Ensemble Kalman Filter based Data Assimilation for Tropical Waves in the MJO Skeleton Model

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Background of the Madden Julian Oscillation (MJO)

- A slow moving planetary scale envelope of convection propagating eastward across the equatorial Indian and western/central Pacific oceans.
- The dominant mode of tropical intraseasonal variability.
- Affect tropical and extratropical weather patterns.
- Interact with the ocean and influence the El Niño-Southern Oscillation (ENSO).

Measurements for MJO:

- Winds at the top and the bottom of the troposphere.
- Outgoing longwave radiation (OLR), a proxy for convection.

Our study

- Predicting the MJO is challenging.
- Since the memory of initial conditions is long in the tropics, could MJO prediction be improved by improving on initial conditions?
- To improve initial conditions, we utilize quadratic programming ensemble QPEns algorithm (Janjic et al. 2014). The EnKF is a control algorithm.
- We study the impact of different physical constraints on the state estimation and prediction of the MJO with the Skeleton model.

The MJO Skeleton Model

The Skeleton model is a dynamical model with intermediate complexity that simulates tropical intraseasonal variability, especially the MJO and its relevant tropical waves, at the planetary scale (Majda and Stechmann, 2011),

$$\frac{\partial u}{\partial t} - yv - \frac{\partial \theta}{\partial x} = 0 \tag{1a}$$

$$yu - \frac{\partial \theta}{\partial y} = 0 \tag{1b}$$

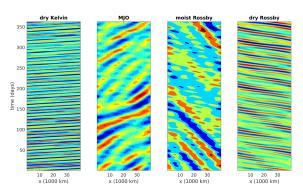
$$\frac{\partial \theta}{\partial t} - \left(\frac{\partial u}{\partial x} - \frac{\partial v}{\partial y}\right) = \overline{H}a - s^{\theta}$$
 (1c)

$$\frac{\partial q}{\partial t} + \overline{Q} \left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} \right) = -\overline{H}a + s^q$$
 (1d)

$$\frac{\partial a}{\partial t} = \Gamma q a. \tag{1e}$$

The model can reproduce

- a deep convective center that is moving eastward at a phase speed of approximately 5 m/s,
- a peculiar dispersion relation with constant intraseasonal oscillation periods of 30-90 days for the leading few zonal wavenumbers, and
- a horizontal structure with positive moisture anomalies to the east of the convective center and a quadrupole wind circulation around the convective center
- Also exhibit plane wave eigenmodes associated with the dry Kelvin, MJO, moist and dry Rossby waves of smallest meridional mode number.



DA relevant climatological properties

The underlying Skeleton model equations have the following two domain integrated energy conservation quantities when equalized background forcing $(s^{\theta}=s^q)$ is assumed:

a moist static energy conservation:

$$\int (\theta + q) = \text{const}, \tag{2}$$

and

a total energy conservation (consisting of contributions from dry kinetic energy, potential energy, moist potential energy and convective energy:

$$\int \left(\frac{u^2}{2} + \frac{\theta^2}{2} + \frac{1}{2} \frac{\overline{Q}}{1 - \overline{Q}} \left(\theta + \frac{q}{\overline{Q}}\right)^2 + \frac{\overline{H}}{\Gamma \overline{Q}} a - \frac{s}{\Gamma \overline{Q}} \ln(a)\right) = \text{const.} \quad (3)$$

A further physical property in the Skeleton model is the strict positivity of convective activity

$$a>0. (4)$$

Quadratic Programming Ensemble (QPEns)

- The idea behind the QPEns (Janjic et al., 2014) is to extend the stochastic EnKF by imposing additional physical constraints on the atmospheric states when updating the ensemble members.
- This can yield more physically plausible states and also allows to consider nonlinear relationships and therefore non-Gaussian moments in the background PDF. If used without constraints, the QPEns equals the stochastic EnKF.
- The QPEns read:

$$\mathbf{x}_{k}^{a,i} = \arg\min_{\mathbf{x}} \mathcal{J}_{k}^{i}(\mathbf{x})$$
subject to $c_{l}(\mathbf{x}) = 0, l \in \mathcal{E}$ and/or $c_{m}(\mathbf{x}) \leq 0, m \in \mathcal{I},$ (5)
with
$$\mathcal{J}_{k}^{i}(\mathbf{x}) = \frac{1}{2} (\mathbf{x} - \mathbf{x}_{k}^{b,i})^{T} \mathbf{P}_{k}^{b-1} (\mathbf{x} - \mathbf{x}_{k}^{b,i}) + \frac{1}{2} (\mathbf{y}_{k}^{i} - \mathcal{H}(\mathbf{x}))^{T} \mathbf{R}_{k}^{-1} (\mathbf{y}_{k}^{i} - \mathcal{H}(\mathbf{x}))$$

➤ An interior-point method is adopted solve the problem sequentially, which uses iteratively updated penalty terms in the objective function for values close to inequality constraint boundaries.

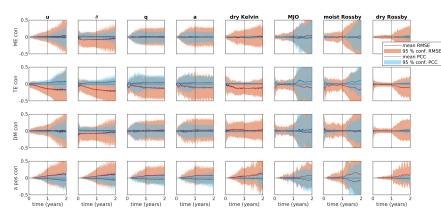
Implementation

In this study, constraints to the following properties are taken into consideration:

- ▶ the total energy (TE),
- the moist static energy (ME),
- ► the dry mass (DM), and
- the positivity of convective activity.

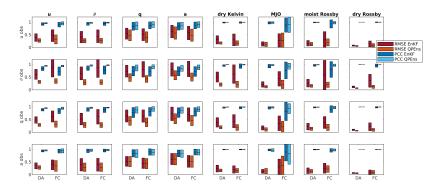
Results: Impact of the different constraints

The differences in the RMSEs and pattern correlations for 1 year of DA followed by 1 year of free forecast. Calculated by subtracting the reference value of the stochastic EnKF from those of the QPEns. Only the zonal wind and the convective activity observed.



- Overall, during DA, the EnKF and QPEns produce more similar RMSEs. However, during the free forecast, initial small error differences amplify.
- There is a significant statistical benefit from the total energy (TE) constraint.

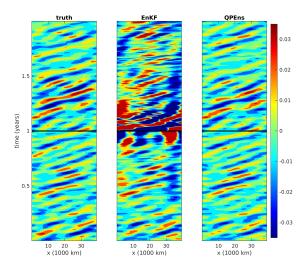
Result: DA skill with total energy constraint but different observational setups



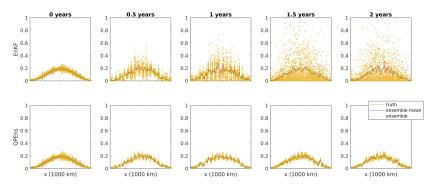
- The total energy constraint can improve DA when observing the zonal wind and the convection activity.
- An even more significant benefit can be seen when including the observations of other variables, especially the potential temperature and the moisture.

Result: A stronger non-Gaussian test case for the QPEns with total energy constraint

Increasing the background warmpool parameter from 0.6 to 0.75 and assimilating zonal wind and the convective activity only.



Result: A stronger non-Gaussian test case for the QPEns with total energy constraint



Accumulation of small convective activity values, that arise from the setting back of negative values in the EnKF to closely above zero values, can be observed at more and more gridpoints and ensemble members with increasing filtering time.

Result is misestimation of the PDF shape due to a self-amplifying effect.

Main References.



Gleiter, T., T. Janjic, and N. Chen. "Ensemble Kalman Filter based Data Assimilation for Tropical Waves in the MJO Skeleton Model." *Quarterly Journal of the Royal Meteorological Society* 148 (2022): 1035-1056, https://doi.org/10.1002/qi.4245.



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