

modRSW ensemble Kalman filter configuration and tuning

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Experiment construction

Experiment construction

- Domain is 500 km wide with orography
- Nature run uses 400 grid points while forecast model uses 200 grid points (2.5 km grid spacing)
- Nature run is used to create pseudo-observations by adding zero-mean Gaussian noise
- Hourly cycling
- Observe all variables every 50 km (30 observations)
- Ensemble Kalman filter with 20 members

Ensemble Kalman filter (EnKF) components

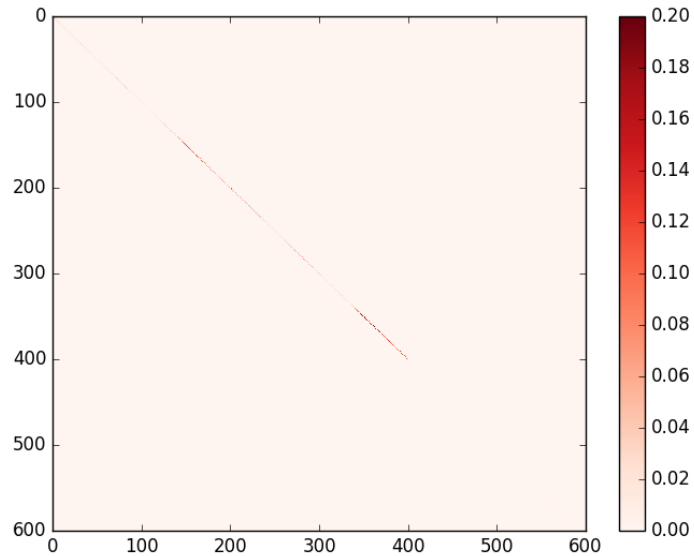
Deterministic EnKF and self-exclusion

- Deterministic EnKF ([Sakov and Oke, 2008](#)) is preferred over the perturbed-observations EnKF for few observations
- Self-exclusion ([Houtekamer and Mitchell, 1998](#); [Hamill and Snyder, 2000](#); [Bowler et al., 2017](#); [Lorenc et al., 2017](#)) limits inbreeding by excluding the member being updated from the forecast-error covariance calculation

Additive inflation

- Additive inflation accounts for model error ([Houtekamer and Zhang, 2016](#))
- Diagonal model-error covariance matrix estimated from sample of differences of high-resolution nature run and low-resolution forecasts, both starting from nature run trajectory points
- Zero-mean Gaussian noise added to the forecast trajectory as a tendency using an Incremental Analysis Update approach ([Bloom et al., 1996](#))
- Treats systematic error as if it was random error
- Apply a scaling factor to compensate

Model-error cov. matrix for $(h^T, (hu)^T, (hr)^T)^T$



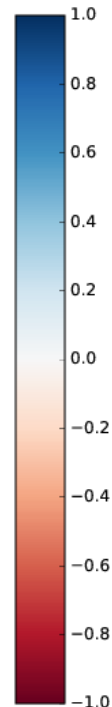
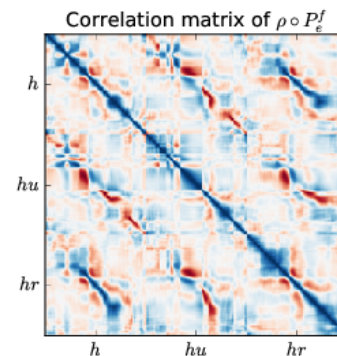
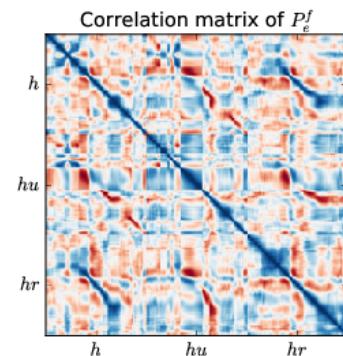
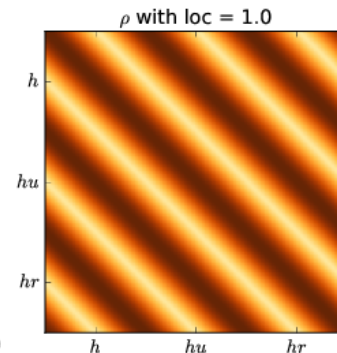
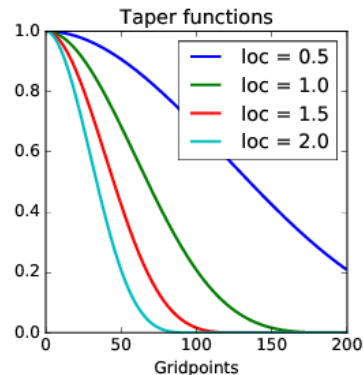
Relaxation to Prior Spread

- RTPS ([Whitaker and Hamill, 2012](#)) applies adaptive multiplicative inflation to the ensemble perturbations from the ensemble mean to compensate for sampling error

$$(x_i^a)' \leftarrow (x_i^a)' \left(\alpha \frac{\sigma_b - \sigma_a}{\sigma_a} + 1 \right)$$

Localisation

- Gaspari-Cohn localisation applied to the forecast-error covariance matrix to suppress correlation values away from the block diagonals
- 45 hours into cycling forecast/assimilation experiment

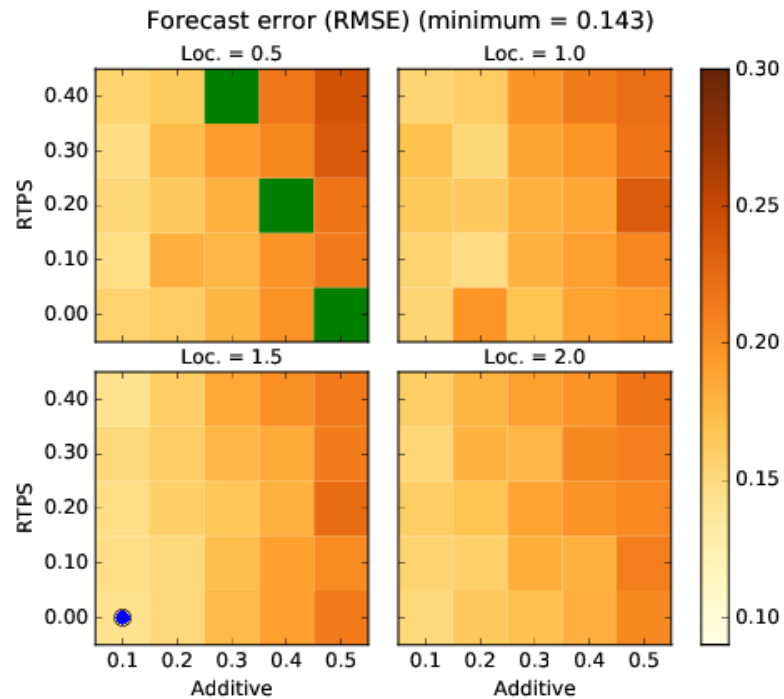
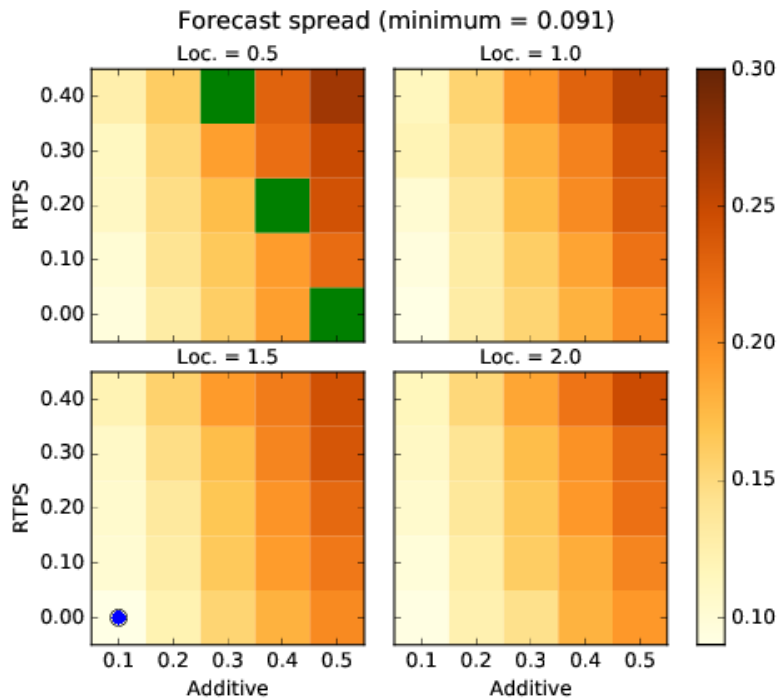


Diagnostics

Generalising approach of [Inverarity \(2015\)](#)

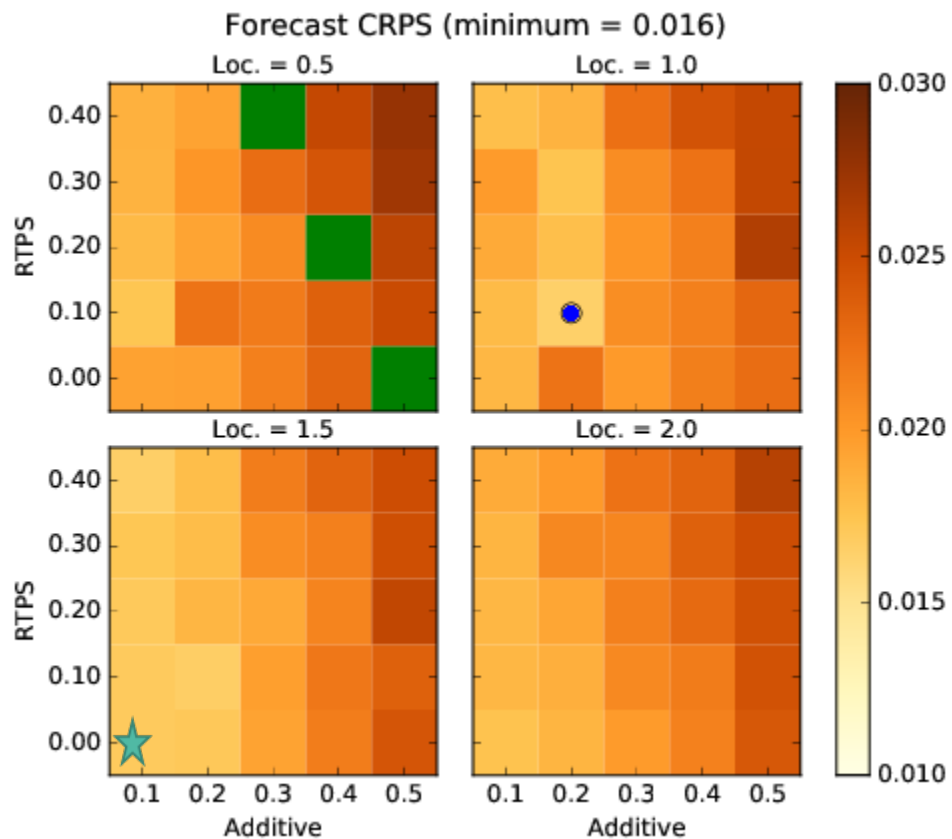
Spread / RMSE

- For an ideal ensemble, the ensemble spread about the ensemble mean should match the root mean square error of the ensemble mean
- A single RMSE score can be calculated over all three dimensionless components h , u and $100 r$ – each of order 1 after scaling the rainfall variable



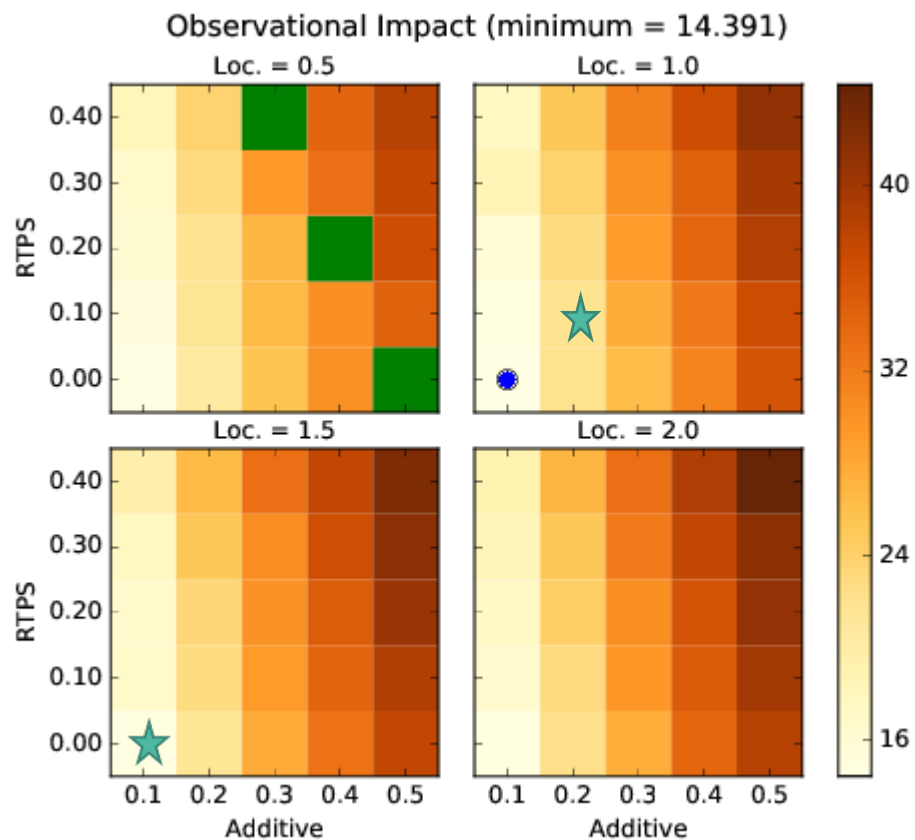
CRPS

- Continuous ranked probability score (e.g. [Hersbach, 2000](#))
- Compares system's empirical cumulative distribution function (cdf) with a reference cdf
- Lower score is better
- Plots compare with cdf derived from nature run

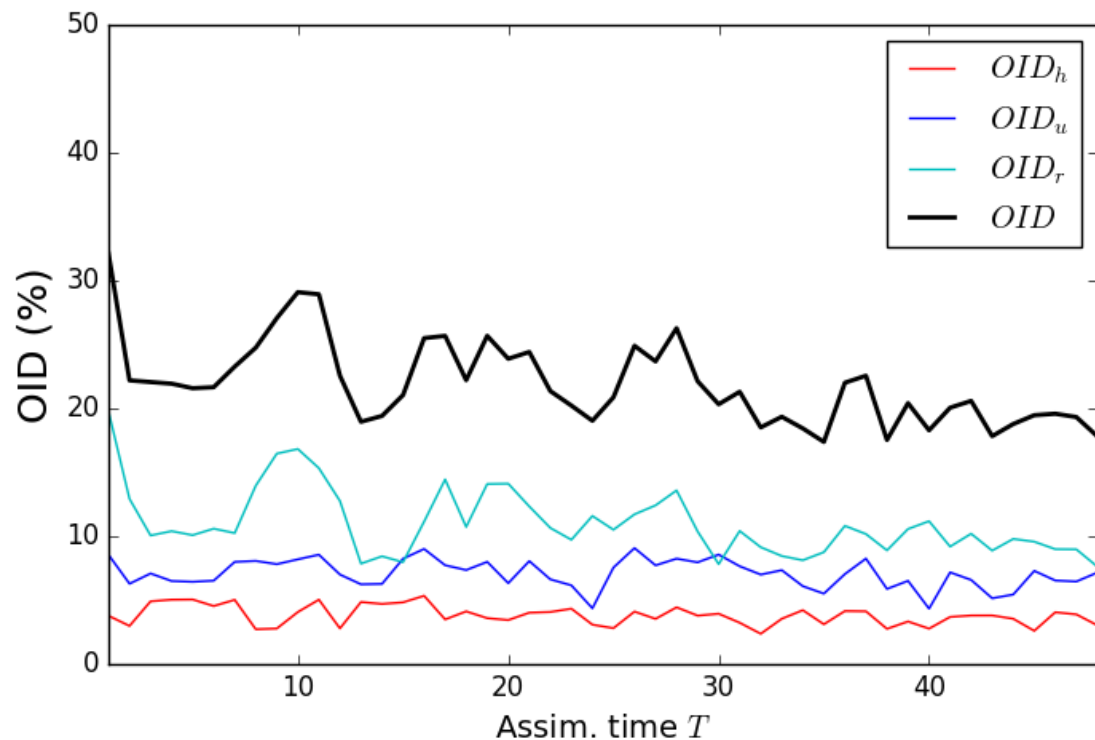


Observational influence

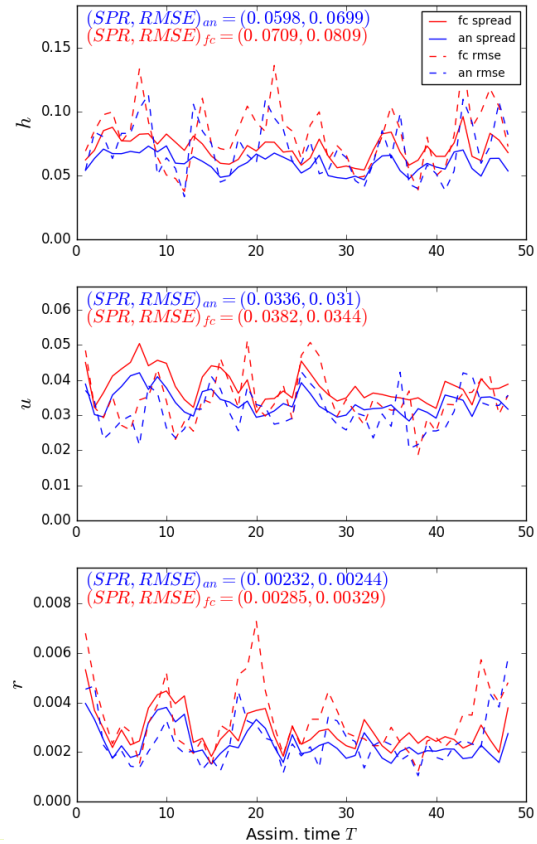
- Degrees of freedom of signal measure of the relative contribution of observations to the analysis ([Cardinali et al., 2004](#)) compared to the previous forecast
- ECMWF value 15% (global forecast)



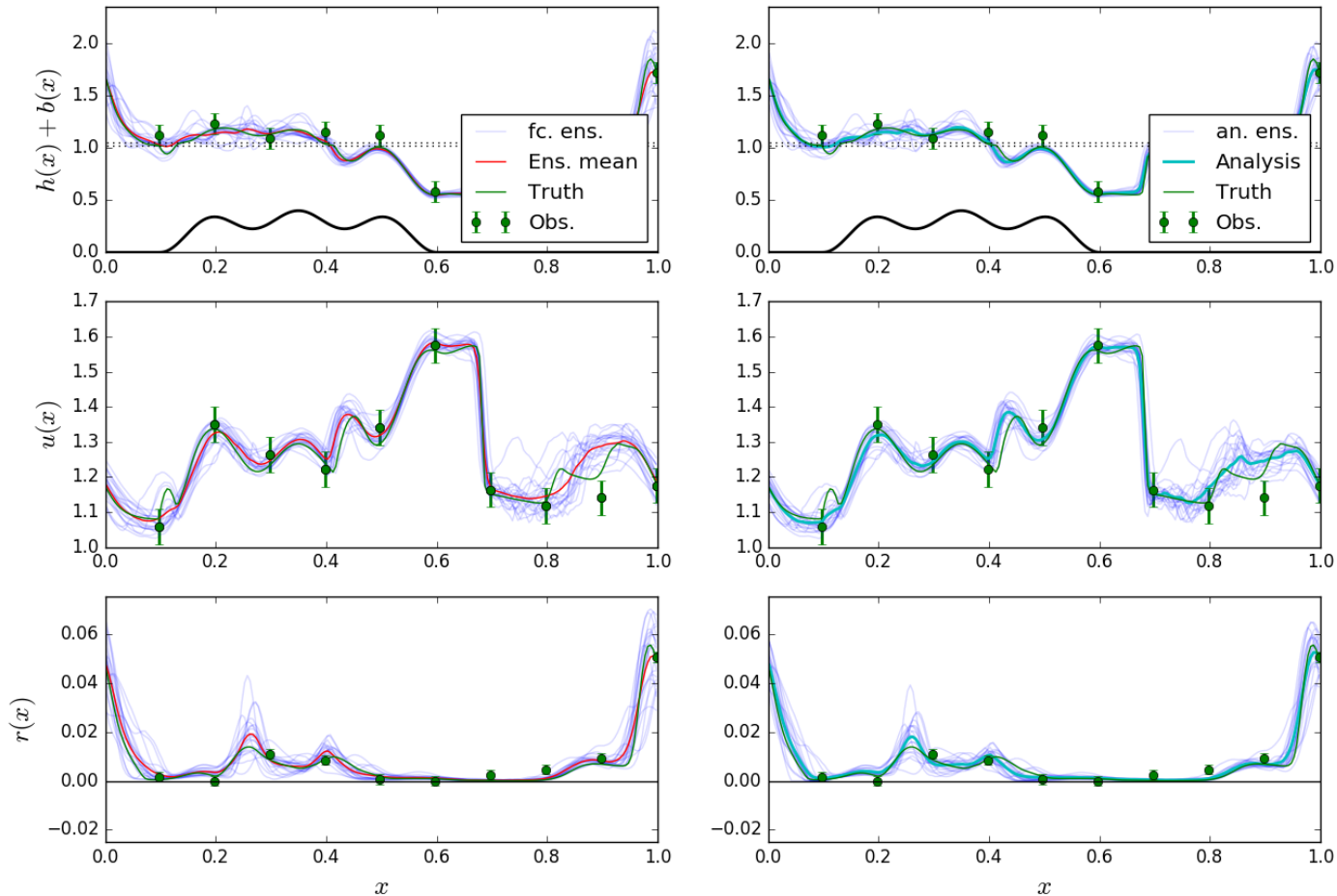
OI diagnostic (N = 20): [loc, add_inf, rtps] = [1.0, 0.2, 0.1]



Domain-averaged error vs spread (N = 20):
[loc, add_inf, rtps] = [1.0, 0.2, 0.1]

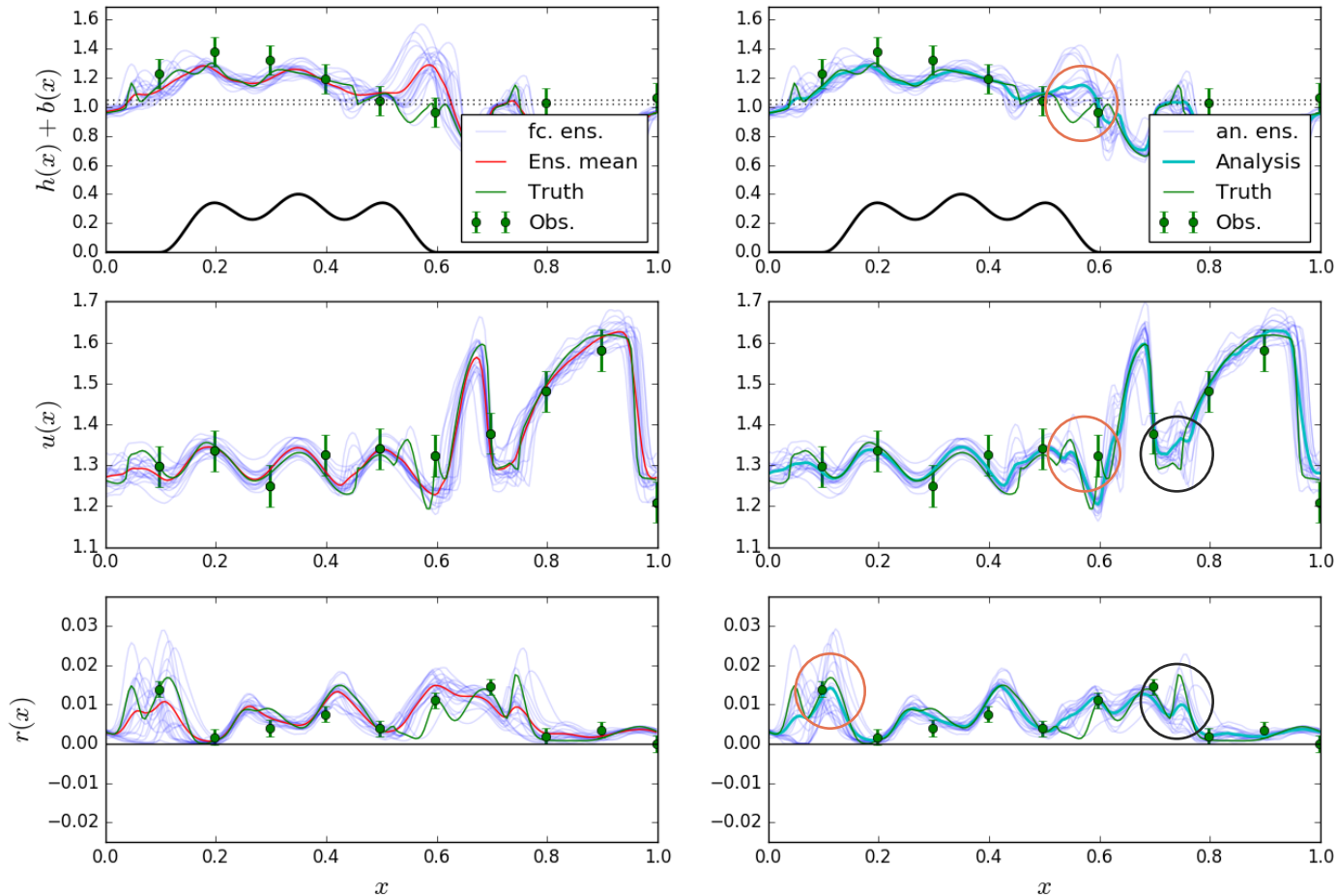


12 hours

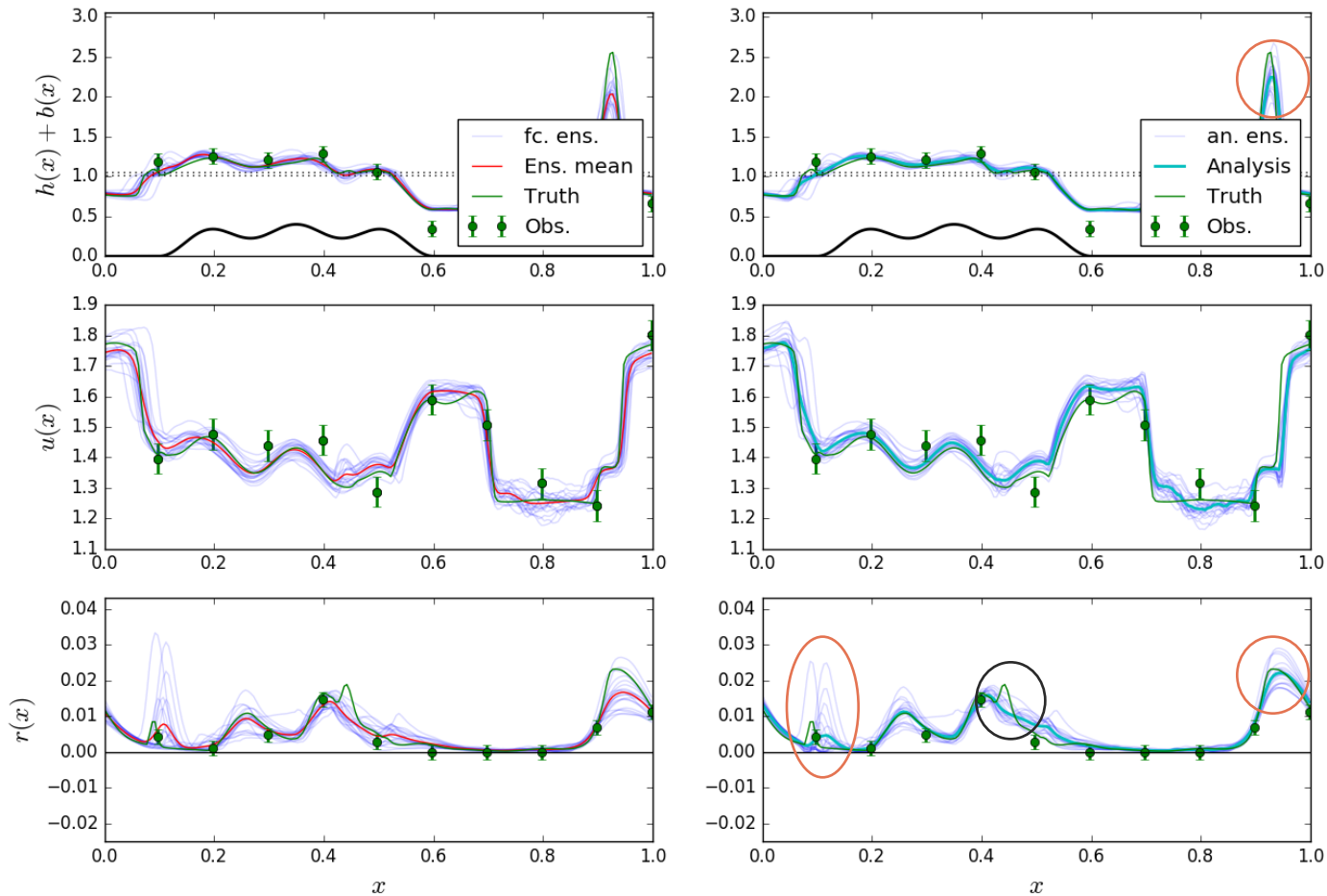


24 hours

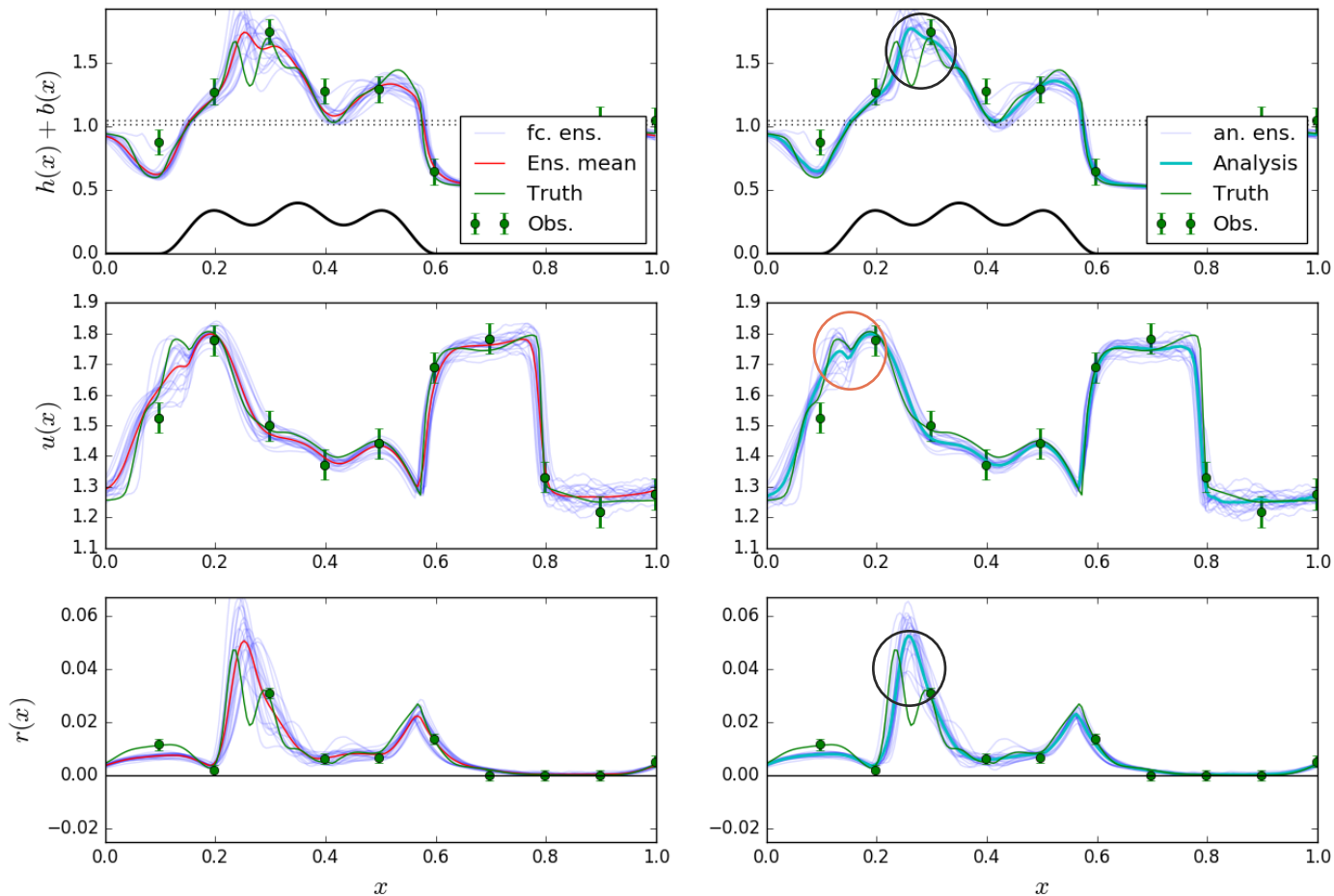
Red for better
Black for worse
or no impact



36 hours



48 hours



Summary

Summary

- Realistic convective-scale data assimilation demonstrated using a deterministic ensemble Kalman filter
- Spread/RMSE of ensemble mean, observational influence and CRPS diagnostics used
- Tuning approach shown for a single observational configuration

Questions?

For more information please contact



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