IMPROVING NONLINEAR OBSERVATION ASSIMILATION THROUGH ITERATIVE FILTERS: IDEALIZED EXPERIMENTS WITH RADAR-LIKE OPERATORS

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1) INTRODUCTION

Assimilating nonlinear observations—such as radar reflectivity—into ensemble-based systems remains a challenge. Standard ensemble Kalman filters, including LETKF, are derived under assumptions of linearity and Gaussianity. However, when the observation operator is highly nonlinear, it often leads to filter divergence or poor performance (Lawson and Hansen, 2004). Recent advances have explored the use of iterative or tempered techniques to enhance robustness in such regimes (Carrassi et al., 2018). Likelihood tempering, in particular, has shown promise by progressively assimilating observational information in multiple steps, thereby reducing the impact of nonlinearity in any single update (Kurosawa and Poterjoy, 2021). In this study, we apply and evaluate this technique in a simplified yet dynamically relevant context using the Lorenz-96 model with a radar-like observation operator.

2) METHODOLOGY

We implement a tempered version of the Local Ensemble Transform Kalman Filter (LETKF) and evaluate its performance under idealized scenarios using the Lorenz-96 model. The nonlinearity is introduced through a radar-like observation operator that transforms state variables into reflectivity-like observations. A tempering approach is applied using multiple assimilation steps, where each step introduces a portion of the likelihood, modulated by a slope parameter (α_s) that controls how sharply information is weighted across steps. The experiments systematically vary the number of tempering steps, the value of α_s, the observational error variance (σ_o^2), ensemble size (Nens), and the spatial density of observations.

3) RESULTS

Single-variable experiments show that three tempering iterations (ETKF-T3) better capture the posterior distribution induced by nonlinear observation operators compared to the standard ETKF. For small observational errors (σ_o^2), tempering notably reduces RMSE (Figure 1). Even for larger errors (e.g., $\sigma_o^2 = 25$), improvements persist but are less pronounced.

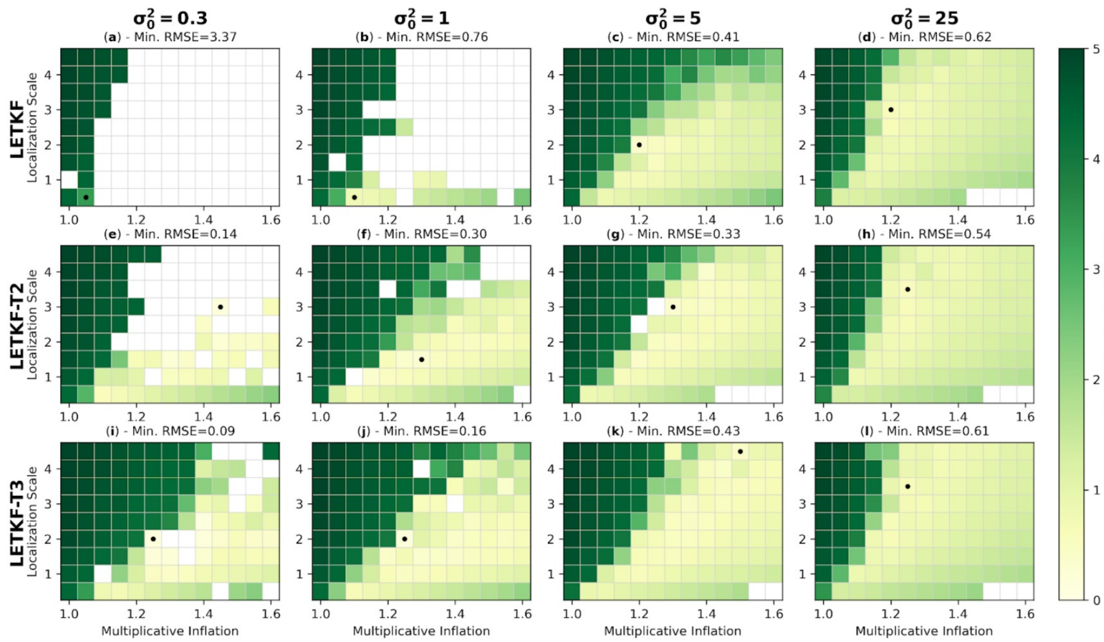

Figure 1: Time-averaged analysis RMSE as a function of multiplicative inflation (x-axis) and localization scale (y-axis), for varying σ_o^2 and assimilation configurations. Rows: LETKF (top), LETKF-T2 (middle), LETKF-T3 (bottom). Columns: increasing σ_o^2. The black dots indicate the location of minimum RMSE for each case.

As shown in Figure 2, the tempering parameter experiments show that α_s around 2.0 typically provides more optimal results across different cases, while a uniform weighting ($\alpha_s = 0$) underperforms in comparison. Meanwhile, ensemble size experiments show that tempering outperforms traditional LETKF, especially when $N_{ens} < 40$. This agrees with the findings of Lawson and Hansen (2004), who noted that ensemble filters become increasingly suboptimal under nonlinear dynamics. The tempered filter also helps prevent filter divergence in sparse-data settings, and when the model is not perfect (not shown), suggesting its applicability in real-world settings.

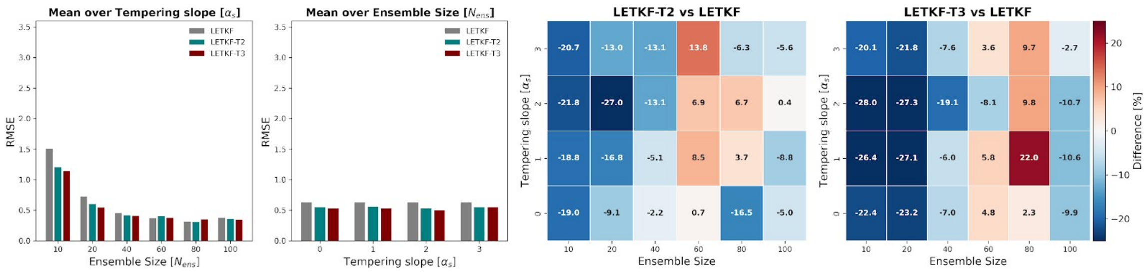

Figure 2: RMSE analysis summary for the fully observed case with $\sigma_o^2 = 5.0$. a) RMSE averaged over tempering slope α_s as a function of ensemble size. b) RMSE averaged over ensemble size as a function of α_s. Right: Relative RMSE reduction (%) from LETKF to LETKF-T2 (c) and LETKF-T3 (d). Negative values indicate improvement.

4) CONCLUSIONS

The results strongly support likelihood tempering as a practical enhancement for ensemble Kalman filters, particularly under nonlinearity and limited ensemble size. Most of the gain is achieved with only 2–3 iterations and a slope parameter α_s around 2.0. The technique stabilizes the filter, improves accuracy, and enhances robustness against both observation operator nonlinearity and model error. Tempered LETKF is a promising candidate for convective-scale and radar data assimilation systems, where traditional filters are prone to instability.

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