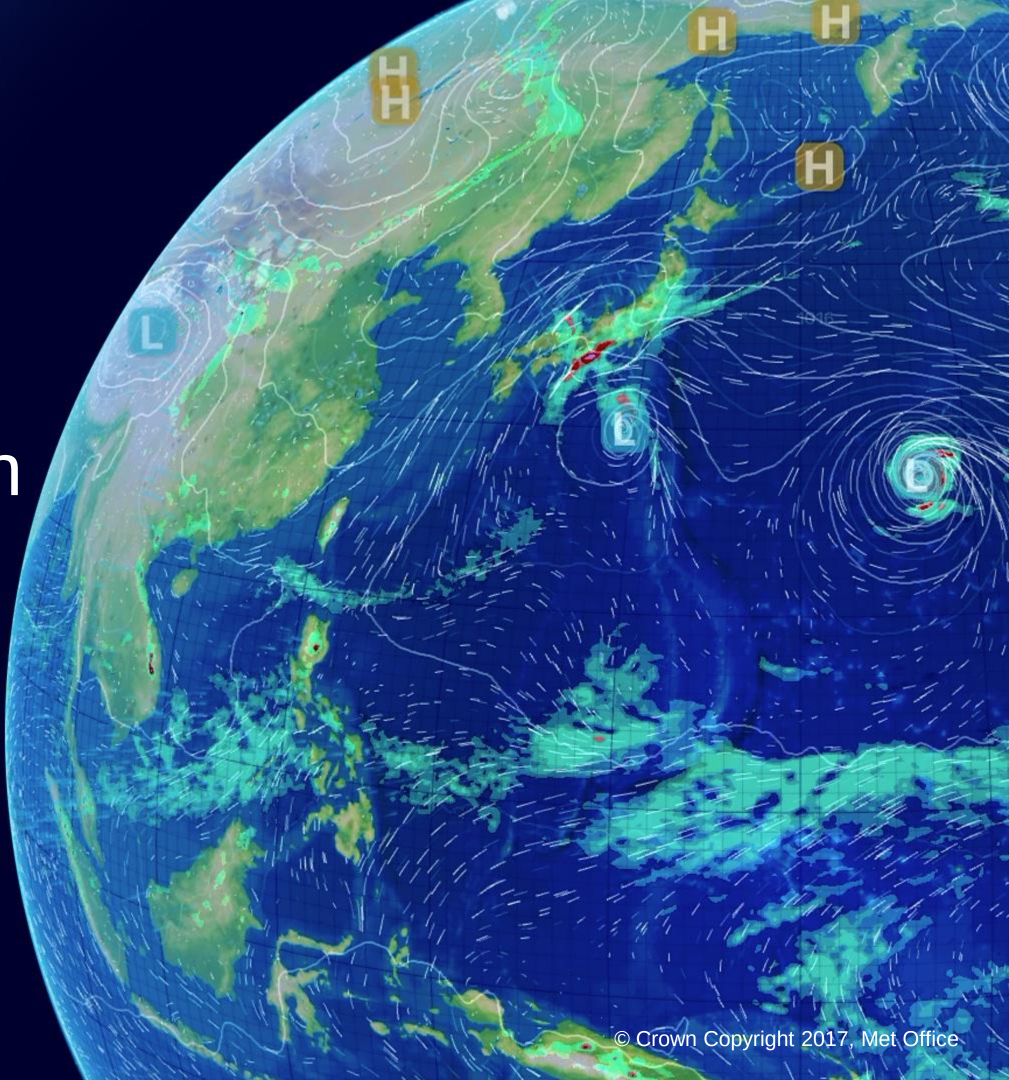
Doppler radial wind spatially correlated observation error: operational implementation and initial results

D. Simonin, J. Waller,

G. Kelly, S. Ballard, S. Dance, N. Nichols

(Met Office, University of Reading)



Met Office

Correlated observation error

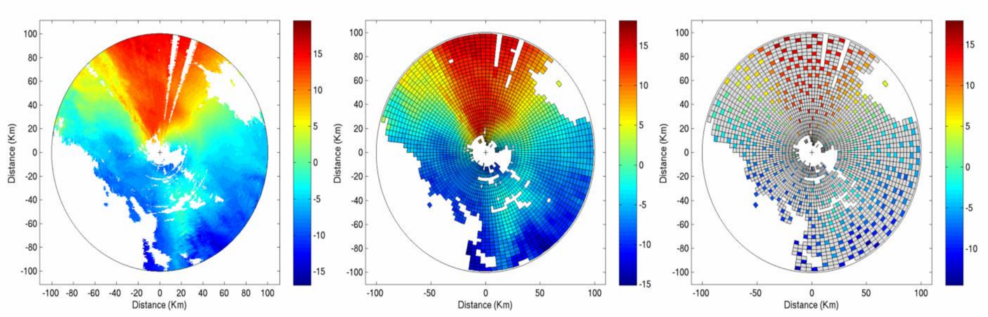
University of Reading

Motivation

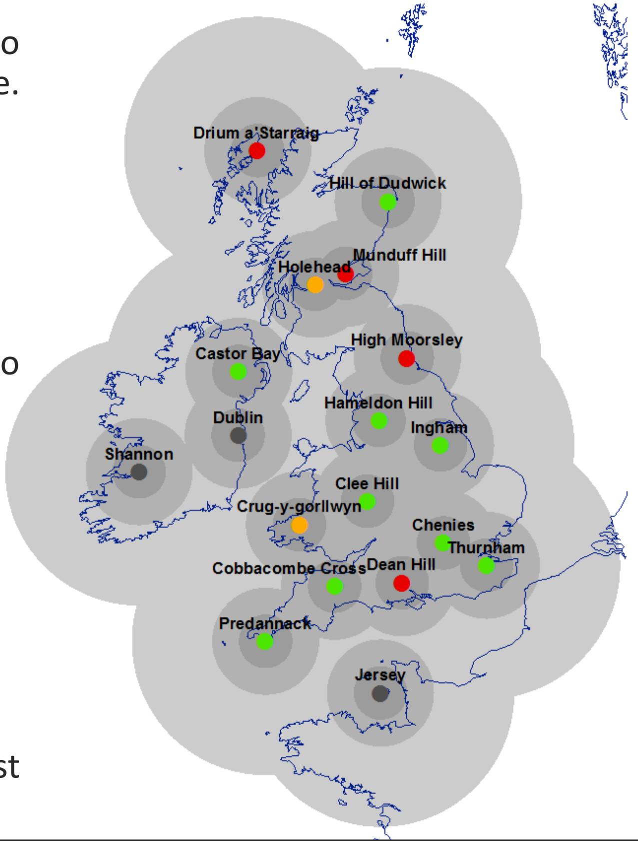
Convective-scale NWP requires a high resolution data assimilation system to provide initial conditions containing information at the appropriate scale. Therefore we require observations that have:

- High resolution
- High repetition time
- Large coverage

Currently observations with these properties are 'Superobbed' or thinned to remove correlated error.



Using correlated observation error statistics can improve assimilation and forecast performance. It also allows the use of observations at the appropriate scale.



Observation errors

Diagnosing observation error statistics

We have studied the *Desroziers et al. (2005)* Diagnostic (*Waller et al., 2016a, 2017*) and used it to estimate errors for:

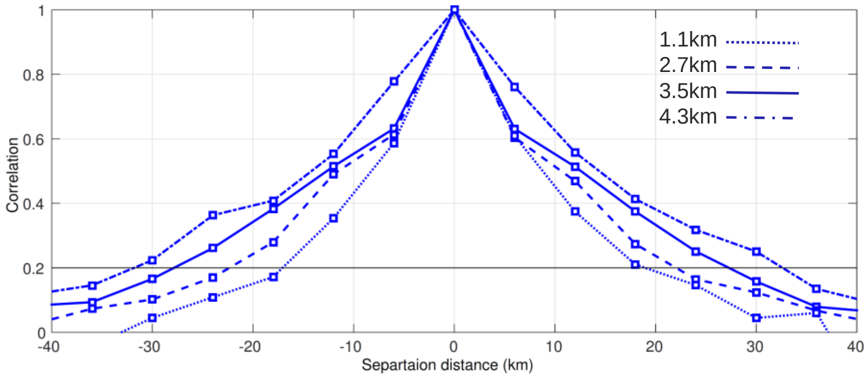
$$\boldsymbol{R} \approx \mathrm{E}[d_a^o {d_b^o}^T]$$

- Doppler radar radial winds (*Waller et al., 2016b*).
- SEVIRI observations (*Waller et al. 2016c*).
- Atmospheric motion vectors (*Cordoba et al. 2017*).

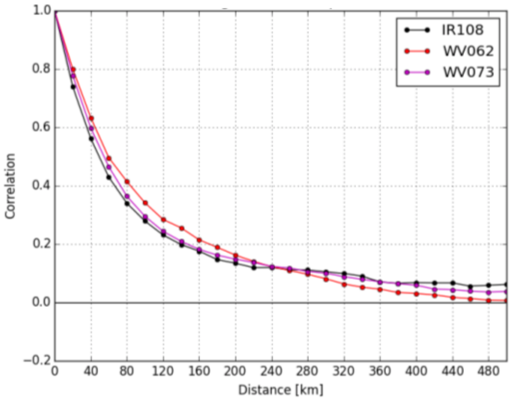
Background residual: $d_b^o = y - H(x^b)$

Analysis residual: $d_a^o = y - H(x^a)$

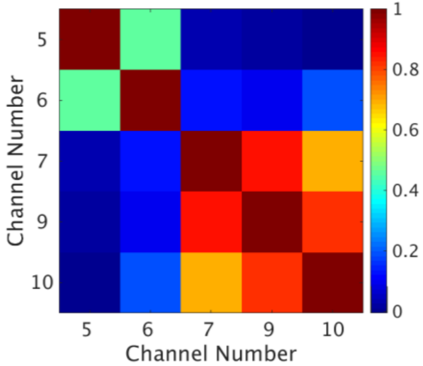
We can now use more of these observations.



Spatial radar error correlations for elevation 2° for different heights.



Spatial AMV error correlations



Inter-channel SEVIRI error correlations

Implementation

Correlated observation error

Implementation - Parallelisation

Traditional Parallelisation

- One model column (Cw) per observation (Obs)
- Each Obs and Cw are distributed across the PE using a domain decomposition → $Obs_{PE} = Cw_{PE}$

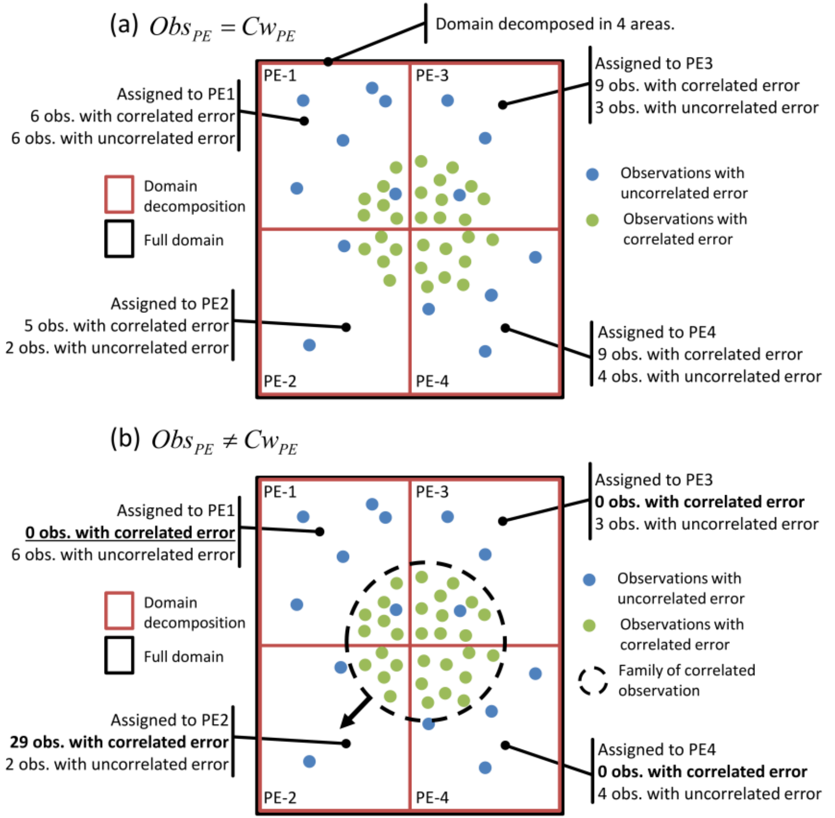
New Parallelisation

- Each Cw are distributed across the PE using a domain decomposition.
- Each Obs are distributed across the PE using a family decomposition

→ $Obs_{PE} \neq Cw_{PE}$

Family

- A family is a group of observations that are correlated.
- Each observation is assigned to a family.

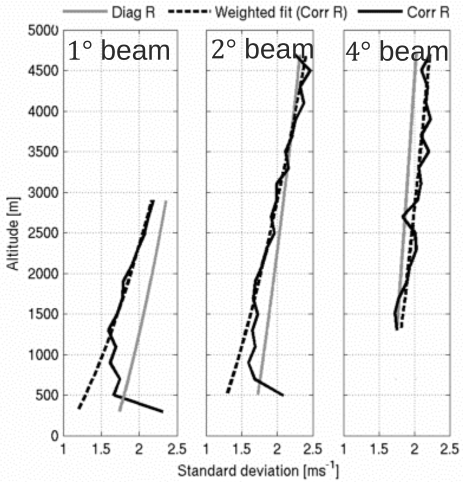


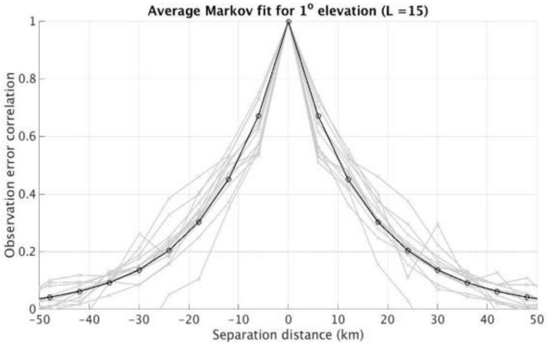
Correlated observation error

Implementation - R

The observation error covariance matrix ($\boldsymbol{R_s} = \boldsymbol{DCD}$) is derived on the fly and the observation penalty can be calculated as follows:

1. Determine $\boldsymbol{R_s} = \boldsymbol{DCD}$, where $C_{i,j} = exp\left(\frac{-|\Delta y_{i,j}|}{L_r}\right)$ and $\Delta y_{i,j}$is the distance between each pair of observations in the family.
2. Calculate a vector of model minus observation differences $d_o^b = (y - H(x))$
3. Calculate the sensitivity $Q = R_s^{-1}(y - H(x))$ using a Cholesky decomposition.
4. The total observation penalty is calculated:
$$J_o = (y - H(x))^T R_s^{-1}(y - H(x))$$





Initial results: Analysis

Results – VAR statistics

Trials

UKV PS37 (3 hourly – 3DVAR)

Three experiments run for 20 days from the 1st April 2016

- 6km thinning with Diagonal R
  → **Control** (~2000 rad obs. per cycle)
- 6km thinning with Correlated R
  → **Corr-R-6km** (~2000 rad obs. per cycle)
- 3km thinning with Correlated R
  → **Corr-R-3km** (~8000 rad obs. per cycle)

System performance

There is no significant difference in iteration count and running time.

Effect on Penalty:

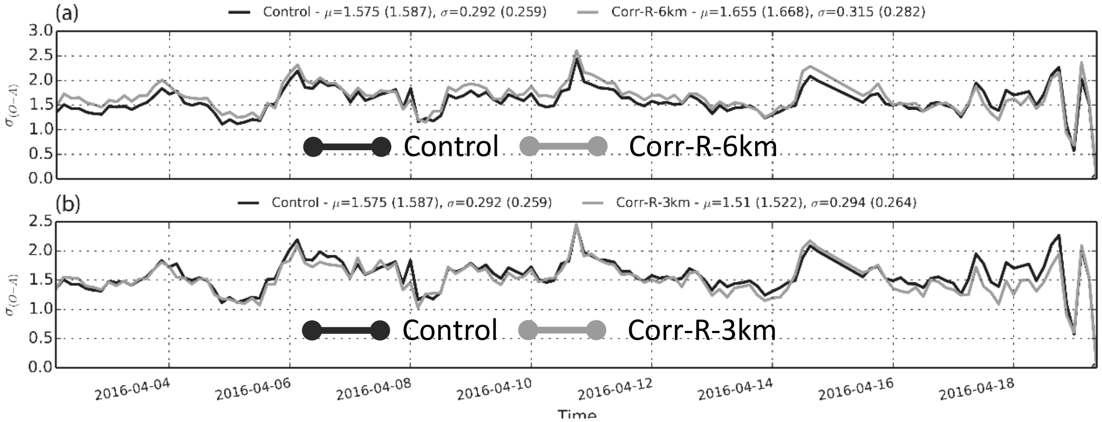
(Compare to the control)

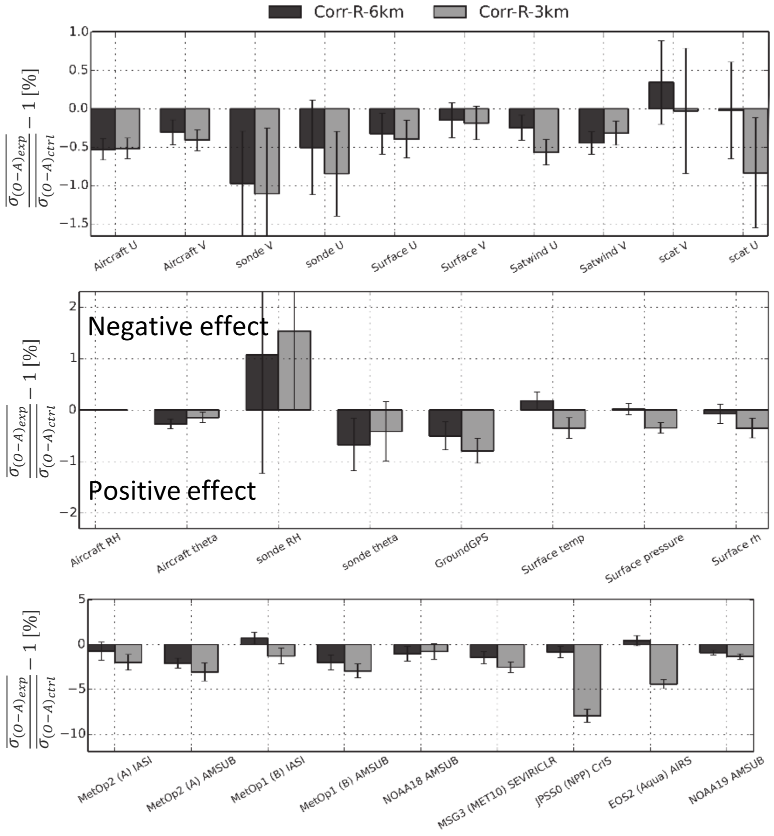
- The **Corr-R-6km** has a smaller background penalty and a larger observation penalty.

→ Correlated R reduces the weight of the observations.

Correlated observation error

Results – VAR statistics 1/2





Effect on $O - A$ statistics

Introduction of correlated R reduces the fit to Doppler observations.

Increasing the observation density shows similar $O - A$ statistics to the control.

Most observations show **a small benefit** from the introduction of the correlated error.

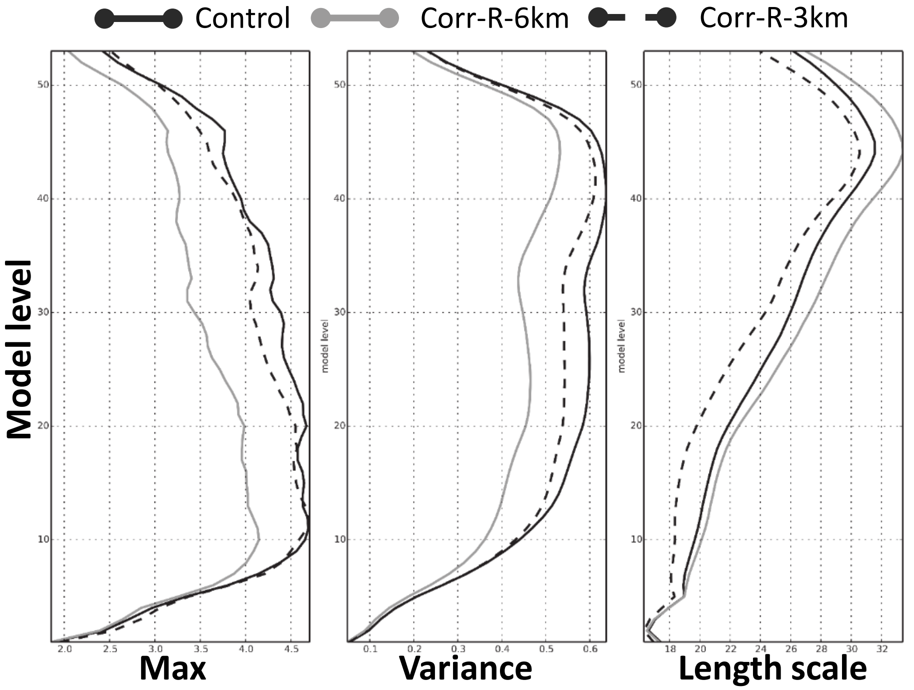
Correlated observation error

Results – VAR statistics 2/2

Effect on wind increments:

(Compared to the control)

- The **Corr-R-6km** wind’s increments are smoother with smaller range.
- The **Corr-R-3km** wind increments show more small scale features with smaller range (bigger than Corr-R-6km).



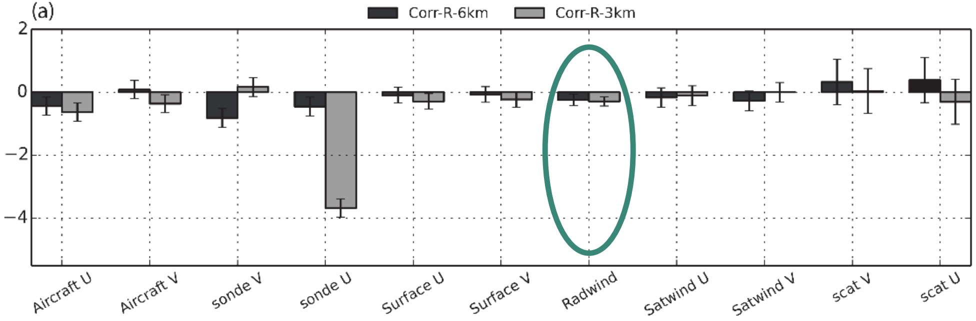
Initial results: Forecast

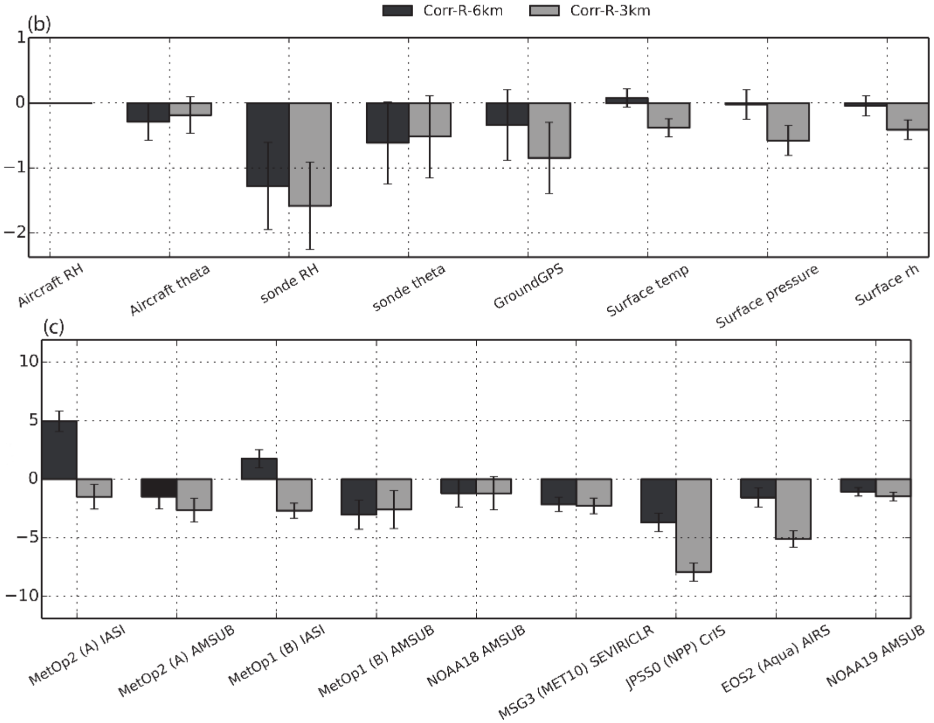
Results – Impact on forecast 1/2

Effect on $O - B$

Most observations show **a small benefit** from the introduction of the correlated error.

$$\frac{\overline{\sigma_{(O-B)exp}}}{\overline{\sigma_{(O-B)ctrl}}} - 1\ [\%]$$





Correlated observation error

Results – Impact on forecast 2/2

Surface verification: Weighted Basket of Indices (ETS & RMS scores)

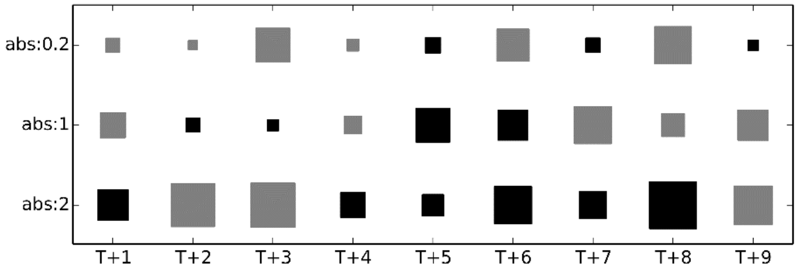
	Corr-R-6km [%]	Corr-R-3km [%]
Vis	+0.027	+0.046
Precip	-0.063	-0.050
Cloud Cover	+0.047	+0.012
Cloud Base Height	-0.013	-0.005
Temp	-0.014	+0.005
Wind	+0.010	+0.013
Overall	**-0.005**	**+0.021**

Very small impact!

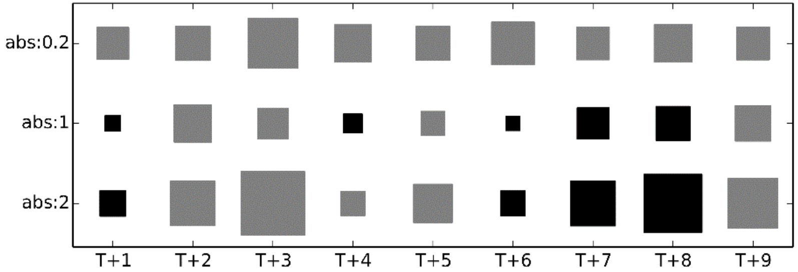
Fraction skill score:

$$\Delta FSS = FSS_{Exp} - FSS_{Ctrl}$$

$\max|\Delta FSS| = 0.009$ [Ctrl: Control, Exp:Corr-R-6km]



$\max|\Delta FSS| = 0.03$ [Ctrl: Control, Exp:Corr-R-3km]



Conclusion

Correlated observation error

Conclusion

- **High resolution NWP requires data assimilation that can assimilated observations at the appropriate spatial and temporal resolution.**
- **Typically observations at these resolutions will have correlated error which should be accounted for.**
- **We have developed parallelisation strategy to account for correlated observation errors in an operational variational data assimilation system.**
- **It has been tested using Doppler radial wind observations.**
  - The system performance is good.
  - Higher resolution observations can be used in the assimilation.
  - Small benefits in the assimilation systems have been seen including the addition of small scale information.
  - The impact on the forecast is neutral.
- **The strategy developed should be applicable to multiple observation types and we plan assess the impact of correlated observation error for AMV and Radar reflectivity observations.**

Correlated observation error

Conclusion

- **High resolution NWP requires data assimilation that can assimilated observations at the appropriate spatial and temporal resolution.**

- **Typically observations at these resolutions will have correlated error which should be accounted for.**

- **We have developed parallelisation strategy to account for correlated observation errors in an operational variational data assimilation system.**

- **It has been tested using Doppler radial wind observations.**
  - The system performance is good.
  - Higher resolution observations can be used in the assimilation.
  - Small benefits in the assimilation systems have been seen including the addition of small scale information.
  - The impact on the forecast is neutral.

- **The strategy developed should be applicable to multiple observation types and we plan assess the impact of correlated observation error for AMV and Radar reflectivity observations.**

Thank you. Any Questions?

References

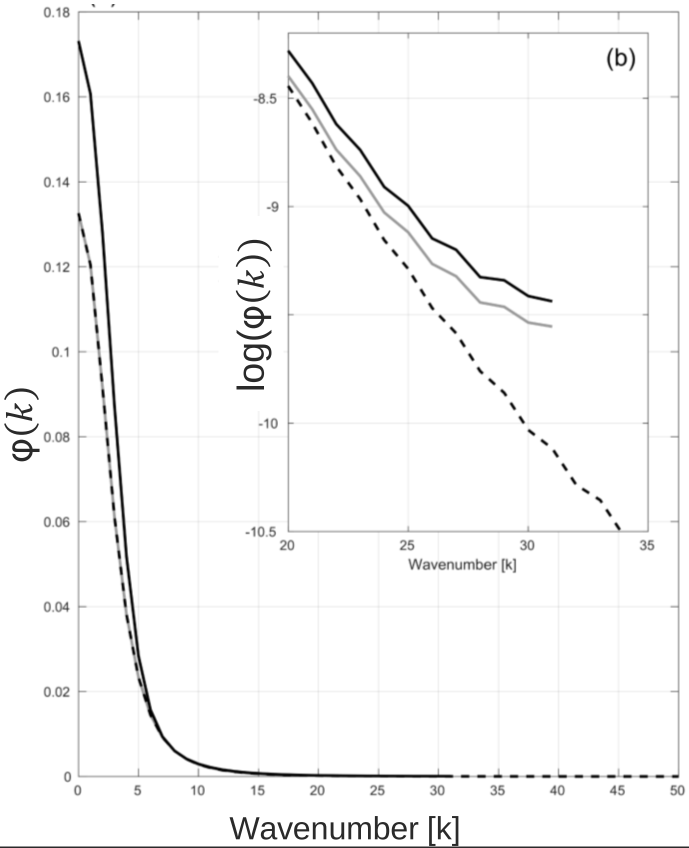
- Cordoba, M., Dance, S. L., Kelly, G. A., Nichols, N. K. and Waller, J. A. (2017) Diagnosing atmospheric motion vector observation errors for an operational high resolution data assimilation system. Quarterly Journal of the Royal Meteorological Society, 143 (702). pp. 333-341. ISSN 1477-870X doi: 10.1002/qj.2925
- Simonin, D., Waller, J. A., Ballard, S. P., Dance, S. L., Nichols, N. K. (2018) Doppler radial wind spatially correlated observation error statistics: operational implementation and initial results. Submitted to Quarterly Journal of the Royal Meteorological Society.
- J. A., Dance, S. L. and Nichols, N. K. (2017) On diagnosing observation error statistics with local ensemble data assimilation. Quarterly Journal of the Royal Meteorological Society. ISSN 1477-870X doi: 10.1002/qj.3117 (In Press)
- Waller, J. A., Simonin, D., Dance, S. L., Nichols, N. K. and Ballard, S. P. (2016b) Diagnosing observation error correlations for Doppler radar radial winds in the Met Office UKV model using observation-minus-background and observation-minus-analysis statistics. Monthly Weather Review, 144 (10). pp. 3533-3551. ISSN 0027-0644 doi: 10.1175/MWR-D-15-0340.1
- Waller, J. A., Ballard, S. P., Dance, S. L., Kelly, G., Nichols, N. K. and Simonin, D. (2016c) Diagnosing horizontal and inter-channel observation error correlations for SEVIRI observations using observation-minus-background and observation-minus-analysis statistics. Remote Sensing, 8 (7). 851. ISSN 2072-4292 doi: 10.3390/rs8070581
- Waller, J. A., Dance, S. L. and Nichols, N. K. (2016a) Theoretical insight into diagnosing observation error correlations using observation-minus-background and observation-minus-analysis statistics. Quarterly Journal of the Royal Meteorological Society, 142 (694). pp. 418-431. ISSN 1477-870X doi: 10.1002/qj.2661
- Waller, J. A., Dance, S. L., Lawless, A. S., Nichols, N. K. and Eyre, J. R. (2014) Representativity error for temperature and humidity using the Met Office high-resolution model. Quarterly Journal of the Royal Meteorological Society, 140 (681). pp. 1189-1197. ISSN 1477-870X doi: 10.1002/qj.2207

Correlated observation error

Impact on analysis error

Simple model experiment using circulant error covariance matrices and direct observations allows us to analyse impact at different scales in the analysis.

Optimal R	Sub-optimal R
Corr R (half obs density) ⇒ Corr-R-6km Corr R (full obs density) ⇒ Corr-R-3km <u>Corr-R-6km:</u> Analysis error reduced at all scales, but most improvement in large scale. <u>Corr-R-3km:</u> Analysis improved at all scales, greater improvement at small scale and additional information at even smaller scales.	Diag R (half obs. density) ⇒ Control



METEOROLOGY DATA ASSIMILATION AT THE UNIVERSITY OF READING

CANDIDATE PACK

- **Professor of Data Assimilation and Director of DA for NCEO**
- **Professor of Data Assimilation for the Exascale Era (with the Met Office)**

Met Office

National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL

University of Reading