# Test of Adaptive Covariance Inflation Methods on the Lorenz-96 model

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#### Lorenz-96 model

 $dx_i/dt = x_{i+1}x_{i-1} - x_{i-2}x_{i-1} - x_i + F$ for cyclic i=1,...,K

K=40  $\Delta t$ =0.05 F=8 40 ensemble members



#### Lorenz-96 model

 $dx_i/dt = x_{i+1}x_{i-1} \cdot x_{i-2}x_{i-1} \cdot x_i + F$ for cyclic i=1,...,K K=40  $\Delta t$ =0.05 F=8 40 ensemble members

Error statistics: RMSE = sqrt( $\Sigma_i (\overline{\mathbf{x}_i} - \mathbf{x}^t_i)^2 / K$ ) ens spread =  $\Sigma_i \operatorname{std}(\mathbf{x}_i) / K$ 





## EnKF

40 ensemble members observations located on each grid points (H=1) random observational error ~ N(0,1)assimilate at each time step



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t=20

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posterior

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use localization, half width=1 => not helping!

use covariance inflation  $\lambda^2 = 1.5$ => solved!



#### **Covariance inflation**

model error: unknown to EnKF prior spread too small (too confident)



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#### **Covariance inflation**



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 $x^a \leftarrow (1-\alpha) x^a + \alpha x^b$ 





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relaxation to prior spread (RTPS) (Whitaker and Hamill 2012)

$$\sigma^{a} \leftarrow (1 - \alpha) \sigma^{a} + \alpha \sigma^{b}$$
  
x<sup>a</sup> \leftarrow \lambda x<sup>a</sup>, where \lambda = \alpha(\sigma^{b} - \sigma^{a})/\sigma^{a} + 1

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adaptive relaxation (new)

 $RMSE^{a\,2} = \lambda^2 \,\sigma^{a\,2} + \sigma^{o\,2}$ 

$$x^a \leftarrow (1 - \alpha) x^a + \alpha x^b = \lambda x^a$$

decrease in spread  $x^b = (\sigma^b/\sigma^a) x^a = \gamma x^a$ (1- $\alpha$ ) +  $\alpha \gamma = \lambda$  $\alpha = (\lambda - 1)/(\gamma - 1)$ 

### Comparison among methods



#### Other error sources

non-Gaussian error covariance

observations located off grid: nonlinearity in the *true* H operator

observations located **randomly**: partial coverage: too sparse / too dense

test inflation methods









domain-averaged inflation

![](_page_26_Picture_1.jpeg)

domain-averaged inflation

domain-averaged RTPP

![](_page_26_Picture_4.jpeg)

#### Conclusion

verified some well-known data assimilation problems

adaptive methods can find the optimum  $\lambda, \alpha$  values during EnKF cycle

randomly located observations cause trouble: need spatially varying methods

Further work: implementation of adaptive RTPP in atmospheric models