Data assimilation (DA) allows information to be squeezed from EO data.

NWP increasingly relies on EO data.

But, DA must be formulated carefully, including well characterised forecast error statistics.

Information from an ensemble can provide information about forecast error statistics.

Study a convective-scale ensemble problem.

How to generate an appropriately spread ensemble.

What useful things can we learn from this ensemble?
What can we learn from forecast ensembles?

**USING AN ENSEMBLE**
Forecast uncertainty and meteorological understanding
- All forecasts are wrong – forecast uncertainty assessment.
- Data assimilation – how to interpret a-priori information.
- How are (errors in) forecast fields correlated?

**CONSTRUCTING AN ENSEMBLE**
What are the respective effects on forecasts of:
- Introducing variability in the initial condition error (i.c.e.)?
- Introducing variability in the model error (m.e.)?

**Forecast assessment and evaluation**
- How does each source of error affect the forecast spread?
- How do they affect the skill?
Simulation of errors

- **Initial conditions must be chosen carefully:**
  - Each written as $x_{ic}(n) = x_0 + \delta x_{ic}(n)$, $1 \leq n \leq N$.
  - $\delta x_{ic}(n)$ must be consistent with available knowledge and its uncertainty and the behaviour of the atmosphere.
  - Initial condition uncertainty, boundary condition uncertainty, model error uncertainty.
  - If variability of $\delta x_{ic}(n)$ too small → range of possible forecasts not represented.
  - too large → forecasts not useful.
Ensemble prediction in the Southern UK domain

MOGREPS-G (Met Office Global and Regional Ensemble Prediction System)
MOGREPS-R (Met Office Global and Regional Ensemble Prediction System)
MOGREPS-UK
MOGREPS-SUK-1.5 (MetO@Reading / Reading Uni)

- Determine a single set of initial condition fields by VAR.
- Add perturbations based on the a-priori ensemble and properties of the observation network used in VAR (ETKF).
- Have $N$ sets of initial condition fields ($N=24$).
- Pass each through forecast model with (optionally) a perturbation of model parameters (the RP – random parameters – scheme).
MOGREPS-SUK-1.5 set-up

- Domain over southern UK (360 x 288 grid points)
- 1.5 km resolution grid
- Control member from 3D-Var analysis
- 23 perturbed members: initial condition perturbations and LBCs from MOGREPS-R
- Hourly-cycling ETKF for the first 6 hours
- 6 hour forecast from 12z
- Options to simulate model error variability with 'RP scheme'
DIAMET IOP-2 case study

20/09/2011

Radar rainfall composite, 15:00Z

Synoptic chart, 18:00Z

Flight trajectory, FAAM aircraft
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC

CTL ensemble (i.c. variability only)
Simulating an additional source of error – model error variability

- Results on previous slides varied initial conditions only.
- Only one realisation of model error.
## Parameters

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Parameter</th>
<th>Description</th>
<th>min</th>
<th>default</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>BL</td>
<td>$g_0$</td>
<td>Flux profile parameter</td>
<td>5</td>
<td>10</td>
<td>20</td>
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<tr>
<td>BL</td>
<td>$R_{i_c}$</td>
<td>Critical Richardson number</td>
<td>0.5</td>
<td>1.0</td>
<td>2.0</td>
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<tr>
<td>BL</td>
<td>$g_{mezcla}$</td>
<td>Neutral mixing length</td>
<td>0.03</td>
<td>0.15</td>
<td>0.45</td>
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<tr>
<td>BL</td>
<td>$\lambda_{\text{min}}$</td>
<td>Minimum mixing length</td>
<td>8</td>
<td>40</td>
<td>120</td>
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<tr>
<td>BL</td>
<td>Charnock</td>
<td>Charnock parameter</td>
<td>0.010</td>
<td>0.011</td>
<td>0.026</td>
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<tr>
<td>BL</td>
<td>$A_1$</td>
<td>Entrainment parameter</td>
<td>0.1</td>
<td>0.23</td>
<td>0.4</td>
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<tr>
<td>BL</td>
<td>$G_1$</td>
<td>Cloud-top diffusion parameter</td>
<td>0.5</td>
<td>0.85</td>
<td>1.5</td>
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<tr>
<td>LSP</td>
<td>$\text{RH}_{\text{crit}}$</td>
<td>Critical relative humidity</td>
<td>0.875</td>
<td>0.9</td>
<td>0.910</td>
</tr>
<tr>
<td>LSP</td>
<td>$m_{ci}$</td>
<td>Ice-fall speed</td>
<td>0.3</td>
<td>1.0</td>
<td>3.0</td>
</tr>
<tr>
<td>LSP</td>
<td>$x_{1r}$</td>
<td>Particle size distribution for rain</td>
<td>$2 \times 10^6$</td>
<td>$8 \times 10^6$</td>
<td>$2 \times 10^9$</td>
</tr>
<tr>
<td>LSP</td>
<td>$x_{li}$</td>
<td>Particle size distribution for ice aggregates</td>
<td>$1 \times 10^6$</td>
<td>$2 \times 10^6$</td>
<td>$1 \times 10^7$</td>
</tr>
<tr>
<td>LSP</td>
<td>$x_{1ic}$</td>
<td>Particle size distribution for ice crystals</td>
<td>$2 \times 10^7$</td>
<td>$4 \times 10^7$</td>
<td>$1 \times 10^8$</td>
</tr>
<tr>
<td>LSP</td>
<td>$ai$</td>
<td>Ice aggregate mass diameter</td>
<td>0.0222</td>
<td>0.0444</td>
<td>0.0888</td>
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<tr>
<td>LSP</td>
<td>$aic$</td>
<td>Ice crystal mass diameter</td>
<td>0.2935</td>
<td>0.587</td>
<td>1.174</td>
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<tr>
<td>LSP</td>
<td>$t_{\text{nuc}}$</td>
<td>Max ice nucleation temperature</td>
<td>-25</td>
<td>-10</td>
<td>-1</td>
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<tr>
<td>LSP</td>
<td>$\text{ec}_{\text{auto}}$</td>
<td>Autoconversion efficiency (converting cloud to rain)</td>
<td>0.01</td>
<td>0.55</td>
<td>0.6</td>
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</tbody>
</table>
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC

RP-fix ensemble (i.c. + fixed parameter variability)
MOGREPS-SUK-1.5 rain rate forecasts

1500 UTC

CTL ensemble (i.c. variability only)
Effect on ensemble spread

1.5m temperature

10m wind speed

Hourly rainfall accumulation

- CTL
- RP-60
- RP-30
- RP-fix
- onlyRP-60
- onlyRP-30
- onlyRP-fix
Effect on forecast skill (CRPS)

CRPS: Continuous Ranked Probability Score

$$\text{CRPS} = \int_{y=-\infty}^{+\infty} dy \ (C_{\text{fore}}(y) - C_{\text{obs}}(y))^2$$

$$C_{\text{fore}}(y) = \int_{y'=-\infty}^{y} dy' \ P_{\text{fore}}(y')$$

$$C_{\text{obs}}(y) = \int_{y'=-\infty}^{y} dy' \ P_{\text{fore}}(y')$$

$$\sim \int_{y'=-\infty}^{y} dy' \ \delta(y' - y_{\text{obs}})$$

Cumulative PDF

Better skill

- CTL
- RP-60, RP-30, RP-fix

surface temperature

rain accumulation

u-wind component

v-wind component
Effect on forecast skill (PSS)

Precipitation skill score for hourly rainfall accumulation

Threshold of 0 mm

Threshold of 0.2 mm

Threshold of 1.0 mm

PSS: Precipitation Skill Score

\[
PSS_{\text{ens}} = 1 - \frac{BS_{\text{ens}}}{BS_{\text{ctl}}}
\]

- \(PSS_{\text{ens}} > 0\) if "ens" better than "ctl"
- \(PSS_{\text{ens}} = 0\) if "ens" as good/bad as "ctl"
- \(PSS_{\text{ens}} < 0\) if "ens" worse than "ctl"

BS: Brier Score

\[
BS = \frac{1}{N} \sum_{i=1}^{N} (P_{\text{fore}}(i) - P_{\text{obs}}(i))^2
\]

- \(P_{\text{fore}}\): Probability of event forecast
- \(P_{\text{obs}}\): 1 if event observed, 0 if not

- CTL
- RP-60, RP-30, RP-fix
Ensemble-derived correlations (3-D)

ensemble derived

$w-q$
correlations (CTL: no RP)

$q$ here (specific humidity)

$w$ (vertical wind component) correlation field

No qualitative changes with model error representation
Ensemble-derived correlations (point-by-point)

$q$-$T$ correlations  \quad $q$-$w$ correlations

$w$ field

No qualitative changes with model error representation
Ensemble-derived variances (model grid)

CTL: No RP (i.c. only)

Fix RP + i.c.

Fix RP only (no i.c.)

Wind speed variance ($m^2s^{-2}$)
Ensemble-derived variances and correlations (spectral)

CTL: No-RP (i.c. only)

RP-fix-only (RP only)
Summary

- Have run a convective-scale EPS for DIAMET IOP 2 (20/09/11) with simulation of different sources of error (initial condition and model error).
  - Central forecast initialized with 3D-VAR (operational observations).
  - Initial condition perturbations found with the Ensemble Transform Kalman Filter.
  - Model error variability with the Random Parameter scheme.
  - This is the kind of essential work that has to be done in preparation for the use of high-resolution EO data for weather forecasting.

- Cold front case with multiple banding in the cloud
  - Believe banding is real (not artefact of radar retrieval).
  - Multiple banding is evident in none of the 24-members, but some show rain in areas of both bands.
  - Forecast error covariance info essential for data assimilation. Have shown examples of how these are flow-dependent at the convective scale.

- Ensemble prediction systems generally do not have enough natural spread. Can the inclusion of model error variability help?
  - Model error shown to increase the spread of some quantities ($T_s$, $|u_s|$), but to reduce the spread of others (rain rate).
  - Model error can give variability at small scales and where moist diabatic processes are very important.

- Does the RP scheme affect skill?
  - CRPS: RP did not improve skill for $T_s$ and rainfall; neutral for $u_s$, $v_s$.
  - BS, PSS: RP better skill for first few hours, worse skill later.

- Have/will also examine for this case:
  - Forecast sensitivity to parameters.
  - Reliability diagrams.
  - Rank histograms.
  - Innovation covariances.
  - 93-member statistics.
  - Large atlas of covariance statistics.
  - Balance properties.
  - Localization techniques.

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