Using an idealised fluid model to investigate the EnKF in the presence of convection

Tom Kent*[1], Onno Bokhove[1], Steven Tobias[1], Gordon Inverarity[2]
(1) School of Mathematics, University of Leeds, UK; (2) Met Office, UK *Email: mmtk@leeds.ac.uk

1. Background

- High-resolution (**convective-scale**) Numerical Weather Prediction (NWP): more dynamical processes related to convection and precipitation are resolved explicitly
- DA techniques need to evolve in order to keep up with the developments in high-res. NWP
  - breakdown of **dynamical balances** at smaller scales
  - strongly nonlinear processes associated with **convection and moisture/precipitation**
  - move towards **ensemble-based** methods
- It may be **unfeasible**, and indeed **undesirable**, to initially investigate the potential of DA schemes on state-of-the-art NWP models. Solution: **idealised models**...
  - capture some fundamental processes
  - computationally inexpensive to implement
  - **extensive** investigation of forecast/ assimilation system in a **controlled** environment
- 'Toy' models: a hierarchy of complexity
  - ODE models (e.g., Lorenz: L63, L95, etc.)
  - **idealised fluid models** (e.g., BV, QG)
  - simplified operational NWP configurations

3. Model: SWEs with 'rain'

An idealised fluid model (after [1],[2]): **atmosphere with moist convection**. Ingredients: rotating shallow water equations (SWEs) + ...

- two threshold heights $H_c < H_r$: when fluid exceeds these heights, different mechanisms kick in and alter the classical SW dynamics.
- modifications to the effective pressure gradient
- evolution equation for model 'rain' coupled to momentum equation

$$\begin{aligned} \partial_t h + \partial_x(hu) &= 0, \\ \partial_t(hu) + \partial_x(hu^2 + P) + hc_0^2\partial_x r & \\ - fhv + Q\partial_x b &= 0 \\ \partial_t(hv) + \partial_x(huv) + fhu &= 0, \\ \partial_t(hr) + \partial_x(hur) + h\widetilde{\beta}\partial_x u + \alpha hr &= 0, \end{aligned}$$

where P and Q are defined via the effective pressure $p = p(h) = \frac{1}{2}gh^2$ by:

$$P(h,b) = \begin{cases} p(H_c - b), & \text{for } h + b > H_c, \\ p(h), & \text{otherwise,} \end{cases}$$

$$Q(h,b) = \begin{cases} p'(H_c - b), & \text{for } h + b > H_c, \\ p'(h), & \text{otherwise,} \end{cases}$$

with p' denoting the derivative of p with respect to its argument h, and:

$$\widetilde{\beta} = \begin{cases} \beta, & \text{for } h + b > H_r \text{ and } \partial_x u < 0, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

(black - standard SWEs; red - modifications)

- h = fluid depth, (u,v) = velocities, r = rain mass fraction; all as a function of (x,t). $b = b(x)$ bottom topography
- H_c, H_r = threshold heights, above which convection and 'rain' processes occur; α, β, and c_0^2 are parameters relating to the removal, production, and evolution of 'rain' in the model

2. Approach

1. Describe a **physically plausible idealised model**; investigate numerically (details in [2])
   - based on rotating SWEs: "1D symmetric"
   - exhibits important aspects of convective-scale dynamics
     - disruption of large-scale balance
     - initiation of daughter cells away from the parent cell by gravity wave propagation
     - convection downstream from a ridge
2. **Ensemble-based** DA: relevant for convective-scale NWP? Algorithm: perturbed obs. EnKF. For meaningful experiments:
   - dynamics: suitable time- and length-scales
   - DA: **"tuning"** the observing system and ensemble configuration
   - exploiting the model's **strong nonlinearity**

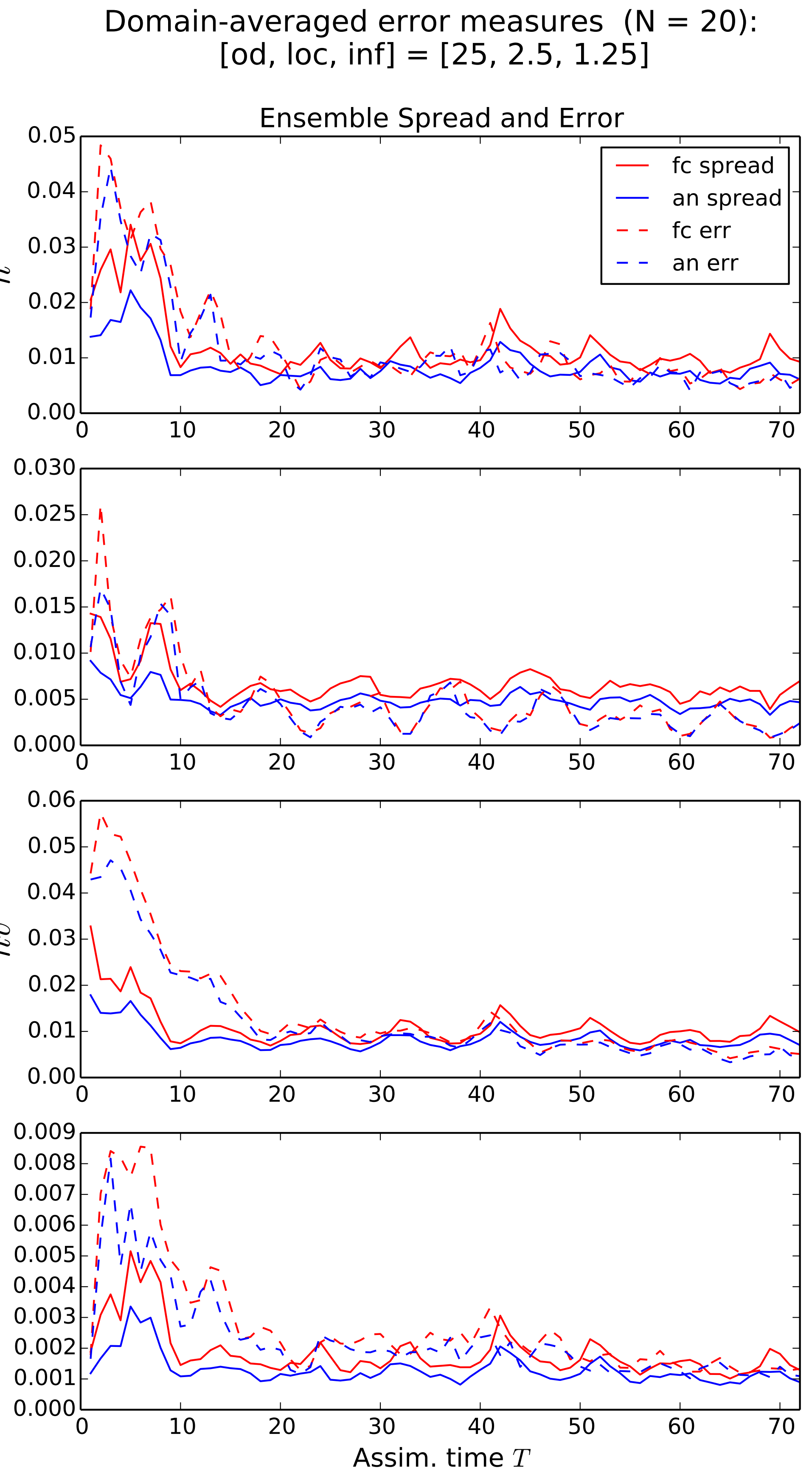
4. Idealised DA experiments

Dynamics: time- and length-scales

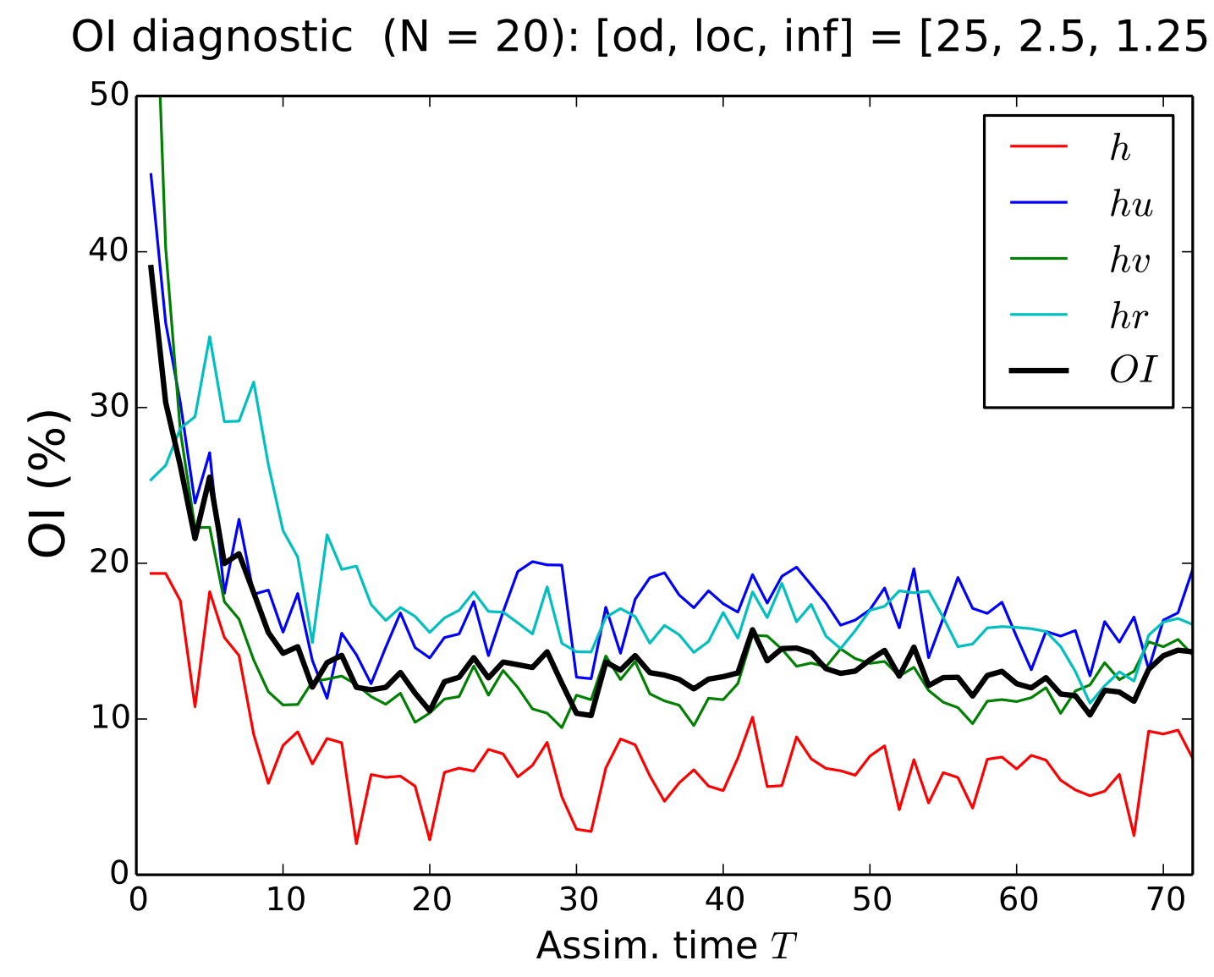
- non-dimensional parameters, Rossby and Froude number: Ro = Fr = 1
- length of domain ~ 500 km: 250 cells implies forecast grid size of ~ 2km

Assimilation: twin model set-up

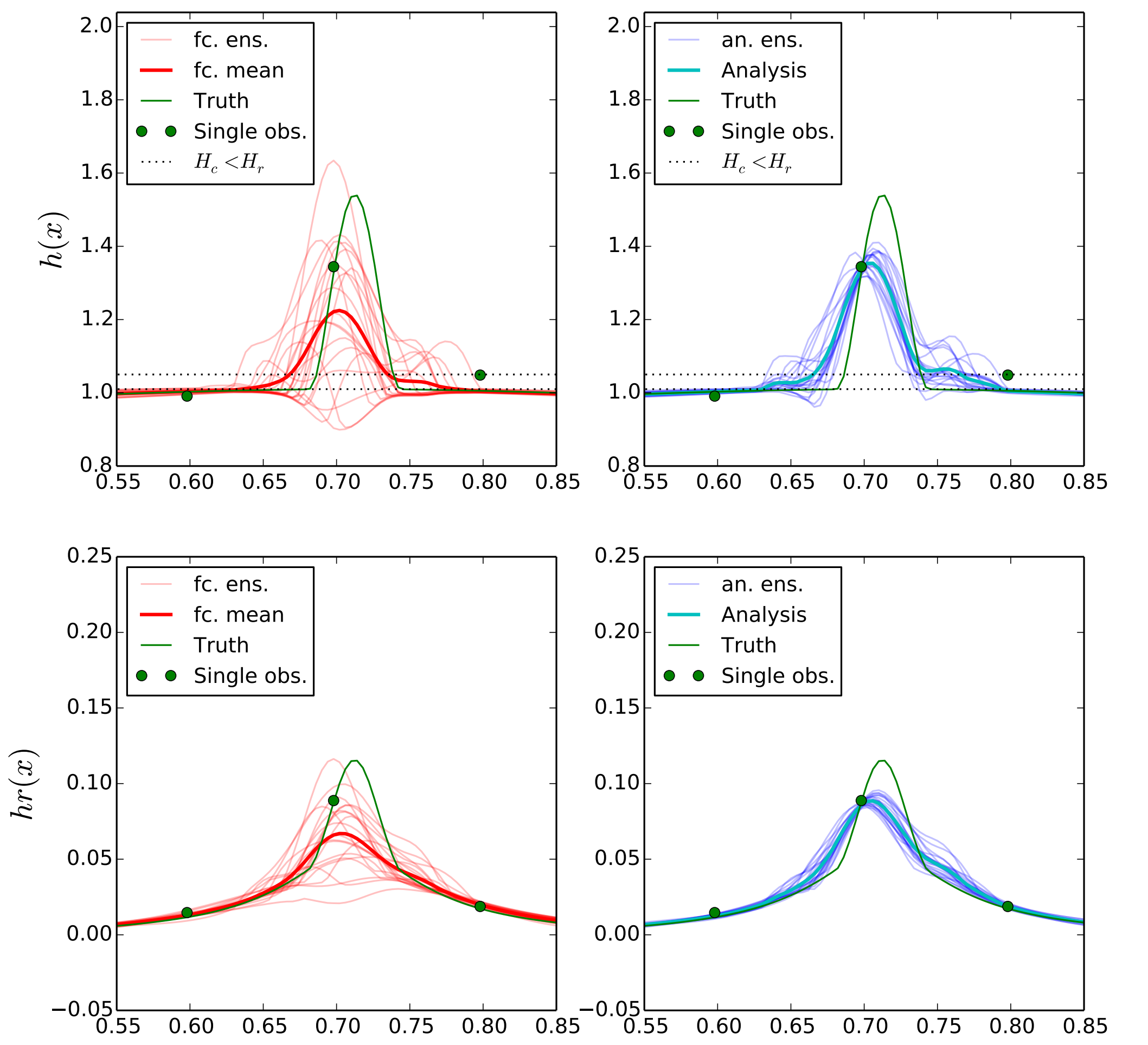
- imperfect model setting: "truth" trajectory run at higher resolution (here, 2 × forecast res.)
- inflation: $\mathbf{x}_i^f \leftarrow \gamma(\mathbf{x}_i^f - \overline{\mathbf{x}}^f) + \overline{\mathbf{x}}^f$
- localisation: $\mathbf{P}_{loc}^f \leftarrow \rho_{loc} \circ \mathbf{P}^f$
- diagnostics: error vs spread, observational influence diagnostic (after [3]): $OI = \frac{tr(\mathbf{HK})}{p}$ where **HK** is Kalman gain matrix in obs. space, p is number of obs.
- hourly cycling for 72hrs (allow ~ 24hrs spin-up and ~48hrs to analyse)
- for N ensemble members, tune the system: obs. noise $\boldsymbol{\sigma}_o$, obs. density (e.g., observe every 50km), localisation scale ρ_{loc}, inflation factor γ.



A well-configured ensemble is key to providing an adequate estimation of forecast error: ensemble spread should be comparable to error in both forecast and analysis



Observing system should be tuned to give a similar OI as operational NWP systems (~ 20%)



Nonlinearity of the thresholds: some members exhibit convection/precipitation while others do not - issues with non-Gaussianity/bi-modality

5. Current and future steps

- Experiments with topography (more gravity wave dynamics)
- Imperfect model via, e.g., misspecified threshold heights to further exploit nonlinearity
- Compare with, e.g., nonlinear iterative EnKF?
- port the model into an open framework for DA research?

Q. How can we use the model to ascertain how DA algorithms manage the strong nonlinearities associated with convection?

References

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