# A General Nonlinear and Non-Gaussian Strongly Coupled Ensemble Data Assimilation Capability

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**Abstract**

Ensemble Kalman filters make implicit assumptions about approximate Gaussianity and linearity. Novel, efficient ensemble algorithms that avoid assumptions of Gaussianity by allowing arbitrary continuous priors and likelihoods for observed variables are described. These methods select posterior ensemble members with the same quantiles with respect to the continuous posterior distribution as the prior ensemble had with respect to the continuous prior distribution. While this can lead to significant analysis improvements for observed variables, these improvements can be corrupted when using standard linear regression to update other state variables. However, doing the regression of observation increments in a bivariate probit probability integral transformed space guarantees that the posterior state ensembles share the advantages of the observation space quantile conserving posteriors. For example, posterior ensembles for bounded state variables like tracer concentration will respect those bounds and other aspects of the continuous prior distributions. This avoids any implicit assumptions of linearity in the ensembles. This Quantile Conserving Ensemble Filtering Framework (QCEFF) significantly improves data assimilation (DA) for distinctly non-Gaussian quantities and nonlinear relationships (for instance between temperature and salinity) found in ocean applications at many spatial scales. The same framework also enables unique general algorithms for strongly coupled DA. These have been implemented in NSF-NCAR's Data Assimilation Research Testbed (DART) and allow any of the dozens of models with DART interfaces to be used with strongly coupled DA with no additional code development. This presentation reviews the two-step ensemble algorithm used in DART. It then describes how this enables QCEFF algorithms and the flexible, general, strongly coupled algorithm. These innovations position DART as a powerful tool for research into improved ensemble prediction and predictability in coupled models.