) observing systems available that can sample atmospheric developments on the spatial and temporal scales of interest, e.g. radar reflectivity and radial winds and GPS ZTDs/slant delays. To pull the model towards the true atmospheric state may prove to be difficult for a data assimilation system because these observations observe only part of the model state and mostly in an indirect way.

When model behavior is non-linear, operational variational data assimilation systems are not well suited to determine the model's initial state because they employ local linearization in the model dynamics, in the physical parameterization and in observation operators. Moreover they erroneously assume that the model is perfect and that errors have a normal distribution. These assumptions and approaches will lead to unpredictable and biased solutions.

Particle filters or sequential Monte Carlo methods do not assume that the model is perfect. They attempt to approximate the posterior density of the model state by a point-mass distribution using a set of model states (particles) with associated importance weights and as such do not impose restrictions on the statistical distribution of model errors or observation noise, nor do they make assumptions about the linearity of the model or the relation between observations and the model state. Running particle filters however is expensive in terms of computing time and memory and a practicable filter for spatially high-dimensional models should require only a small number of particles to produce accurate solutions and to remain stable. Filter stability is related to the (lack of) variance in the importance weights and the weights are determined by the consistency of the particles with available observations. Filter stability and the avoidance of degeneracy where the analyzed model state depends on only one or few particles is a major concern in particle filter design. This concern may be true even more so for models with large spatial dimensions.

To assess the potential of particle filters for atmospheric data assimilation we address some of the challenges by studying particle filter application to simpler but representative geophysical models. We will present a particle filter that employs importance sampling through a proposal distribution that takes into account the latest observational information to reduce the risk of degeneracy in the importance weights. We discuss implementation details related to model dimensionality and demonstrate the performance of the particle filter when applied to the Lorentz63 and Lorentz95 models using different types of simulated indirect observations.