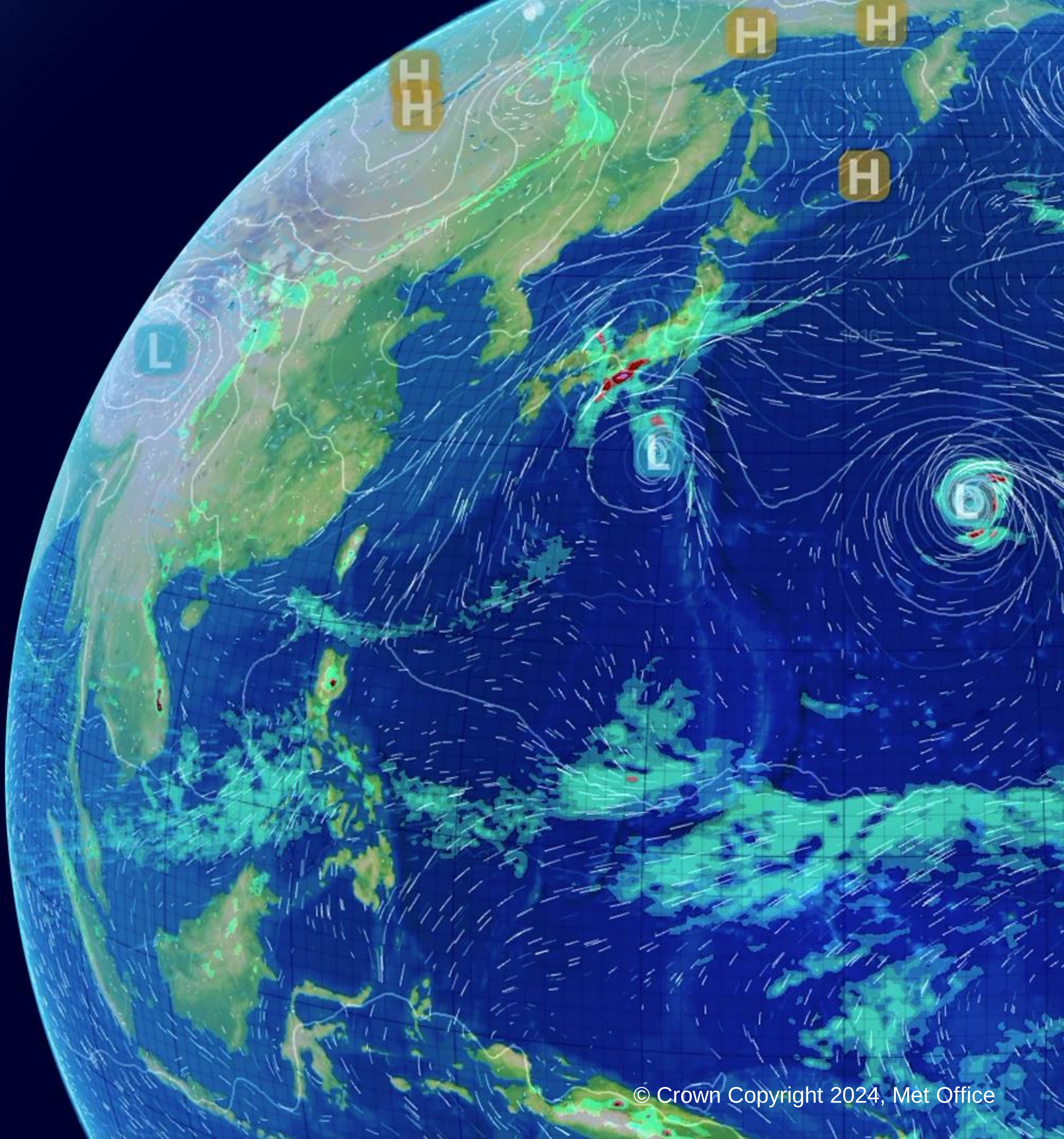
Met Office

Improving the assimilation of surface-based observations in the Met Office: current success and future challenges

J. A. Waller, L. D. Hawkness-Smith,
D. Simonin, C. Thomas

7th May 2024



Overview

Motivation

- Illustrate how DA is used in practice

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- Show its proven benefits …

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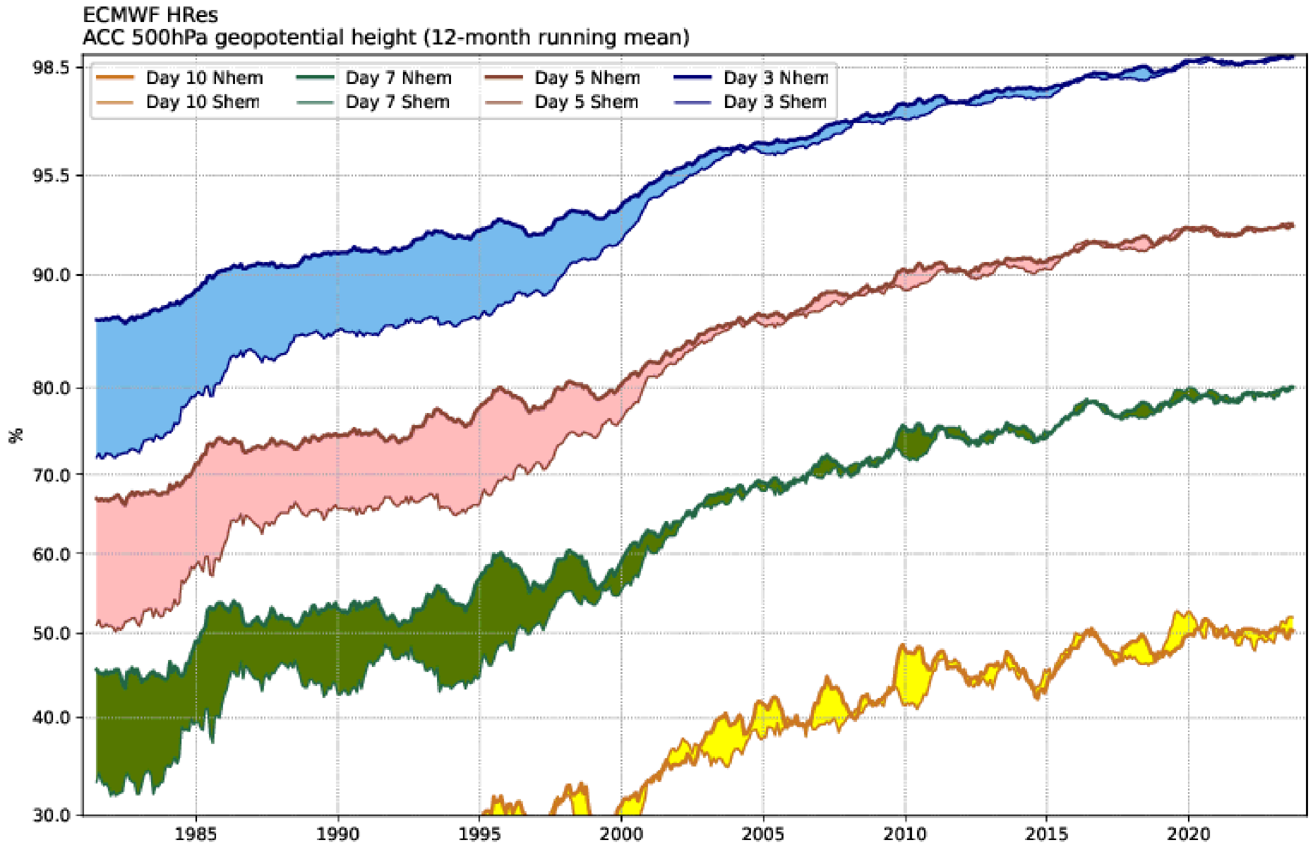

Figure from https://charts.ecmwf.int/products/plwww_m_hr_ccaf_adrian_ts?single_product=latest

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- and some of the challenges

What challenges do you think exist?

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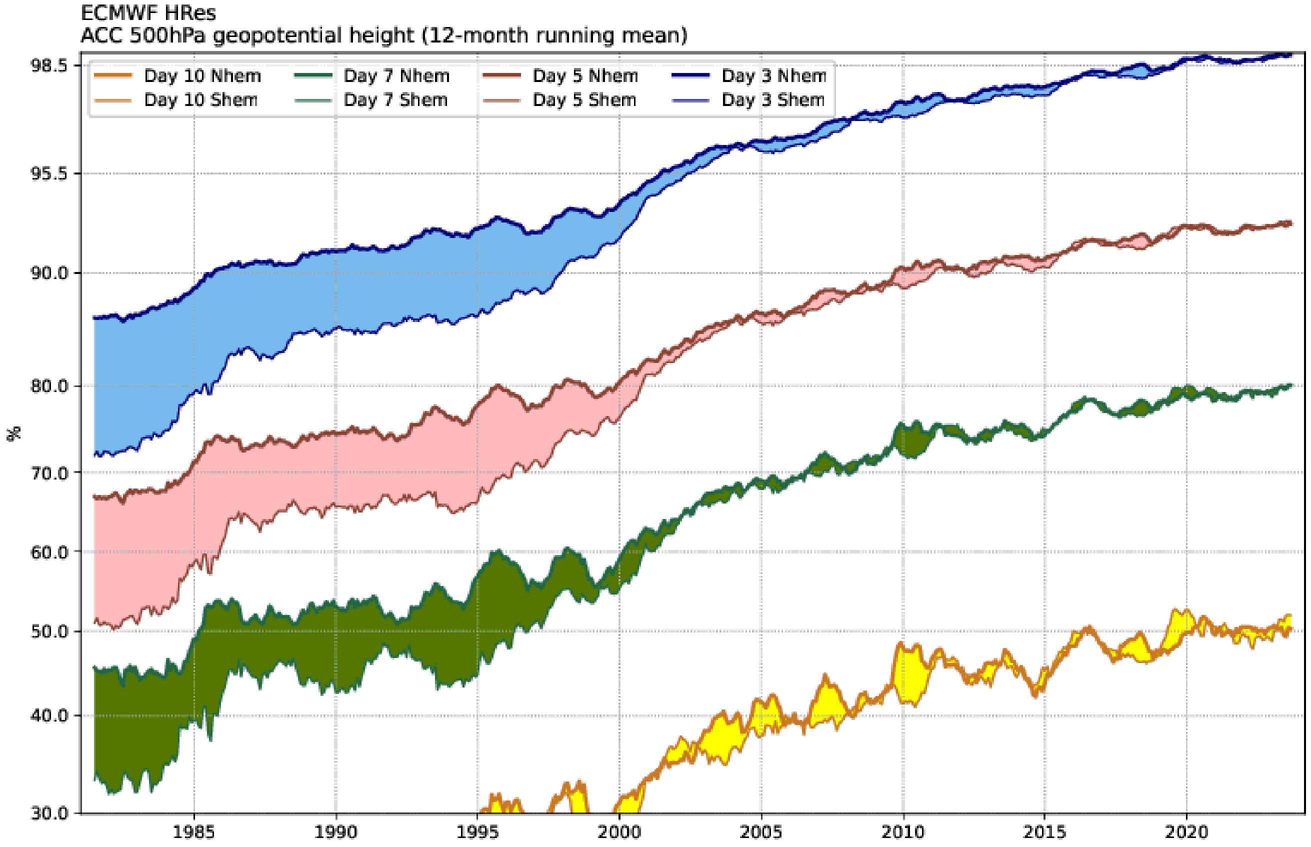

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Motivation

- Illustrate how DA is used in practice
- Show its proven benefits …
- and some of the challenges

What challenges do you think exist?

Novel observations   Affordability

Coupled systems   Multiscale   Non-Gaussianity

Error representation   Non-linearity

Efficiency   Observation usage   Data volume

Machine learning   Scalability

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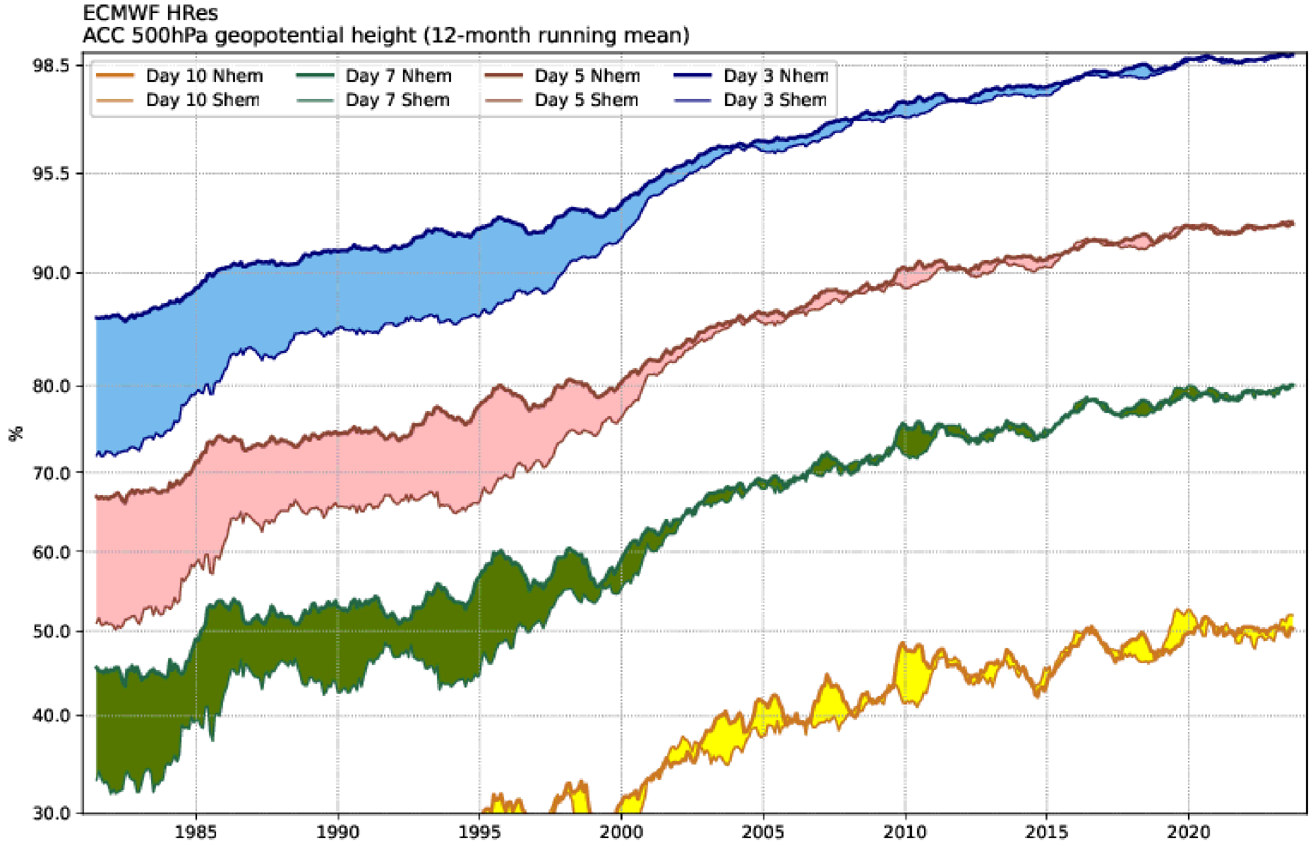

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Overview

- Introduction
- Next Generation Processing and Assimilation of Observations
- Surface based observations
- Novel Observations
  - Radiosonde descents
  - Radar assimilation - Direct assimilation of reflectivity
- Observation usage
  - Roadside observations
  - Radar assimilation - Correlated observation error statistics
- Summary

Introduction

Met Office Atmospheric NWP

Model

- Unified Model used for prediction across a range of timescales.
- Dynamical core solves the compressible non-hydrostatic equations of motion.
- Sub-grid scale processes represented by parameterizations.

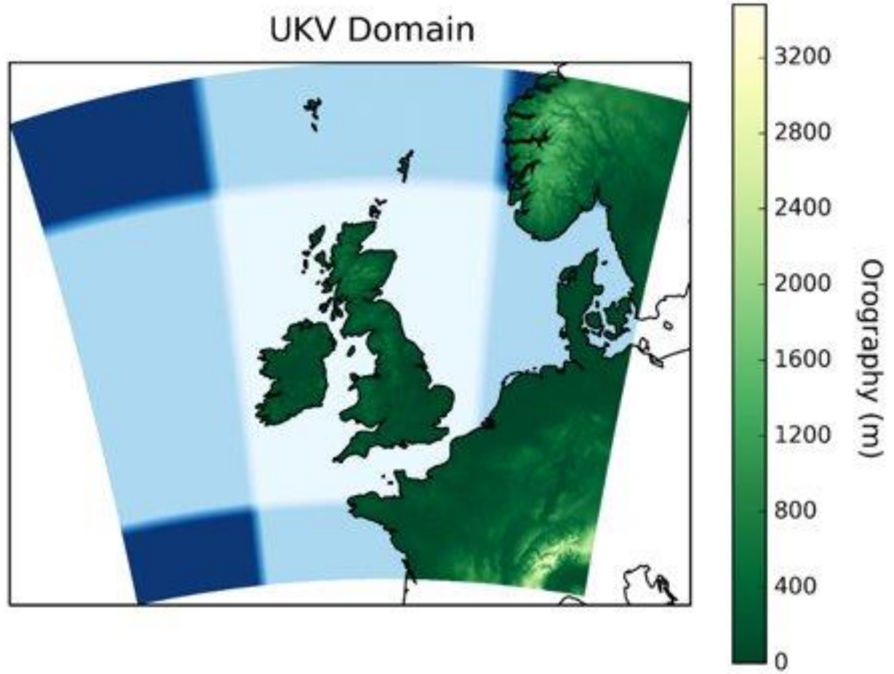
Deterministic Global NWP

- 10 km resolution
- 70 vertical levels - the model top has an altitude of 80 km
- Forecasts t+168

UKV NWP

- Variable resolution 4km (outer region) to 1.5km (inner region)
- 70 vertical levels - the model top has an altitude of 40 km
- Lateral boundary conditions are updated every 6 hours from the Global deterministic model.
- Forecasts to t+120 hrs (2/day), t+54 (6/day) and t+12 (16/day)

Met-Office Regional Domain



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Approximately 350 million grid points

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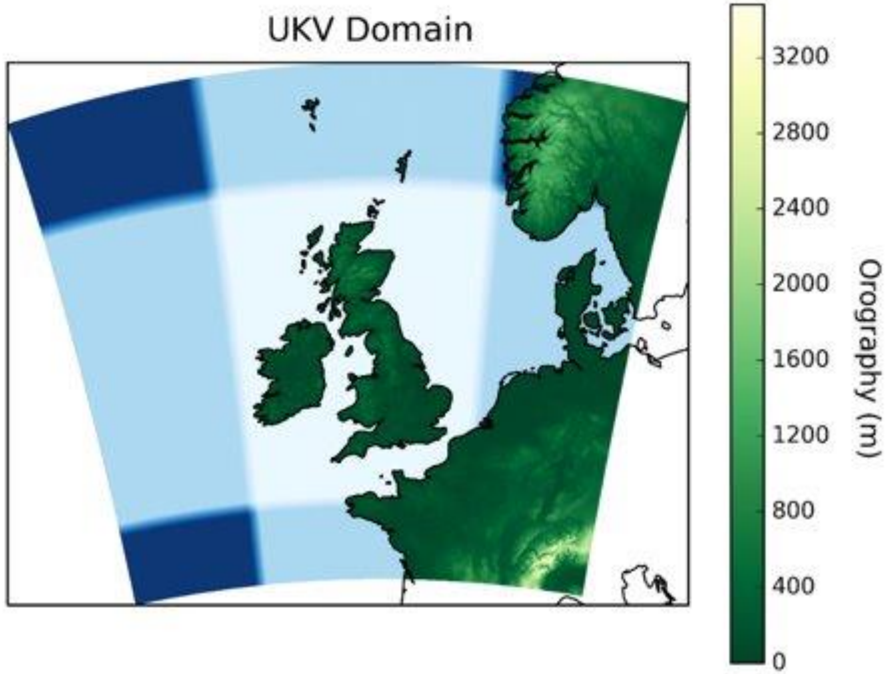
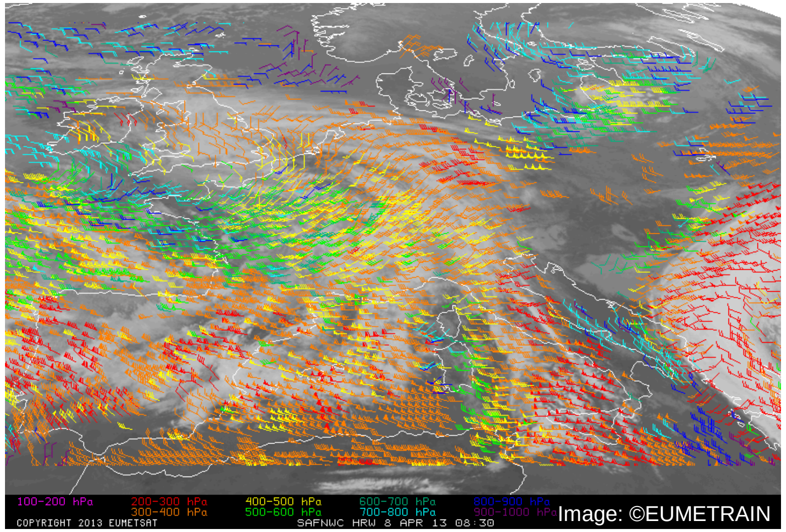


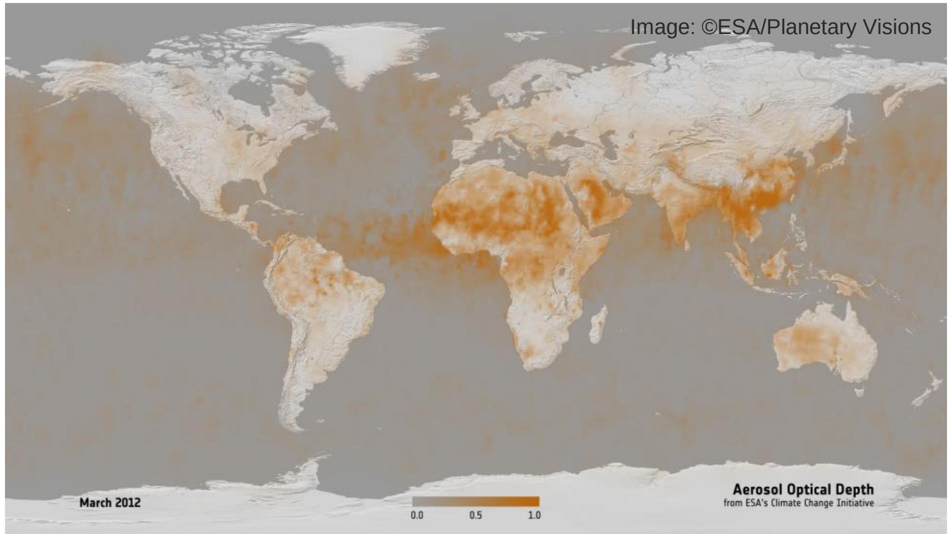
Met Office

Observations

21 atmospheric observation types

- Satellite radiances
- Satellite winds and active sensors
- Conventional and radar data
- Level 2 products (cloud, aerosol optical depth)

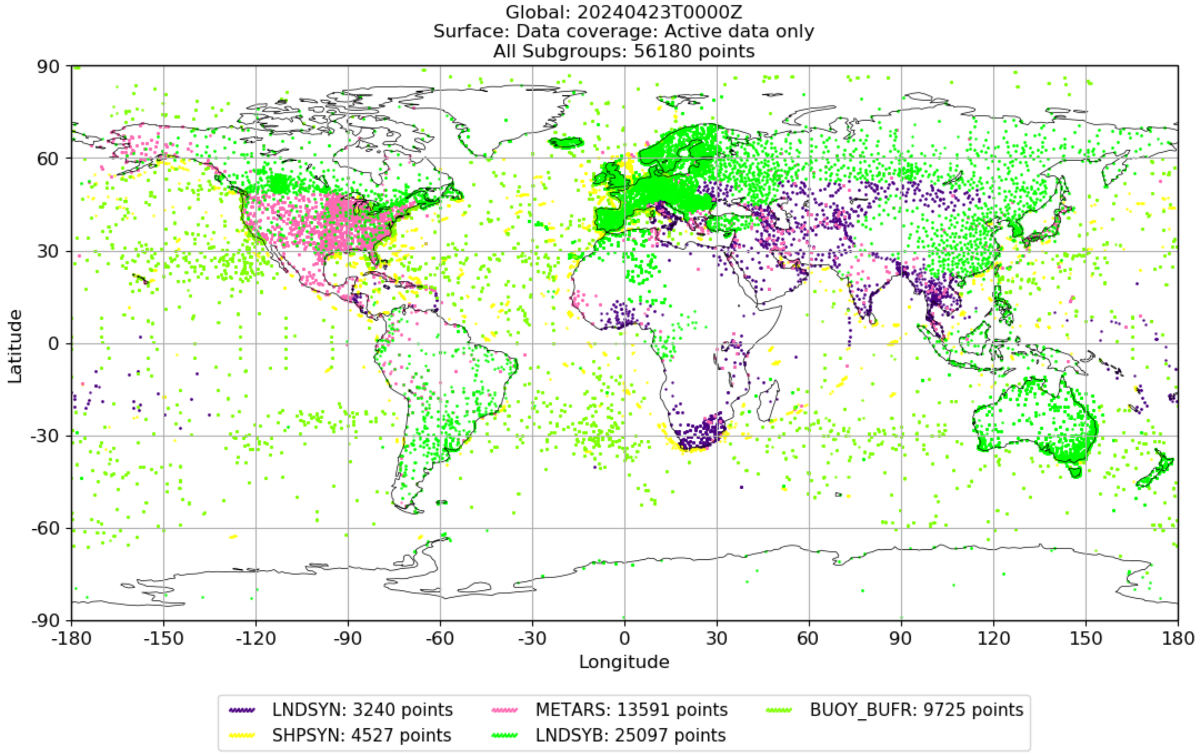




21 atmospheric observation types

Each provides different coverage and information on a variety of variables:

- Temperature
- Humidity
- Wind
- Cloud-top height and amount
- AOD
- TCWV
- Sea surface temperature
- Sea ice
- Snow cover
- Soil moisture
- Surface pressure
- Visibility
- Precipitation



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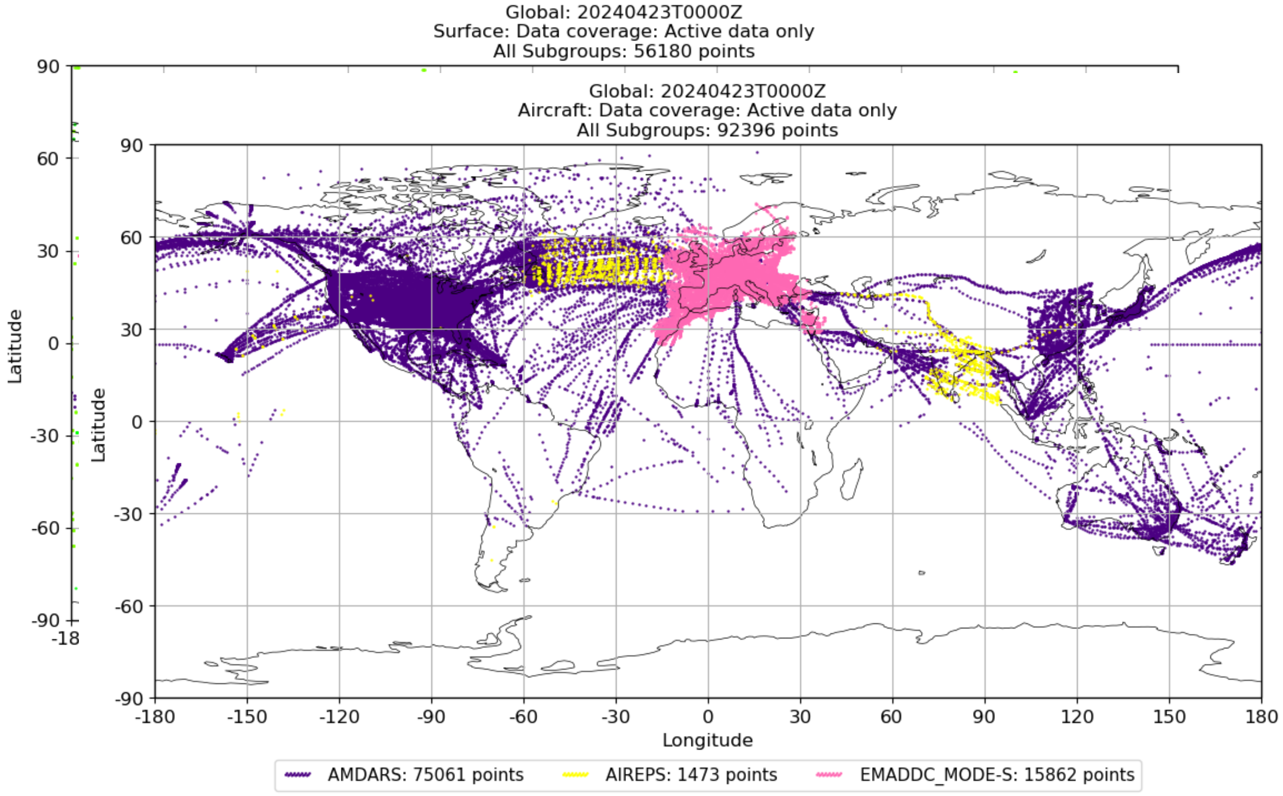

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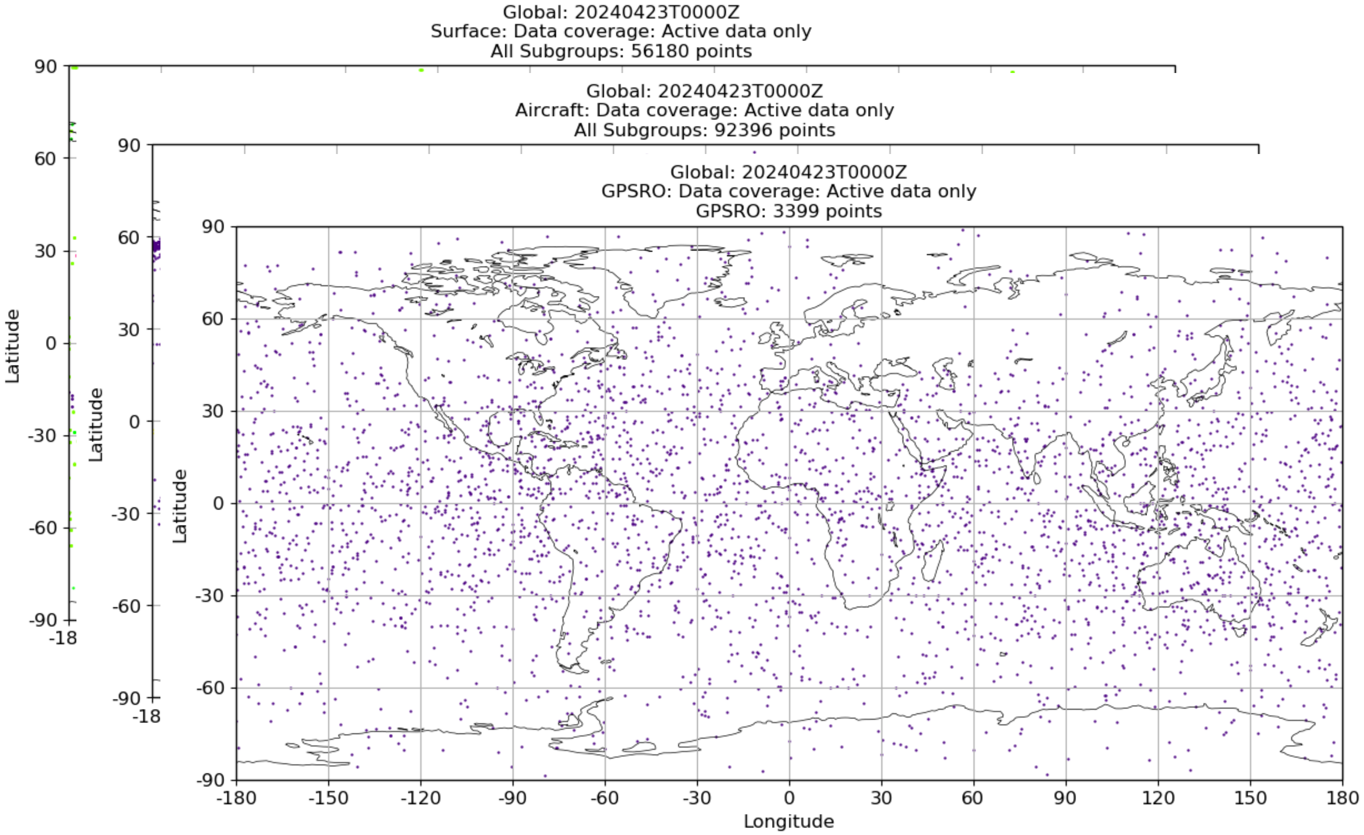

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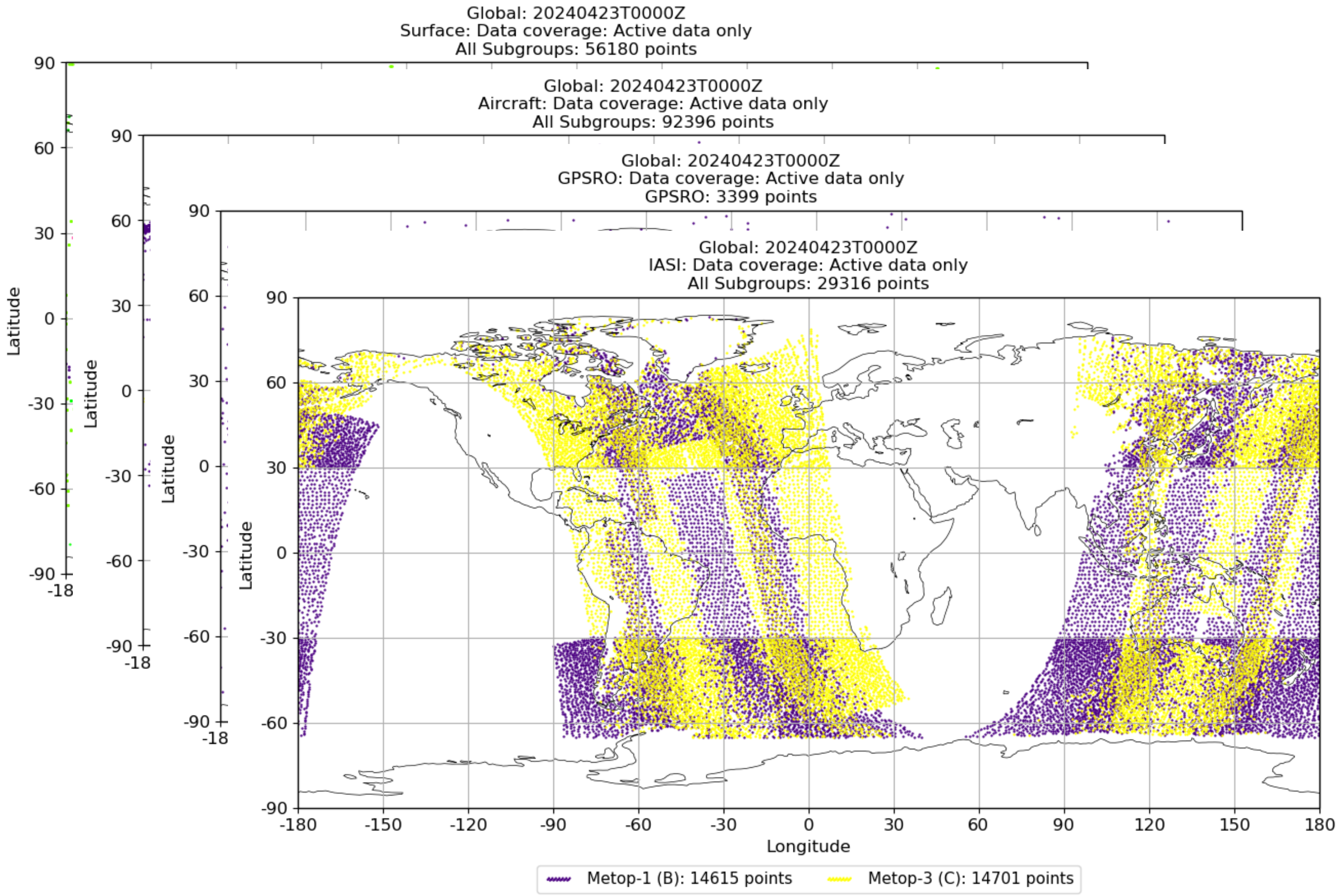

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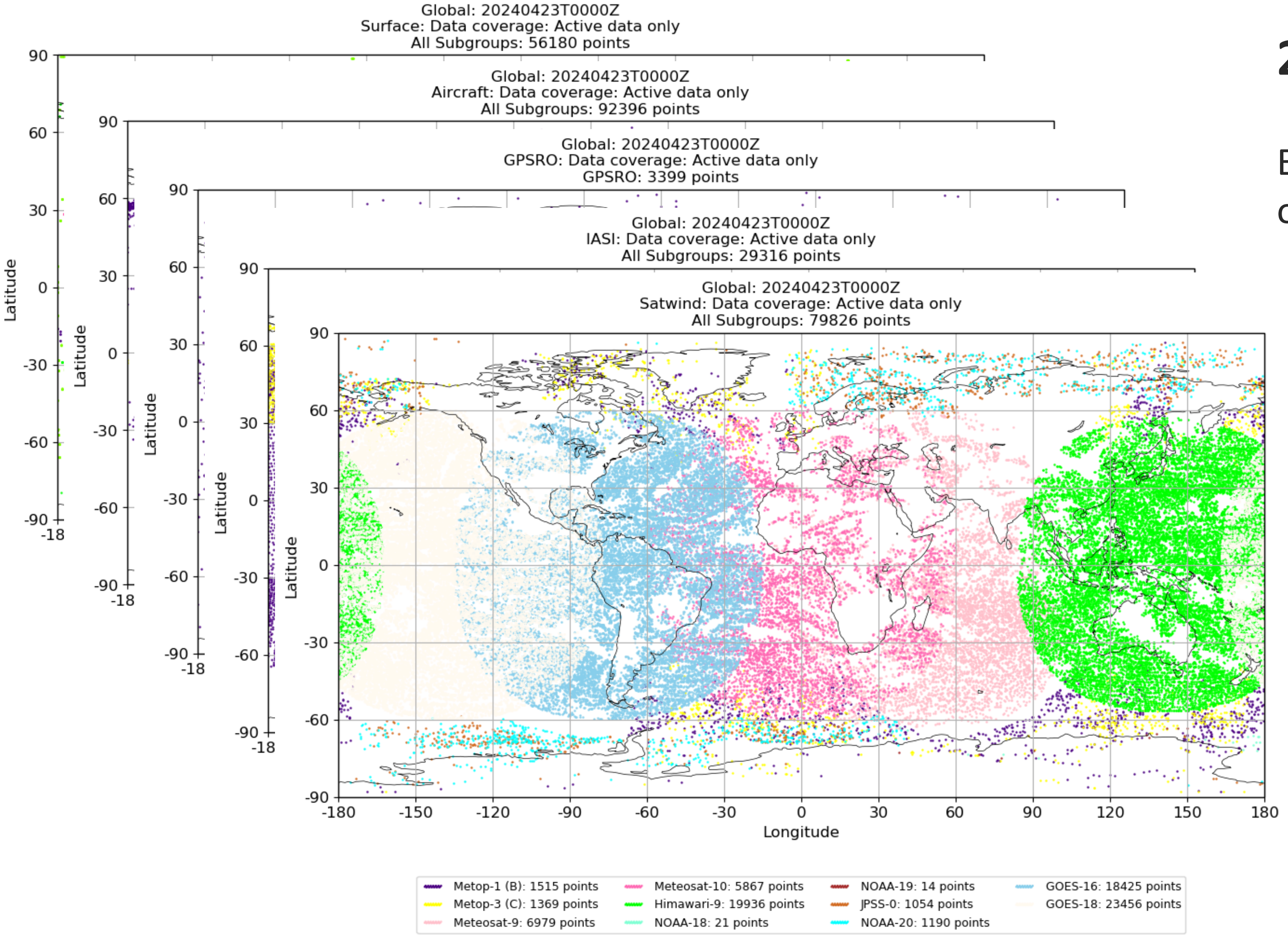

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Our current systems
OPS and VAR

OPS

Observation processing

OPS processes in excess of 30,000,000 individual atmospheric observation locations in a 6-hour window. Each location can have multiple channels/levels.

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- Satellite radiances
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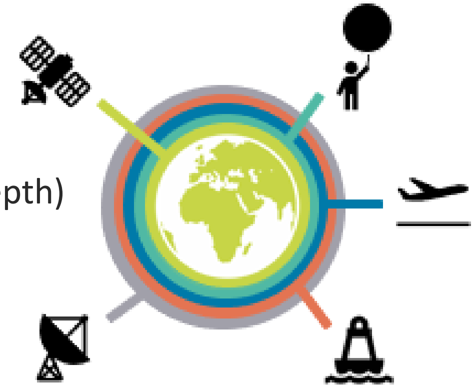
6 marine observation types

- Sea surface temperature (SST)
- Sea ice
- Ocean sounding and colour
- Altimeter



OPS carries out data selection, quality control (QC), error assignments, bias correction, 1D-Var, thinning, observation processing and the application of the observation operator.

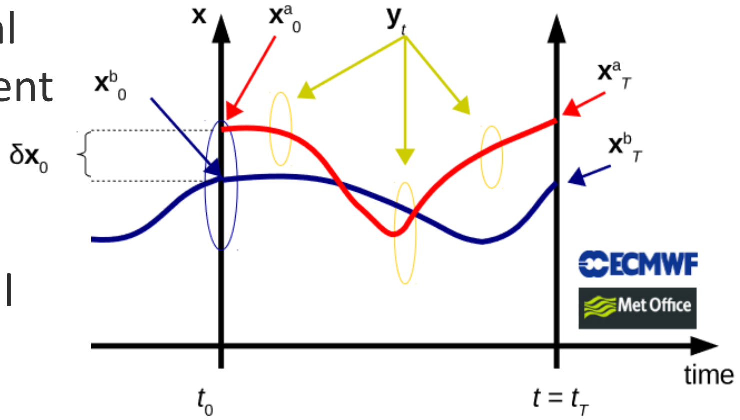
VAR

Data assimilation

Used to provide the initial conditions for numerical prediction in a range of components of the Earth System.

Global: hybrid incremental 4D-Var with flow-dependent background errors.

Limited area: continuous hourly-cycling incremental 4D-Var.



Make computationally quicker by:

- Solving a low-resolution variational problem
- Using control variable transforms
- Calculating observation term of the cost function separately for each observation.

Met Office

Next Generation Processing and Assimilation of Observations

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VAR

Data assimilation
…combines observations with prior …kground, to produce an 'optimal' …te of a particular system.

… to provide the initial conditions …diction in a range of components of the …

…y;
- land surface
- space weather.

The current global forecasting system uses a hybrid 4DVar assimilation scheme.

Current system…

In our current system, the logical chain of processing is "**static**".

OPS

The Joint Effort for Data assimilation Integration (JEDI) project

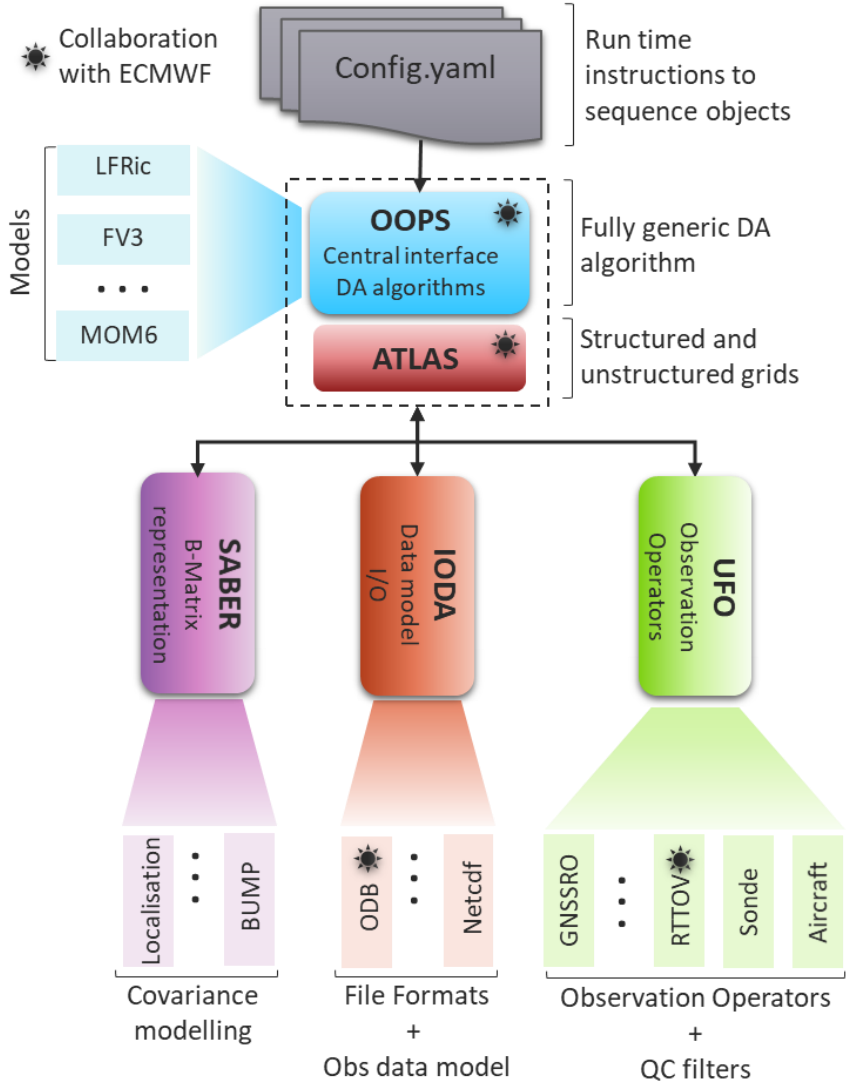
JEDI

JEDI is a collaborative development between JCSDA partners to develop a unified data assimilation system:

- → From toy models to Earth system coupled models
- → Unified observation (forward) operators (UFO)
- → For research and operations
- → Share as much as possible without imposing one approach (one system, multiple methodologies/configurations)

Motivation

Changes in HPC landscape	Fully exploit future generations of supercomputers Scalability, efficient I/O Memory and novel parallelism in era of large (1000s) ensemble DA
Technical	Increased modularity (more object-oriented capabilities) Expanded range of platforms (traditional HPC, cloud, laptop, etc)
More complex science	Flow-dependent QC, ensembles Strongly-coupled earth system DA, etc.
Future Applications	Nowcasting, cloud analysis, city-scale DA, composition DA, multi-models, etc.
Human	Current OPS/VAR too complex for wide-spread use Need to encourage wider collaboration (academic users, those working on other models)



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JEDI is a collaborative development between JCSDA partners to develop a unified data assimilation system:

→ From toy models to Earth system coupled models

New system

The logical chain of processing is applied "**dynamically**". Code free of any science

Collection of bricks
functions, methods, classes, procedures

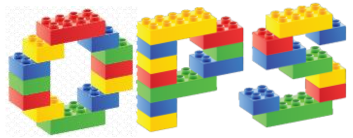
\+

```
window_begin: 2018-04-14T21:00:00Z
window_end: 2018-04-15T03:00:00Z
LinearObsOpTest:
coefTL: 0.1
toleranceTL: 1.0e-13
toleranceAD: 1.0e-11
Observations:
ObsTypes:
- ObsOperator:
name: VertInterp
VertCoord:
air_pressure
```

Configuration file

Instructions how to assemble the bricks.

Assemble the bricks using modern computation techniques



Mot[ivation]

Chan[ging] lands[cape]	Memory and novel parallelism in era of large (1000s) ensemble DA
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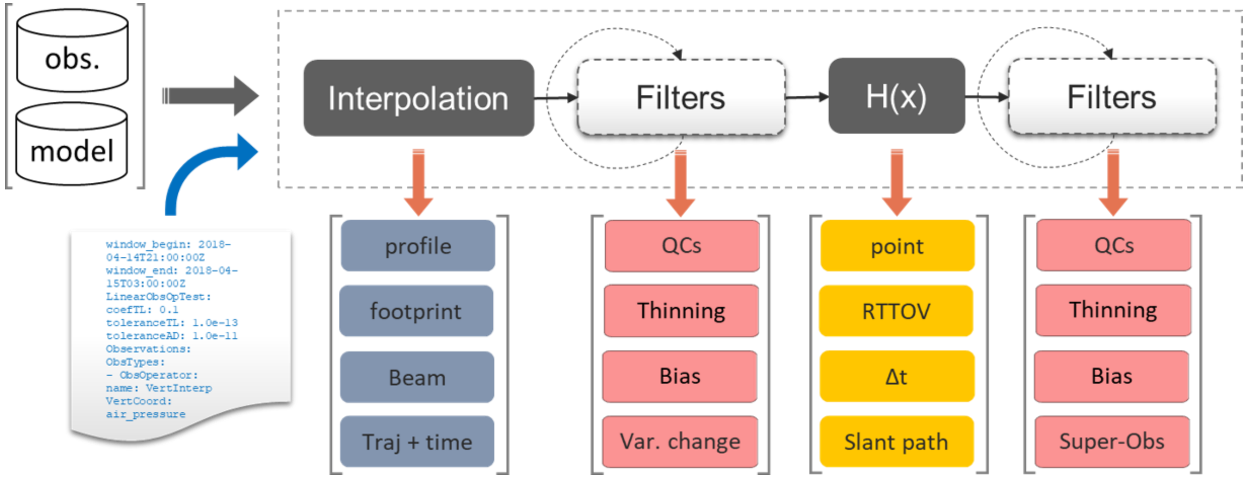
Our new projects JOPA and JADA

JOPA — JEDI-based Observation Processing Application

Aim: Replicate our current observation processing for atmospheric and ocean data assimilation



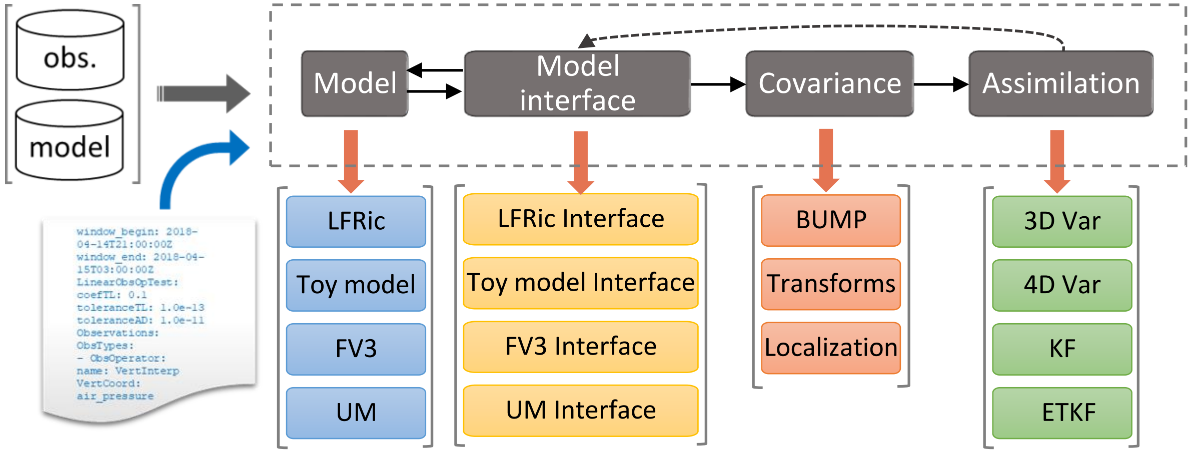
New code in UFO for:

- Data selection
- Quality control
- Error assignments
- Bias correction
- 1D-Var
- Thinning
- Observation operators

All code validated against OPS to ensure the close match.

JADA — JEDI-based Application for Data Assimilation

Aim: Develop new science and code to redesign our data assimilation capabilities and allow us to "put ensembles at the heart of everything we do".



Start with an ensemble 3DVar then extend to 4DVar adding:

- Hybrid background error covariance
- Control-perturbation method
- Hybrid ensemble TLM
- Rapid update cycling

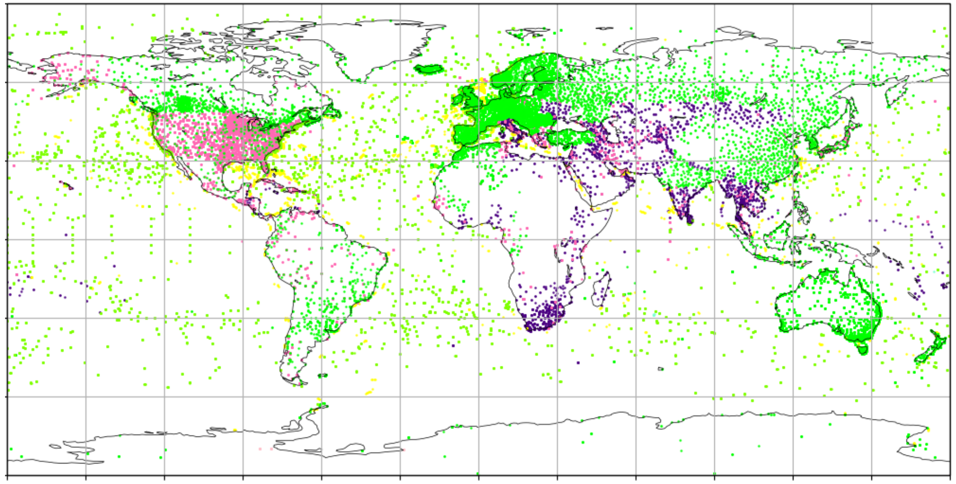
As well as developing the new DA system, JADA will provide:

- A model interface to connect LFRic to JEDI
- A testing suite to allow JADA/VAR comparison

Surface-based observations

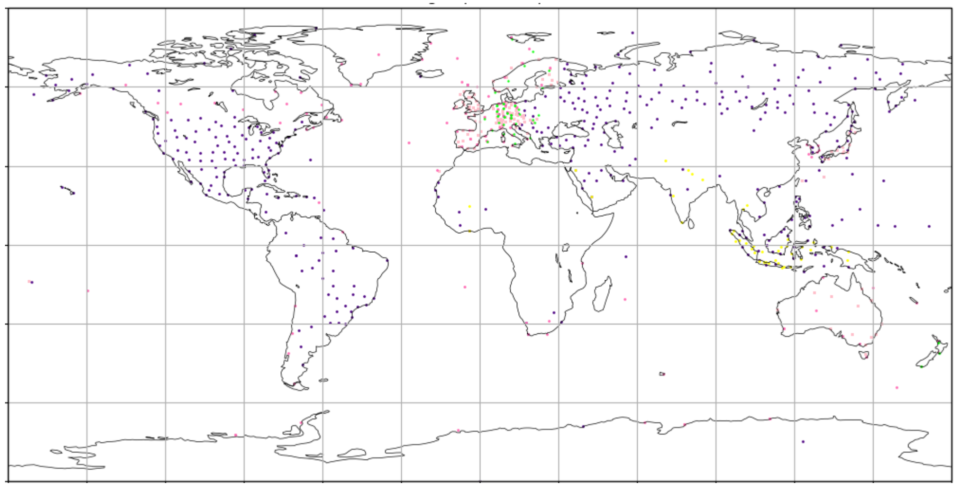
Surface-based observations

Surface



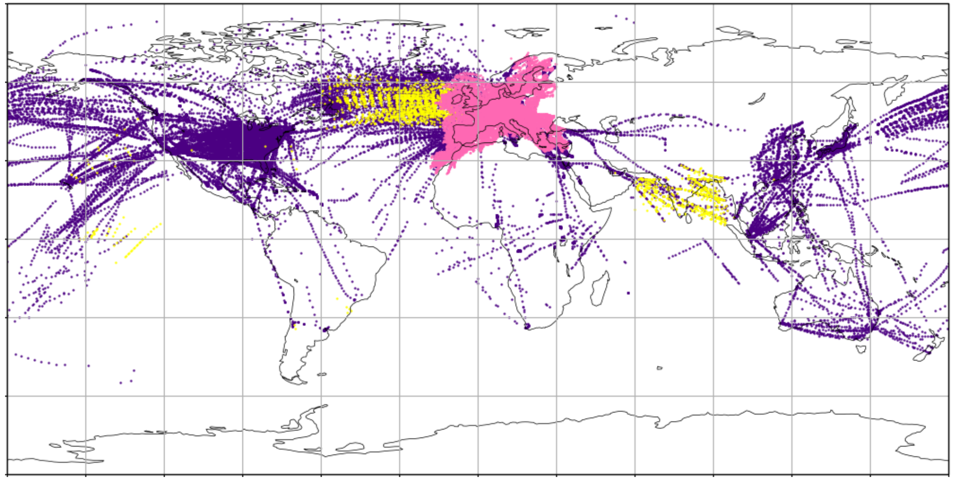
- Global and UKV
- 7 types
- 11 variables
- Only source of pressure observations

Profile



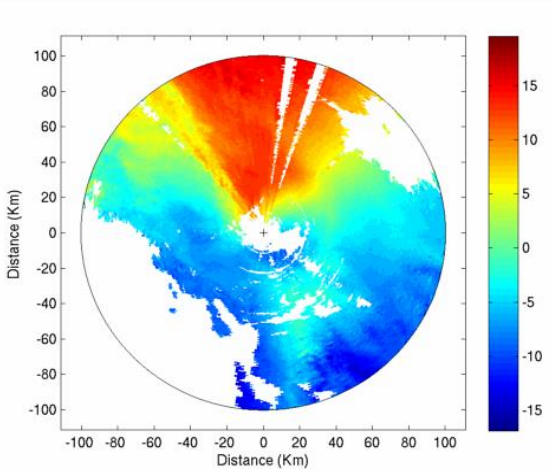
- Global and UKV
- 5 types
- 4 variables

Aircraft

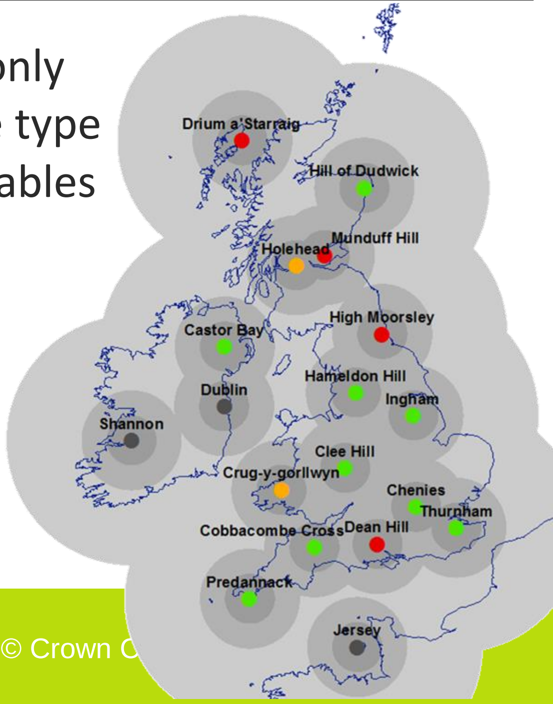


- Global and UKV
- 3 types
- 3 variables
- Dense data, but not evenly distributed

Radar



- UKV only
- Single type
- 3 variables



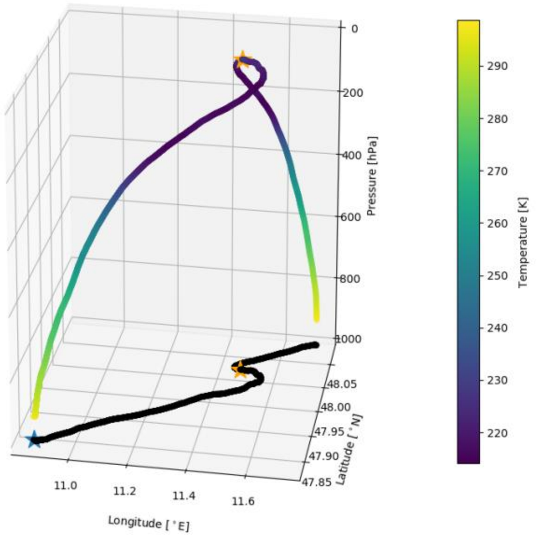
Novel Observations

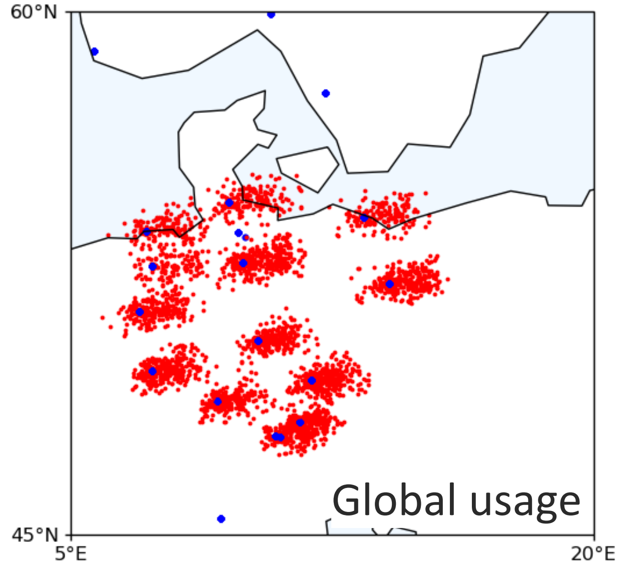
Sonde descents

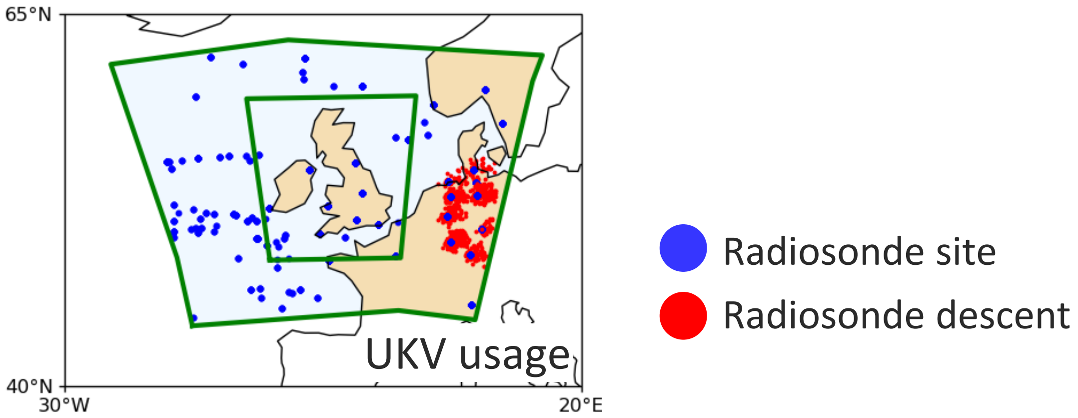
With thanks to Chris Thomas

Radiosonde descents

- Descending radiosonde observations can provide additional atmospheric profile information at little cost.
- Assess the impact of assimilating descents in both the global and UKV models by running global and regional trials.
- Descents restricted to Germany, and reports below the stratosphere due to data quality.



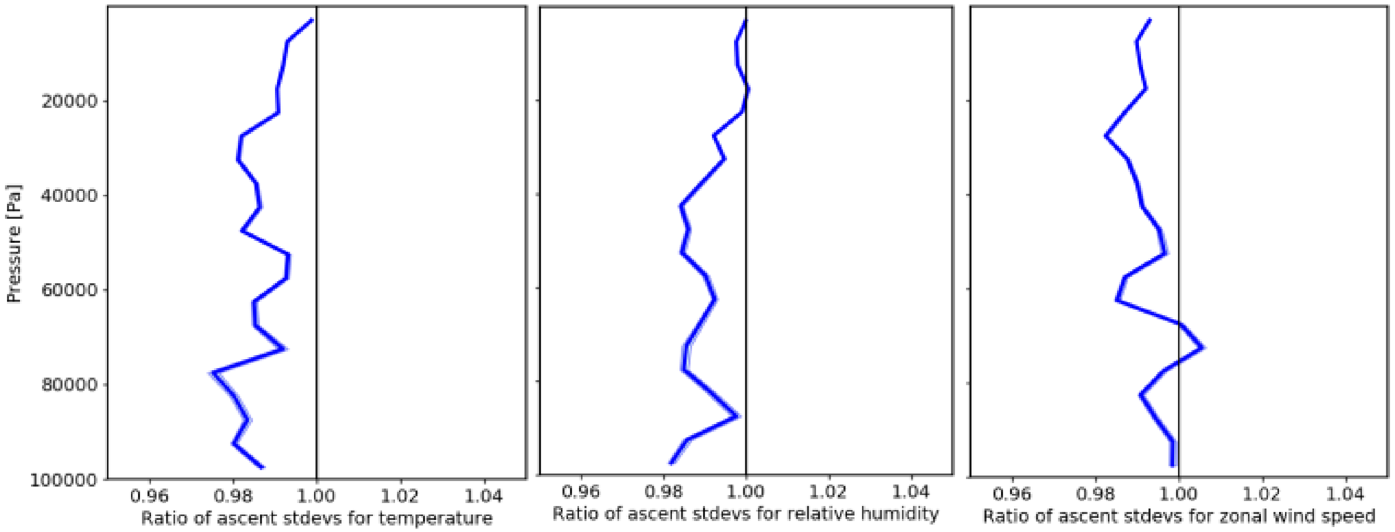




Impact in observation region

- Examine innovations over full model region, and over Germany to assess impact of descent assimilation.
- Ratio of innovation standard deviations are predominantly < 1 for all variables in both global and regional models suggesting assimilation quality is improved in this region.
- For global trial standard deviation of O-B innovations is improved for temperature and wind speed and remains mostly unchanged for relative humidity.
- In both systems the forecast impact is mostly neutral but there are improvements seen over Europe.
- Sonde descents now assimilated in both global and regional models. Plan to extend usage to other regions.

Global innovation standard deviation ratios



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Direct assimilation of reflectivity

With thanks to Lee Hawkness-Smith

Treatment of Radar Reflectivity Observations

Information from radar reflectivity observations, in the form of a surface precipitation product, has been incorporated into the UKV via latent heat nudging (LHN) for over 25 years.

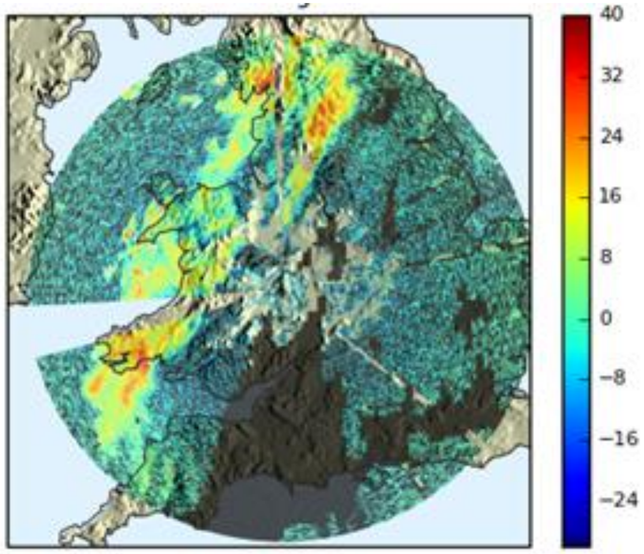
Determine if moving to direct assimilation of radar reflectivity observations is more beneficial than latent heat nudging.

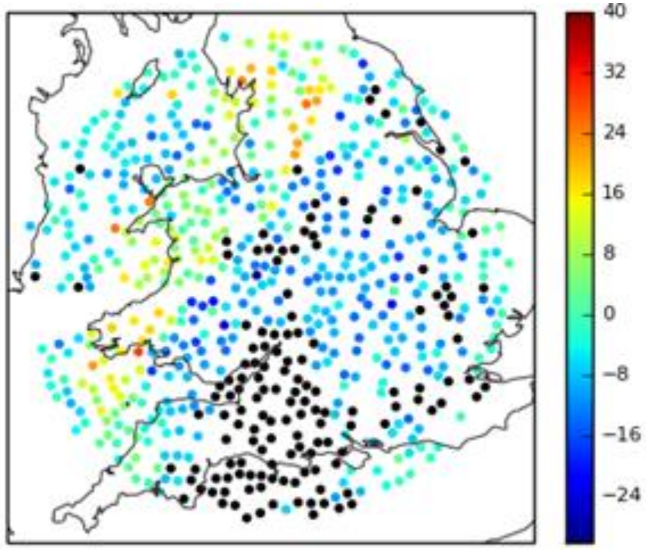
Quality control

- reject non-hydrometeorological echoes
- reject obs where background T < 3C, to avoid bright band melting layer.

Super-Observation and Poisson thinning

- Super-Observation size: 15º by 15km
- Thinning: 15km for precip - 30km Dry obs.





Hawkness-Smith, LD, Simonin, D. Radar reflectivity assimilation using hourly cycling 4D-Var in the Met Office Unified Model. Q J R Meteorol Soc. 2021; 1516– 1538.

Observation operator and processing

Observation Operator

- Operator uses interpolation to a point and a simple Z-q_r relation for rain

$$Z_R = 1.63x10^3 q_r^{7/4.0}$$

- Transform units to $\sqrt{Z_R + 1}$, this compress the range and scale with the water mass.

Observation error:

- 60 $[\sqrt{Z_R + 1}]$ for dry
- 30 $[\sqrt{Z_R + 1}]$ for precip.

Assimilation Strategy

- 3 volumes scans (0, 15, 30 minutes)
- Both dry and wet observations are used.
- Initially apply for UK radar

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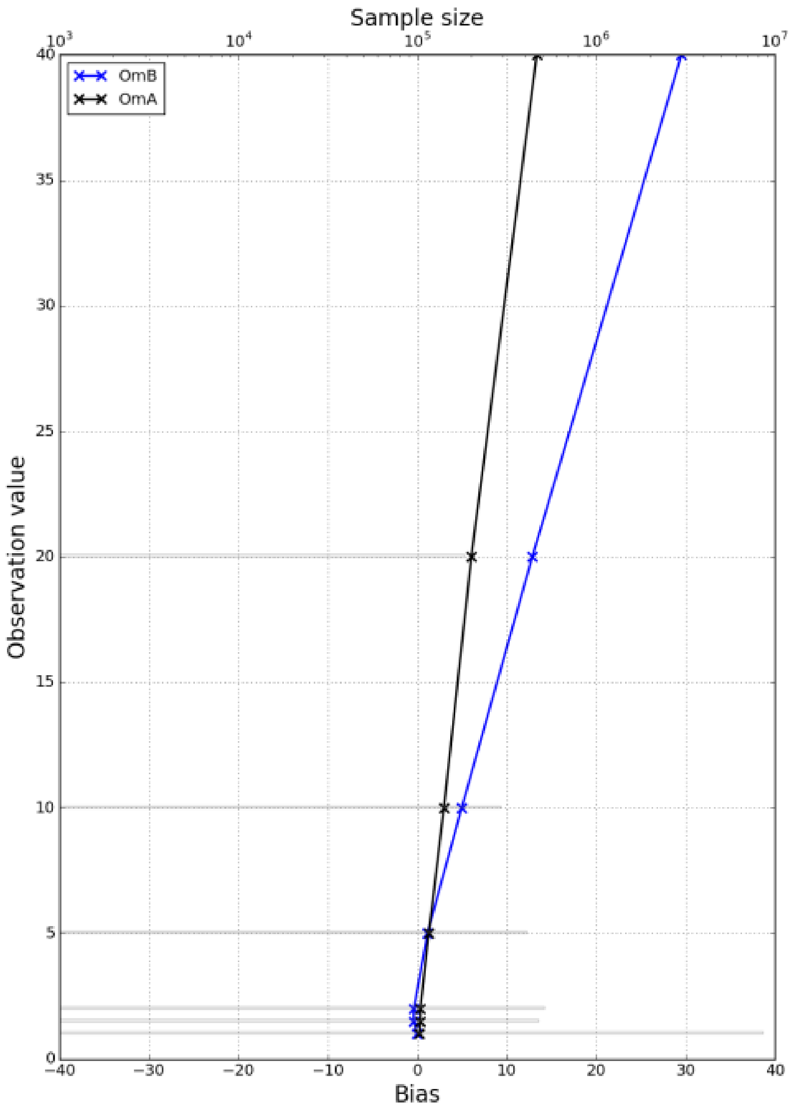


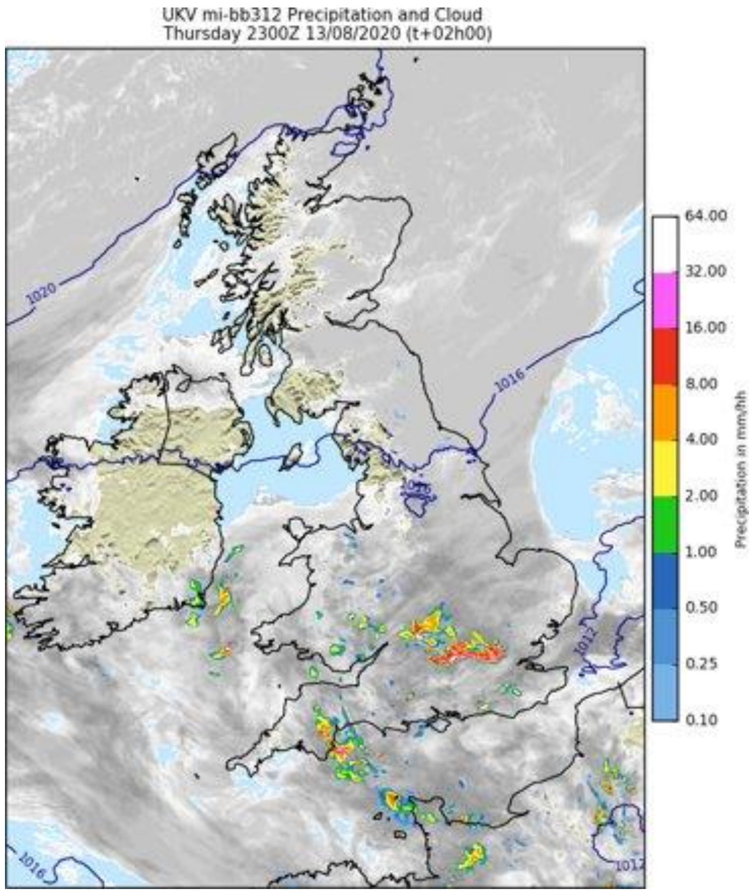
Initial results suggested bias innovations and mis-specified observation error statistics, so operator and error variances were retuned.

Hawkness-Smith, LD, Simonin, D. Radar reflectivity assimilation using hourly cycling 4D-Var in the Met Office Unified Model. Q J R Meteorol Soc. 2021; 1516– 1538.

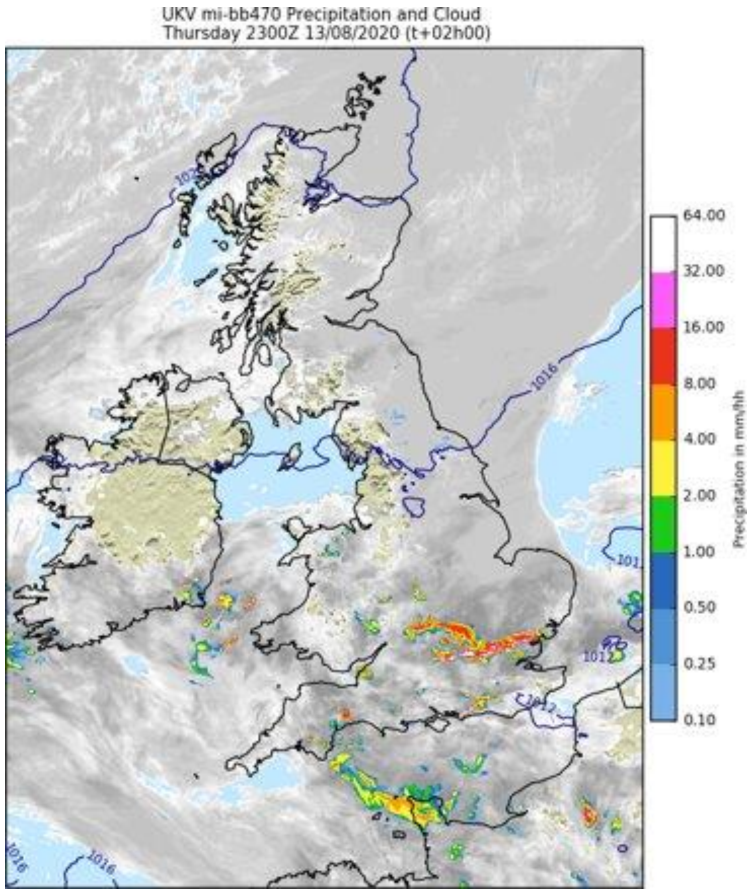
13 Aug 2020, T+2 2300

Improved organisation of bands of convection across southern England and Channel

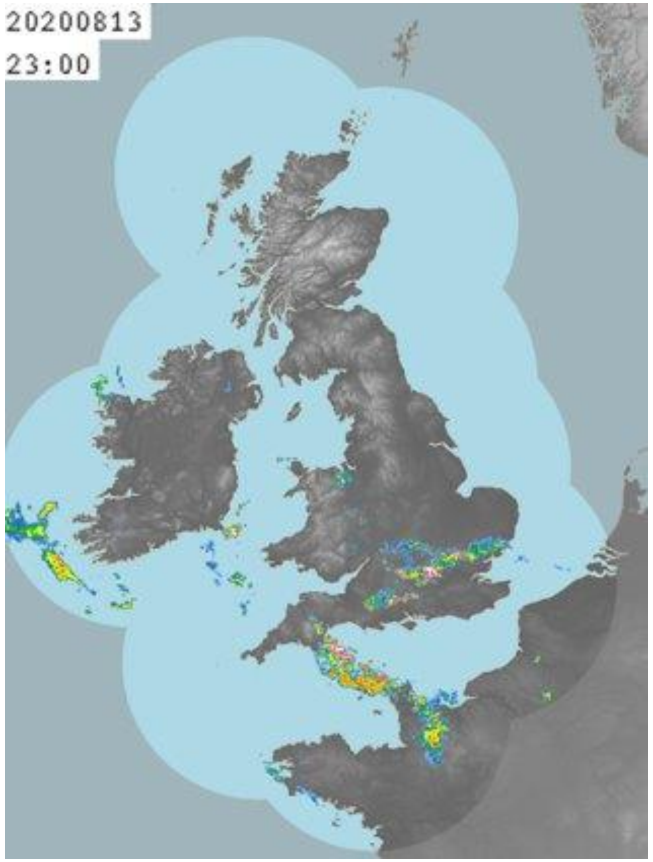
Control



Radar reflectivity experiment



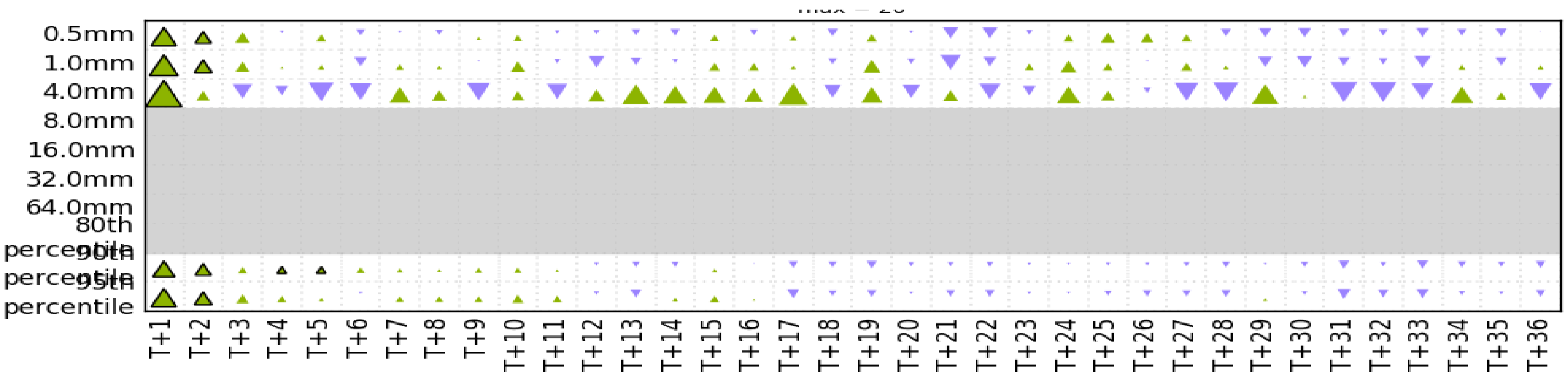
Radar composite



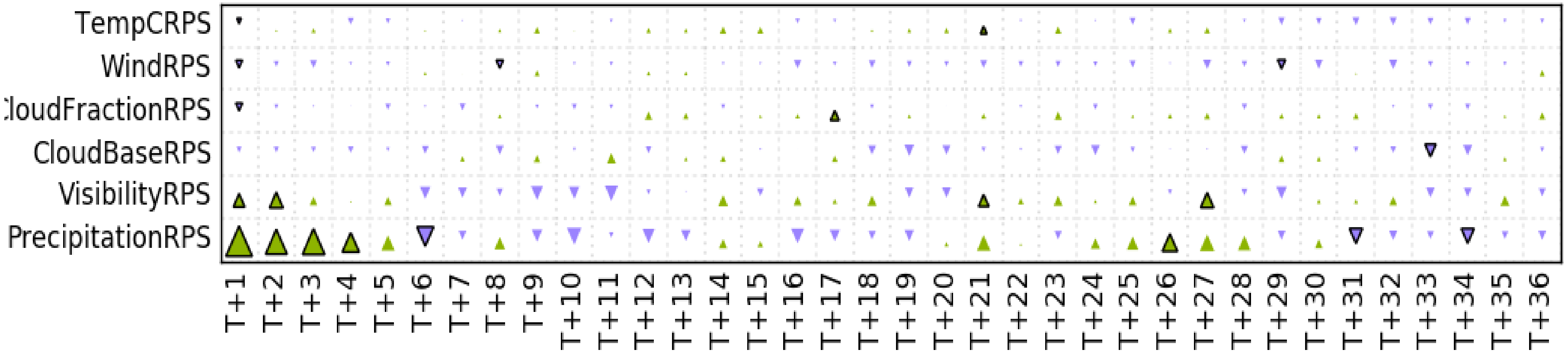
[Hawkness-Smith, LD, Simonin, D. Radar reflectivity assimilation using hourly cycling 4D-Var in the Met Office Unified Model. Q J R Meteorol Soc. 2021; 1516– 1538.]

Results

Improved Fractions Skill score at all thresholds in the first few hours.



Improved Precipitation Rank Probability Score, and neutral impact on other scores.



- Direct assimilation of radar reflectivity now operational for UK & Ireland radars.
- Extension to French and German radars planned for 2024

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Observation usage

Roadside observations

OPENROAD data and motivation

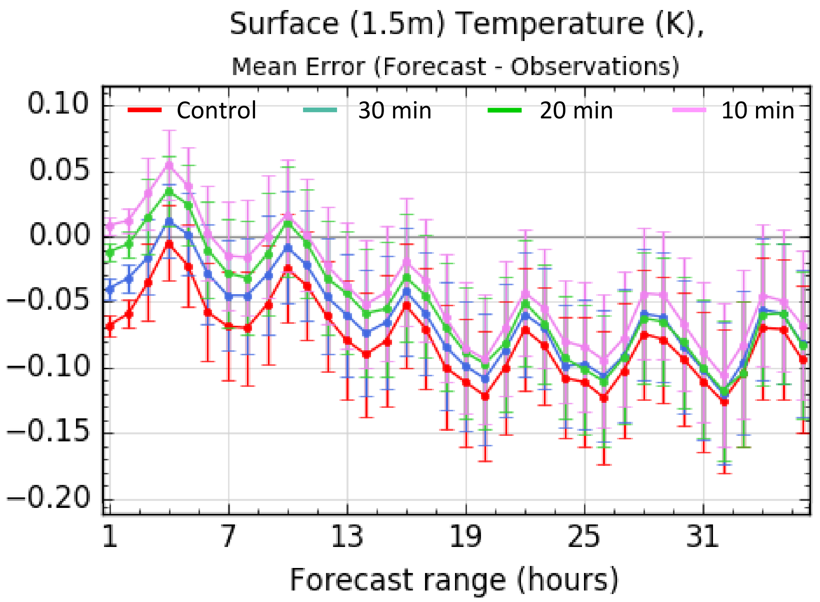
- Data is recorded by approximately 700 automated roadside sites.
- Stations observe data at a frequency of 10 minutes.
- The move to hourly cycling 4D Var for the UKV provides an opportunity for observations to be assimilated at higher temporal frequency
- Assess the impact of increasing OpenRoad assimilation frequency from 60 minutes to 30, 20 or 10 minutes.

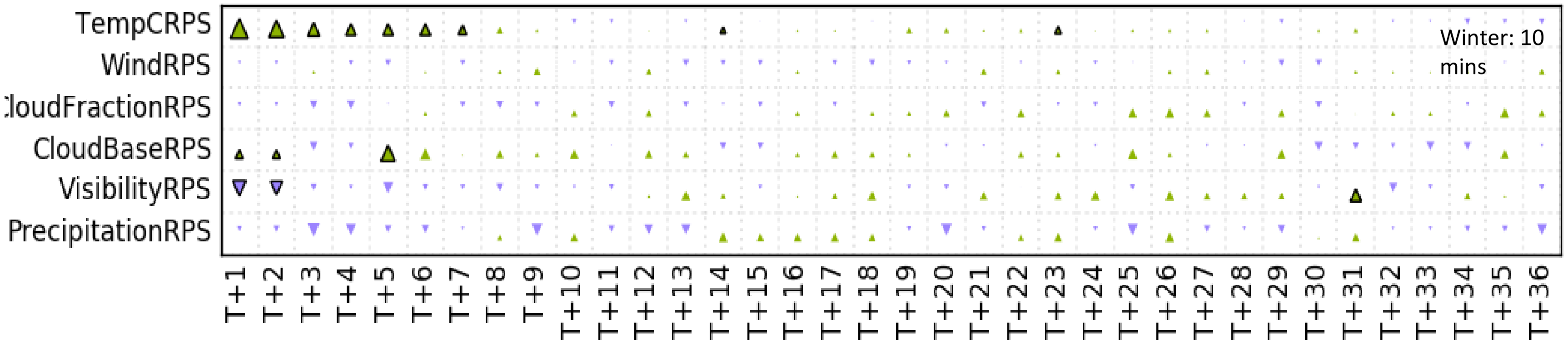
Image credit: https://www.fleetpoint.org/road-building-repairs/highways-england/new-weather-stations-helping-to-keep-traffic-moving/

Increasing assimilation frequency

Increasing the assimilation frequency of roadside data results in:

- Improved fit of analysis and background to surface observations (except log vis), slight degradation for other observations
- Reduction in temperature forecast bias for both summer and winter. Impact neutral for other forecast variables.
- Significant improvement in temperature CRPS for until T+7.
- Impacts larger in winter than summer.
- Most benefit from 10 minute assimilation frequency which is now included in operational system.





	Cont.	30 min	20 min	10 min
Temp	1270	1563	1945	2814
RH	1121	1400	1764	2591
log vis	548	552	555	566

Average number of surface observations assimilated per cycle

Correlated observation error statistics

With thanks to David Simonin

Observation Uncertainties

In data assimilation the observation error statistics consists of a measurement error and a representation error, **R = E + F.**

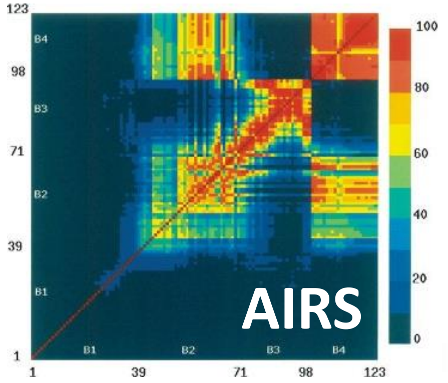
In practice to satisfy the current assumption of uncorrelated observation error:

- the observations are thinned,
- the error variances are inflated

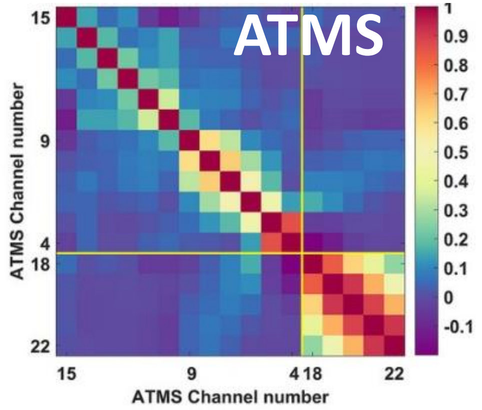
This reduces the observation usage to approximately 5%.

In global NWP, inter-channel error correlations are accounted for as the use leads to:

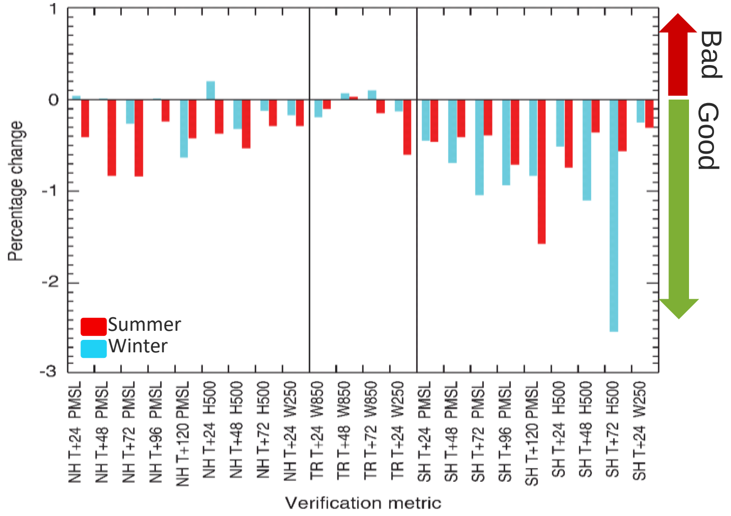
- Increase in the analysis accuracy.
- Improved fit of background to observations.
- Improvement in the forecast skill score.



Inter-channel error covariance matrix for AIRS
Figure from Garand et al 2007



Inter-channel error covariance matrix for ATMS
Figure from Campbell et al. 2017



Change in RMSE and weighted skill against observations when accounting for IASI correlated errors. *Figure from Weston et al. 2014*

Spatial error correlations

Inter-channel error correlation success sparked interest in spatial error correlations.

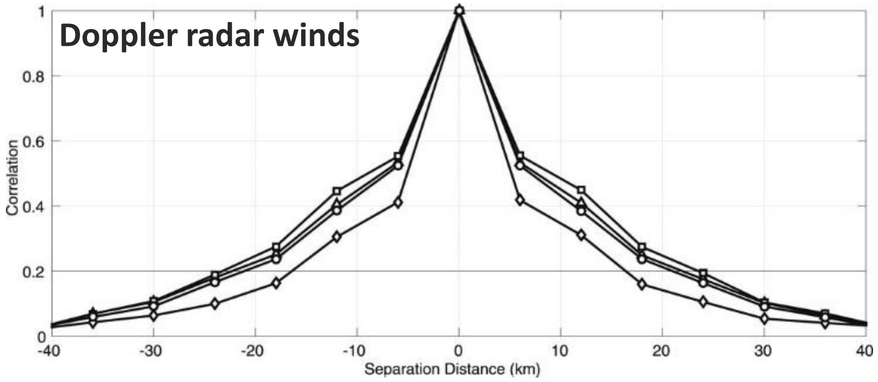


Figure from Waller et al. 2016b

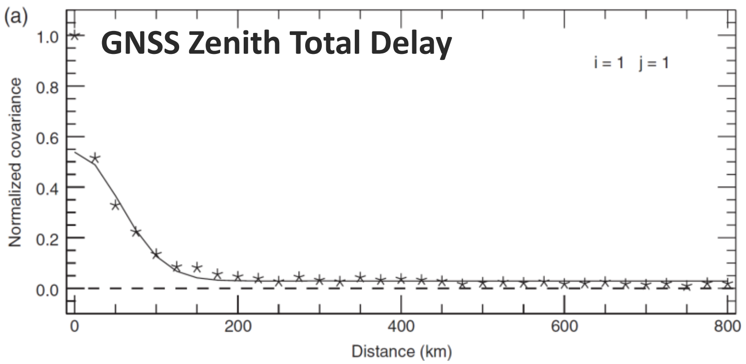


Figure from Macpherson & Laroche 2019

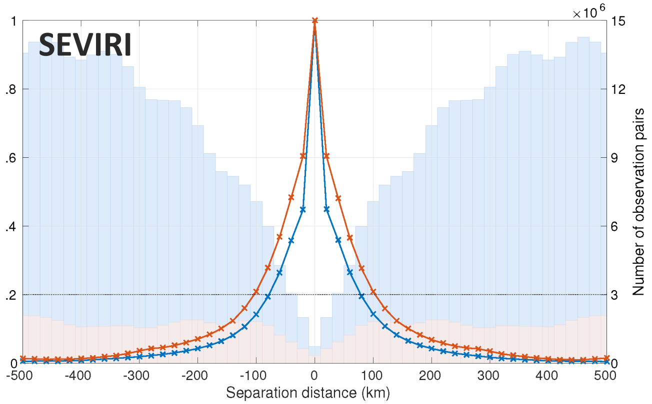


Figure from Waller et al 2016a

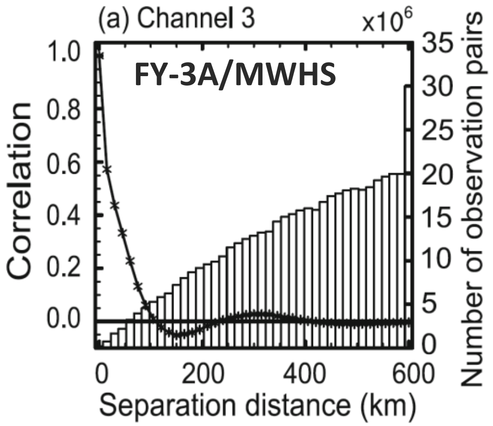


Figure from Wang et al. 2018

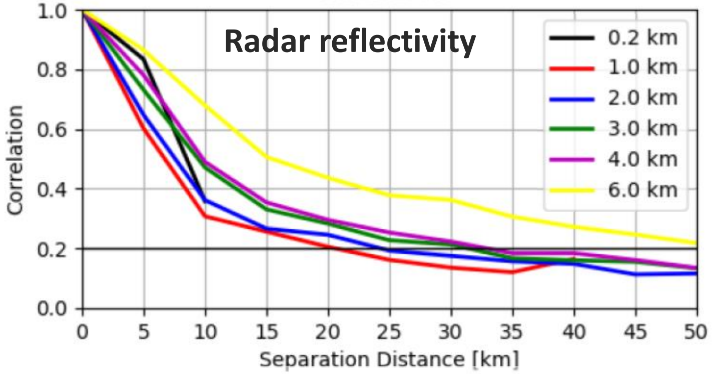


Figure from Zheng et al. 2021

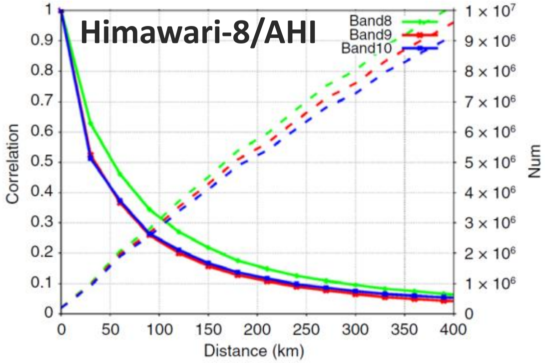


Figure from Okamoto et al. 2019

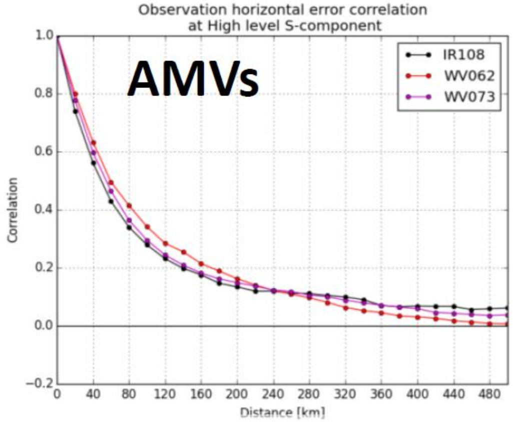


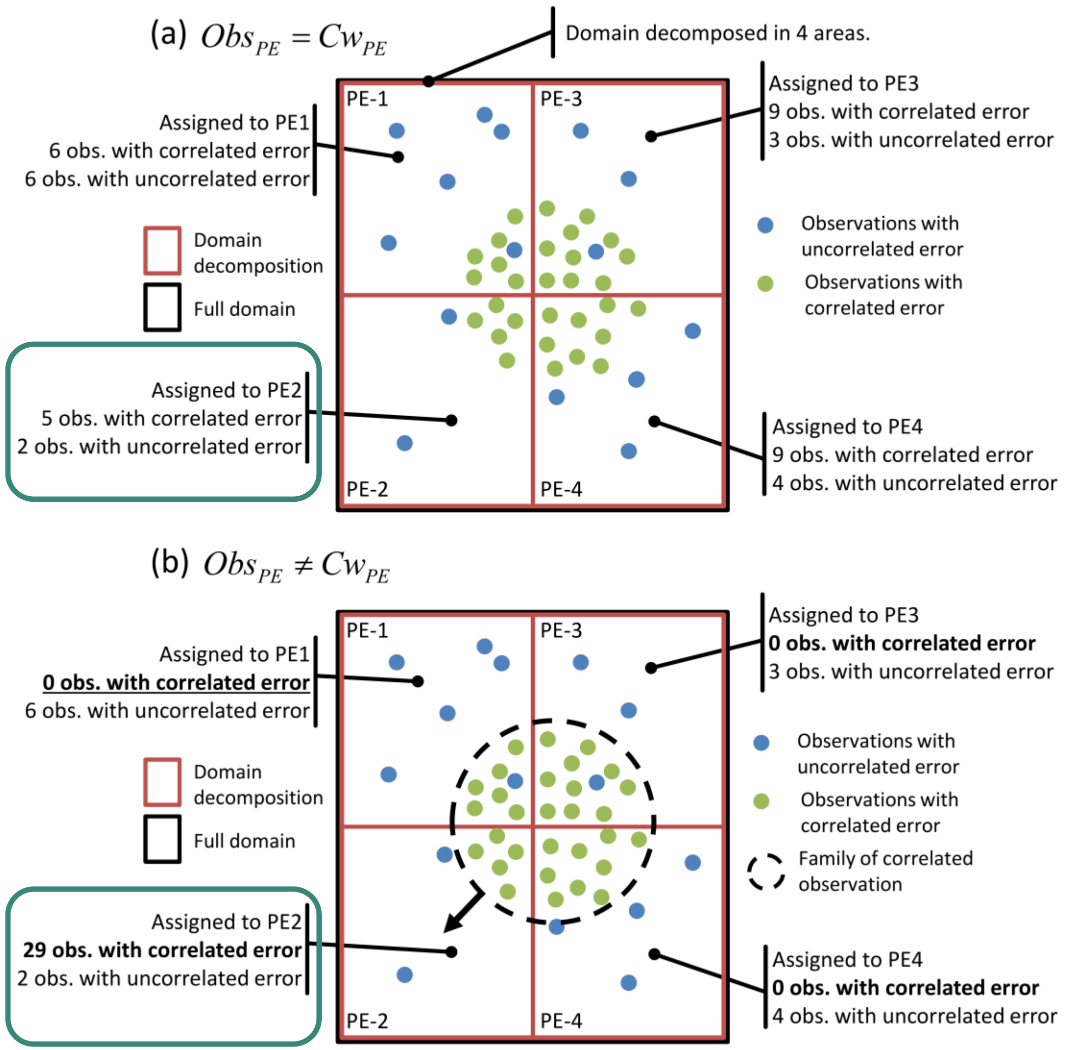
Figure from Cordoba et al. 2017

Can we efficiently account for them in assimilation?

Family Method

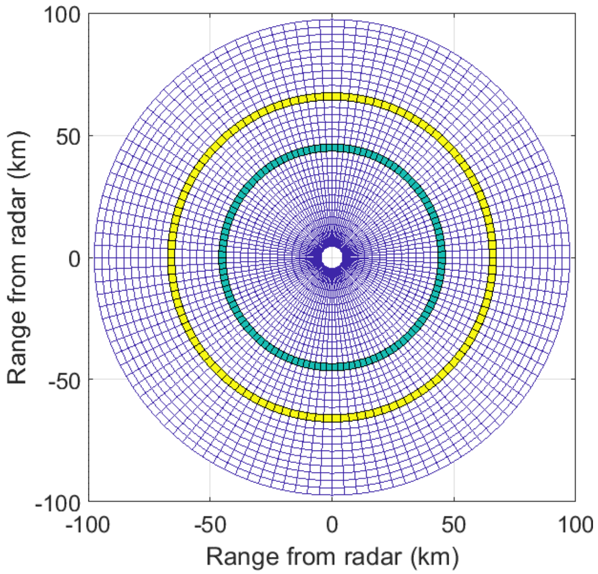
- A family is a group of observations that have correlated errors.
- Instead of sending observations to processors based on location or equal distribution families are kept on single processors.
- The observation error covariance matrix is calculated on the fly for each assimilation cycle.

Pros	Cons
Simple to apply - application of ***R*** similar to inter-channel approach	Sets of observations with correlated errors must be sufficiently small.
R used in assimilation is not further approximated.	Large correlation length scales may be costly to handle

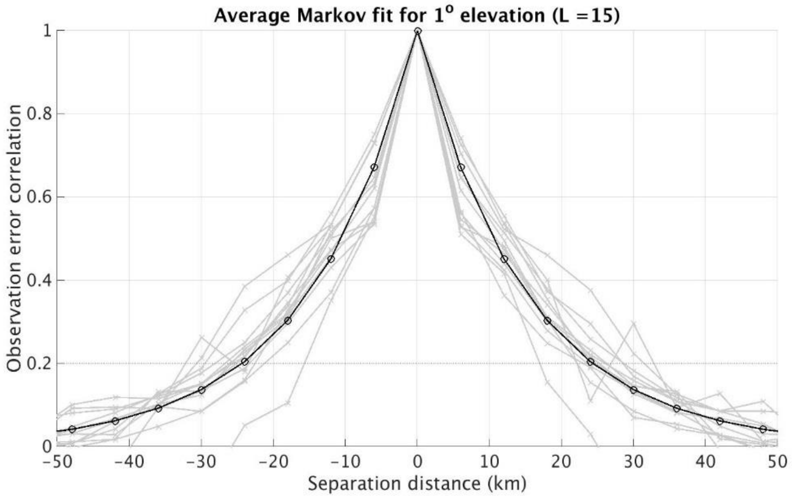


[Figure from Simonin et al. 2019]

Correlated errors for radar winds



- UK radar network provides very high resolution observations that are under exploited in assimilation.
- Radar wind errors shown to have considerable correlation (Waller et al. 2016b).
- Use family method to include correlation and allow increased assimilation density Simonin et al. 2019.

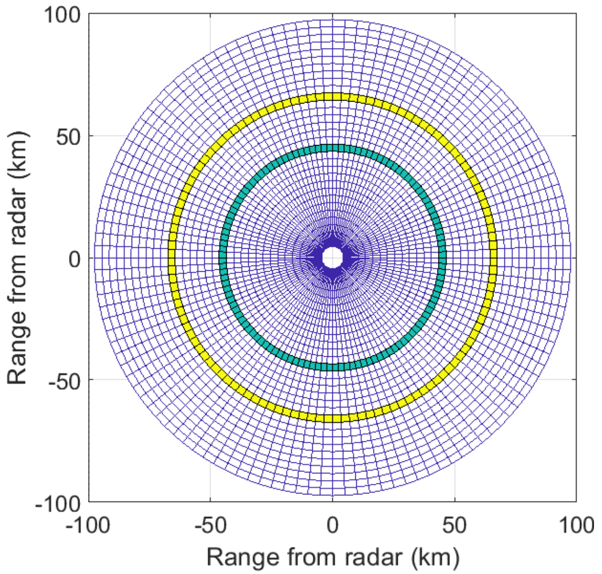


Doppler radar radial wind error correlations

Experiment	Doppler wind observation error matrix	Observation thinning distance
Control	Diagonal ***R*** (Operational)	6 km (~2000 rad obs. per cycle)
Corr-R-6km	Correlated ***R***	6 km (~2000 rad obs. per cycle)
Corr-R-3km	Correlated ***R***	3 km (~8000 rad obs. per cycle)
Diag-R-3km	Diagonal ***R*** (Operational)	3 km (~8000 rad obs. per cycle)

Simonin, D. Waller, JA. et Al. 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; 2772–2790

Correlated errors for radar winds



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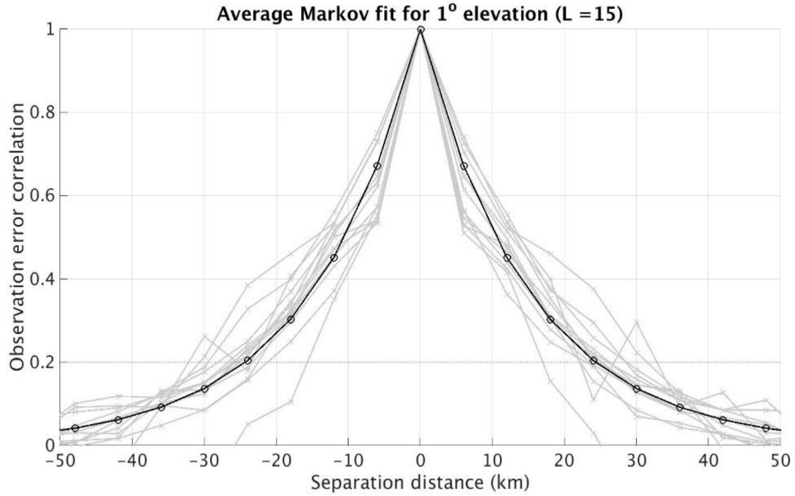


Doppler radar radial wind error correlations

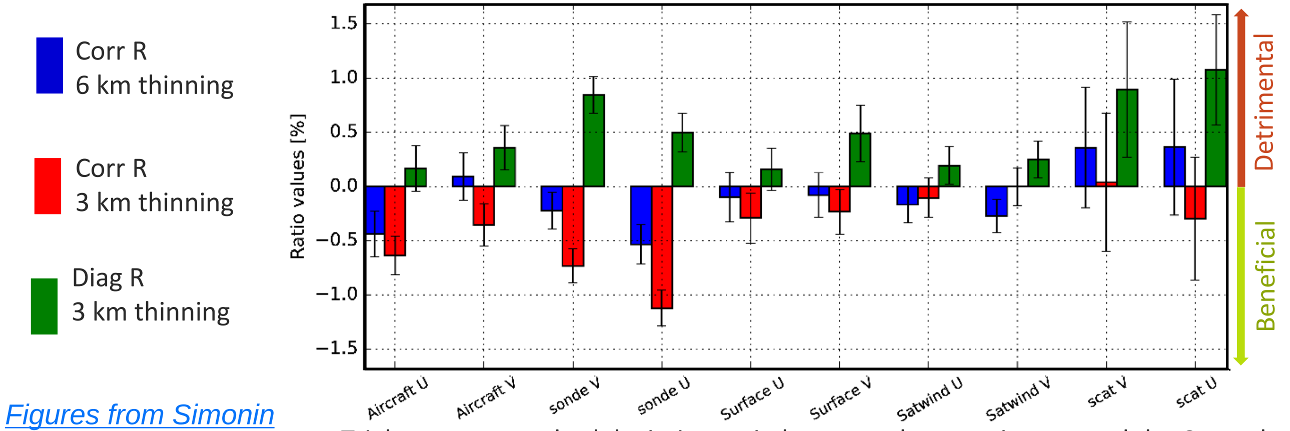
Very important! Additional cost of using error correlations not significant.

Experiment	Doppler wind observation error matrix	Observation thinning distance	Average time (s)
Control	Diagonal ***R*** (Operational)	6 km (~2000 rad obs. per cycle)	272
Corr-R-6km	Correlated ***R***	6 km (~2000 rad obs. per cycle)	293
Corr-R-3km	Correlated ***R***	3 km (~8000 rad obs. per cycle)	288
Diag-R-3km	Diagonal ***R*** (Operational)	3 km (~8000 rad obs. per cycle)	-

Simonin, D. Waller, JA. et Al. 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; 2772–2790

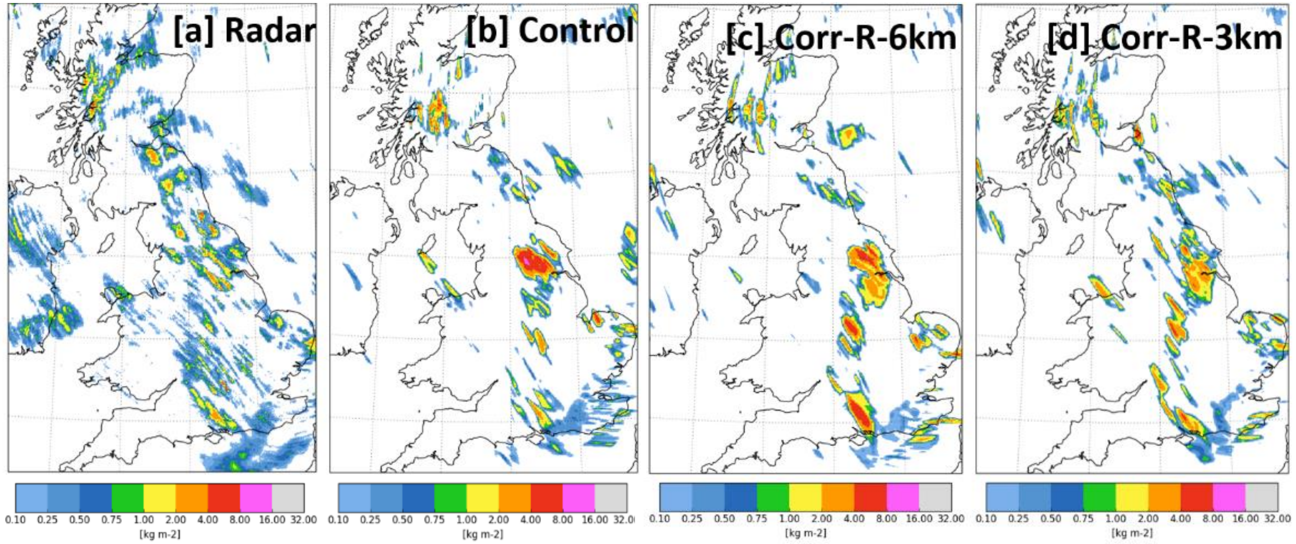
Results

- Improved fit to observations when observations assimilated with correlated errors.
- Further when observation density is increased.
- Increasing observation density without accounting for error correlations is very detrimental to fit to observations.
- Precipitation forecast has more small-scale information in when assimilating observations with correlated errors.
- Radar observations now assimilated with correlated errors in regional model.



[Figures from Simonin et al. 2019]

Trial average standard deviation ratio between the experiments and the Control



Hourly accumulated precipitation forecasts for 1500 UTC on 7 April 2016 at T+3.

[Simonin, D. Waller, JA. et Al. 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; 2772–2790]

Summary and conclusion

Summary and Conclusion

- Data assimilation is one of the contributors to the increase in forecast skill in recent decades.
- Operational DA is complex as it requires:
  - Complex processing of millions of heterogeneous observations.
  - Unification and communication between multiple observations and modelling systems.
  - An efficient and robust DA scheme that can ingest observations quickly.
- Next generation data assimilation systems are being developed that benefit from shared code and expertise.
- One of the challenges in DA is extracting the maximum amount of information from all the available observations. Forecasts have been improved by:
  - Introducing new observation types.
  - Making better use of existing observations.
- There are many upcoming challenges for operational data assimilation. For injecting small scale information into the analysis, accounting for correlated observation errors is crucial.

Met Office

Thank you
Any questions?