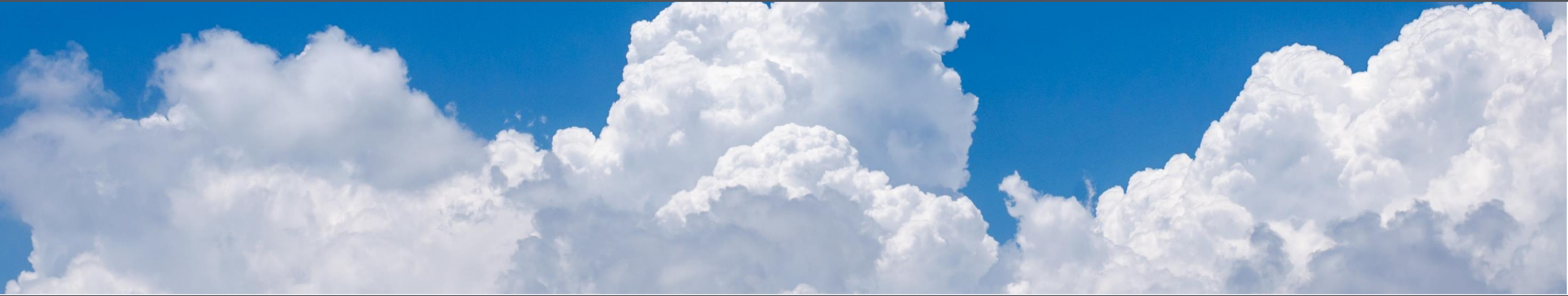
Department of Meteorology
Department of Mathematics & Statistics

University of Reading

Exploiting new observations and data assimilation techniques for improved forecasting of convective precipitation



Sarah L Dance, s.l.dance@reading.ac.uk ,

@DrSarah Dance

With thanks to Elisabeth Bauernschubert, Zak Bell, Alison Fowler, Anthony Illingworth, Nancy Nichols, Roland Potthast, David Simonin, Jacqueline Sugier, Robert Thompson, Joanne Waller

http://research.reading.ac.uk/dare

DARE: Data Assimilation for the Resilient City

Engineering and Physical Sciences Research Council

NERC SCIENCE OF THE ENVIRONMENT

Met Office

Outline

Data assimilation for km-scale NWP

- Why?
- Key issues for DA techniques
- Key issues for observations

Observation uncertainty and multiscales

- What and Why?
- Estimation
- Implementation and forecast impacts

The future ?

- Hectometer-scale and global km-scale
- Novel observation types

Motivation – High impact weather

- Convection-permitting (km-scale) NWP has been operational in many countries for years (e.g. UK since 2005)

- Particularly suited to hazard forecasting (convective rainfall, windstorms, fog, snow etc)

- Typically hourly cycling, limited area models
- Lead times 0-36 hours
  - Including NWP-based nowcasting and/or blending with extrapolation-based nowcasting in first 6 hours.

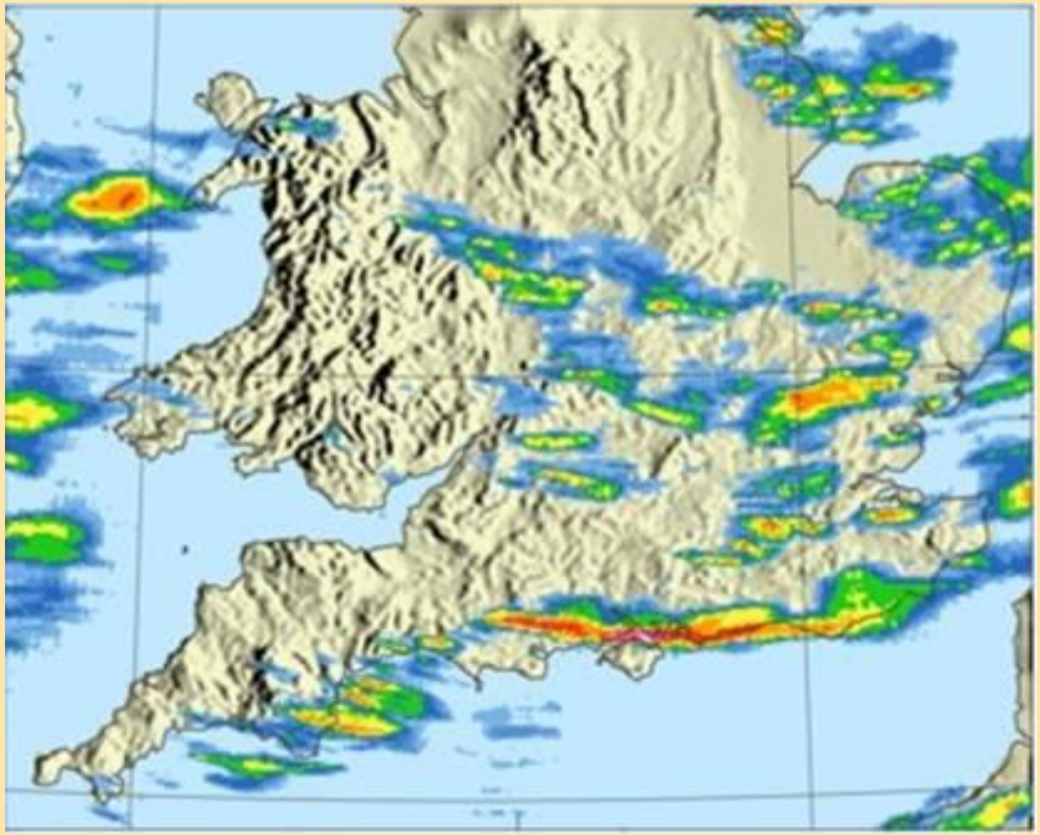
Snowfall London 2nd March 2018 © Business Insider UK

Flooding Birmingham 27th May 2018 ©Birmingham Mail

Key issues

- Some benefits from forecasting on these scales come from improved orography and modelling
- Significant benefit from DA (Gustafsson et al, 2018)
- Many of the fundamental problems for DA techniques on the km-scale pointed out in the early days have still not been solved

(e.g. Dance, 2004, Dance et al, 2019)



Radar data from the floods of July 11, 2012

Challenge: DA for convection permitting NWP

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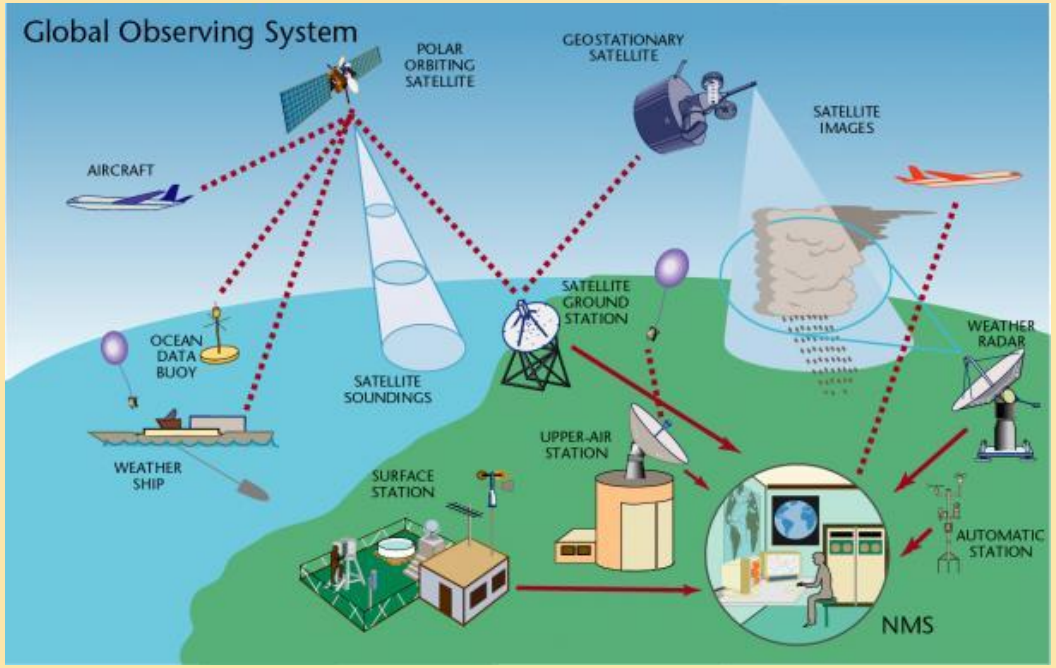
	Global/synoptic scales	Convection permitting scales
Model grid spacing	10 - 40 km	1- 4 km
Error growth timescale (nonlinearity validity)	2 or 3 days	10 mins – a few hours
Features	Cyclones, fronts etc	Convective storms
Important quantities	Vorticity, pressure, divergence, humidity	+ vertical velocity, temperature, cloud water & ice, surface quantities...
Diagnostic relationships	Hydrostatic balance Linear balance (except tropics)	??
Bg Statistics	Quasi-Gaussian – homogeneous and isotropic assumptions adequate with “right” variables	Non-Gaussian, non-homogeneous, non-isotropic. Fully 3D-multivariate
Other complications		Limited area model: -Lateral boundaries -Multiscaling

Observations for km-scale NWP

- Observation spatio-temporal frequency
  - Horizontal spacing
  - Vertical resolution
  - Temporal frequency

- All weather, 24 hour capabilities
  - Satellite data
  - Radar data
  - Mode-S EHS



Observations Gap analysis for EUCOS region
(slide from Jaqueline Sugier, Met Office/EUMETNET)

Gap analysis for high-resolution NWP application area
Requirement taken from the WMO OSCAR RRR
https://www.wmo-sat.info/oscar/applicationareas/view/2

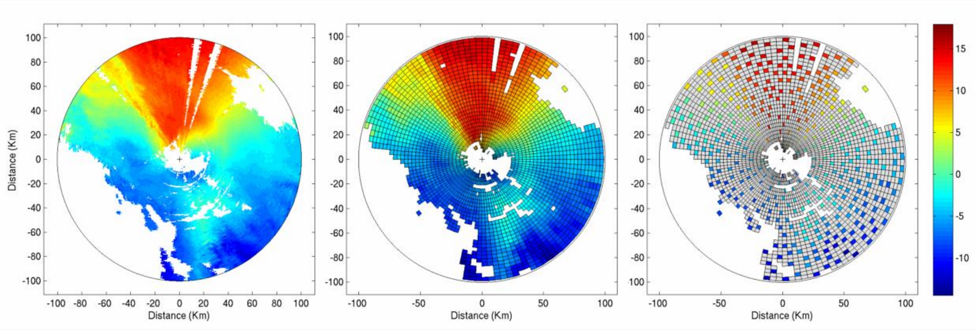
Capability location	Layer	Accuracy		Horizontal spacing		Vertical resolution		Observation cycle		Timeliness		Accuracy		Horizontal spacing		Vertical resolution		Observation cycle		Timeliness	
		Land Domain										Marine Domain									
Surface-based	Near Surface	T	w	T	w			T	w	T	w	T	w	T	w			T	w	T	w
		q	P	q	P			q	P	q	P	q	P	q	P			q	P	q	P
	PBL	T	w	T	w	T	w	T	w	T	w	T	w	T	w	T	w	T	w	T	w
		q	iwv	q	iwv	q		q	iwv	q	iwv	q		q		q		q		q	
		'Cloud free' Domain										'Nearly all weather' Domain									
Space-based	**PBL**	T	w	T	w	T	w	T	w			T	w	T	w	T	w	T	w		
		q		q		q		q				q		q		q		q			

- High priority variables for km-scale forecasting: Humidity, wind and temperature
- Major gaps in horizontal spacing and observation cycle
- MTG will help narrow the gap for humidity and temperature but less so in the PBL

Shading	
	Meeting OSCAR goal requirement
	Meeting OSCAR breakthrough requirement
	Meeting OSCAR threshold requirement
	Insufficient information available
	Falling below OSCAR minimum requirement

Key issues

- Not affordable to increase network density to meet user demand (WMO Oscar req)
- Need to understand **where and what investment** will have the **biggest impact,** now and for future systems (sub-km?)
- **Better tools** to evaluate impact of observations on km-scale models and compare between NWS (FSOI for LAM)
- Improving impact of **existing observations** (e.g, radar, all sky radiances over land)



Example

Doppler radar winds:

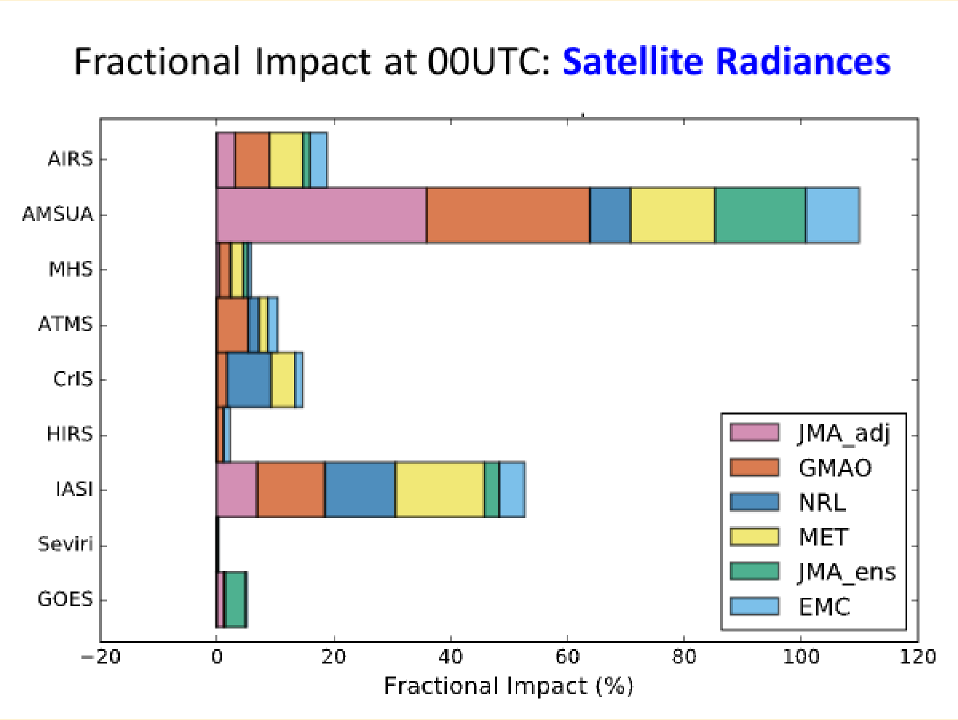
- Every 75m every 10-15 mins
- Operational use superobs thinned to 6km
- Use 4x #obs with spatially correlated obs errors (3km thinning)

Simonin et al (2019)

Observation impact measures

- How can we measure observation impact for our own systems?
  - Benefits for particular weather types/seasons – statistical sampling issues
  - Spatial verification for rainfall
  - Measures of interest to stakeholders
  - FSOI does not apply to km-scale (nonlinearity, statistical sampling)

- How can we compare with other systems (and learn from comparison)?
  - Different domains
  - Optimized for local severe weather (e.g., UK, Switzerland, tornado alley (USA))
  - No common scorecard

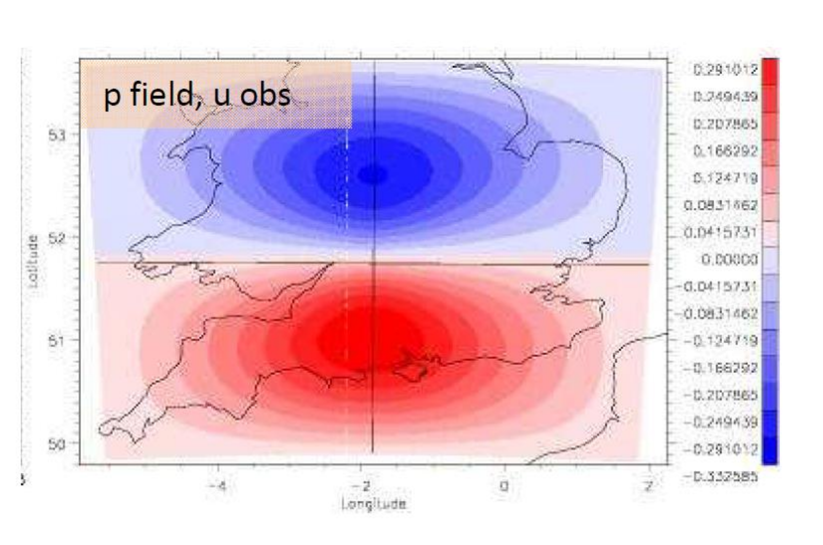


Auligne et al FSOI intercomparison experiment – now routine JCSDA IOS system

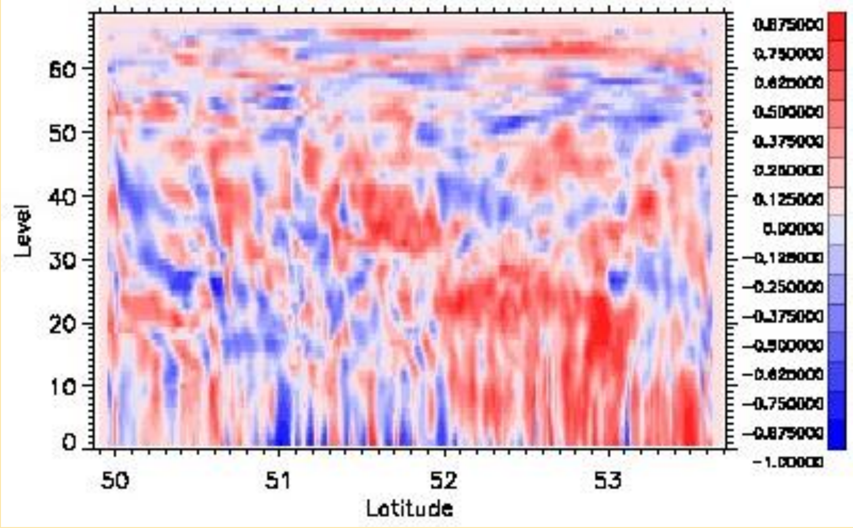
Improving observation impact

- Obtaining observation impact on required scales –
  - Microphysics
  - Complex observation operators vs CPU time
  - Rain-out (physical consistency)
  - Over/Under-smoothed increments
  - Observation uncertainty vs CPU time

Global DA system increment



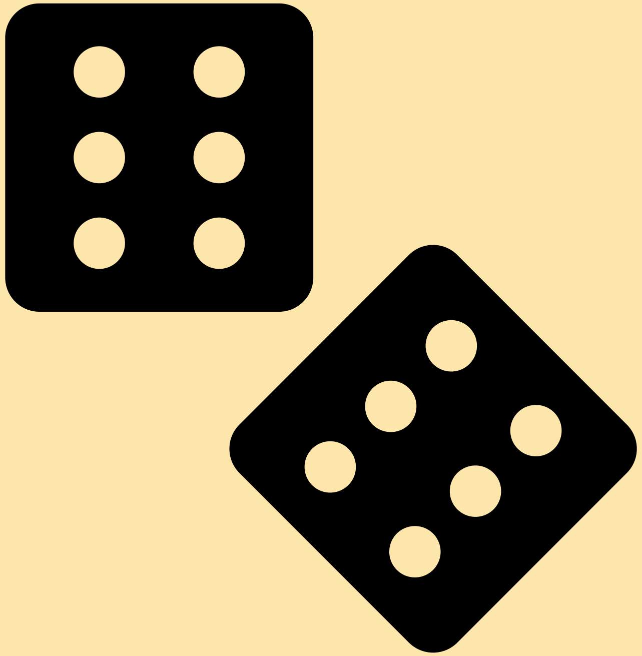
Ensemble w-q correlations for 20 July 2011



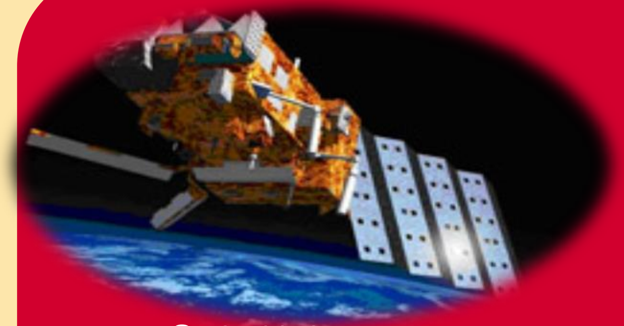
From Ross Bannister (2013)

Observation uncertainty

- What?
- Why?
- Uncertainty estimation
- Implementation
- Forecast impacts

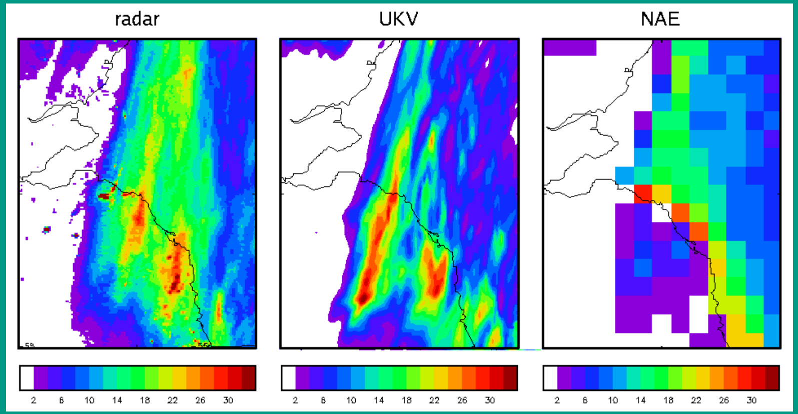


Observation errors (Janjic et al 2018)



© ESA 2013

Instrument error



Scale mismatch error

Observation operator error

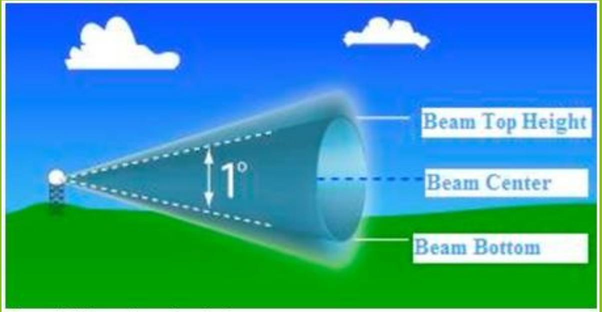
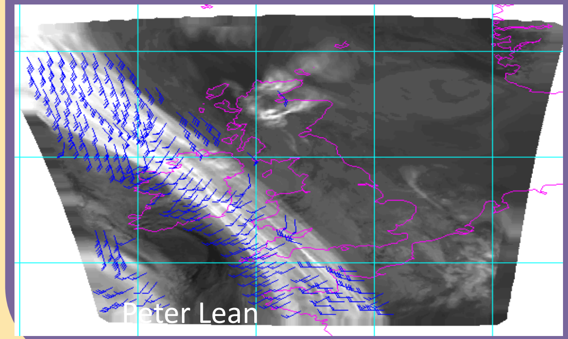


Figure 1 Illustration of radar beam

Observation processing



Current treatment

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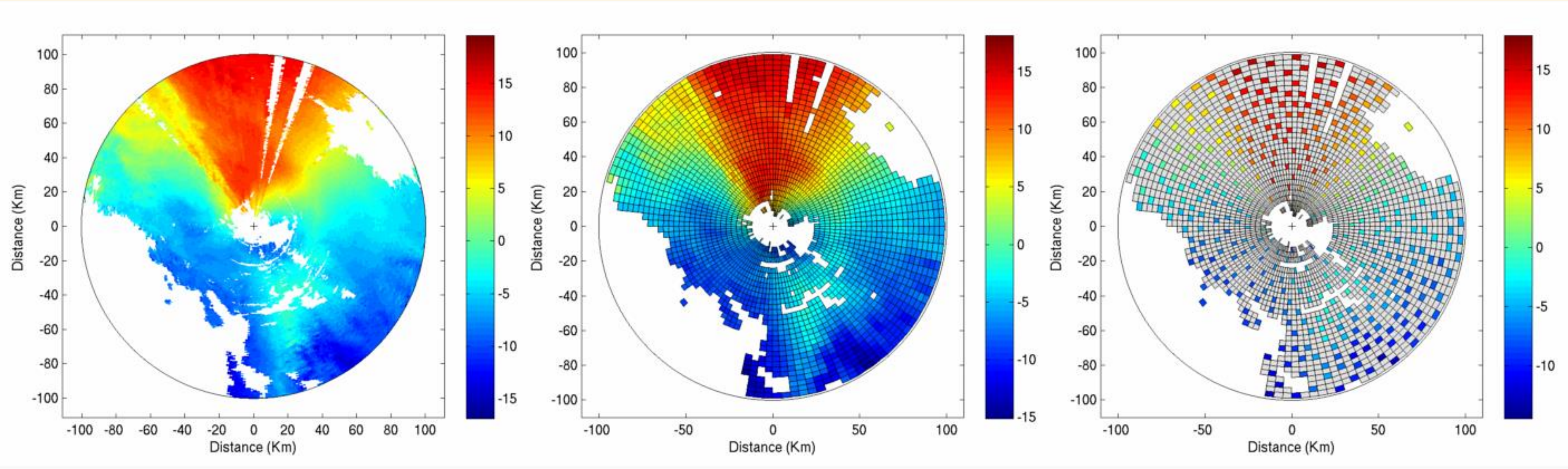
- Only 5 % of some obs types are utilised in atmospheric data assimilation.
- This is in part due to the unknown observation error statistics.
- Currently errors are assumed uncorrelated. This is achieved by 'superobbing' and thinning.



Met Office DRW data

Images from Waller/ Simonin

Processed raw observations

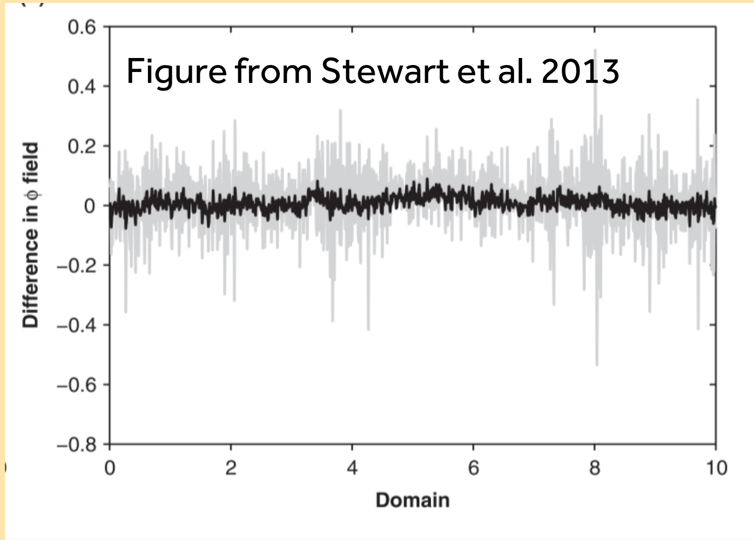
Super-observations

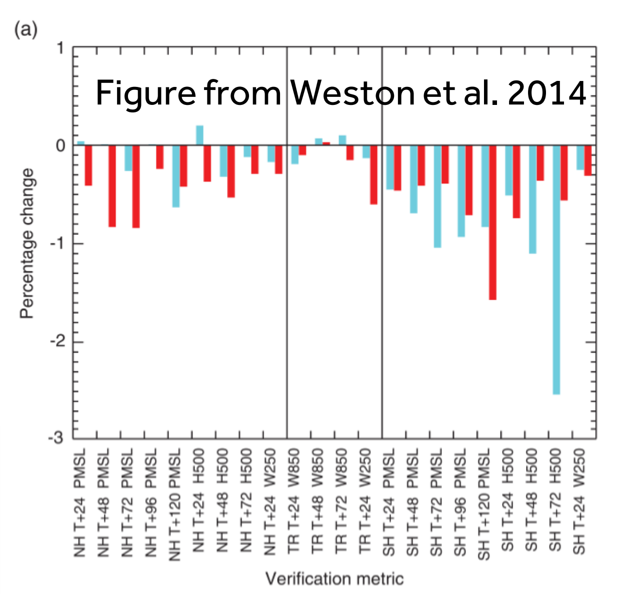
Thinned super-observations

Why use correlated errors?

Using correlated errors:

- Leads to an increase in the analysis accuracy (Stewart et al. 2013).
- Leads to an increase in the NWP skill score (Weston et al. 2014).
- Allows more use of the available data.
- May provide more detail on fine scales …..



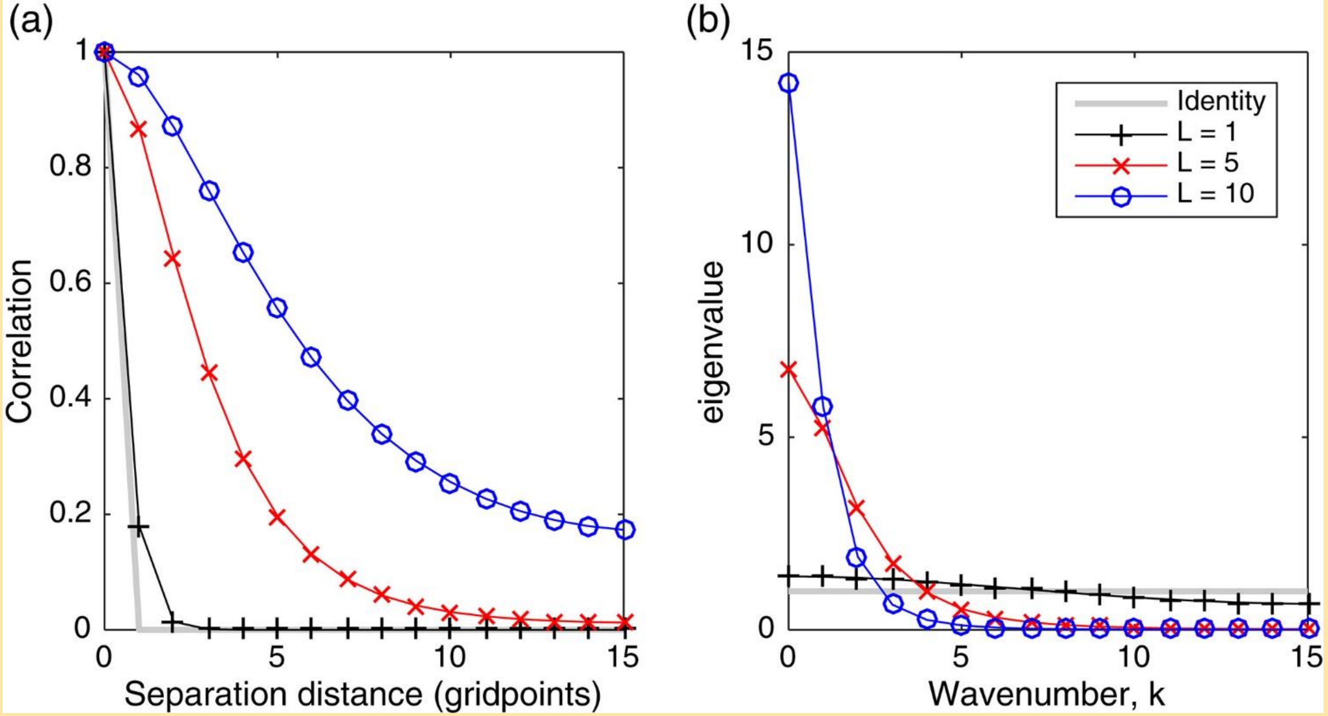


Bad

Good

Observation impact and correlated errors (Fowler et al 2018)

- The sensitivity of the analysis to the observations depends on the correlations in both the R and the B-matrix.

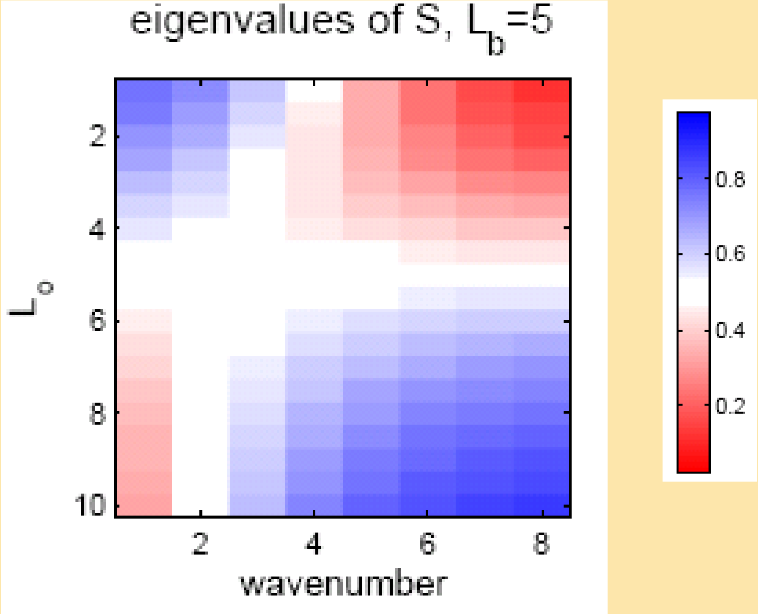


- For SOAR matrix
- LH plot shows correlations in physical space for different lengthscales
- RH plot shows correlations in spectral space

Increase in length-scale

⇒increase in uncertainty at large scales
& decrease in uncertainty at small scales.

Observation impact and correlated errors (Fowler et al 2018)



Eigenspectrum of S when the correlation in R and B are both described by the SOAR matrix and L_b=5

- Assuming H=I the analysis sensitivity to the observations is given by

$$\mathbf{S} = \mathbf{B}(\mathbf{B}+\mathbf{R})^{-1}$$

•When B=R (L_o=5) the analysis is equally sensitive at all scales.

•When L_o>L_b the observations are more accurate than the prior at small scales and less accurate than the prior at large scales

⇒the analysis is more sensitive to observations of smaller scale features and less sensitive to larger scale features (high-pass filter of ob increments).

•When L_b>L_o the opposite is true (low-pass filter of ob increments).

Diagnosing observation error statistics

Observation error statistics can be estimated (Desroziers et al., 2005),

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

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

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

- Inexact estimate depends on assumed statistics for B and R
- Using method with ensemble localization needs extra care

BUT it is still very useful!

Waller et al 2016a, 2017

Example – Doppler radar winds
Waller et al (2016b), joint work with UK Met Office

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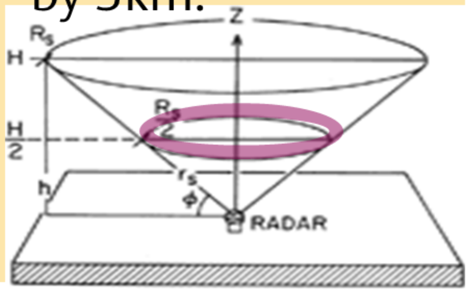
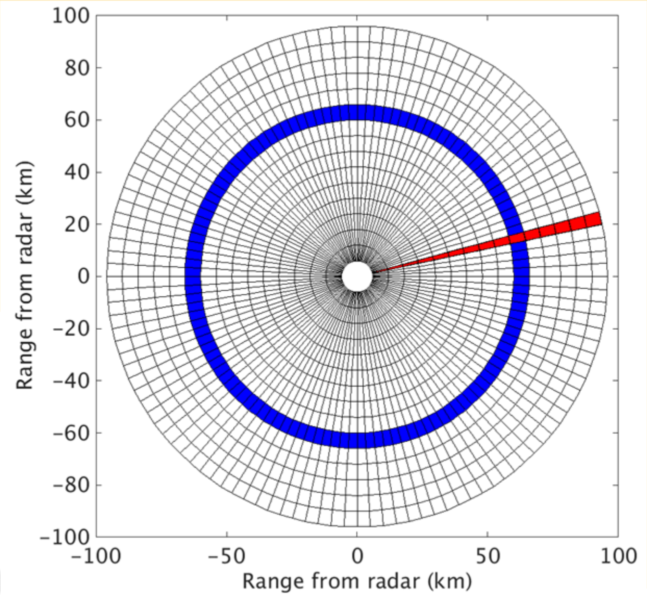
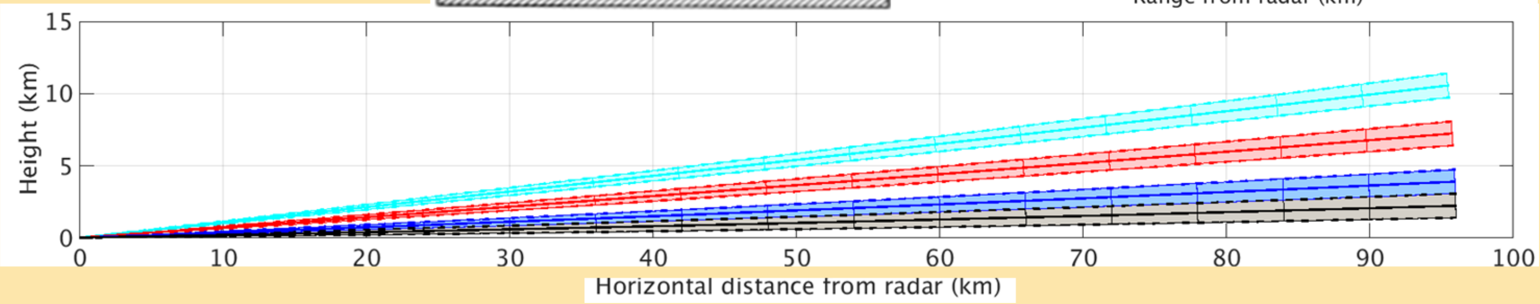
Each radar beam produces observations of radial velocity out to a range of 100km with measurements taken:

- Every 75m along the beam.
- Every degree.
- At five different elevation angles.
- Superobbed to 3^{o} by 3km.
- Thinned to 6km.

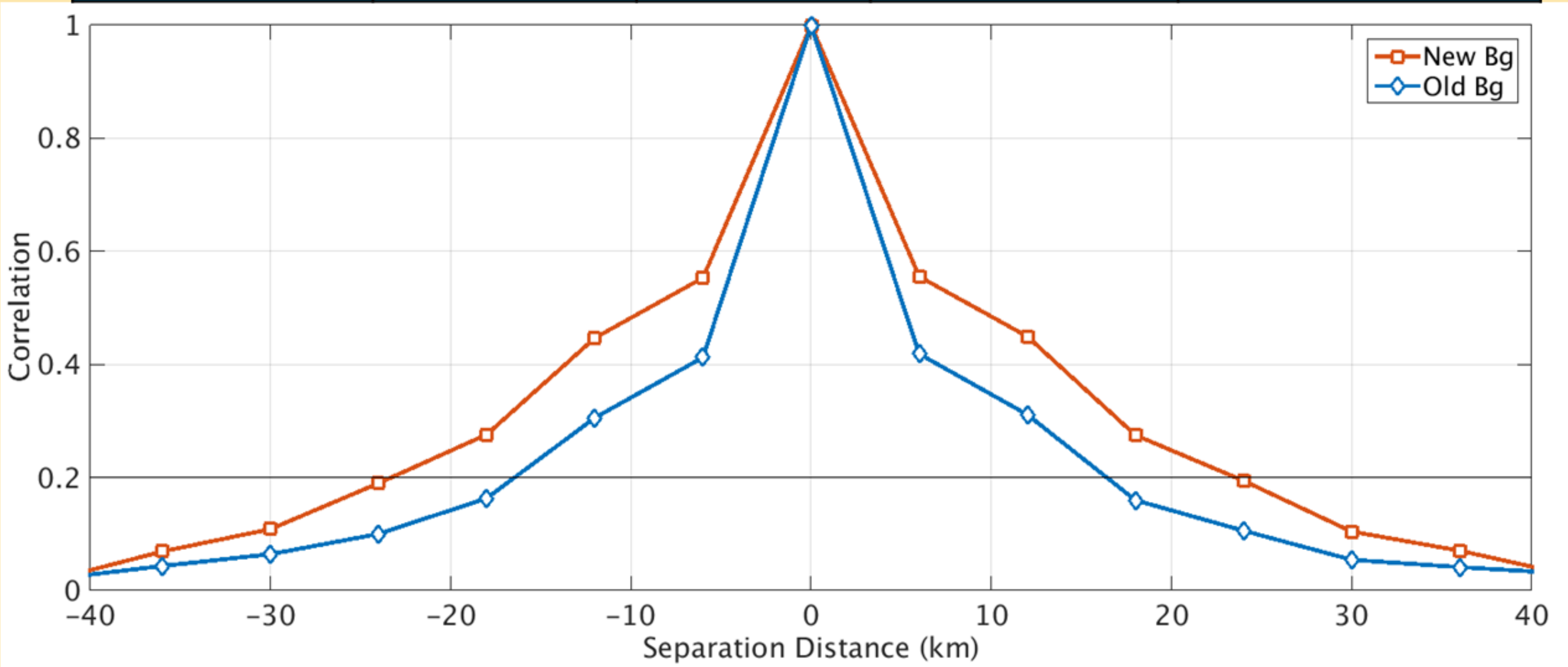






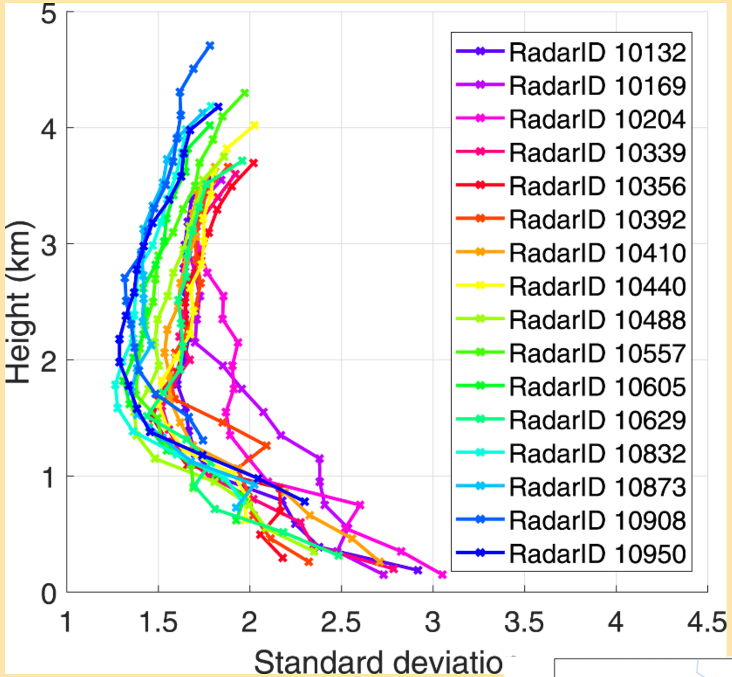
Sensitivity to assumed-B

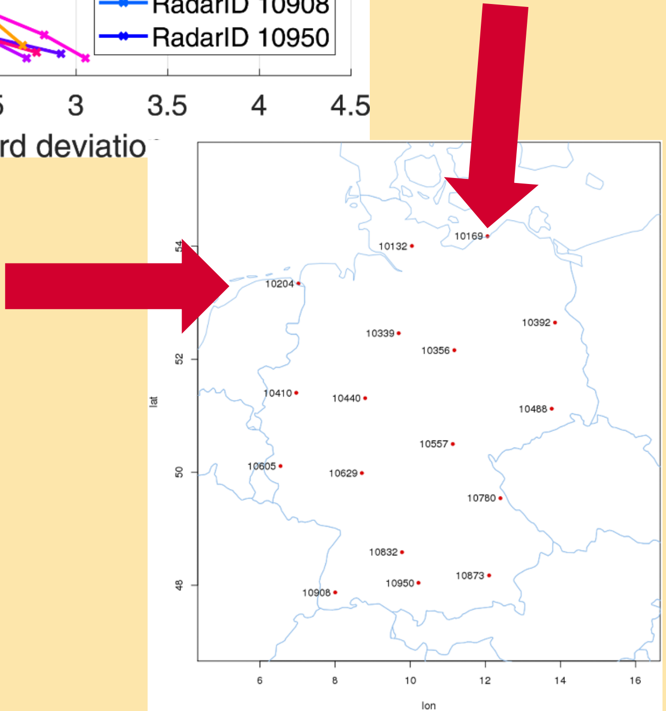
Case	B statistics	Superobs	Observation operator	Standard deviation (m/s)
New Bg	New	Yes	Old	1.97
Old Bg	Old	Yes	Old	1.57



- Increasing variance and lengthscale in assumed-**B** reduces variance and lengthscale in diagnosed **R**e.
- Consistent with Waller et al (2016a) theory

Example: Using the method to find problems





- Waller, Bauernschubert et al (2019). Similar experiment but with COSMO-KENDA and German radar
- Std for 0.5 degree beam with height
- Radars 10169 and 10204 have much larger std.
- These observations were contaminated by ship tracks and wind turbines

Operational implementation (Simonin et al 2019)

• David Simonin's talk for effect on forecast skill !

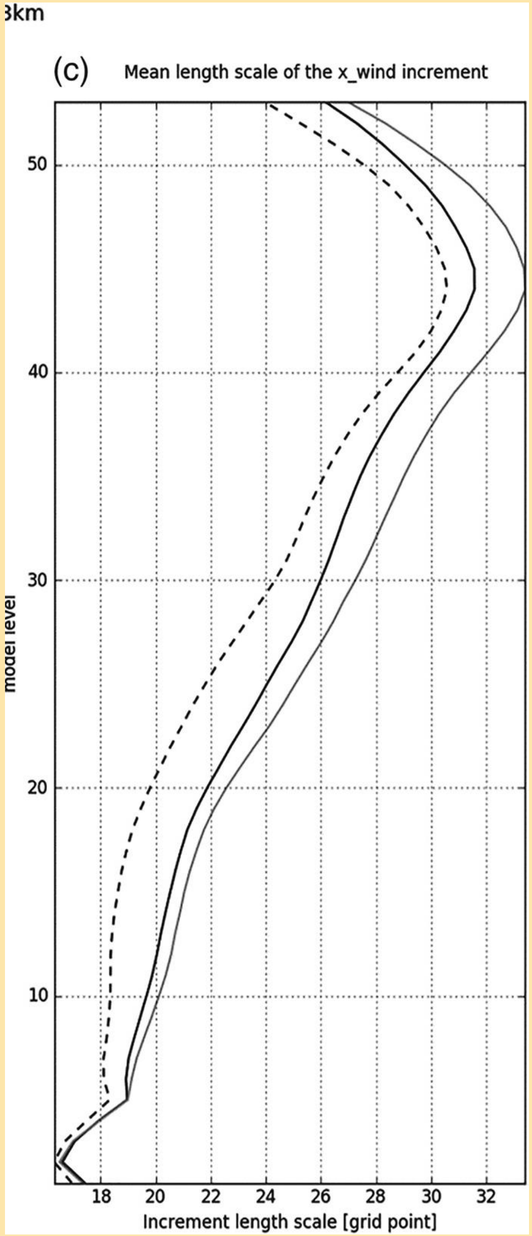
Control, 6km thinning, no correlations = black line

Corr+6km thinning = grey line

• Low pass filter on obs – increases weight on background (consistent with Fowler et al 2018)

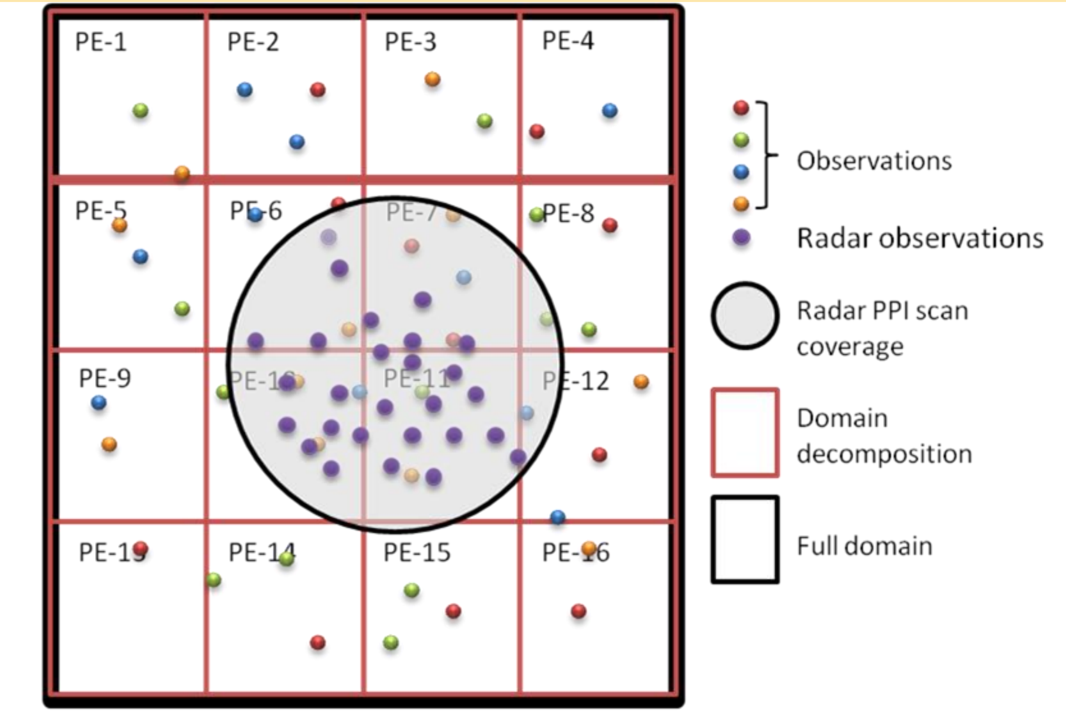
Corr + 3km thinning = dashed line

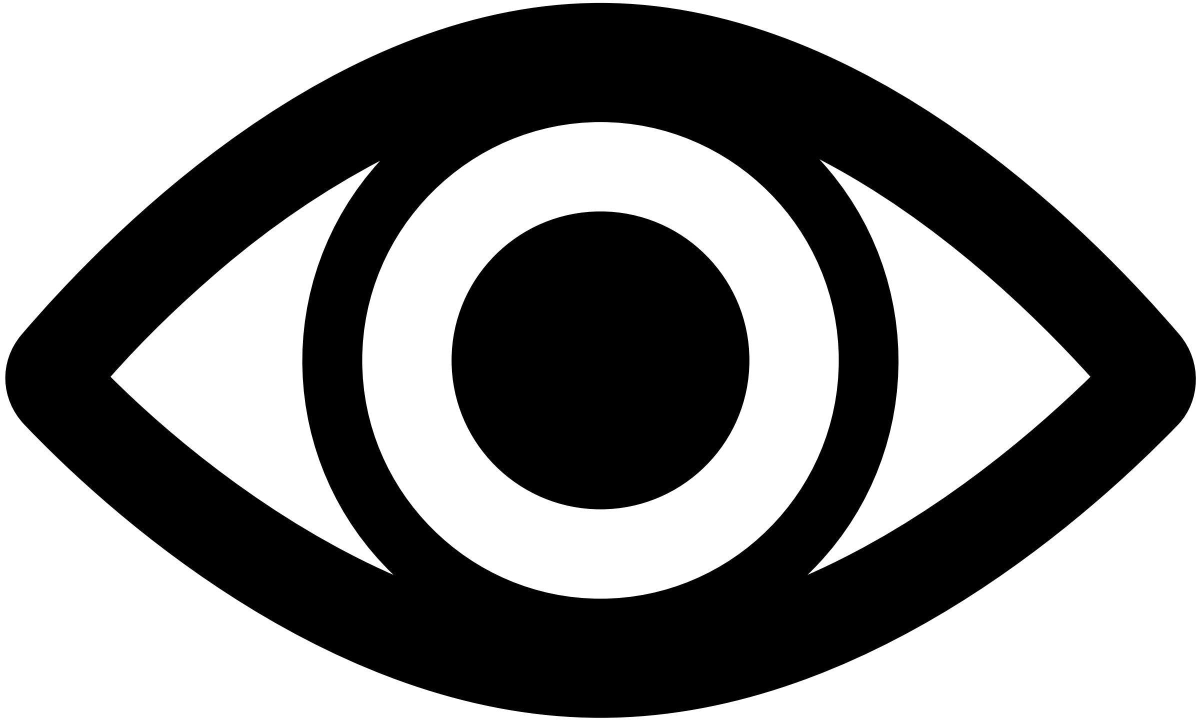
• Smaller lengthscales due to increased observation density – more able to represent smaller features



Practical implementation considerations

- Met Office reparallelization to allow different distribution of obs across PEs
- Load balancing so no impact on overall computation time
- Computational feasibility for other obs types ?
- How to implement long spatial correlations across whole domain ? (e.g. geostationary satellite)



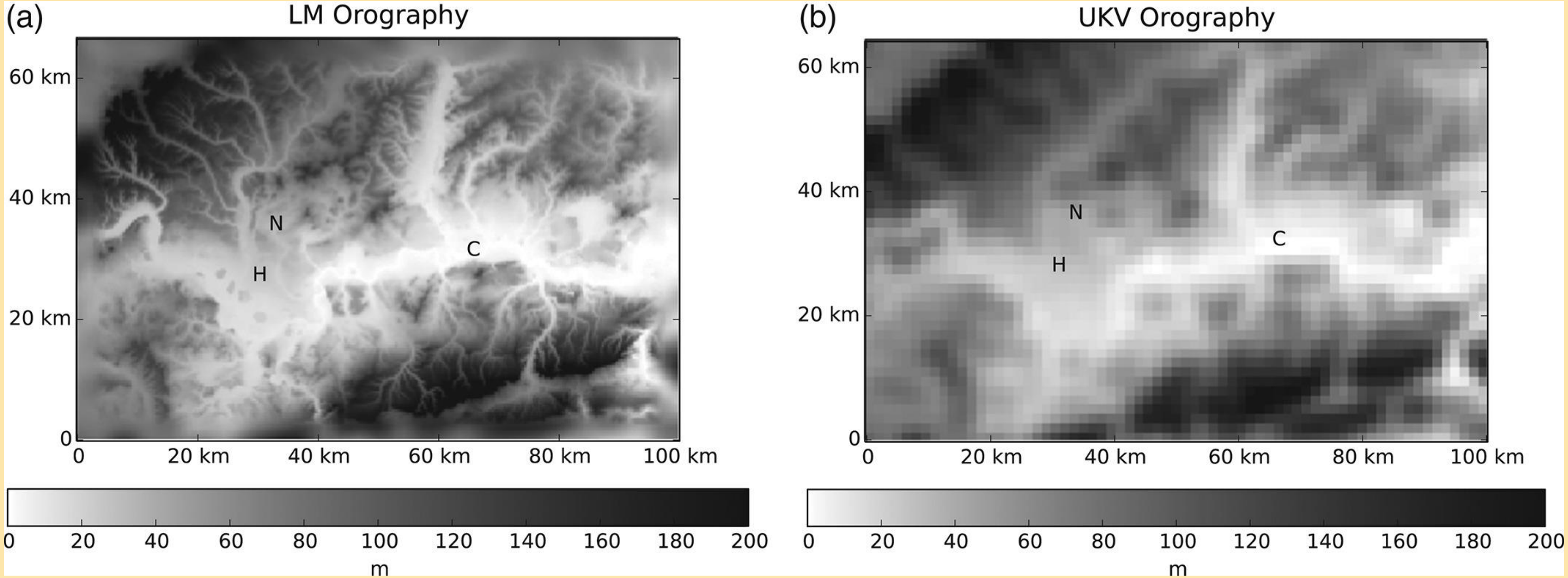


The future?

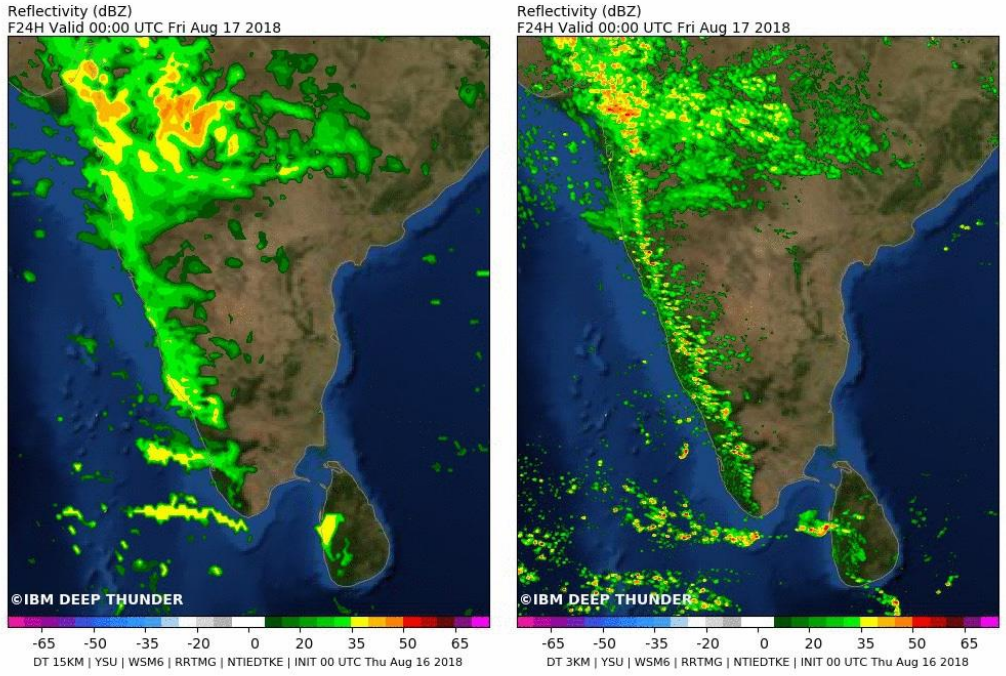
- Hectometer-scale forecasting
- Global km-scale forecasting
- Novel observation types

Hectometer O(100m) models

- Met Office routinely runs O(300m) London model twice a day - urban focus
- Improved forecasts of fog (Boutle et al, 2016)
- Partially resolves turbulence, but good bulk statistics (Lean et al 2019)
- No DA currently



Km-scale global models



An August 2018 monsoon in India, shown at left by the best current weather model that operates at 13-kilometer resolution. At right, the new IBM Global High-Resolution Atmospheric Forecasting System (IBM GRAF) operates at 3-km resolution and updates 6 to 12 times more often. Source: IBM

- Example from IBM
- ECMWF plans, RIKEN “Fugaku” simulations…

- Commercial ambition?
  - Personalized forecasting for the street corner
  - More use of deep learning rather than physical process-based models?

- Convective grey-zone
- May still need smoothed DA for medium-range forecasting?

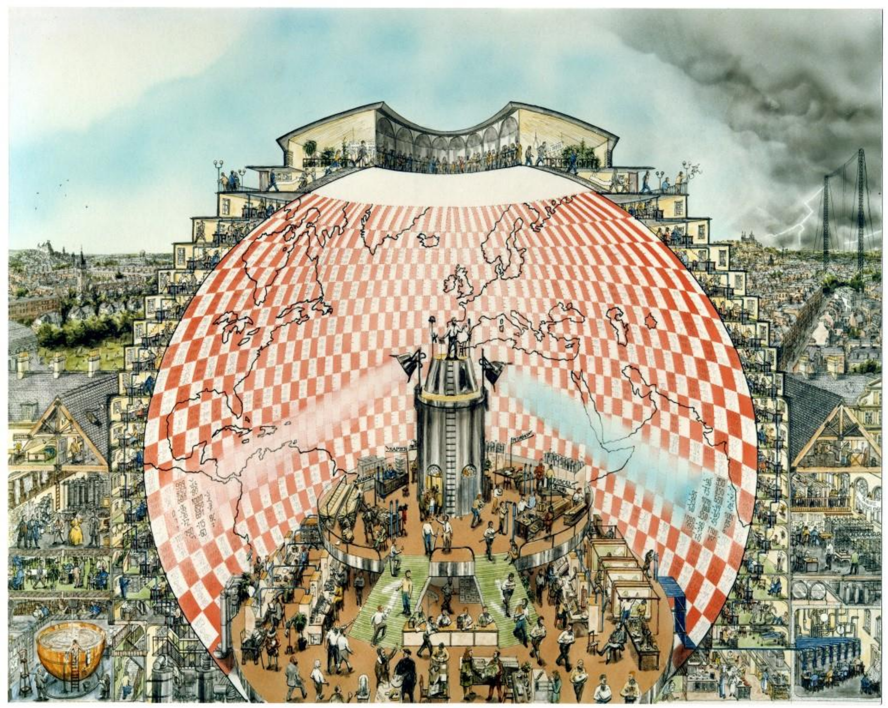
Which is the right modelling approach for the future?

- Large ensemble, limited area km-scale
- Limited area hectometer scale
- Global km-scale
- Coupling with land-surface?

Depends on what you want to forecast e.g. fog, floods, snow, ice, tornados, hurricanes, urban heat stress, air quality

On which lead times: Nowcasting - Seasonal

And for which users…probabilistic or deterministic forecasts?



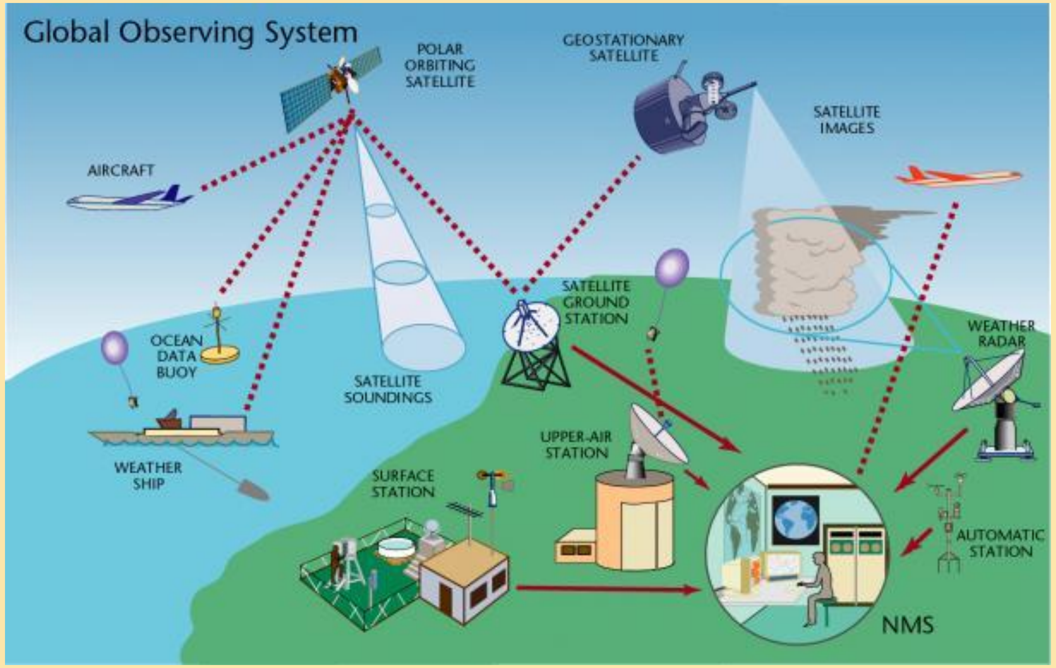
L F Richardson's forecast factory

Future observing networks

- Likely to be more heterogeneous
- Pragmatic, flexible approach
  - use what we have to our best advantage
  - ready to adapt quickly

- Better use of existing observations

- Novel observation types
  - Scientific
  - Commercial
  - Non-conventional (crowd-sourced, opportunistic)



Rob Thompson, Anthony Illingworth

Radar reflectivity attenuation problem

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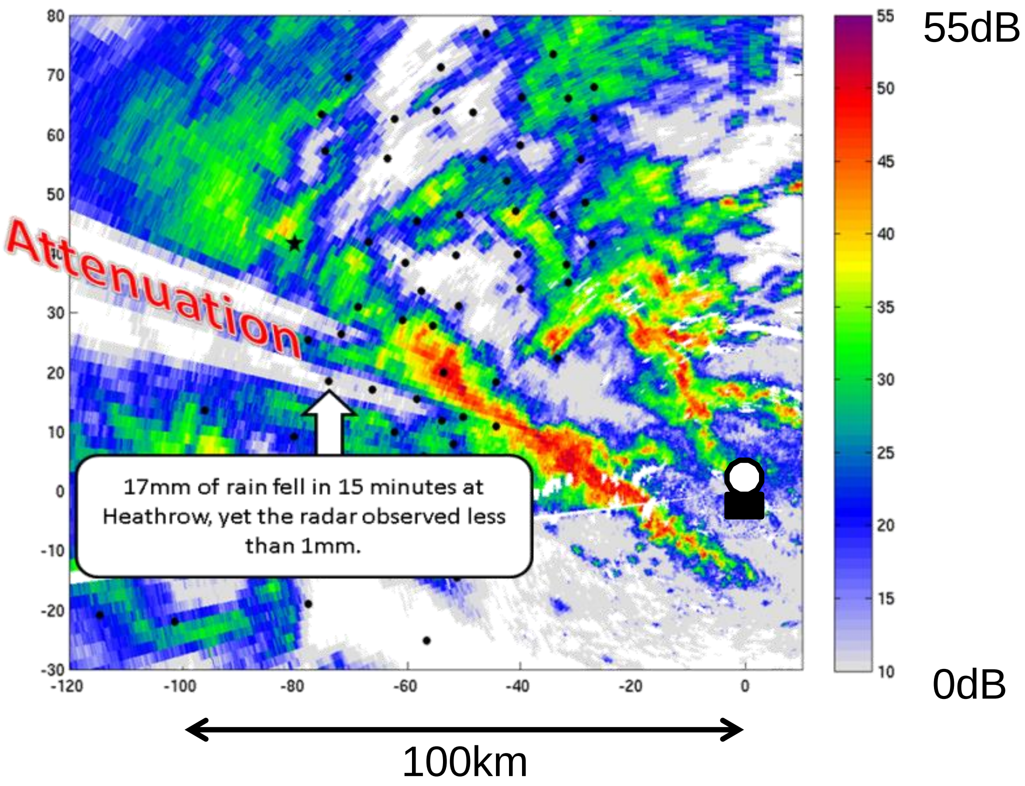
- Attenuation was a big problem for intense rainfall estimation at C-band
- In London floods of 2007, large areas of 60% underestimates

LONDON FLOODS 20 JULY 2007



Radar is fantastic for measuring rainfall - apart from when we really need it in heavy flood producing rainfall

Rob Thompson, Anthony Illingworth

University of Reading

Detecting emission with radar

- Attenuation is seen as increase in background noise from attenuators

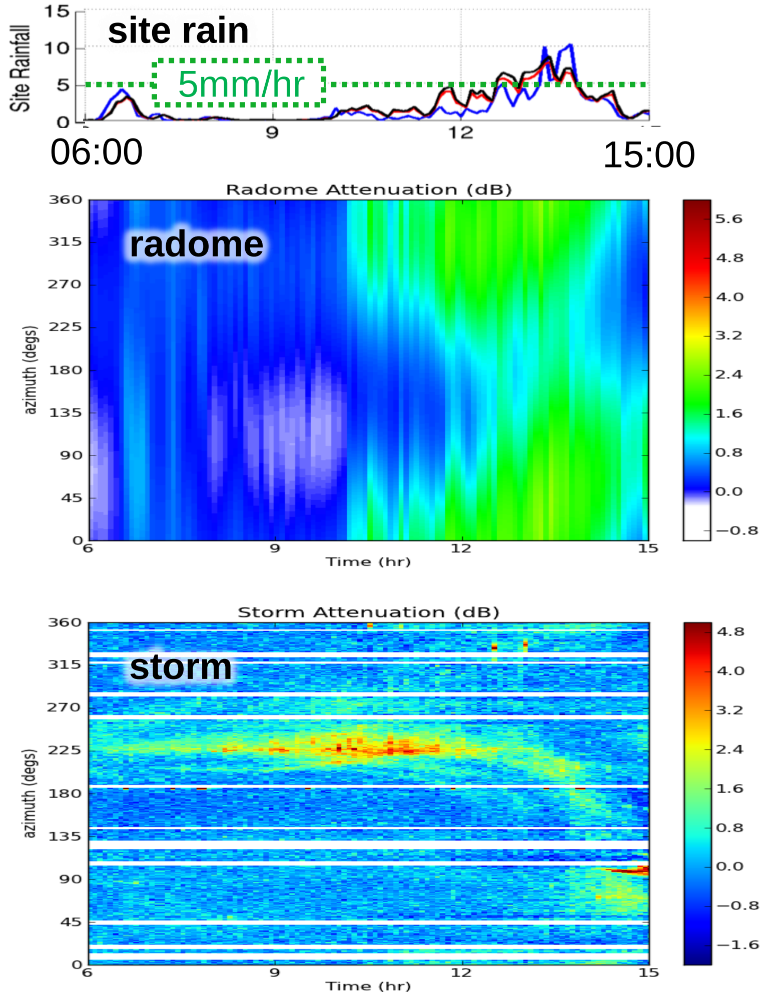
"all absorbers are emitters"

- Total attenuation can be calculated and split into radome and storms.
- Radome corrections affect the whole radar scan – more effect seen into the wind
- Storm attenuation affects only some rays.
- Use dual polarisation to correct attenuation constrained by the emission derived total

Radome monitoring operational at Met Office since Sept 2015

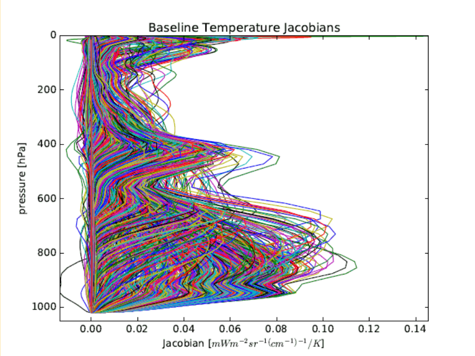
Storm attenuation operational at Met Office since Nov 2016

More details in Dance et al (2019)



New observing types

- Geostationary hyperspectral infrared sounders
  - GIIRS now operational aboard China’s FY-4A
  - IRS on EUMETSAT MTG-S expected late 2023

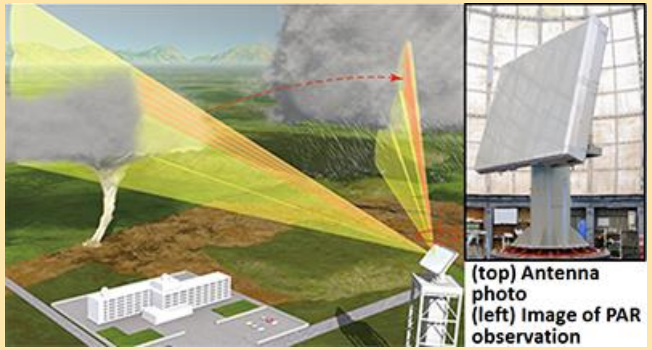


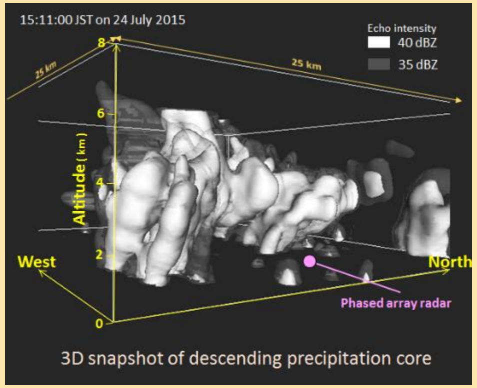
Images from EUMETSAT

- Drones

NASA

- Phased array weather radar
  - 100 elevations in 10-30s





Images from MRI-JMA

Commercial weather observations

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- Cube-sat weather

Microwave radiometer
cube-sat
MIT Lincoln Labs

Commercialization danger?

- Already seeing data licensing problems with commercialization of GNSS satellite data

- Need to ensure weather observations (paid for only once) are made available for research, forecasting and the public good

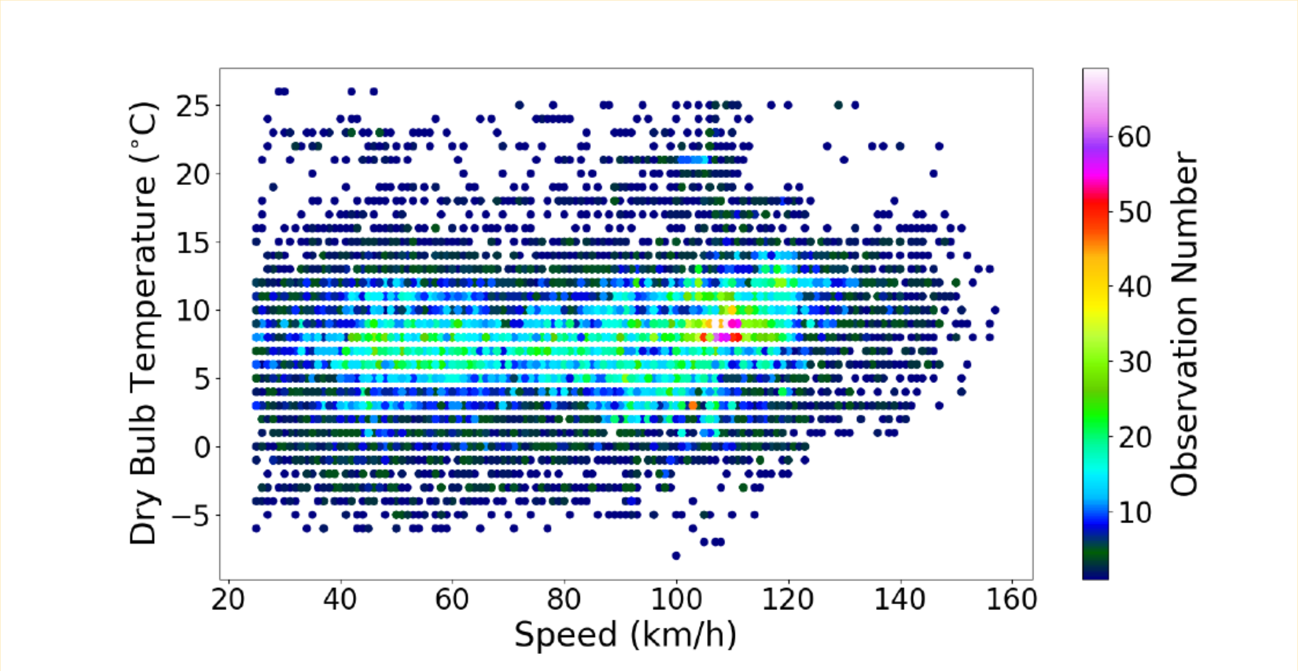
Emerging Observations (e.g., many more)

High density near surface observations

- Citizen networks, Crowdsourced data
- Private weather stations
- Vehicles
- Smartphones…. (Hintz et al, 2019)

Potential issues

- QC and provenance
- Privacy
- Data ownership
- Data volumes



Bell et al 2020 – Temperatures from Private Cars

2nd International Verification Challenge

Conclusions

- Reviewed issues in convection-permitting data assimilation
- Focussed on multi-scaling – using **observation error correlations** to allow denser observations and **more detail at fine scales**
- Future systems
- How can we measure observation impact to ensure that we get the most out of existing and future observations?

References

- Zackary Bell, Sarah L. Dance, and Joanne A. Waller (2020) Exploring the characteristics of a vehicle-based temperature dataset for numerical weather prediction (Manuscript in preparation)
- Boutle, I.A., Finnenkoetter, A., Lock, A.P. and Wells, H. (2016), The London Model: forecasting fog at 333 m resolution. Q.J.R. Meteorol. Soc., 142: 360-371. doi:10.1002/qj.2656
- S.L. Dance (2004) Issues in high resolution limited area data assimilation for quantitative precipitation forecasting. Physica D, 196(1-2) pp 1-27
- Dance, S.L. et al (2019) Improvements in Forecasting Intense Rainfall: Results from the FRANC (Forecasting Rainfall Exploiting New Data Assimilation Techniques and Novel Observations of Convection) Project. Atmosphere 2019, 10, 125 doi:10.3390/atmos10030125
- Fowler, A. M., Dance, S. L. and Waller, J. A. (2018), On the interaction of observation and prior error correlations in data assimilation. Q.J.R. Meteorol. Soc., 144: 48-62. doi:10.1002/qj.3183
- Gustafsson, N, Janjić, T, Schraff, C, et al. Survey of data assimilation methods for convective-scale numerical weather prediction at operational centres. Q J R Meteorol Soc. 2018; 144: 1218– 1256. https://doi.org/10.1002/qj.3179
- Hintz, KS, O'Boyle, K, Dance, SL, et al. Collecting and utilising crowdsourced data for numerical weather prediction: Propositions from the meeting held in Copenhagen, 4-December 5, 2018. Atmos Sci Lett. 2019; doi:10.1002/asl.921
- Janjic T, Bormann N, Bocquet M, Carton JA, Cohn SE, Dance SL, Losa SN, Nichols NK, Potthast R, Waller JA, Weston P. On the representation error in data assimilation, Q J R Meteorol Soc. 2018;144:1257-1278. https://doi.org/10.1002/qj.3130
- Lean, HW, Barlow, JF, Halios, CH. The impact of spin-up and resolution on the representation of a clear convective boundary layer over London in order 100 m grid-length versions of the Met Office Unified Model. Q J R Meteorol Soc 2019; 145: 1674– 1689.https://doi.org/10.1002/qj.3519
- Simonin, D. , Waller, J. A., Ballard, S. P., Dance, S. L. and Nichols, N. K. (2019), A pragmatic strategy for implementing spatially correlated observation errors in an operational system: an application to Doppler radial winds. Q J R Meteorol Soc. 2019; 145: 2772-2790. doi:10.1002/qj.3592
- L.M. Stewart, S.L. Dance, N.K. Nichols. Data assimilation with correlated observation errors: experiments with a 1-D shallow water model. *Tellus A* **65**: 1–14. 2013
- Waller, J. A., Dance, S. L. and Nichols, N. K. (2016) 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. and Nichols, N. K. (2017), On diagnosing observation-error statistics with local ensemble data assimilation. Q.J.R. Meteorol. Soc., 143: 2677-2686. doi:10.1002/qj.3117
- P. P. Weston, W. Bell, and J. R. Eyre. Accounting for correlated error in the assimilation of high resolution sounder data. QJRMS , 2013.