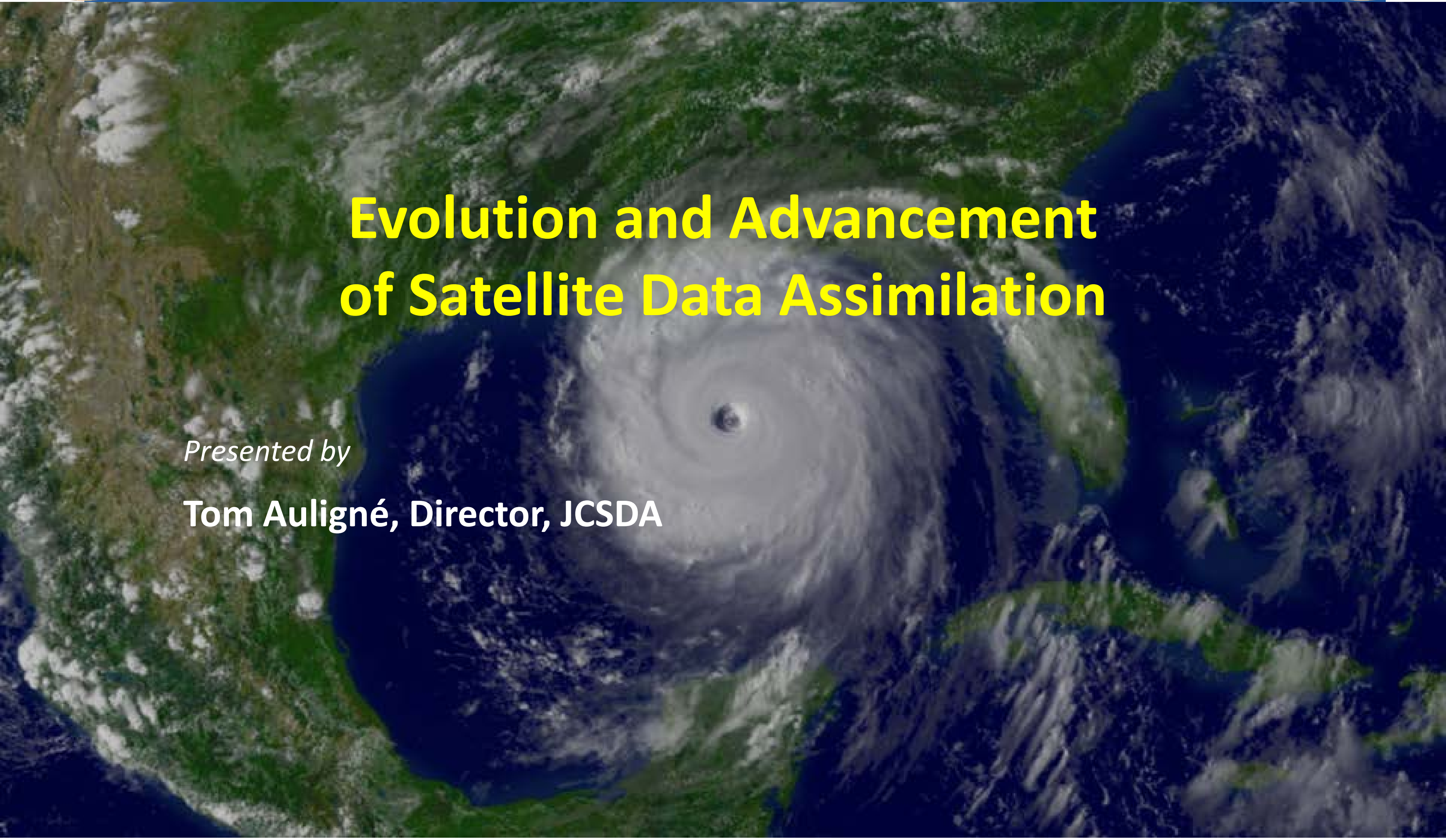


Evolution and Advancement of Satellite Data Assimilation

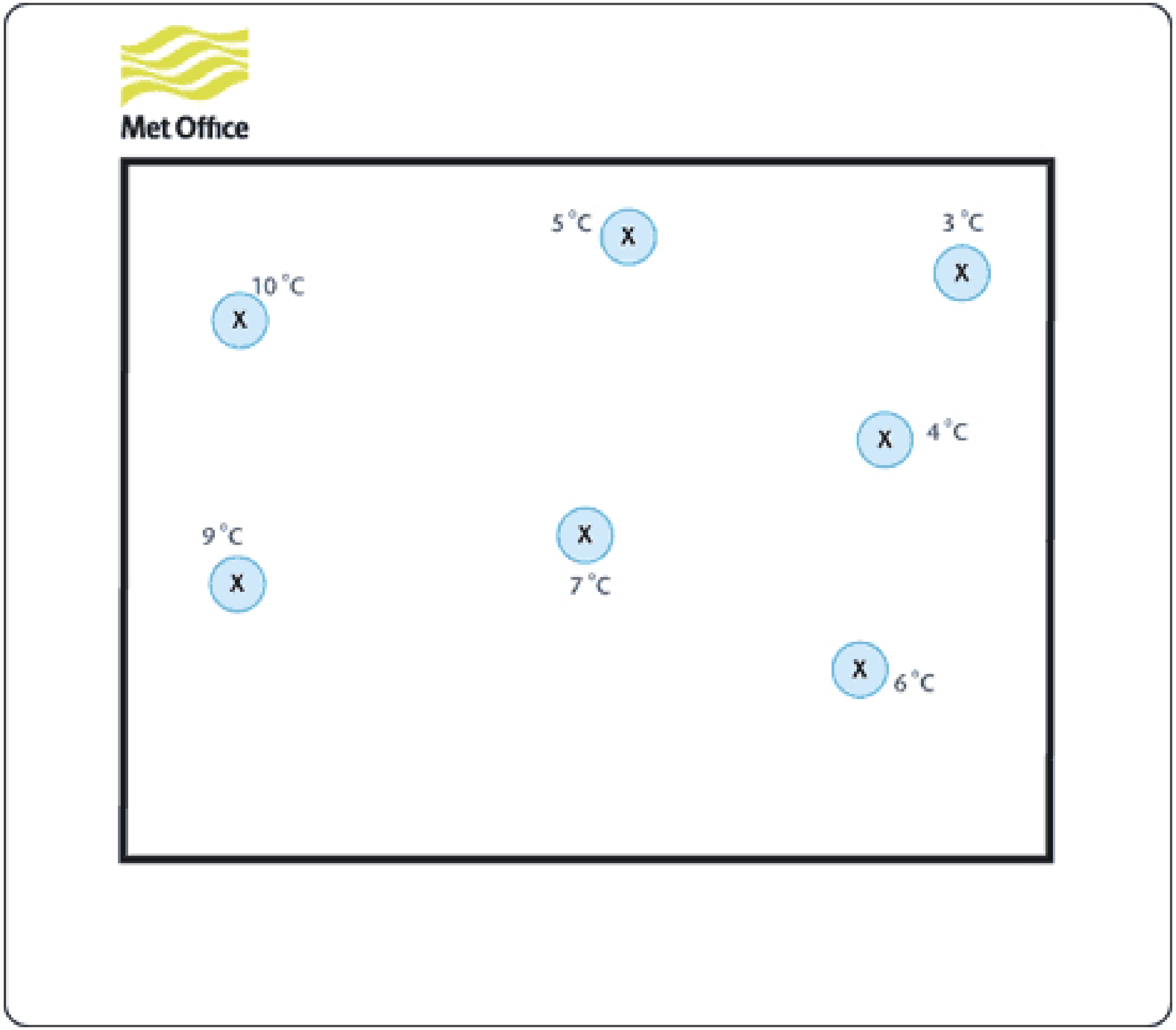
Presented by

Tom Auligné, Director, JCSDA

Motivation: Why Data Assimilation?

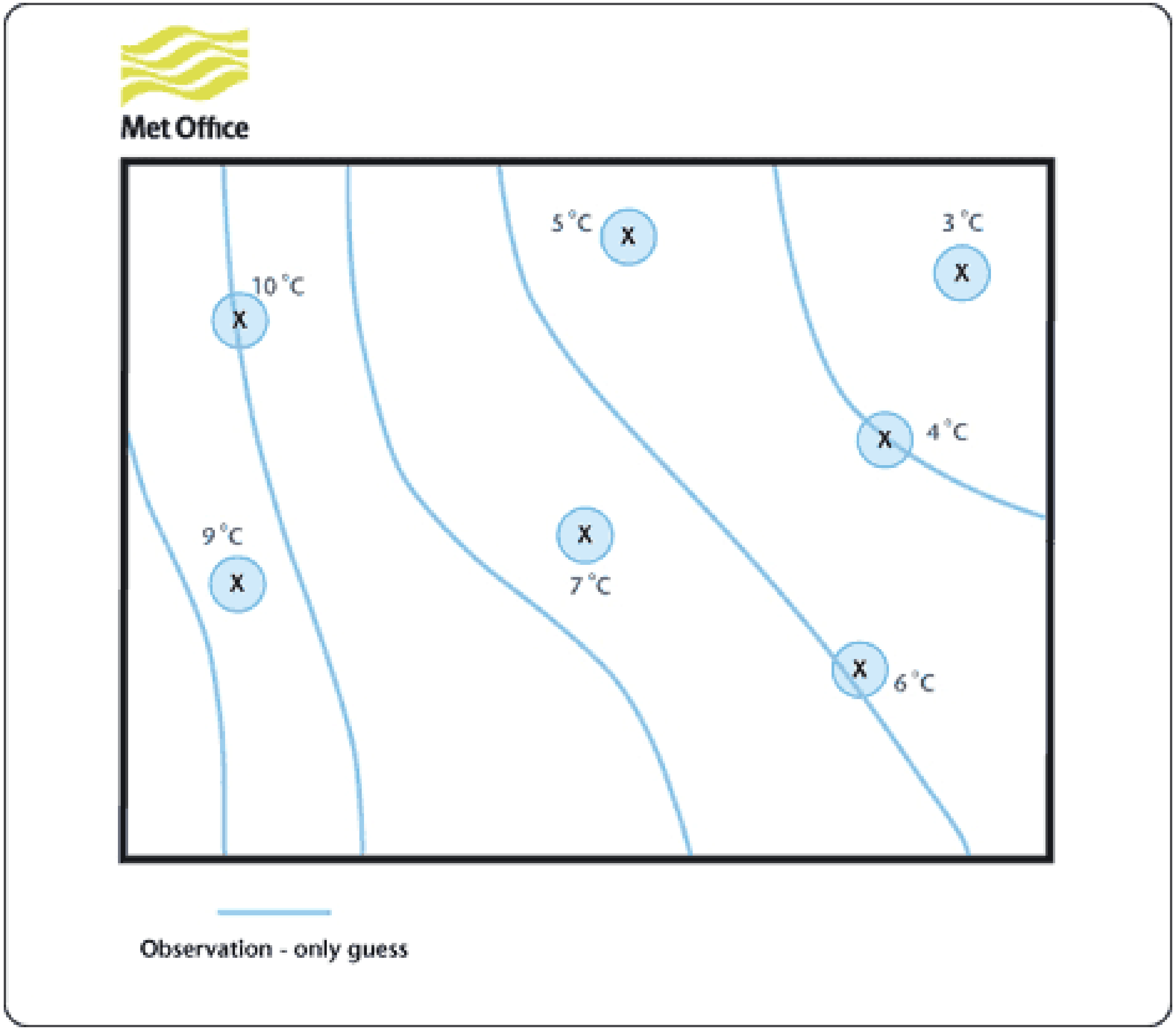
- Situational Awareness
- Initial conditions for Numerical Models
- Calibration and validation
- Observing system design, monitoring and assessment
- Reanalysis
- Better understanding (Model errors, Data errors, Physical process interactions, *etc*.)

Introduction



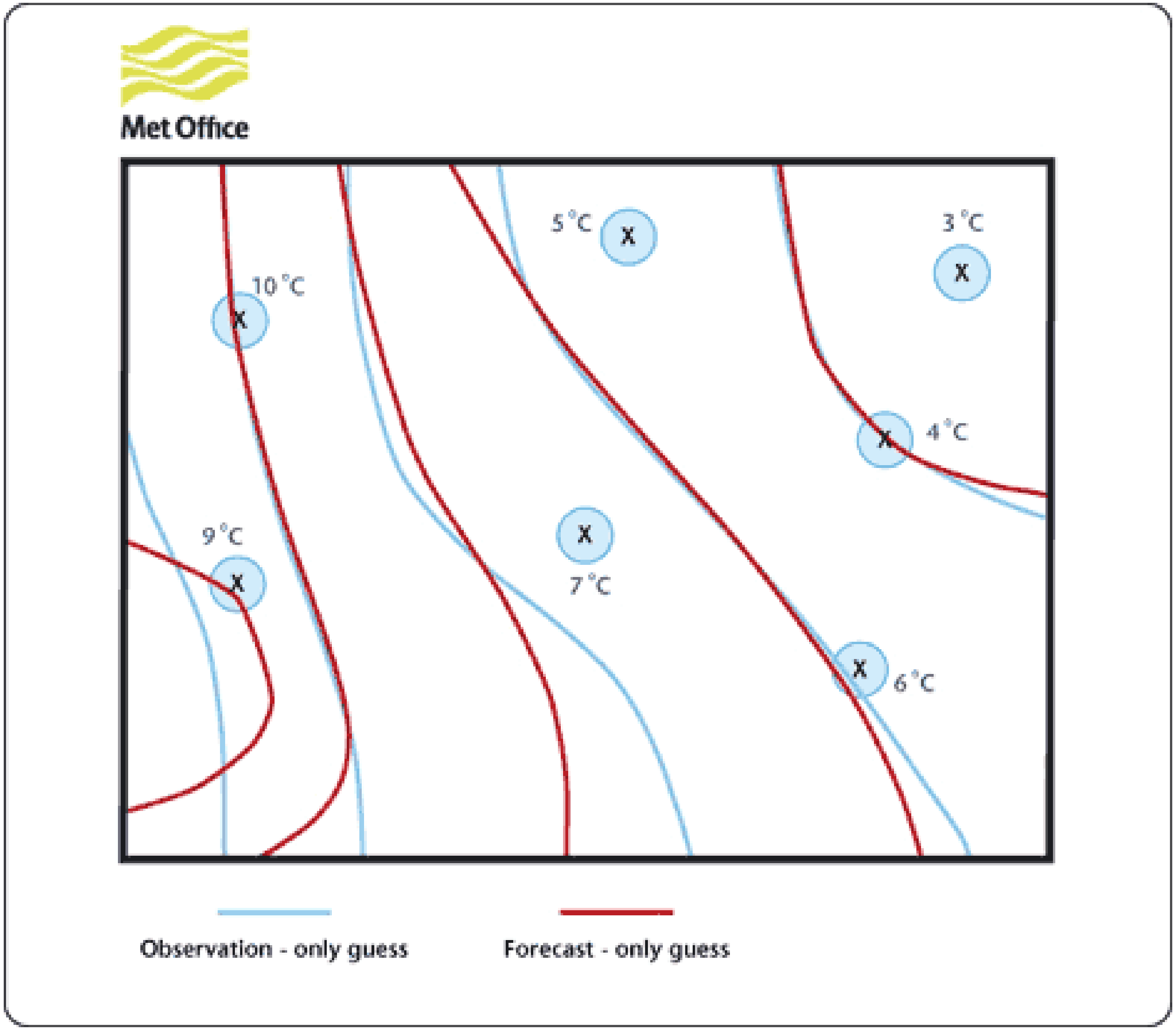
Source: Met Office

Introduction



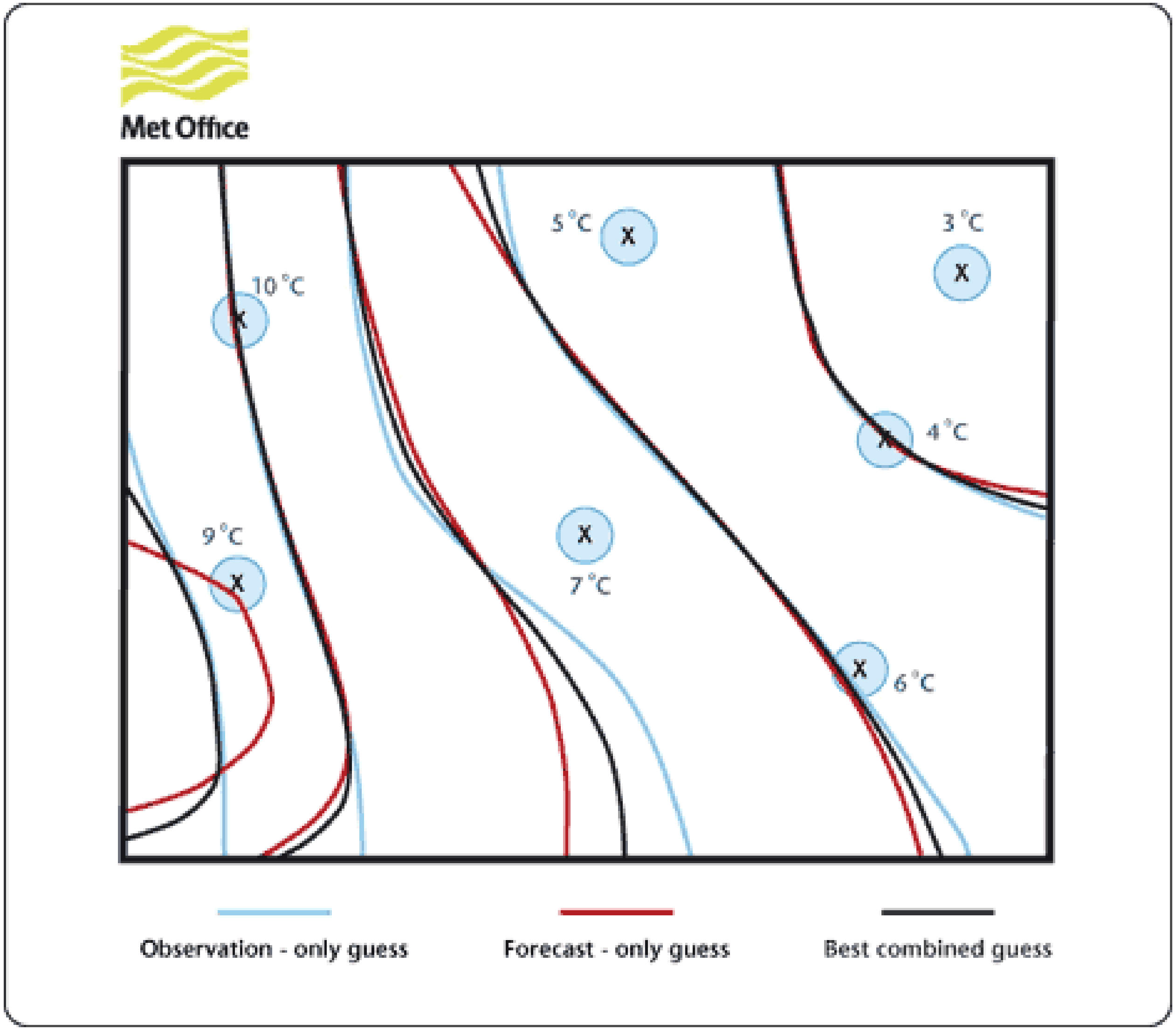
Source: Met Office

Introduction



Source: Met Office

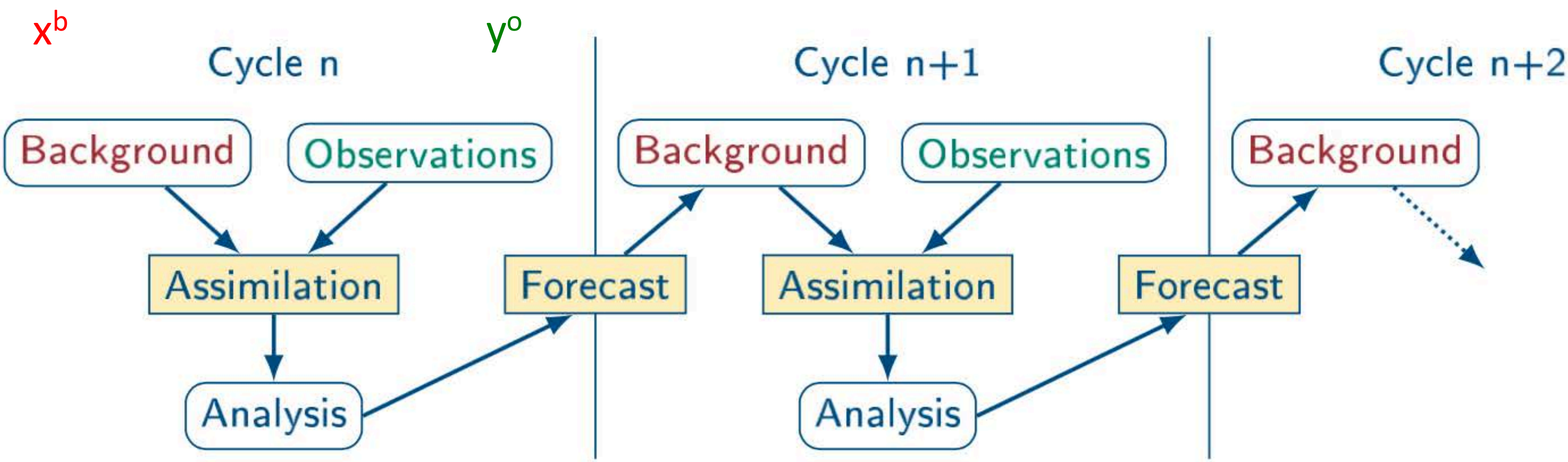
Introduction



Source: Met Office

Introduction

Data assimilation systems usually combine together information from a short term forecast, a set of observations and possibly other information to estimate the most probable state of atmosphere.



Courtesy: Ménétrier

Evolution of Data Assimilation

- Semi-empirical DA methods
  - Successive Correction Method (SCM: Cressman 1959)
  - Each observation is given a radius of influence with its weight varying with the distance to the model grid point
  - Relaxation functions are somewhat arbitrary
  - Noisy observations can create unphysical analysis

- Modern Data Assimilation (DA) = Kalman Filter algorithm

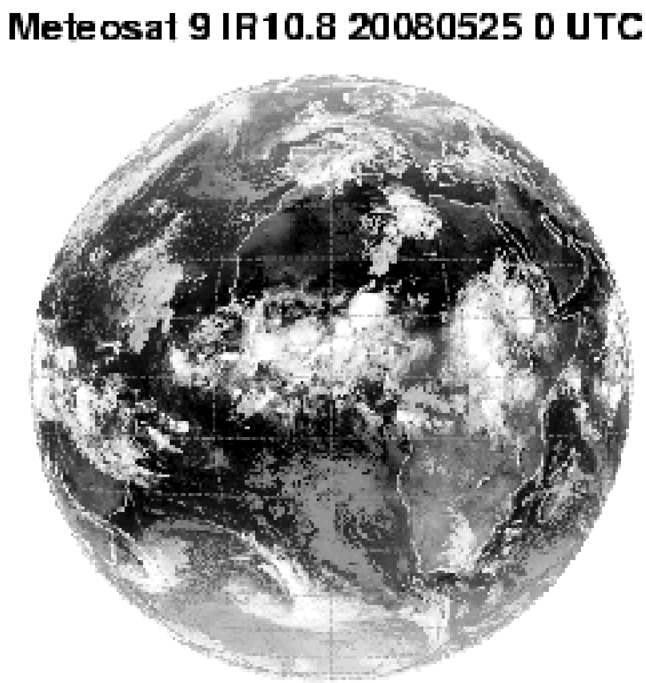
- *Notations*
  - *Observation operator* $\boldsymbol{H}: x \rightarrow y$

    (from model state to observation state)

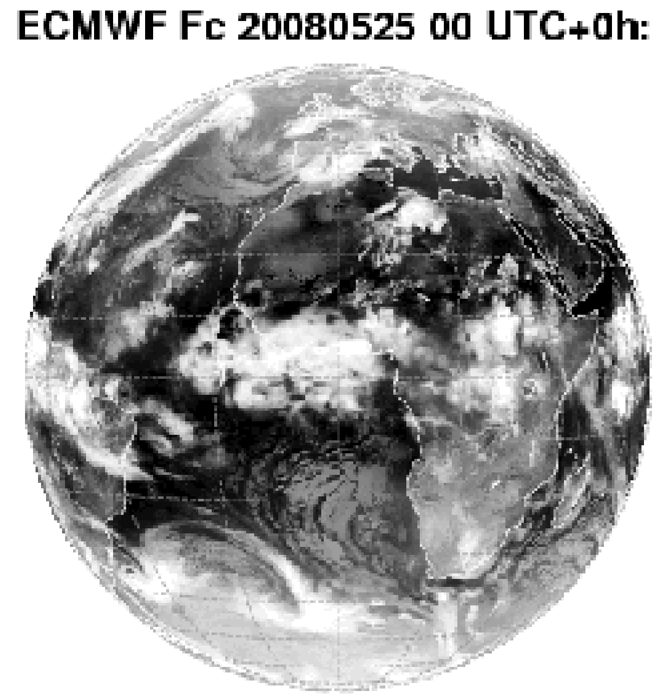
  - *Departure:* $d = y^o - \boldsymbol{H}x^b$

Major Milestones *(over-)simplified*

- 1990's: Variational DA and Assimilation of radiances
- 2000's: 4-dimensional DA algorithm (4DVar)
- 2010's: Variational Bias Correction and Ensemble Covariances

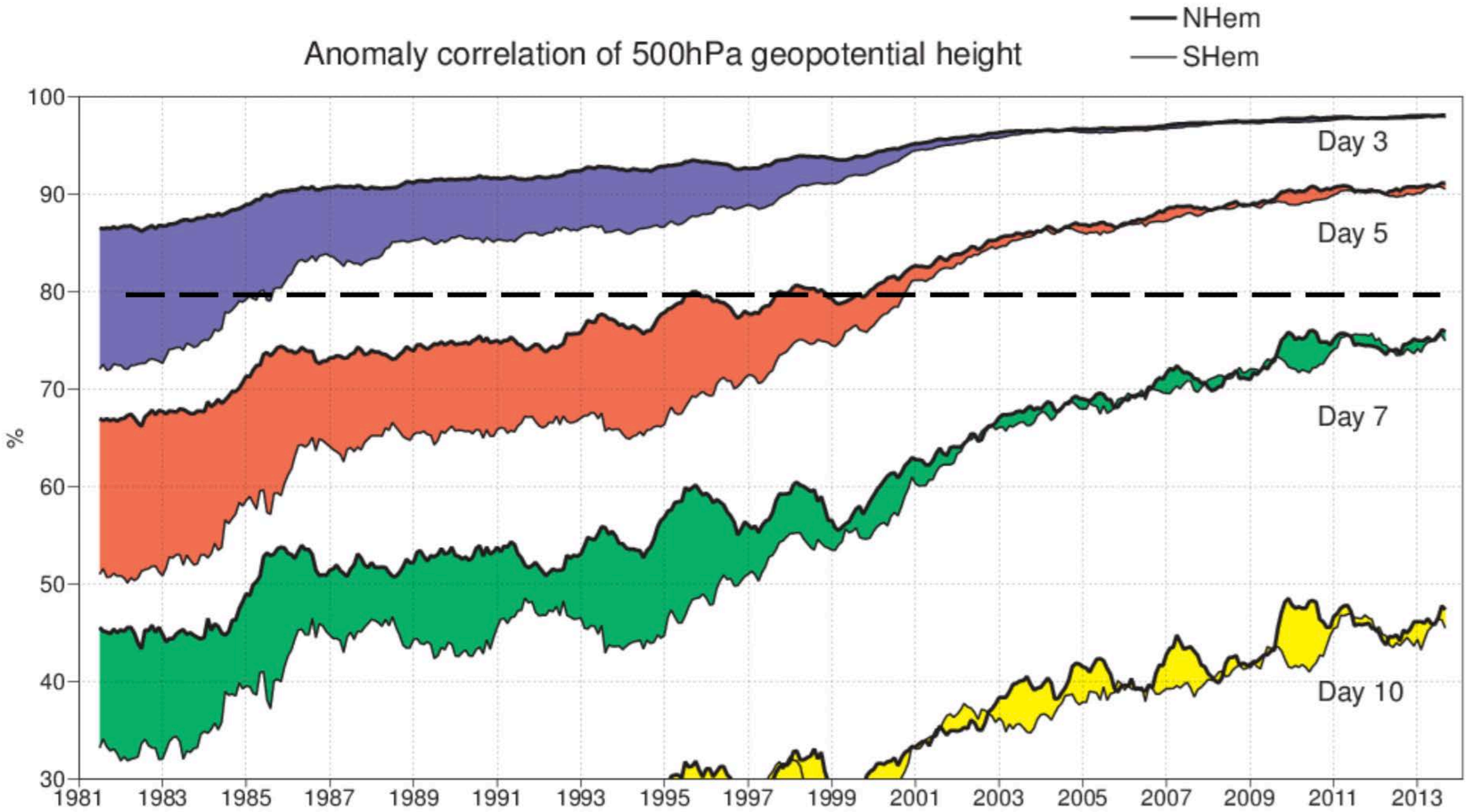


Observation: y^o



Model: $\mathbf{H}x^b$

Source: ECMWF



Source: ECMWF

- Skill improvement ~ 1d/decade
- Estimated socio-economic benefit of NWP >$75B/y

Source: Riishojgaard

Current Status of Satellite DA

Modern DA on a Paper Napkin

Hypotheses: Background and observation errors are uncorrelated, unbiased, normally distributed, with known covariances **B** and **R**

$$\mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T+\mathbf{R})^{-1}$$

- Kalman Filter analysis:

$$x^a = x^b + \mathbf{K}d \qquad \mathbf{A} = (\mathbf{I}-\mathbf{K}\mathbf{H})\mathbf{B}$$

- Model forecast:

$$x^b \leftarrow M(x^a) \qquad \mathbf{B} \leftarrow \mathbf{M}\mathbf{A}\mathbf{M}^T + \mathbf{Q}$$

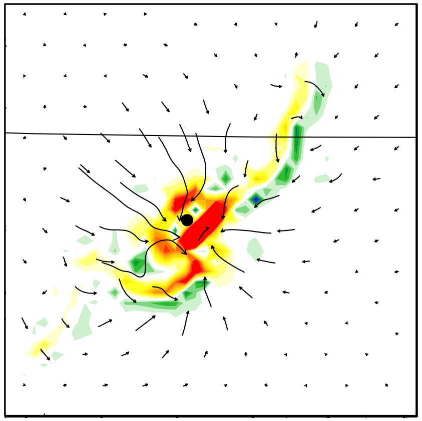
Background Error Covariance Modeling

- The *B* matrix spreads information between variables and imposes balance. Since it is the last operator in the analysis equation, the analysis increments lies in its subspace.

- We don't know the true state → cannot produce error samples

- We can infer proxies of background errors
  - from departures
  - from time-lagged forecasts
  - from ensemble perturbations

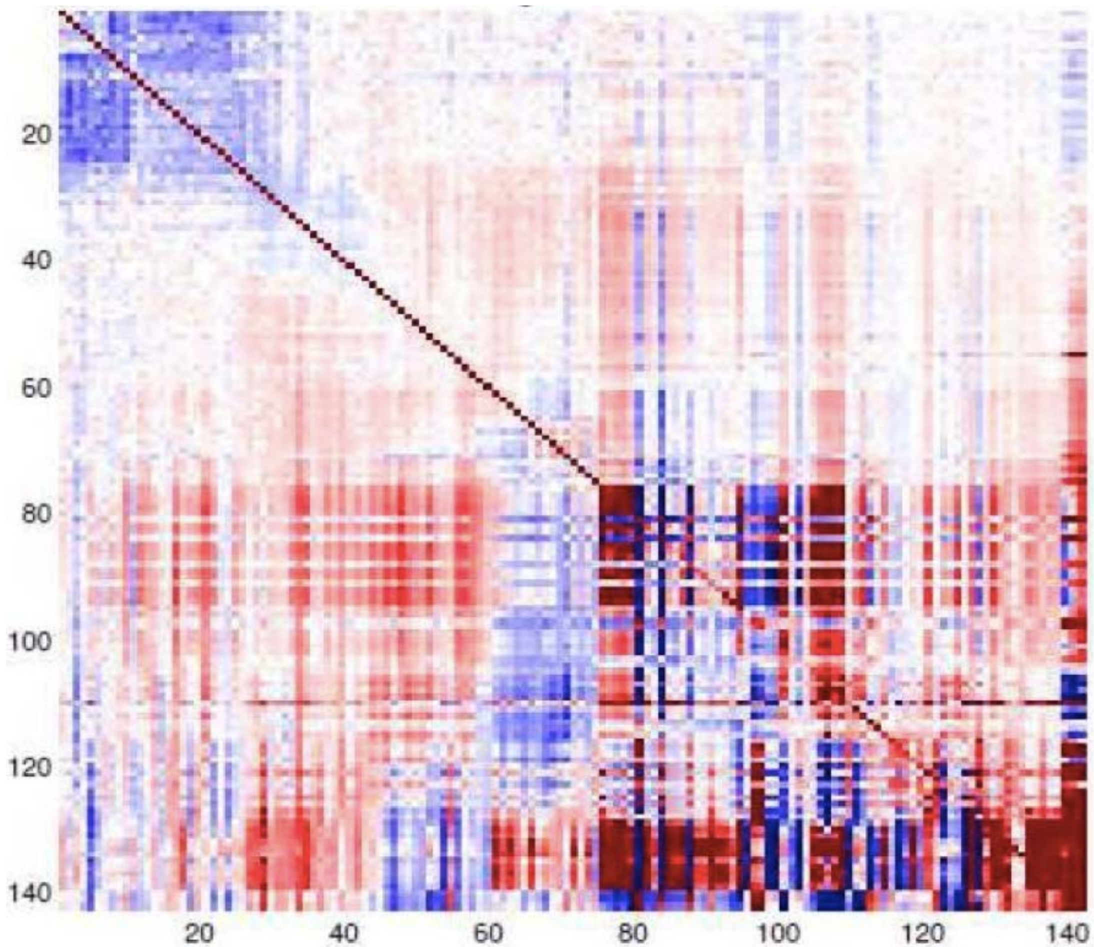
- Two "schools" to represent the B matrix:
  - Variational algorithms (3DVar, 4DVar, etc)
  - Ensemble Kalman Filter algorithms (EnKF, ETKF, etc)



Mini-4DVar (10min) *Wang, Sun, Zhang, Huang and Auligné (MWR 2013)*

Observation Error Covariances

AIRS Diagnostic R Matrix



Correlated errors
(esp. for moisture channels)

At least partly due to
representativeness error
(Waller et al. 2014)

Source: Weston (2011)

Current State of the Art

- Good estimates of the observational AND forecast error structure are necessary. Much of our effort is directed towards improving the specification of these error structures.

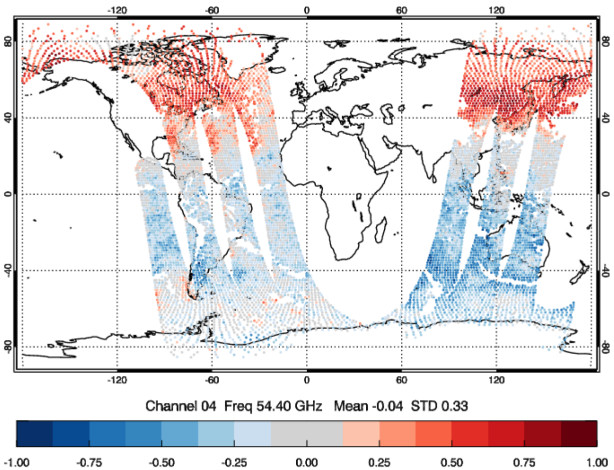
- In addition, determining the set of observations to use in an analysis is very important.
  – Quality control
  – Observation Operator (incl. CRTM)
  – Bias Correction

- Also, assimilation system must be efficient enough to complete in operational time window (~20 minutes for current global system).
  – Approximations necessary.

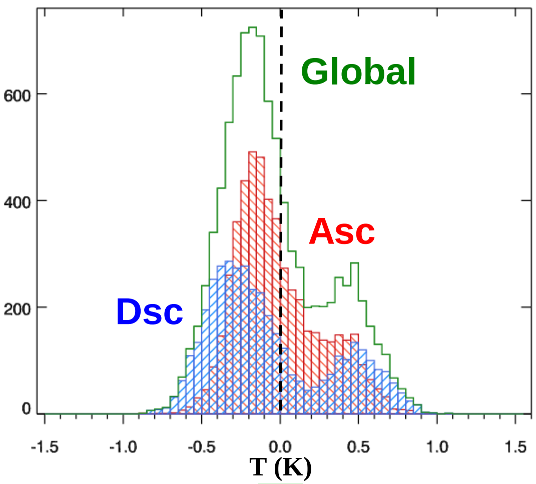
Application of NWP
Bias Correction for SSMIS F18

Using Met Office SSMIS Bias Correction Predictors

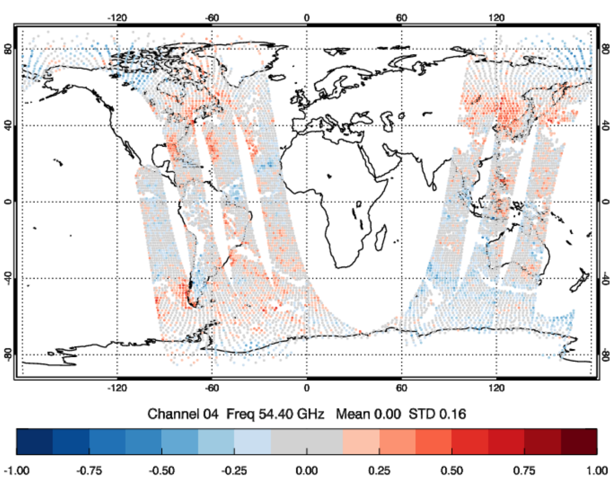
O-B Before Bias Correction



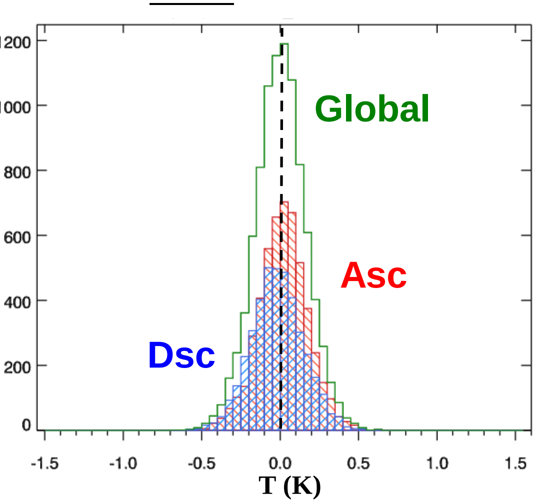
O-B Before Bias Correction

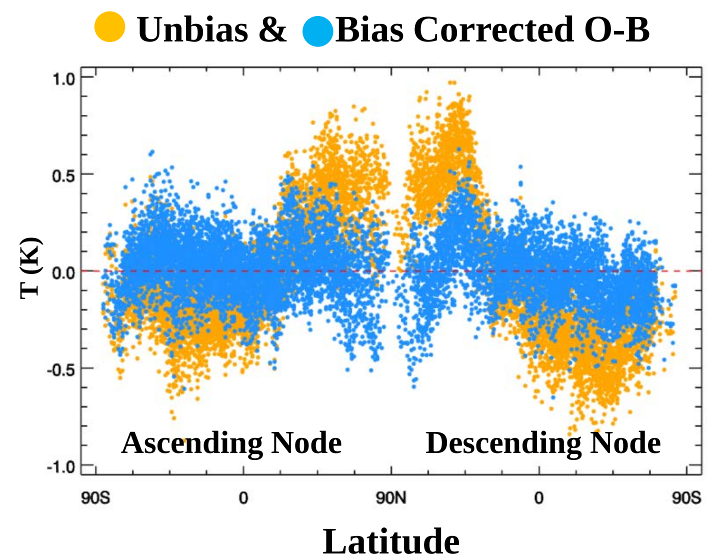


O-B After Bias Correction



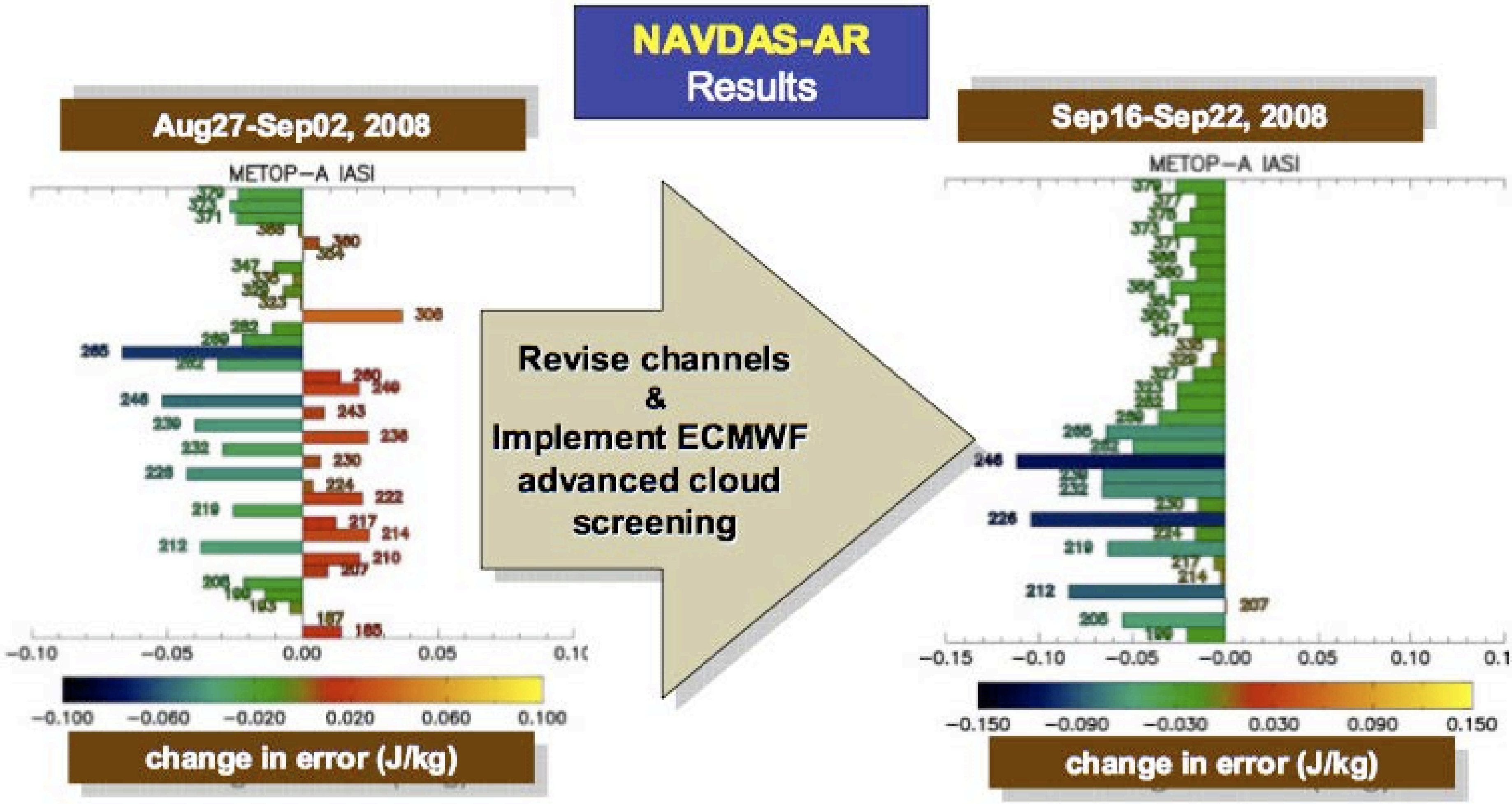
O-B After Bias Correction





Courtesy: Andrew Collard

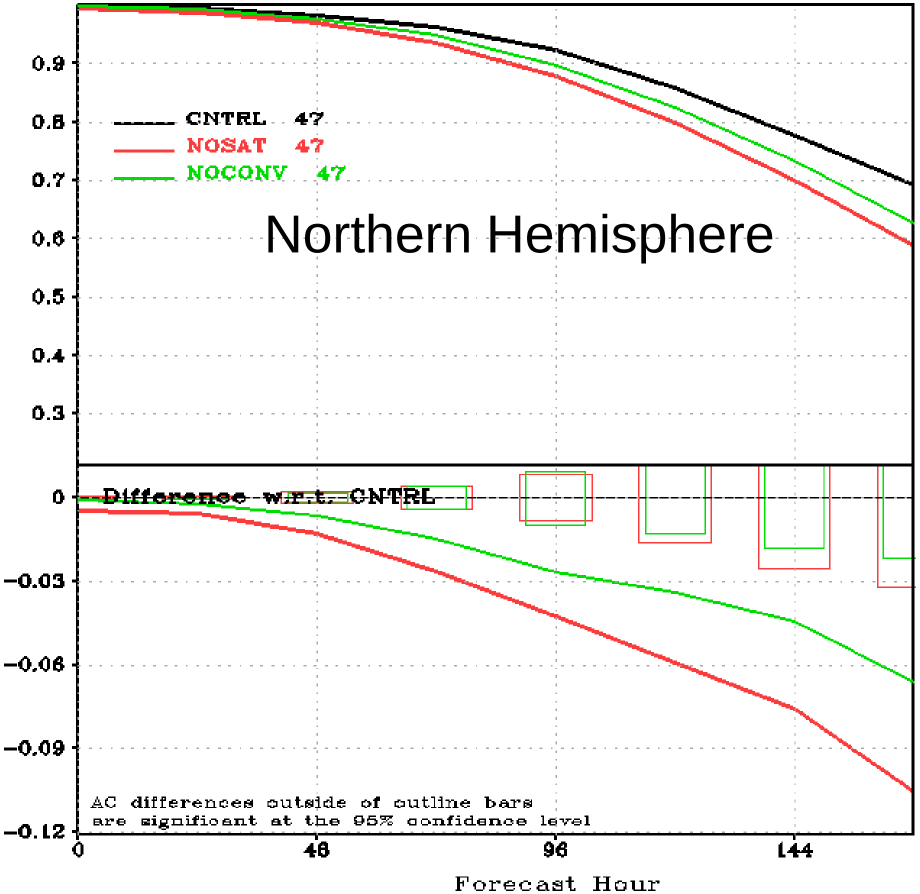
Forecast Sensitivity to Observation Impact

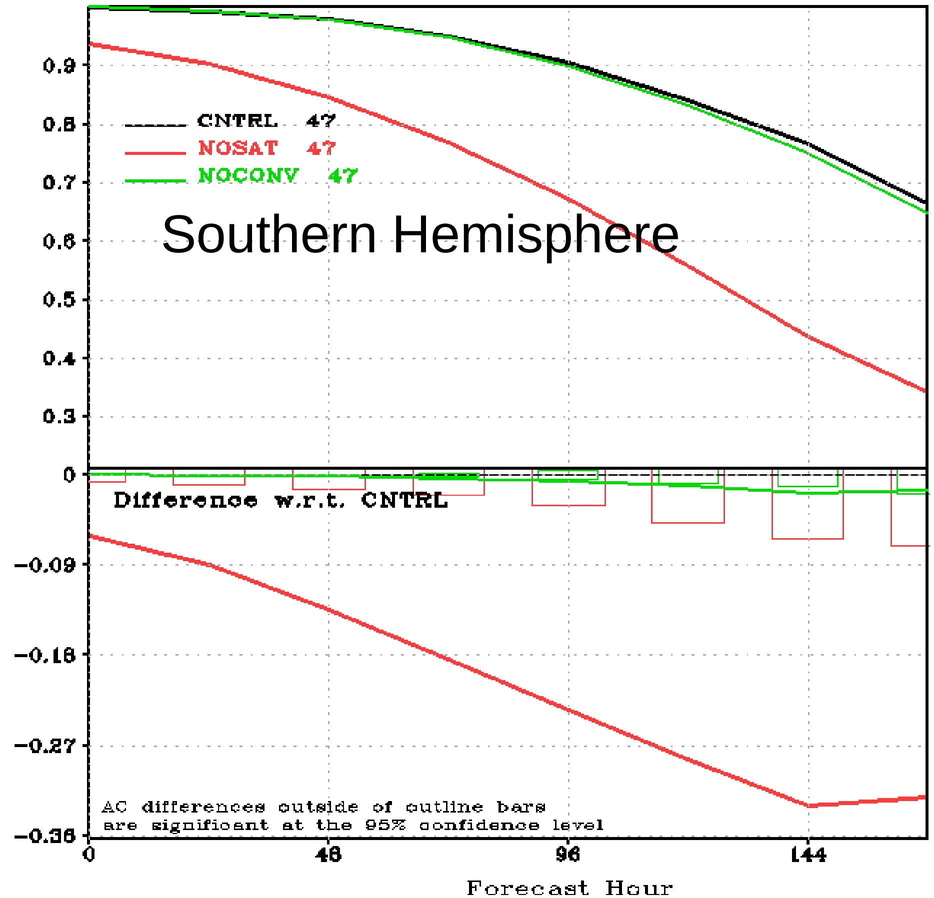


from Langland 2009

Satellite Data Crucial in NWP

No Satellite / No Conventional Data





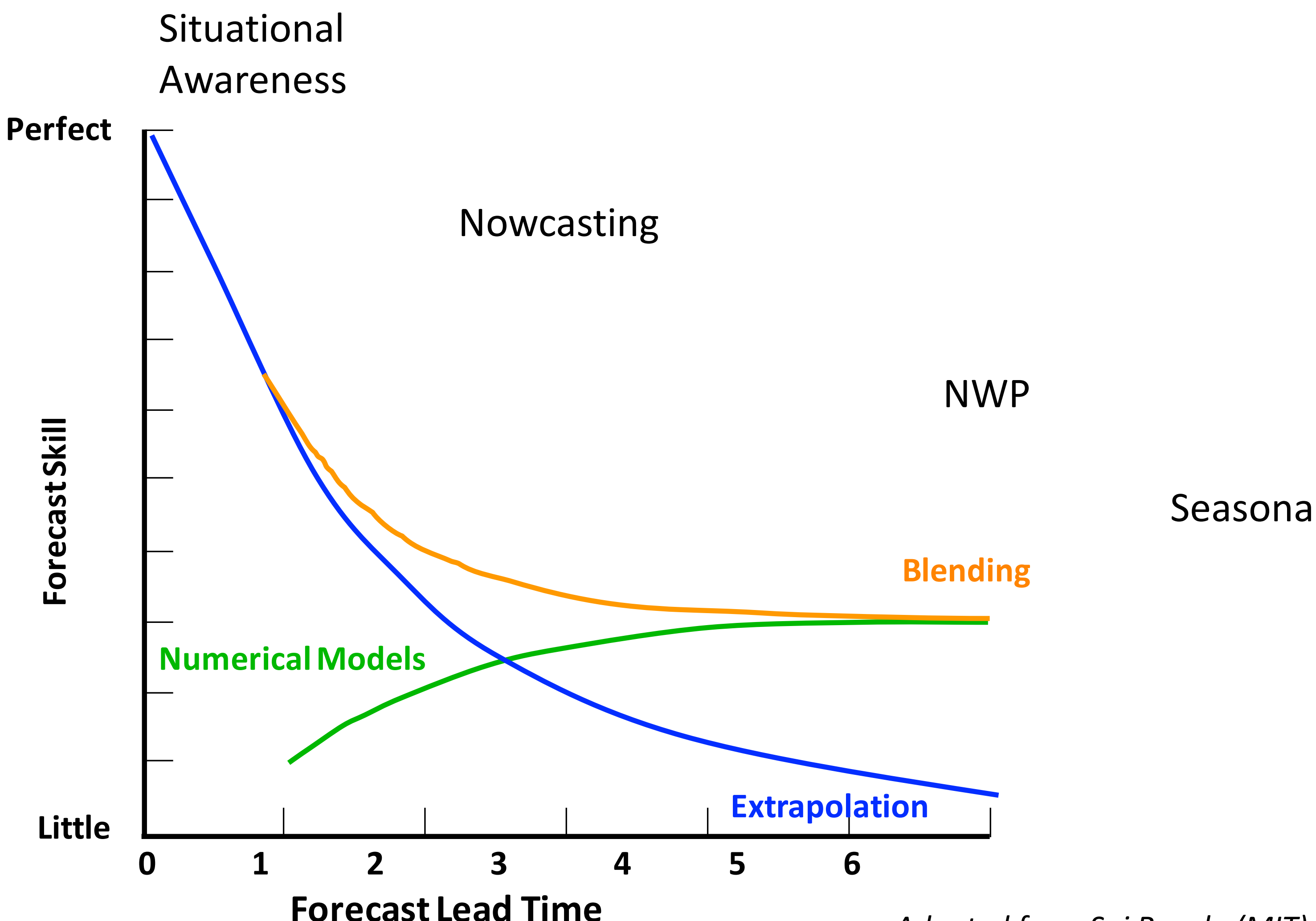
500 hPa Anomaly Correlations

15 Aug – 30 Sep 2010

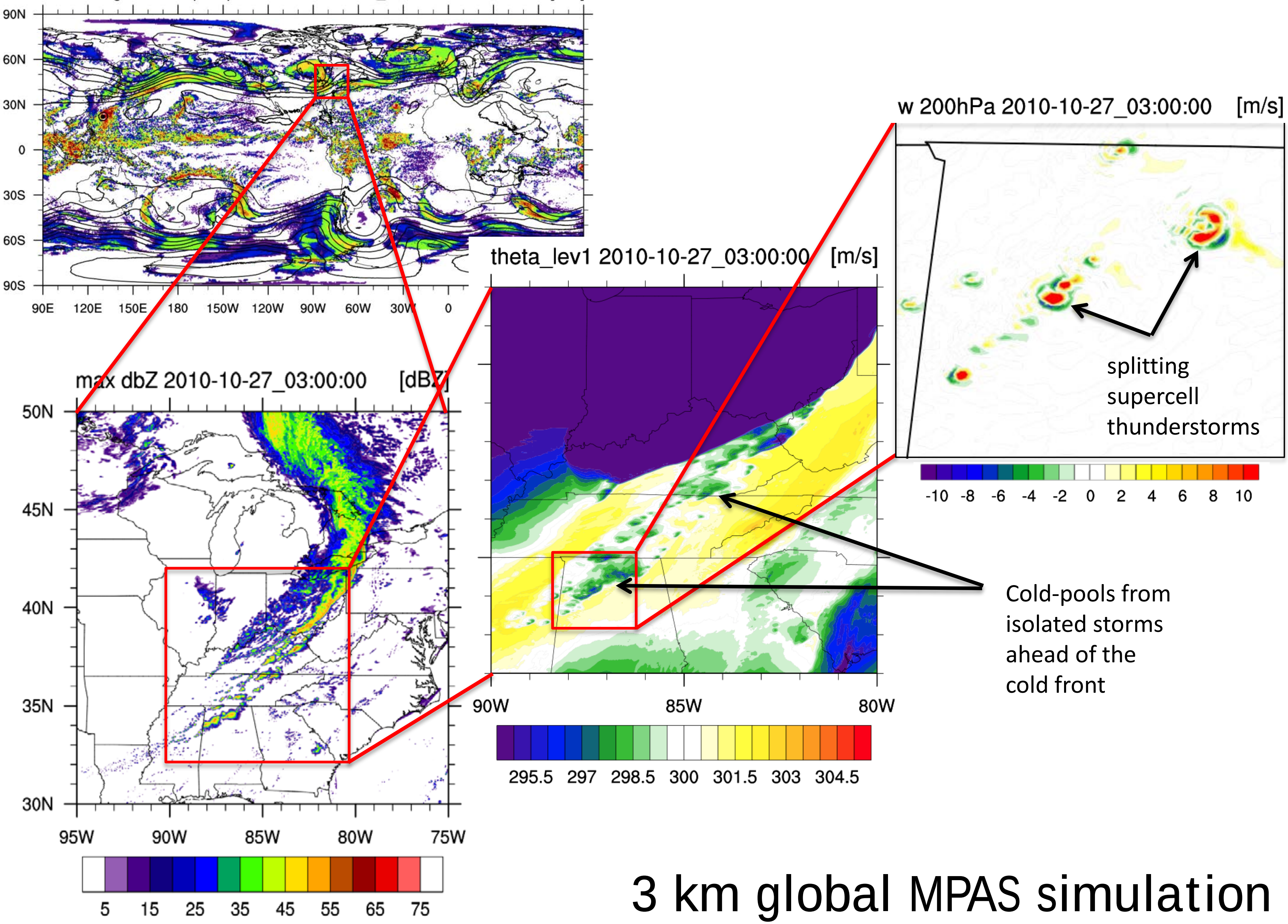
Source: Jung (2012)

Looking into the future

Multiple Converging Applications with DA



Adapted from Sai Ravela (MIT)



3 km global MPAS simulation

Source: Bill Skamarock

Data Fusion & Convective Scale DA

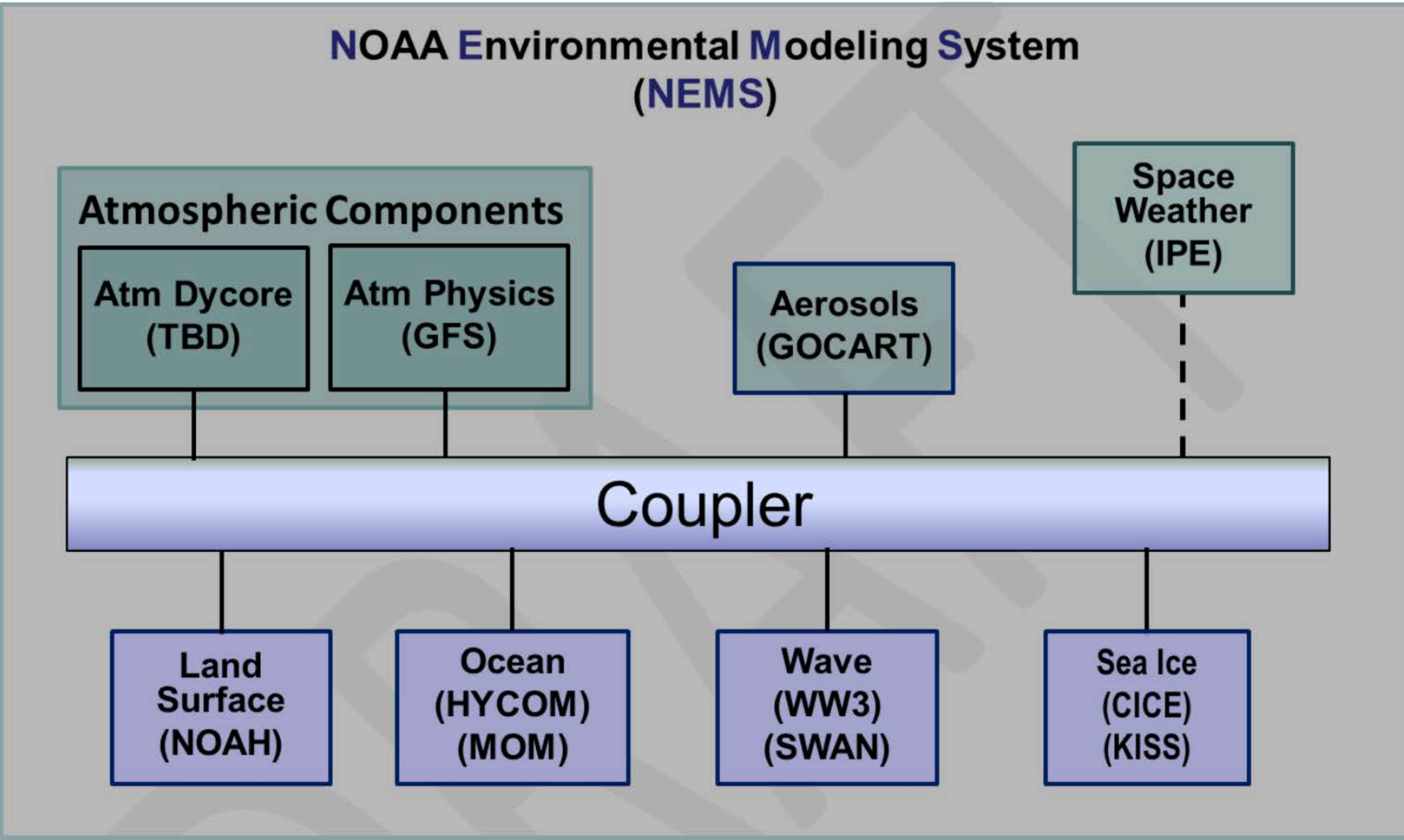
Smaller spatial and temporal scales

- More timely use of satellite data (short cut-off) → fight data latency
- Quick turnaround (4DVar penalized) → calculations off critical path
- Process data (tanking, QC, 1DVar, etc) on the fly
- Uncertainties and predictability (probabilistic forecasts)

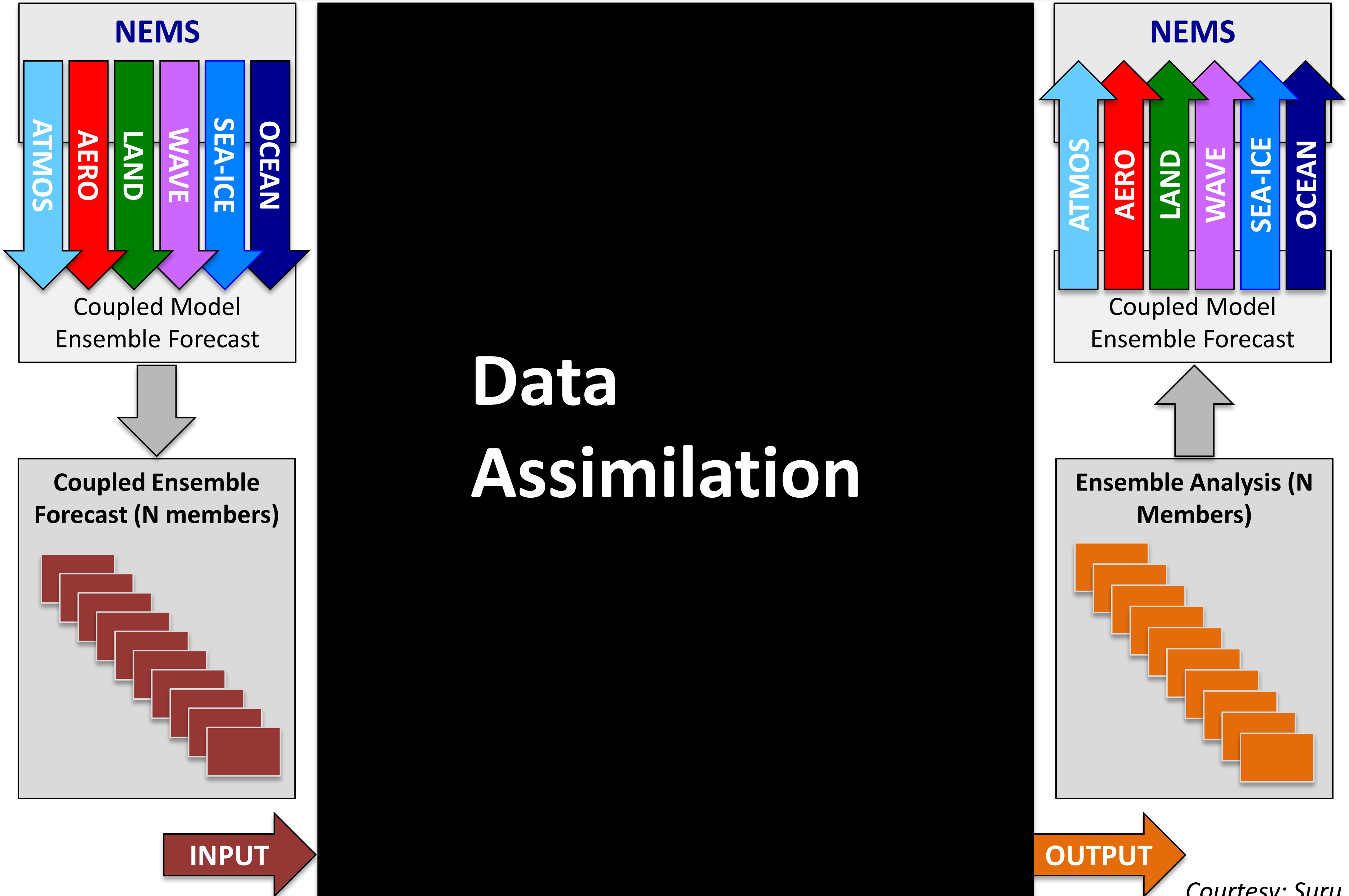
Cycling requirements

- **Wait** for valuable observations
- **Hurry** to get skillful forecast
- Rapid Update Cycling (hourly or sub-hourly) → Continuous DA

From NWP to Earth System Modeling



NCEP Coupled Hybrid Data Assimilation and Forecast System



Courtesy: Suru

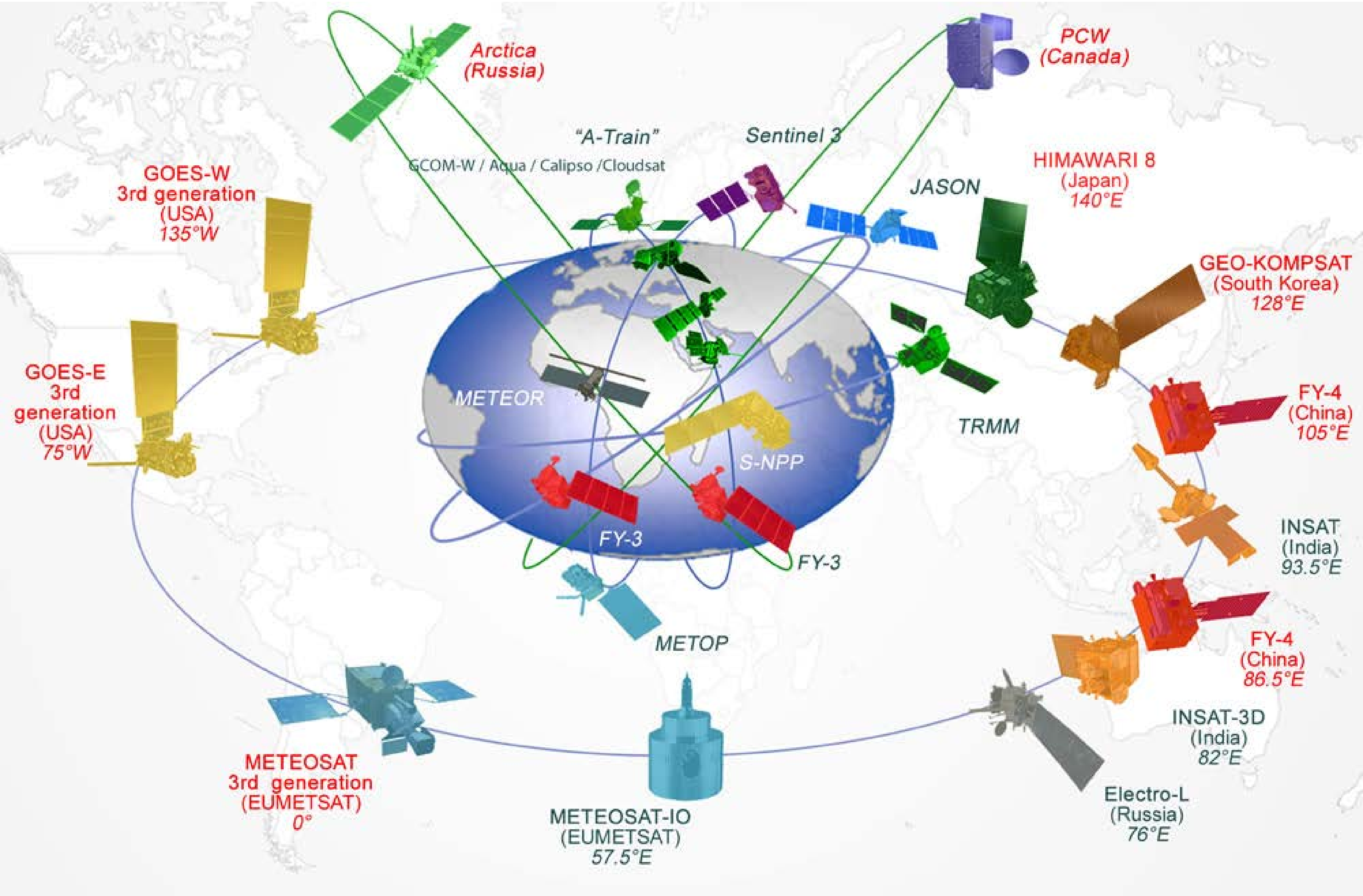
Major Trends in GSO

- An explosion of new sensors and data volume have occurred and will continue to occur in the near future

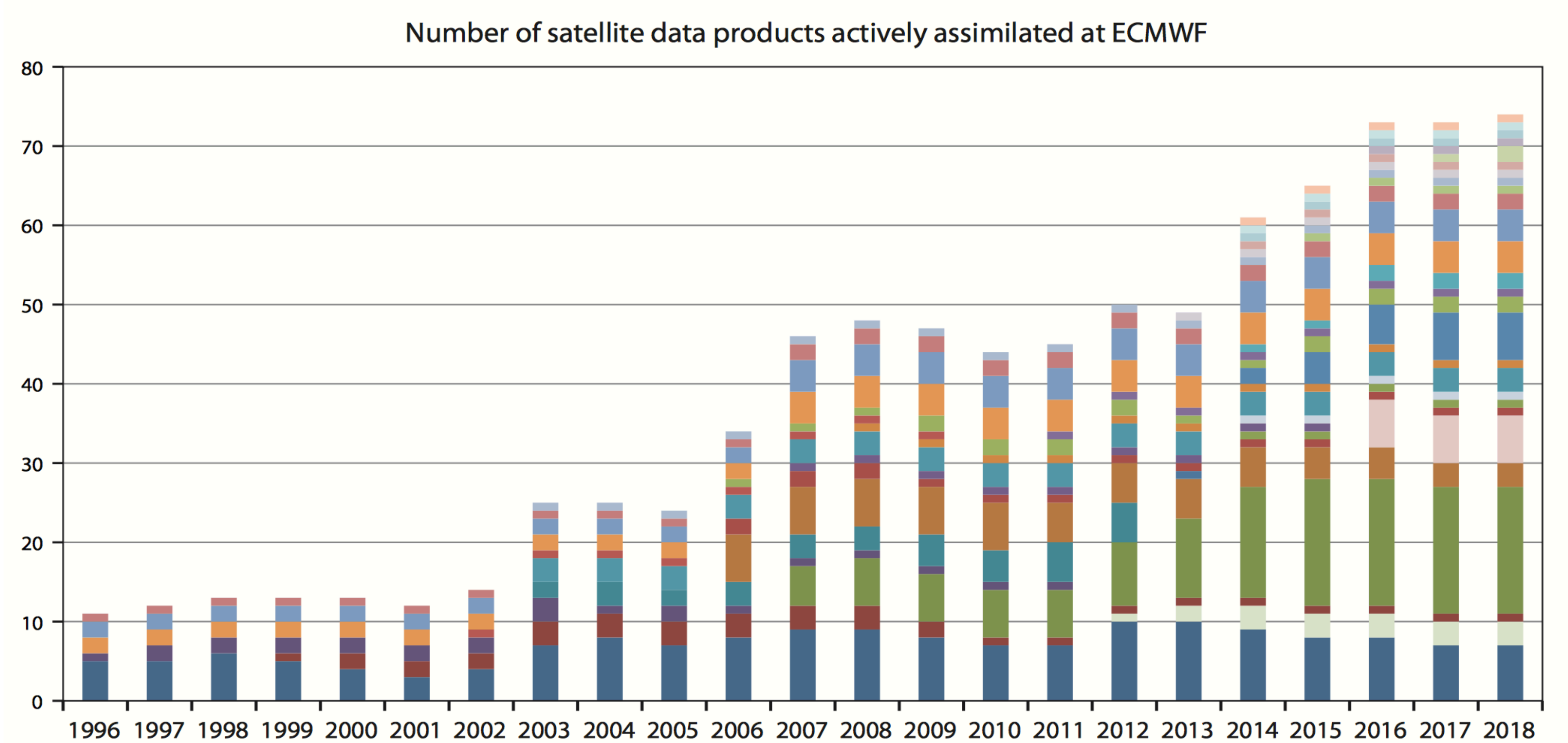
- New technologies are allowing more measurements (new) to be made, more frequently, better

- Overall, more nations are building and launching satellite-based Earth Observing sensors

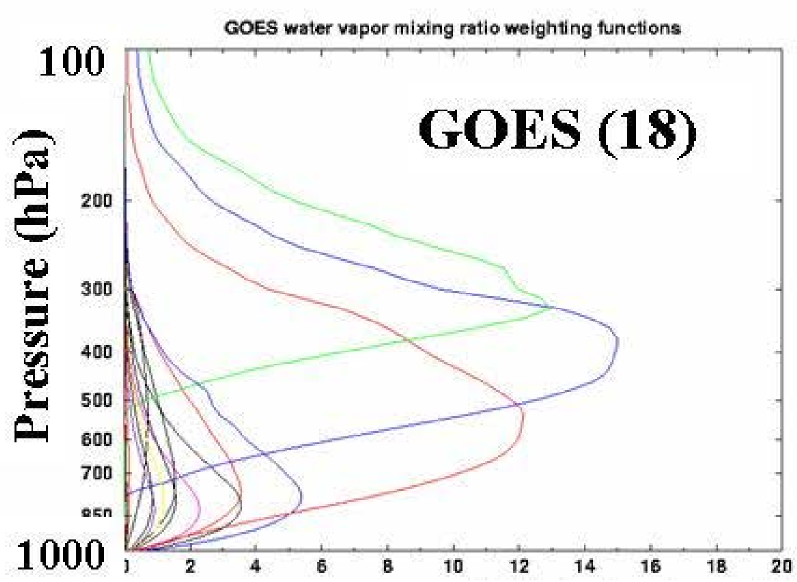
- Clearly be we might be in the middle of a golden era of satellite-based earth observation sensors



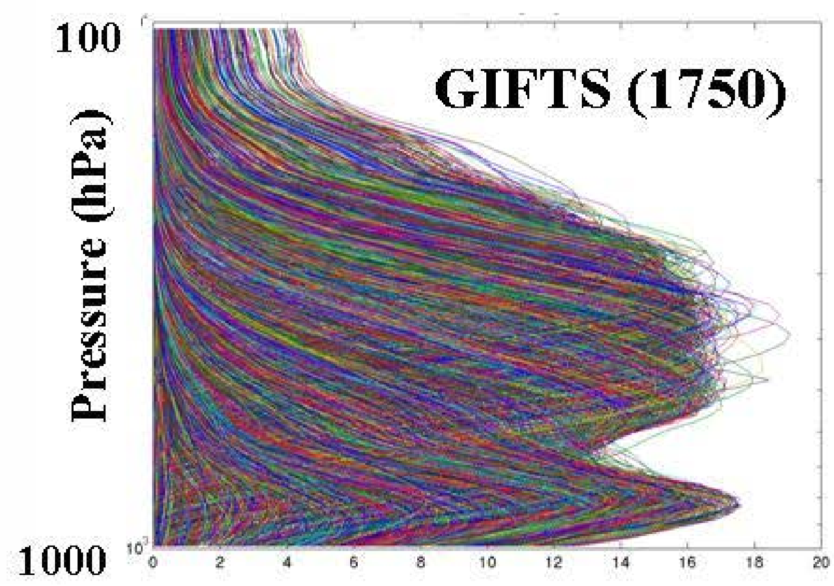
Arctica
(Russia)
PCW
(Canada)
"A-Train"
GCOM-W / Aqua / Calipso /Cloudsat
Sentinel 3
HIMAWARI 8
(Japan)
140°E
JASON
GOES-W
3rd generation
(USA)
135°W
GEO-KOMPSAT
(South Korea)
128°E
GOES-E
3rd
generation
(USA)
75°W
METEOR
TRMM
FY-4
(China)
105°E
S-NPP
FY-3
FY-3
INSAT
(India)
93.5°E
METOP
FY-4
(China)
86.5°E
INSAT-3D
(India)
82°E
METEOSAT
3rd generation
(EUMETSAT)
0°
METEOSAT-IO
(EUMETSAT)
57.5°E
Electro-L
(Russia)
76°E



Number of satellite data products actively assimilated at ECMWF
80
70
60
50
40
30
20
10
0
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018



GOES water vapor mixing ratio weighting functions
GOES (18)
Pressure (hPa)
100
200
300
400
500
600
700
1000
2
4
6
8
10
12
14
16
18
20

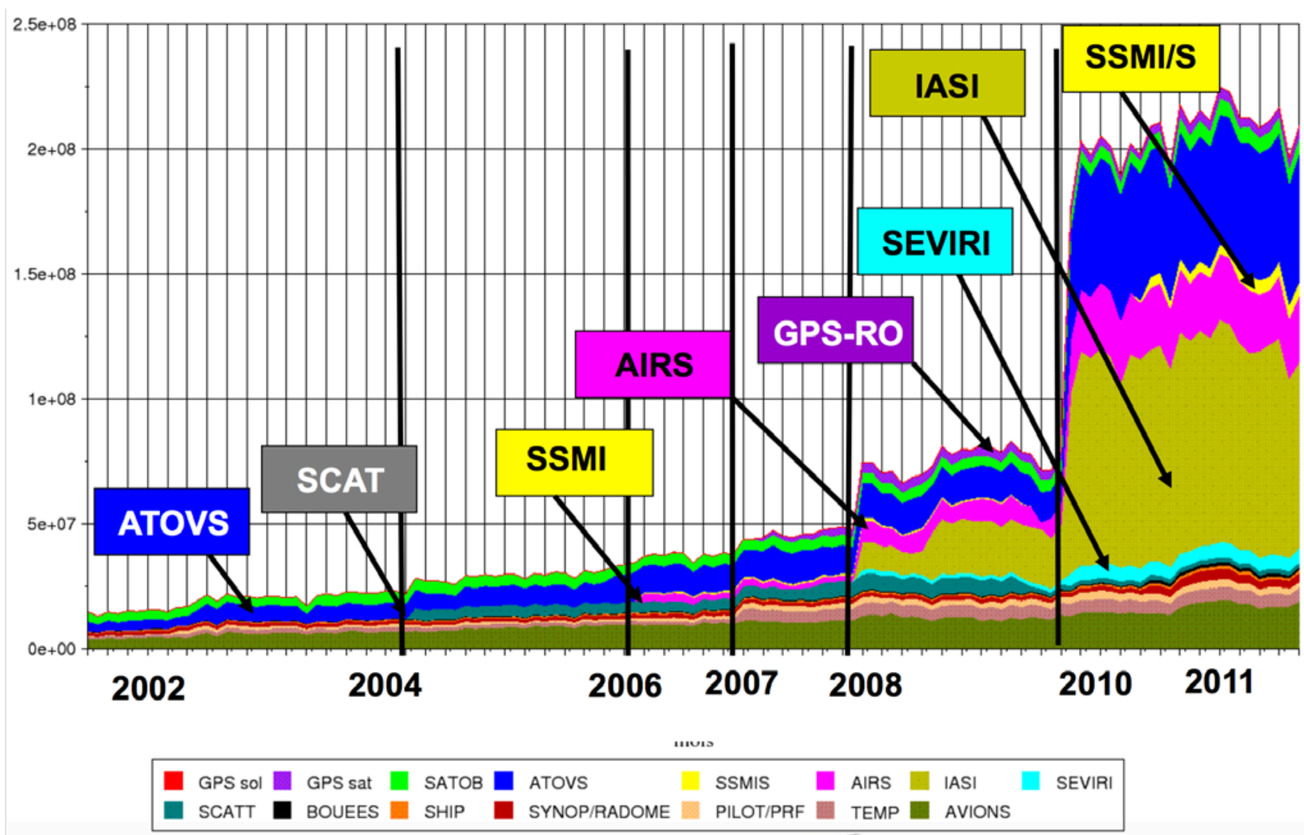


GIFTS (1750)
Pressure (hPa)
100
1000
0
2
4
6
8
10
12
14
16
18
20

"Big Data" Paradigm

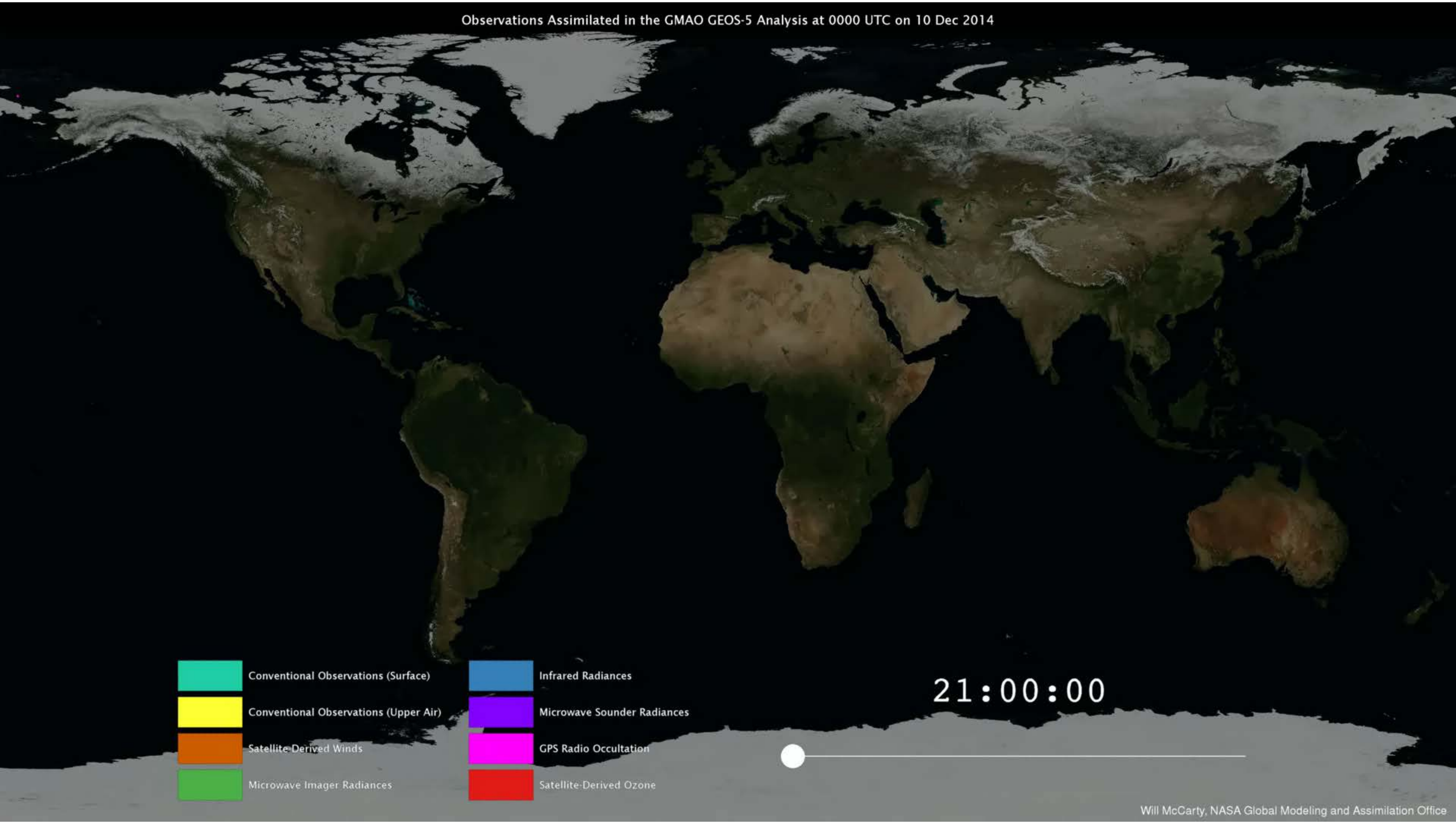
- Meteorology has faced massive data issues for some time
- Supercomputers do not compensate for time constraints
- Big data is good: robustness, anchoring via redundancy

- **Volume,**
- **Velocity,**
- **Variety,**
- **Variability,**
- **Complexity**



Source: Météo-France

Conclusion



Source: Will McCarty (NASA/GMAO)


Questions?