



How do we account for position errors in forecasts and observations in mesoscale data-assimilation?

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Classical formulations for data-assimilation, whether sequential, ensemble-based or variational, can be viewed as amplitude-adjustment methods. Such approaches do not deal well with position errors, which can be seen readily, for example, when a forecast localized weather event is displaced from its observed location. What's worse is that position errors are present in observations too! We observe from rain-storm data that in many satellite derived observations - AMSU, TRMM, SSMI - well-defined rain-cells at the same assimilation time are typically separated in position that should be at the same place. Whilst some of these errors can be seen as timing errors, it is non-trivial to figure out their exact position at assimilation time. In fact, the sources of position error are many and either by construction or due to computational limitations, popular methods are inadequate for handling inherently non-linear and hard to diagnose error sources.

Correcting position errors is essential for predicting strong, localized weather events such as tropical cyclones and rainstorms. However, in the presence of sparse observations, typical assimilation approaches (3D-Var, EKF, EnKF) will tend to "smear" the state if the adjusted variables do not have a direct impact on position errors. This is now well-known, but the problem is exacerbated when the observations have position errors too.

In earlier work, we showed how to correct for position errors by formulating the assimilation problem in the space of positions and amplitudes. We then showed that this method is valid for variational and ensemble formulations. We showed that it works well for multivariate problems and preserves dynamical balance. However, this work was limited to the case where no position errors are expected in observations, that is we assumed the positions of observed mesoscale phenomena was perfect. In this pa-

per, we propose a new algorithm that addresses the situation where we have position errors between a forecast (or an ensemble of forecasts) and a set of observations and, further, the observation fields also have position errors from each other.

The proposed solution uses an algorithm to estimate the first two moments of position-error and amplitude-error statistics from observations. Thus, the mean of a set of position separated observation fields is not their average amplitude, which will distort the shape of the mesoscale structure, but an average amplitude at a mean position derived from a displacement vector field estimated for each observation field in the observation set.

Starting from this idea, we reformulate the assimilation problem as a variational problem, whose solution consists of a sequence of steps. First it aligns observation fields to a mean position that respects individual position uncertainties, then it aligns the forecast ensemble (or forecast) with the position-adjusted amplitude-mean observation field. Finally, it adjusts the amplitudes of the aligned ensemble members, which can be interpreted as a classical method such as EnKF or 3DVAR. It is important to note that the alignment operation that is fundamental to this solution does not detect features. Position adjustments or displacements are proper vector fields, computed from the observation and forecast fields. The equations for doing so are synthesized directly from a regularized solution to the variational assimilation problem. We demonstrate this technique with real rainstorm data and a rainfall model and show that applying this step produces better analyses than traditional methods.