

中央氣象局全球資料同化系統

發展現況與未來規劃

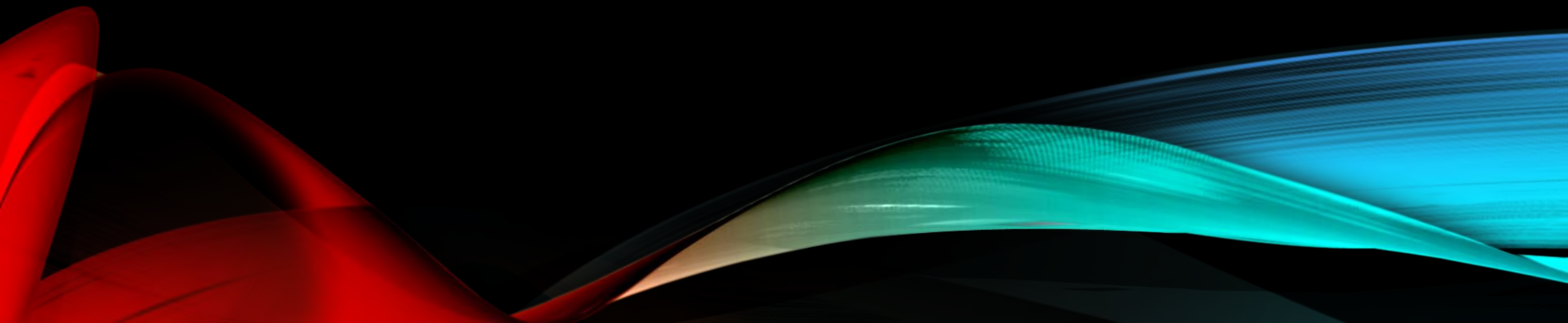
陳登舜、林宗翰、鄧雯心、趙子瑩、黃子茂

大綱

- 為何要做資料同化？
- 資料同化方法的發展
- 資料與同化
 - 資料
 - 種類
 - 傳統觀測、衛星觀測、掩星觀測、雷達觀測、氣膠觀測、臭氧觀測
 - 品質控管(Quality Control, QC)
 - 疏稀化(Thinning)
 - 同化
 - 變分同化(3DVar、4DVar)
 - 系集同化(EnKF、EnSRF、EAKF、ETKF、LETKF)
 - 混成同化(3DEnVar、4DEnVar、En4DVar、HG-EnDA)
- 中央氣象局全球資料同化系統
 - 全球預報系統
 - 資料同化系統
 - 觀測資料
 - 資料同化分組規劃

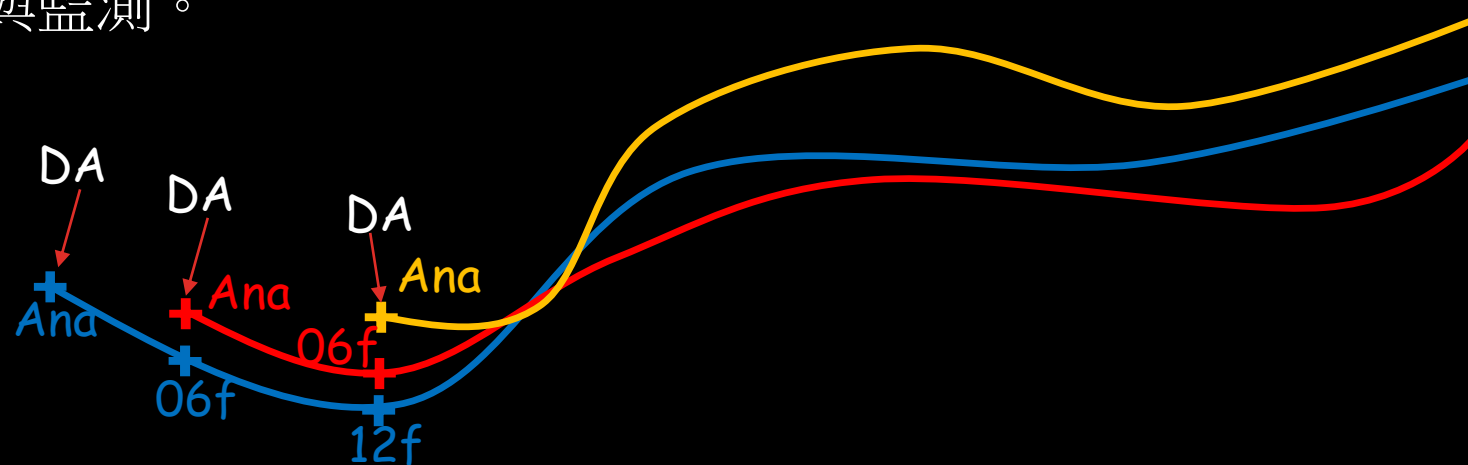
為何要做資料同化？

資料同化的功能？



資料同化的功能

- 透過觀測(y^o)與模式背景場(x^b)，提供最佳的模式初始條件(x^a)。
- 透過觀測算子(H)將模式背景場(x^b)投影至觀測空間，以分析與診斷模式誤差與偏差。
- 設計觀測系統與監測。
- 再分析。



模式十二小時預報誤差 = $12f - Ana$

分析與診斷模式誤差與偏差

背景觀測： $\mathbf{y}^b = \mathbf{H}(\mathbf{x}^b)$
(Bending angle)

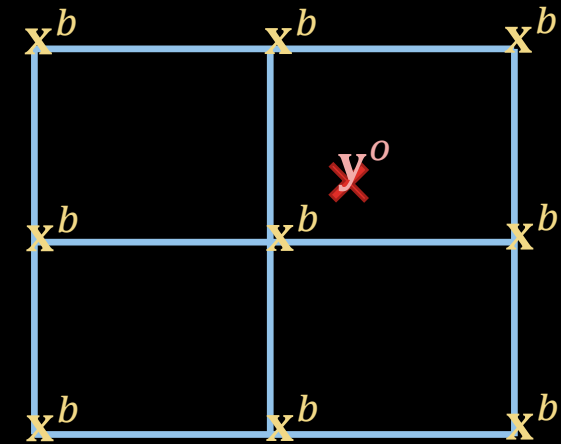
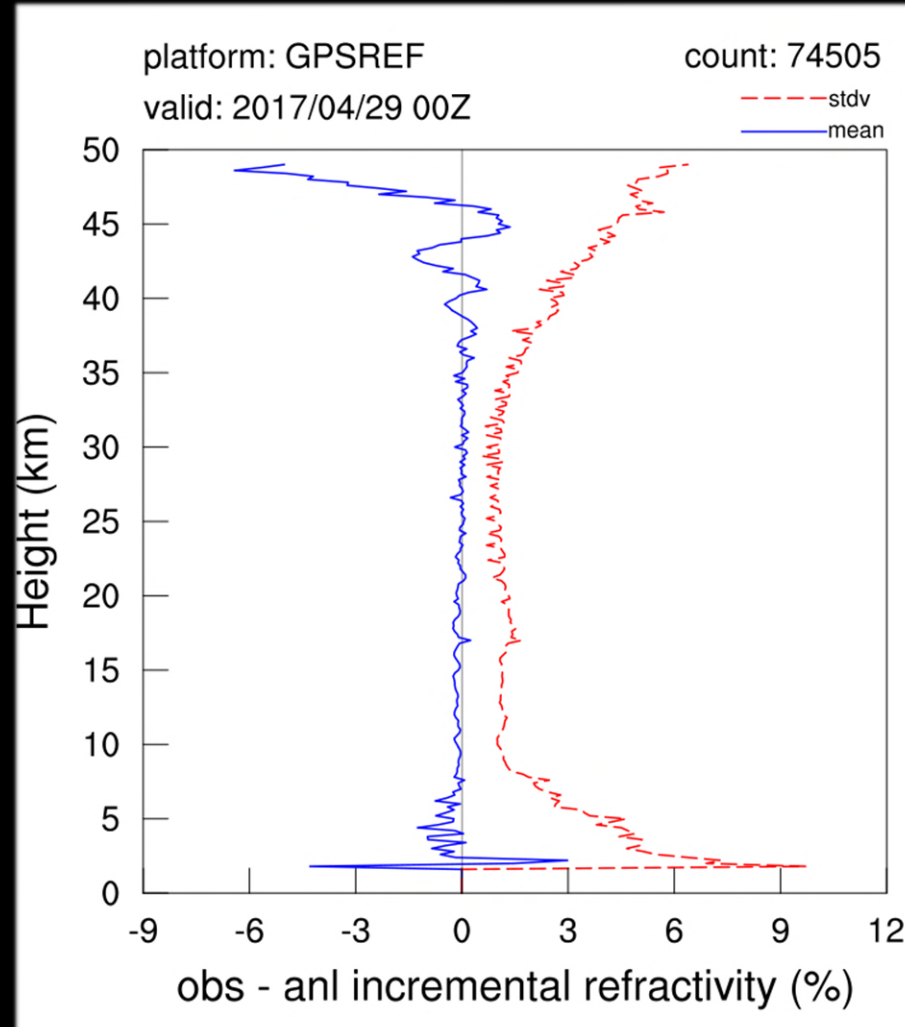
$$\text{O-B} : \boldsymbol{\sigma}^o = \mathbf{y}^o - \mathbf{y}^b$$

H : **GPSRO** 觀測算子

$$N = k_1 \left(\frac{P_d}{T} \right) Z_d^{-1} + k_2 \left(\frac{P_w}{T} \right) Z_w^{-1} + k_3 \left(\frac{P_w}{T^2} \right) Z_w^{-1}$$

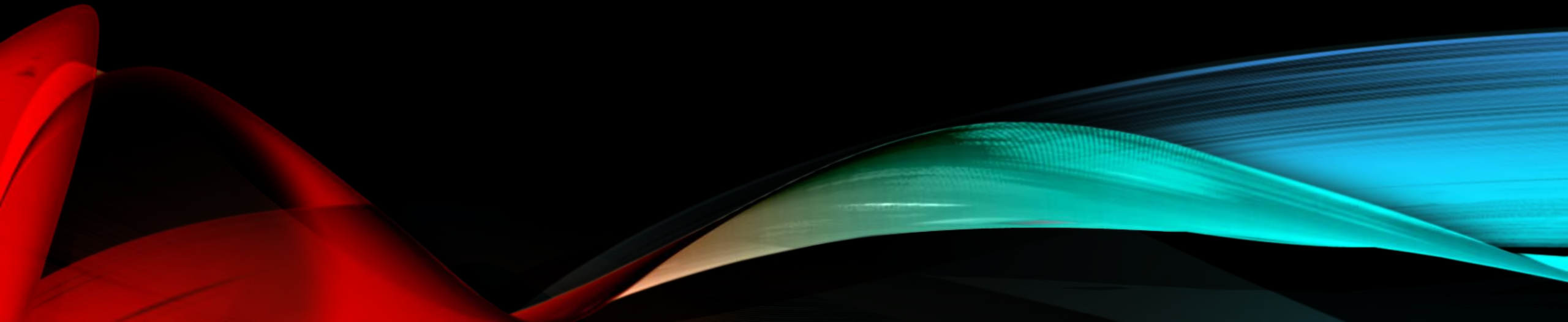
$$\alpha(a) = -2a \int_a^\infty \frac{d \ln n / dx}{(x^2 - a^2)^{1/2}} dx$$

$$x = nr, \quad N = (n - 1) \times 10^6$$



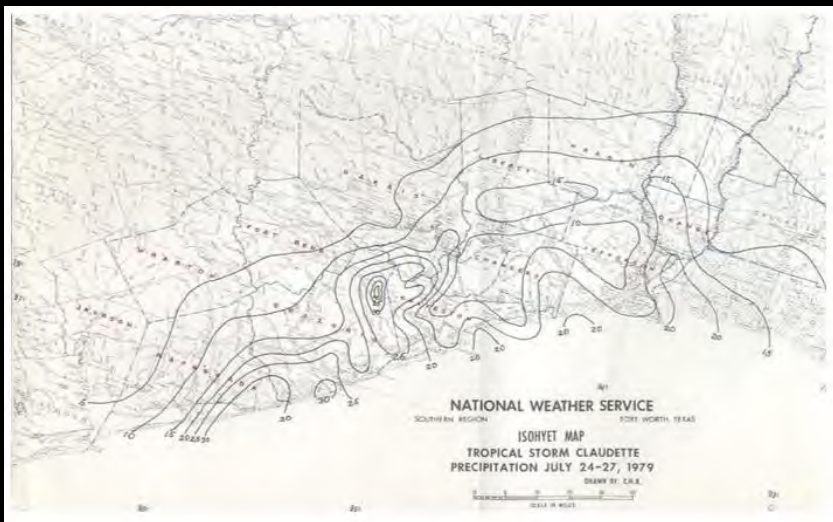
黃子茂 繪

資料同化的發展



資料分析與網格化方法

主觀分析
Subjective Analysis



客觀分析
Objective Analysis

$$\varphi(\mathbf{r}) = \varphi_b(\mathbf{r}) + \sum_{j=1}^{N_d} w_j d_j$$

資料同化
Data Assimilation

多變量
Multivariate

$$N = k_1 \left(\frac{P_d}{T} \right) Z_d^{-1} + k_2 \left(\frac{P_w}{T} \right) Z_w^{-1} + k_3 \left(\frac{P_w}{T^2} \right) Z_w^{-1}$$

模式平衡約束
Model Balance
Constraint

$$\mathbf{x}_c = \mathbf{C} \mathbf{x} = [\mathbf{I} + \mathbf{V} \mathbf{S} \mathbf{D} \mathbf{S}^{-1} \mathbf{V}^{-1} \mathbf{T}]^p \mathbf{x}$$

客觀分析

- 逐步訂正法 (Successive Corrections Methods, SCM)

$$f^{n+1} = f^n + \frac{\tilde{\omega}(r)}{\tilde{\omega}(r) + \varepsilon^2} [f^o - f^n], \quad \varepsilon^2 = \frac{E(\sigma_o^2)}{E(\sigma_b^2)}$$

- 納進/牛頓鬆弛法 (Nudging/Newtonian Relaxation Methods)

$$\frac{\partial u}{\partial t} = -v \cdot \nabla u + fv - \frac{\partial \phi}{\partial x} + \frac{u_{obs} - u}{\tau_u}$$

- 最小平方法 (Least-squares methods/BBLUE)

$$X_a = \alpha X_b + \beta X_o, \quad \alpha = 1 - \beta,$$

$$\text{minimize}[E(\sigma_a^2)] \Rightarrow \alpha = \frac{E(\sigma_o^2)}{E(\sigma_b^2) + E(\sigma_o^2)}, \beta = \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)}$$

逐步訂正法 (SCM)

$$f^{n+1} = f^n + \frac{\tilde{\omega}(r)}{\tilde{\omega}(r) + \varepsilon^2} [f^o - f^n]$$

Cressman method (1959)

$$\begin{aligned}\tilde{\omega}(r) &= \frac{R^2 - r^2}{R^2 + r^2} & \text{for } r < R \\ &= 0 & \text{for } r \geq R\end{aligned}$$

Barnes method (1964)

$$\tilde{\omega}(d) = e^{-\frac{d^2}{2R^2}}$$

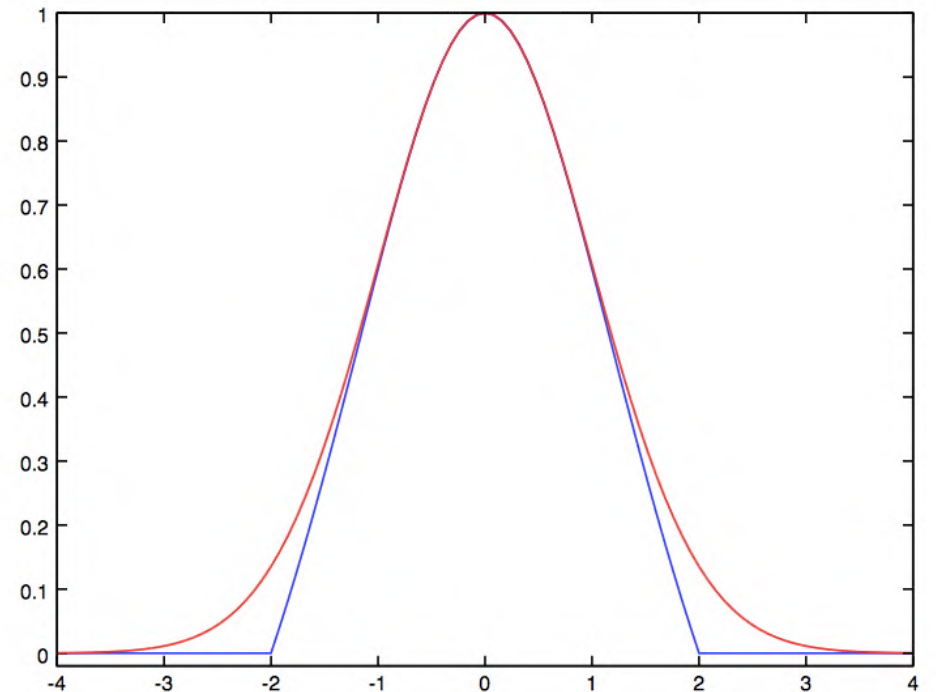


Figure 1.7: Cressman weights for $R = 2$ (blue) and Barnes weights for $R = 1$ (red).

CRESSMAN V.S BARNES

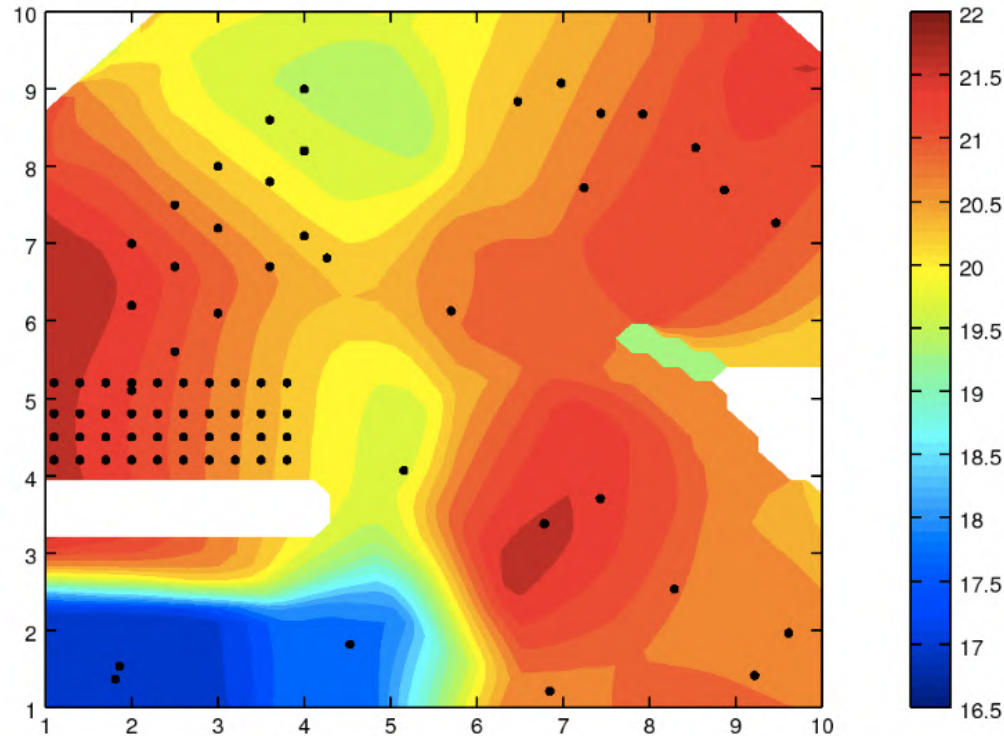


Figure 1.8: Gridded field by Cressman weighting

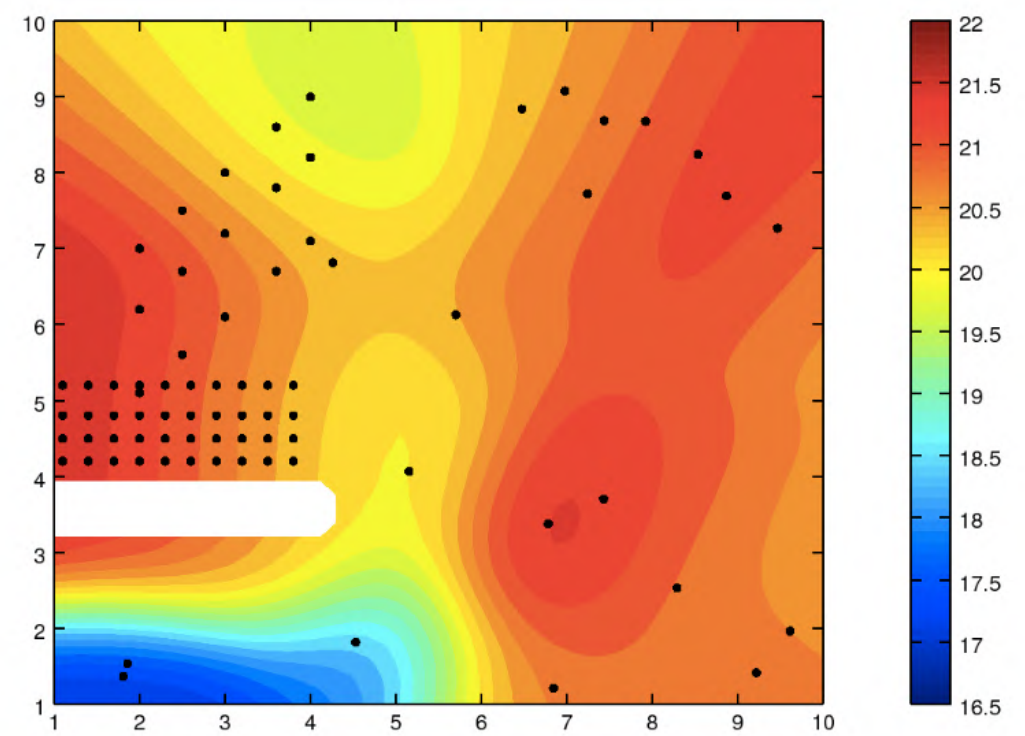


Figure 1.9: Gridded field using Barnes weights

BLUE(BEST LINEAR UNBIASED ESTIMATION)

0-dimension example

- The optimal interpolation (OI) scheme can be derived as the Best Linear Unbiased Estimator (BLUE)

$$X_a = \alpha X_b + \beta X_o, \quad \alpha = 1 - \beta$$
$$= X_b + \beta(X_o - X_b)$$

Linear

$$\sigma_a = X_t - X_a$$
$$= X_t - \alpha X_b - \beta X_o$$
$$= \alpha(X_t - X_b) + \beta(X_t - X_o)$$
$$= \alpha\sigma_b + \beta\sigma_o$$

$$\sigma_a^2 = (X_t - X_a)(X_t - X_a)$$
$$= [\alpha\sigma_b + \beta\sigma_o][\alpha\sigma_b + \beta\sigma_o]$$
$$= \alpha^2\sigma_b^2 + \beta^2\sigma_o^2 + 2\alpha\beta\sigma_b\sigma_o$$

$$\sigma_b = X_t - X_b, \quad \sigma_o = X_t - X_o, \quad E(P) = \sum_{k=1}^K \frac{1}{K} P_k$$

$$E(\sigma_a^2) = E(\alpha^2\sigma_b^2 + \beta^2\sigma_o^2 + 2\alpha\beta\sigma_b\sigma_o)$$
$$= \alpha^2E(\sigma_b^2) + \beta^2E(\sigma_o^2) + 2\alpha\beta E(\sigma_b\sigma_o)$$

Assume $E(\sigma_b\sigma_o) = 0$, $E(\sigma) = 0$

$$E(\sigma_a^2) = \alpha^2E(\sigma_b^2) + \beta^2E(\sigma_o^2)$$

Unbiased

$$\text{minimize}[E(\sigma_a^2)] \Rightarrow \alpha = \frac{E(\sigma_o^2)}{E(\sigma_b^2) + E(\sigma_o^2)}, \beta = \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)}$$

Best

$$X_a = \frac{E(\sigma_o^2)}{E(\sigma_b^2) + E(\sigma_o^2)} X_b + \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)} X_o$$

KALMAN FILTER V.S. VARIATIONAL OPTIMIZATION

Kalman Filter(minimum variance)

分析更新

$$X_a = X_b + \beta(X_o - X_b), \quad \beta = \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)}$$

誤差斜方差更新

$$\begin{aligned} E(\sigma_a^2) &= \alpha^2 E(\sigma_b^2) + \beta^2 E(\sigma_o^2) \\ &= \left(\frac{E(\sigma_o^2)}{E(\sigma_b^2) + E(\sigma_o^2)} \right)^2 E(\sigma_b^2) + \left(\frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)} \right)^2 E(\sigma_o^2) \\ &= \frac{E(\sigma_o^2)^2 E(\sigma_b^2) + E(\sigma_b^2)^2 E(\sigma_o^2)}{(E(\sigma_b^2) + E(\sigma_o^2))^2} \\ &= \frac{E(\sigma_o^2) E(\sigma_b^2) [E(\sigma_o^2) + E(\sigma_b^2)]}{(E(\sigma_b^2) + E(\sigma_o^2))^2} \\ &= \frac{E(\sigma_o^2) E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)} = (1 - \beta) E(\sigma_b^2) \end{aligned}$$

Variational(maximum likelihood)

$$\begin{aligned} J(X_a) &= (X_a - X_b) E(\sigma_b^2)^{-1} (X_a - X_b) + (X_a - X_o) E(\sigma_o^2)^{-1} (X_a - X_o) \\ \text{Minimize } J &\Rightarrow \frac{\partial J}{\partial X_a} = E(\sigma_b^2)^{-1} (X_a - X_b) + E(\sigma_o^2)^{-1} (X_a - X_o) = 0 \end{aligned}$$

$$\begin{aligned} X_a &= \frac{E(\sigma_b^2)^{-1} X_b + E(\sigma_o^2)^{-1} X_o}{E(\sigma_b^2)^{-1} + E(\sigma_o^2)^{-1}} \\ &= \frac{E(\sigma_b^2)^{-1} X_b + E(\sigma_o^2)^{-1} X_b + E(\sigma_o^2)^{-1} X_o - E(\sigma_o^2)^{-1} X_b}{E(\sigma_b^2)^{-1} + E(\sigma_o^2)^{-1}} \\ &= X_b + \frac{E(\sigma_o^2)^{-1} (X_o - X_b)}{E(\sigma_b^2)^{-1} + E(\sigma_o^2)^{-1}} \\ &= X_b + \frac{E(\sigma_o^2)^{-1} (X_o - X_b)}{E(\sigma_b^2)^{-1} + E(\sigma_o^2)^{-1}} \times \frac{E(\sigma_b^2) E(\sigma_o^2)}{E(\sigma_b^2) E(\sigma_o^2)} \\ &= X_b + \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)} (X_o - X_b) \\ X_a &= X_b + \beta (X_o - X_b) \end{aligned}$$

Background

Analysis

Weights

Observation

代價函數

$$\text{Likelihood of } X_t \text{ given } X_b: \frac{1}{\sqrt{2\pi}\sigma_b} \exp \left[-\frac{(X_t - X_b)^2}{2\sigma_b^2} \right]$$

$$\text{Likelihood of } X_t \text{ given } X_o: \frac{1}{\sqrt{2\pi}\sigma_o} \exp \left[-\frac{(X_t - X_o)^2}{2\sigma_o^2} \right]$$

$$\text{Joint Likelihood of } X_t: P = \frac{1}{2\pi\sigma_b\sigma_o} \exp \left[-\frac{(X_t - X_o)^2}{2\sigma_o^2} - \frac{(X_t - X_b)^2}{2\sigma_b^2} \right]$$

$$\text{To get } X_a, \quad \text{let } \max[P] \Rightarrow \min \left[\frac{(X_a - X_o)^2}{2\sigma_o^2} + \frac{(X_a - X_b)^2}{2\sigma_b^2} \right] = \min[J(X_a)]$$

$$J(X_a) = (X_a - X_b)E(\sigma_b^2)^{-1}(X_a - X_b) + (X_a - X_o)E(\sigma_o^2)^{-1}(X_a - X_o)$$

multivariate

$$J(X_a) = (X_a - X_b)E(\sigma_b^2)^{-1}(X_a - X_b) + (H(X_a) - y_o)E(\sigma_o^2)^{-1}(H(X_a) - y_o)$$

3DVar

$$J(\mathbf{x}_a) = (\mathbf{x}_a - \mathbf{x}_b)\mathbf{B}^{-1}(\mathbf{x}_a - \mathbf{x}_b)^T + [H(\mathbf{x}_a) - \mathbf{y}_o]\mathbf{R}^{-1}[H(\mathbf{x}_a) - \mathbf{y}_o]^T$$

資料同化

- Optimal Interpolation(OI)

Single point (BLUE)



NWP (OI)

分析更新

$$X_a = X_b + \beta(X_o - X_b),$$
$$\beta = \frac{E(\sigma_b^2)}{E(\sigma_b^2) + E(\sigma_o^2)}$$

誤差斜方差更新

$$E(\sigma_a^2) = (1 - \beta)E(\sigma_b^2)$$

分析更新

$$\mathbf{x}_a = \mathbf{x}_b + \mathbf{W}[\mathbf{y}_o - H(\mathbf{x}_b)],$$
$$\mathbf{W} = \frac{E(\boldsymbol{\varepsilon}_b^2)\mathbf{H}^T}{\mathbf{H}E(\boldsymbol{\varepsilon}_b^2)\mathbf{H}^T + E(\boldsymbol{\varepsilon}_o^2)} = \frac{\mathbf{B}\mathbf{H}^T}{\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R}}$$

誤差斜方差更新

$$\mathbf{A} = (\mathbf{I} - \mathbf{W}\mathbf{H})\mathbf{B}$$

資料同化

- Tangent Linear Normal Mode Constrain(TLNMC) - Strong constraint)

$$\mathbf{x}_c = \mathbf{C} \mathbf{x} = [\mathbf{I} + \mathbf{V} \mathbf{S} \mathbf{D} \mathbf{S}^{-1} \mathbf{V}^{-1} \mathbf{T}]^p \mathbf{x}$$

where

$\mathbf{T}$ = tangent linear of dry adiabatic spectral model,

$\mathbf{V}$ = $n \times m$ matrix of m vertical modes (n =# vert levels)

$\mathbf{S}$ = spherical harmonic to lat-lon grid transform

$\mathbf{D}$ = Temperton spectral implicit NMI operator

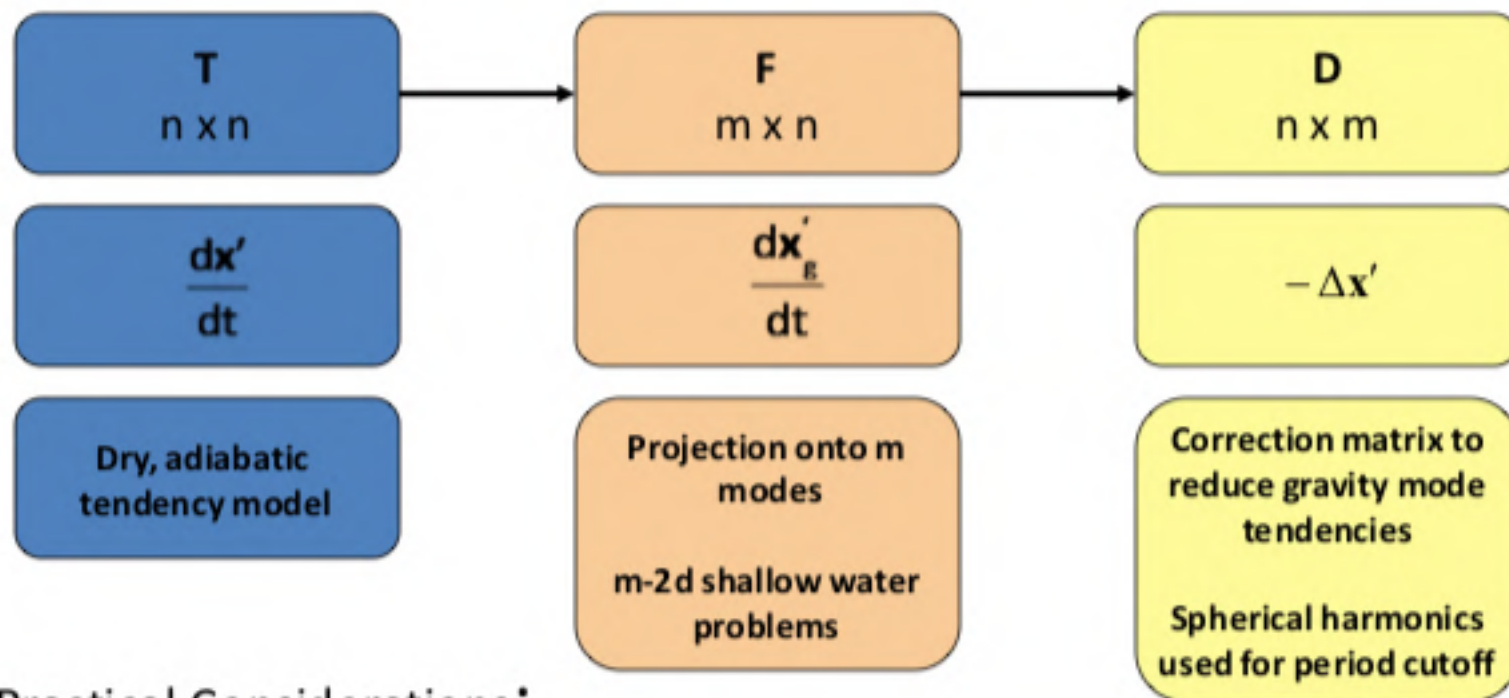
(computes corrections to $\mathbf{x}$ which reduce the
amplitude of propagating gravity waves)

p = number of iterations for Machenhauer scheme

($p = 1$ is default and probably best setting)

“Strong Constraint” Procedure

$$\mathbf{C} = [\mathbf{I} - \mathbf{DFT}] \mathbf{x}'$$



- Practical Considerations:
 - $\mathbf{C}$ is operating on $\mathbf{x}'$ only, and is the tangent linear of NNMI operator
 - Only need one iteration in practice for good results
 - Adjoint of each procedure needed as part of minimization/variational procedure

- 資料

- 種類

- 傳統觀測、衛星觀測、掩星觀測、雷達觀測、氣膠觀測、
臭氧觀測

- 品質控管(Quality Control, QC)

- 疏稀化(Thinning)

- 同化

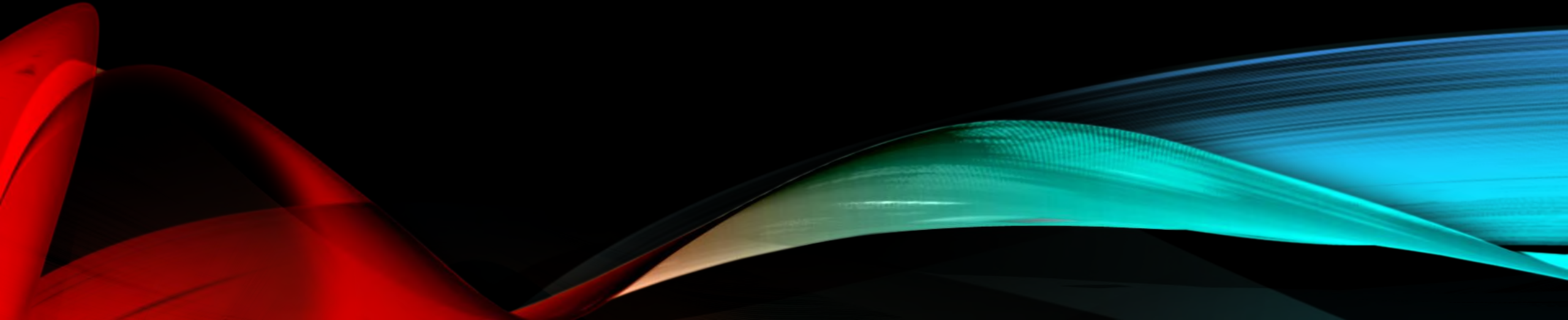
- 變分同化(3DVar、4DVar)

- 系集同化(EnKF、EnSRF、EAKF、ETKF、LETKF)

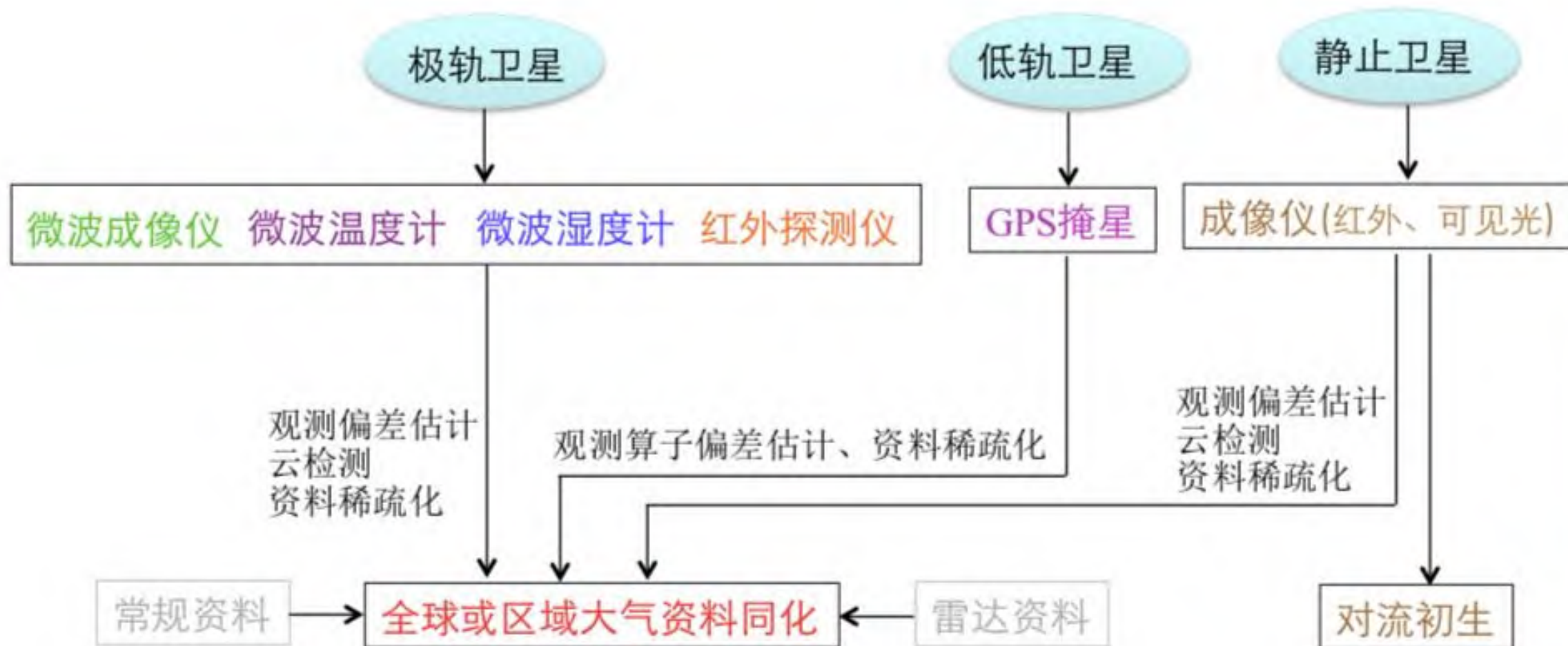
- 混成同化(3DEnVar、4DEnVar、En4DVar、HG-EnDA)

資料與同化

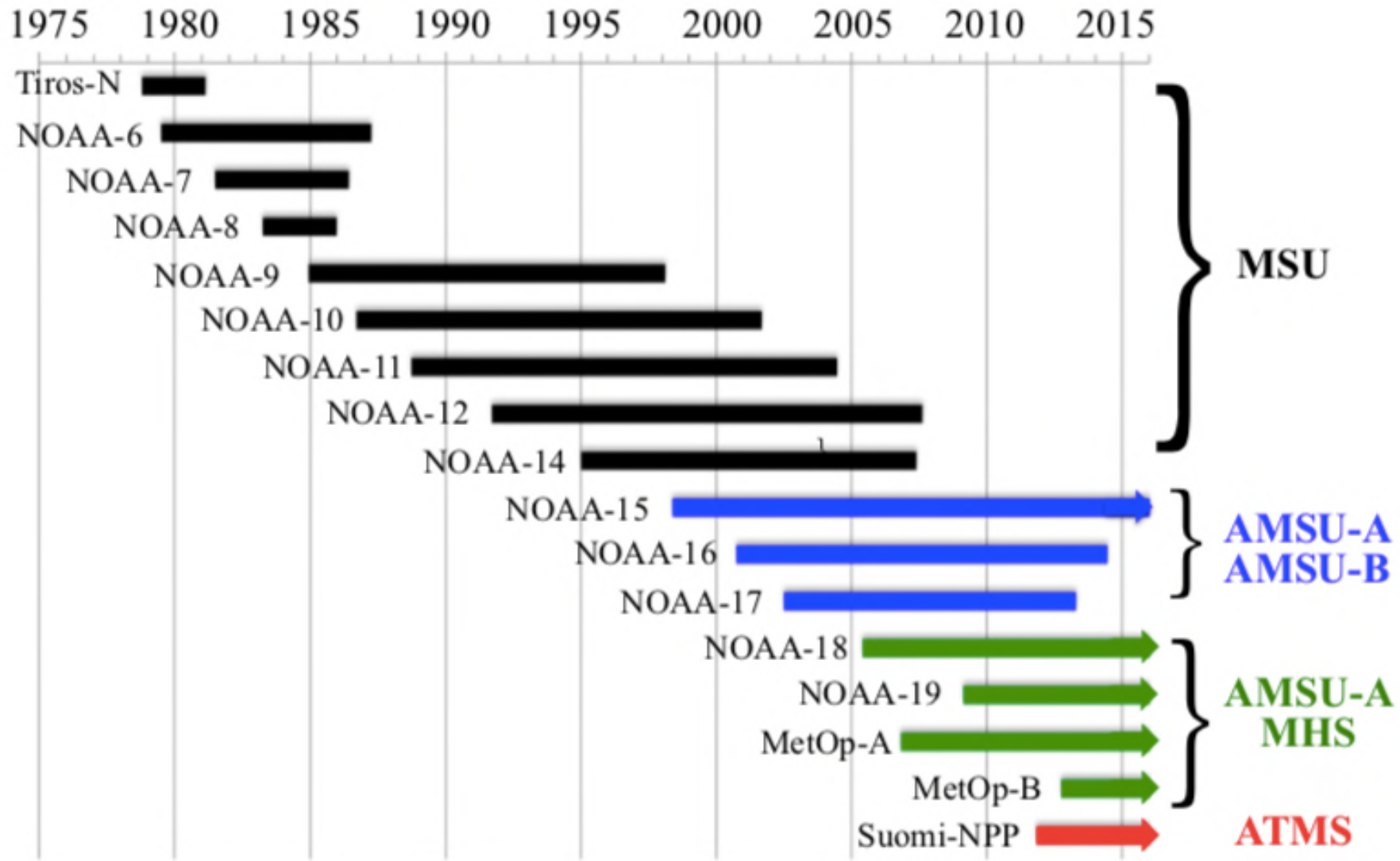
DATA AND ASSIMILATION



应用在天气研究和数值预报中的主要气象卫星资料



NOAA Satellite Microwave Instruments



Three Challenging Areas for Satellite Data Assimilation

1. Bias Correction

- Instrument bias
- Air mass dependent bias

2. Quality Control

- Observation errors
- Cloud Detection

3. Data Thinning

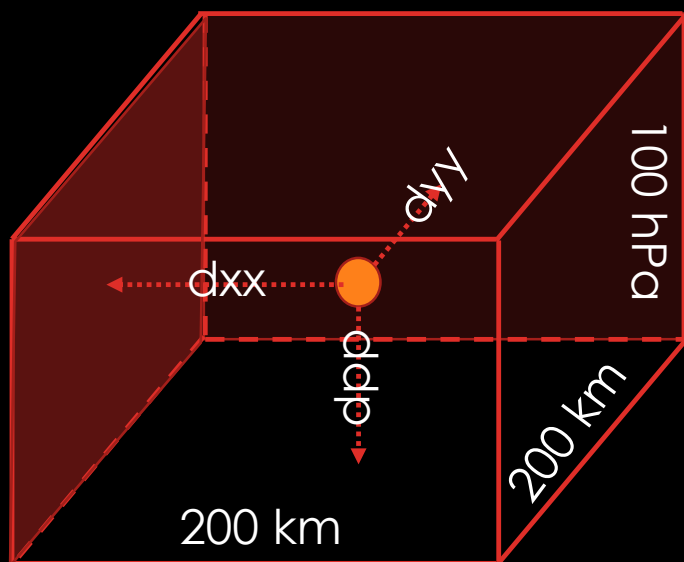
- Spatially correlated data
- Spectrally correlated channels

品質控管

- 重大誤差檢驗 (gross check) : missing value or unreasonable
- 增量檢驗 (incremental check) : omb
- 水平檢驗 (horizontal check) : OI analysis
- 垂直檢驗 (vertical check) : check increment one above and one below
- 淨力穩定檢驗 (hydrostatic check) : virtual temperature
- 基線檢驗 (baseline check) : hydrostatic determined height v.s. elevation

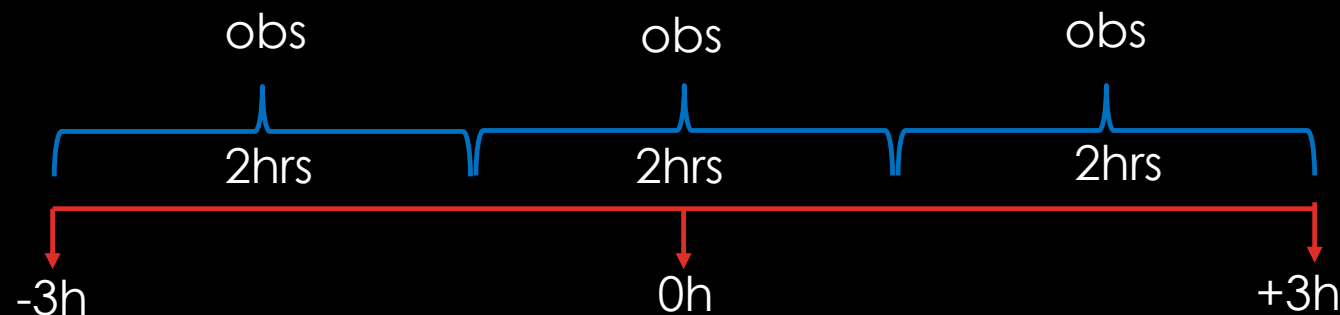
資料疏化

Himawari-8 AMV
(200km,200km,100hPa,2hrs)



- ! quality indicator for observation (smaller = better)
 $\text{crit1} = \text{half}$
- ! Compute distance metric (smaller is closer to center of cube)
 $\text{dist1} = (\text{dxx} * \text{dxx} + \text{dyy} * \text{dyy} + \text{dpp} * \text{dpp}) * \text{two} / \text{three} + \text{half}$
- ! Determine "score" for observation. Lower score is better.
 $\text{crit} = \text{crit1} * \text{dist1}$

每兩小時時間區間找 crit 最小值的觀測

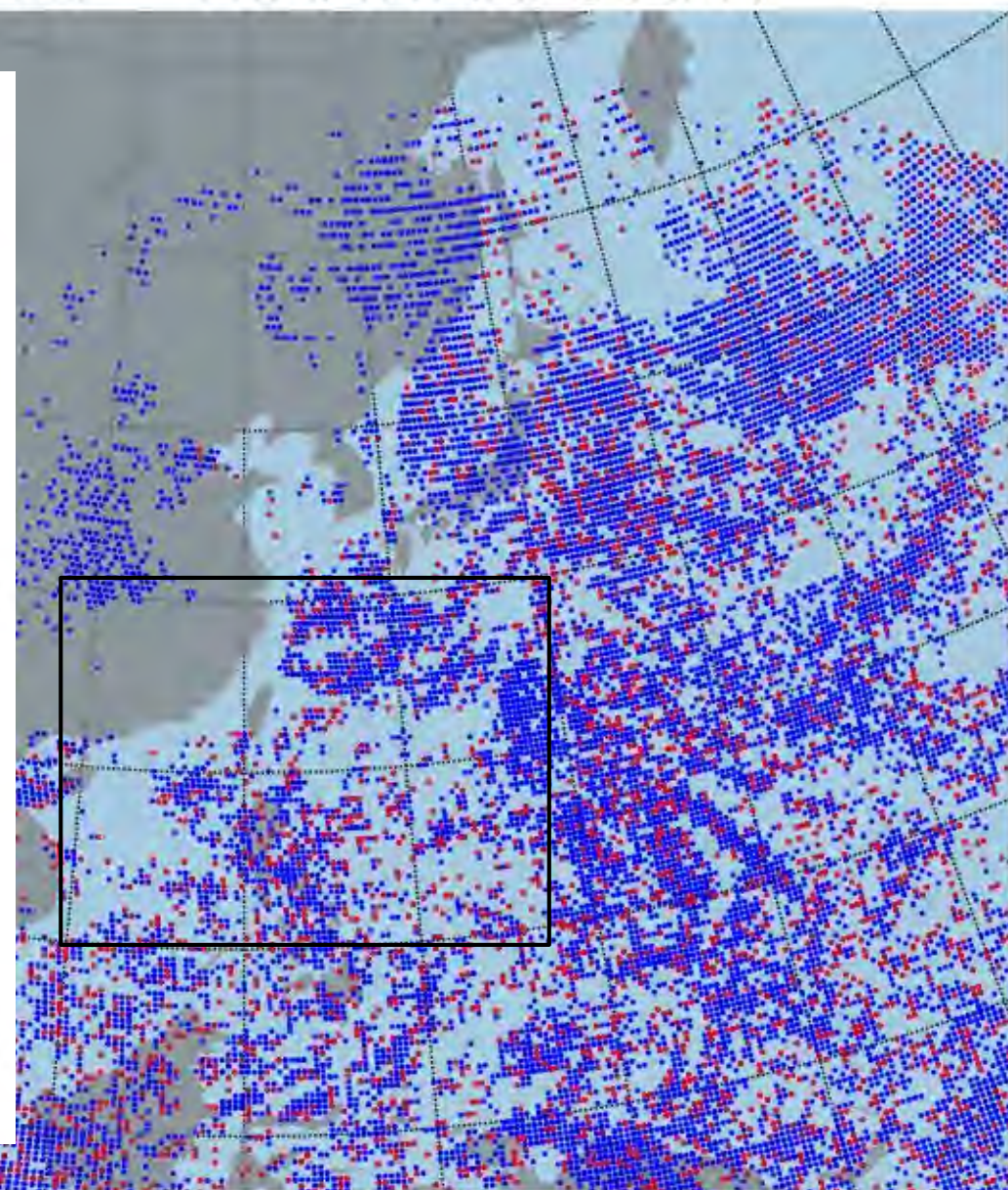
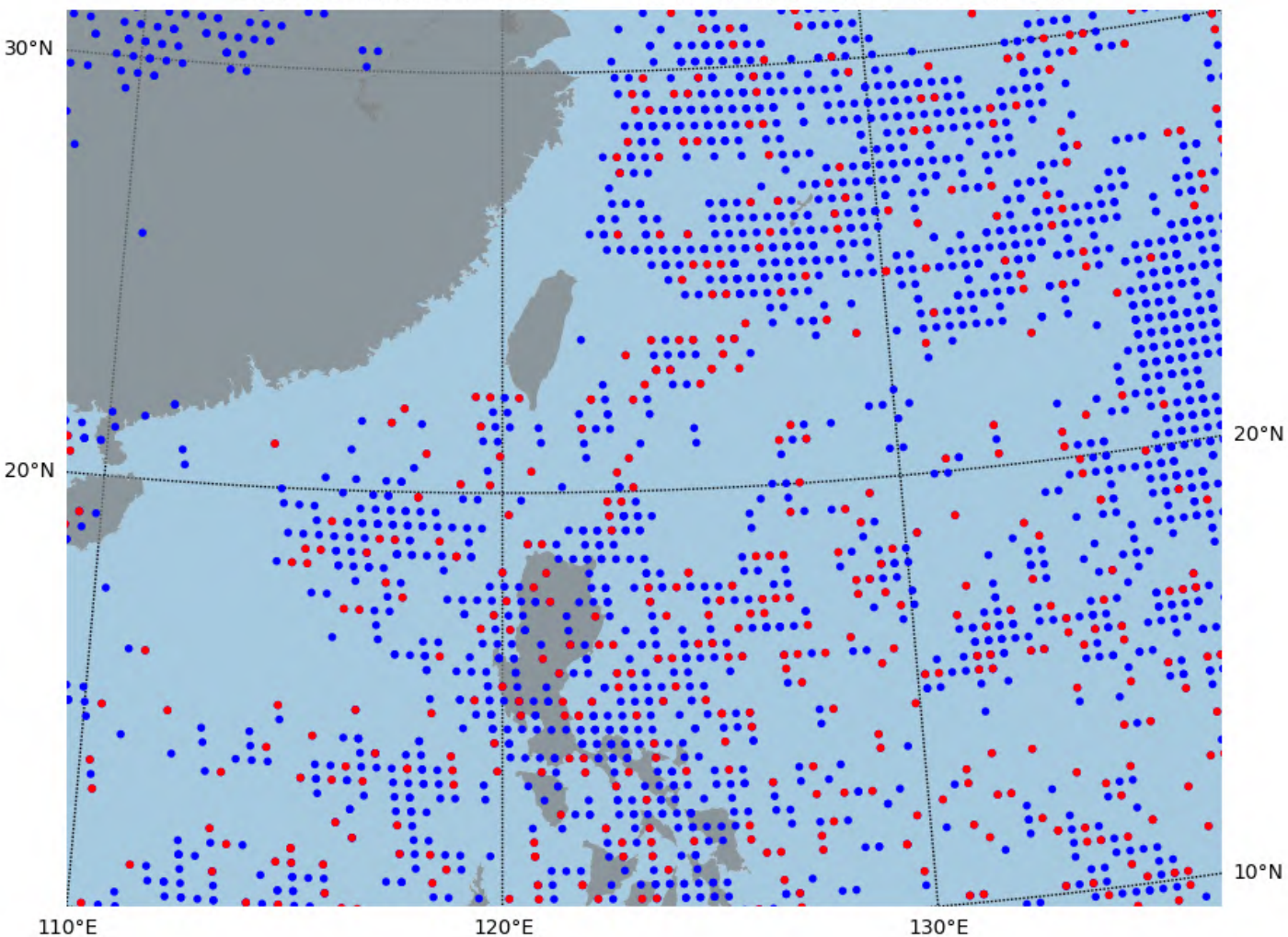


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HIMAWARI-8 AMV

2017091712

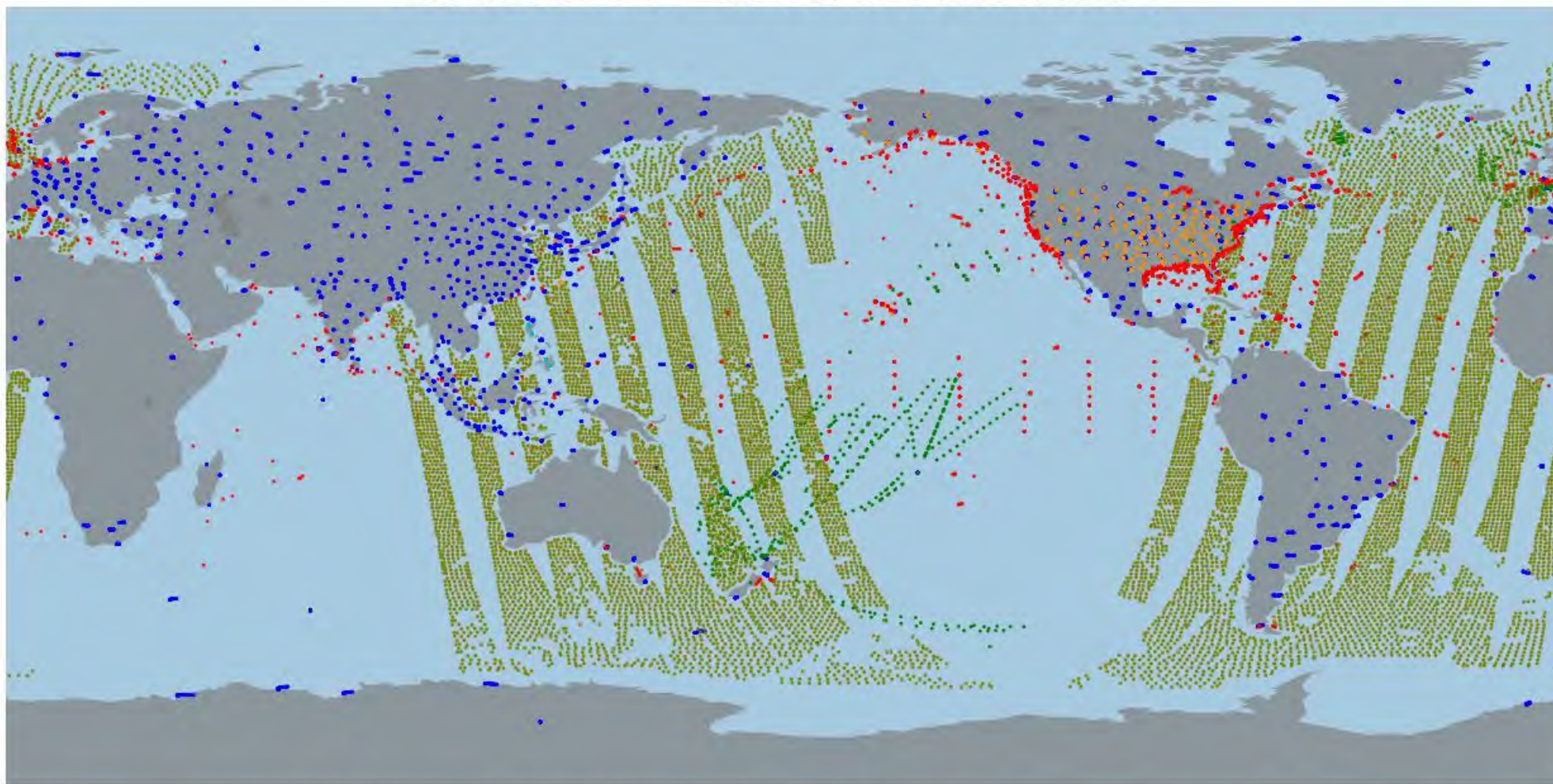
HIMAWARI-8 AMV



● All Observation - 44774

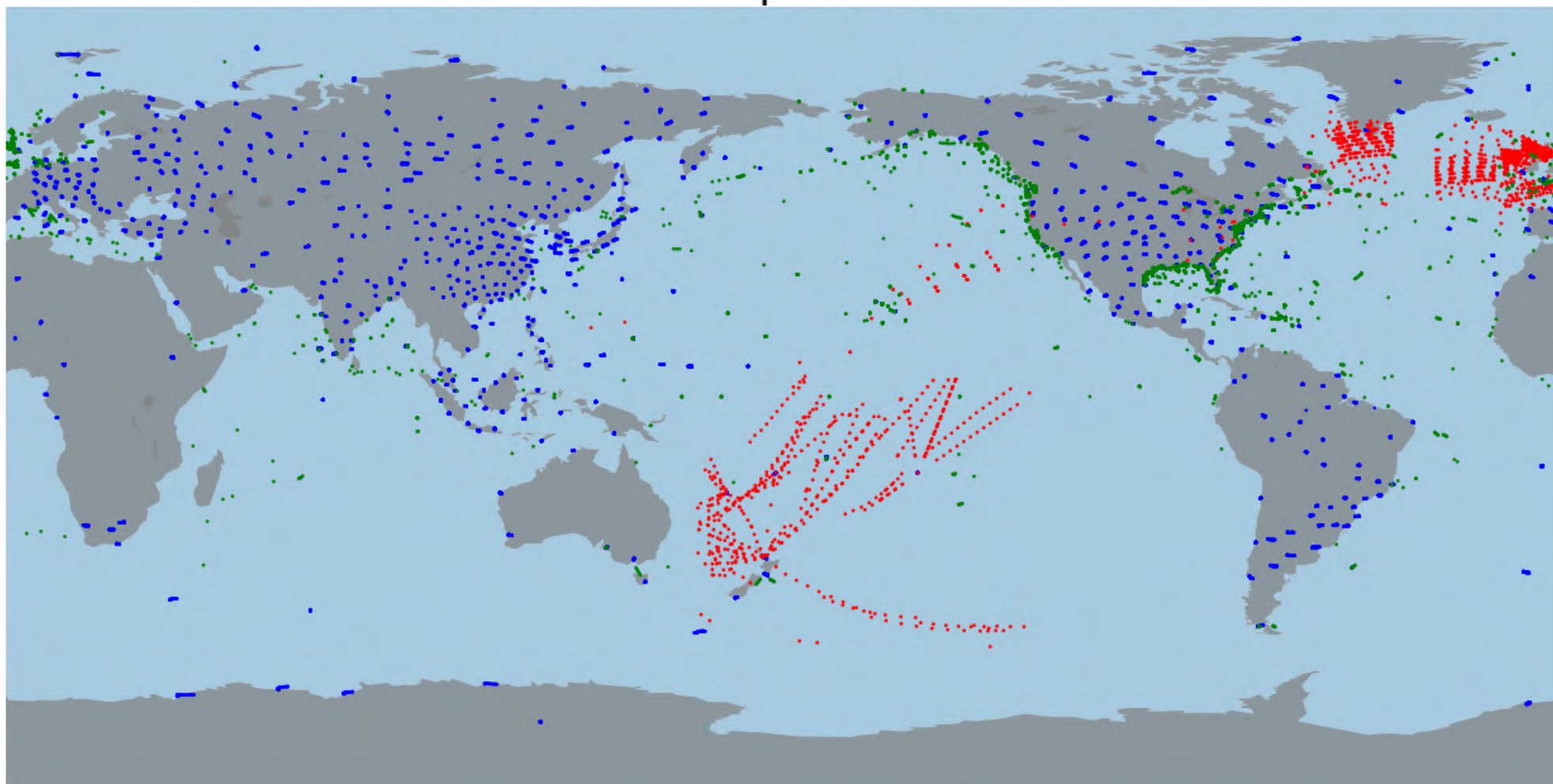
● Assimilated - 7979

2018051312 U-Wind Assimilated



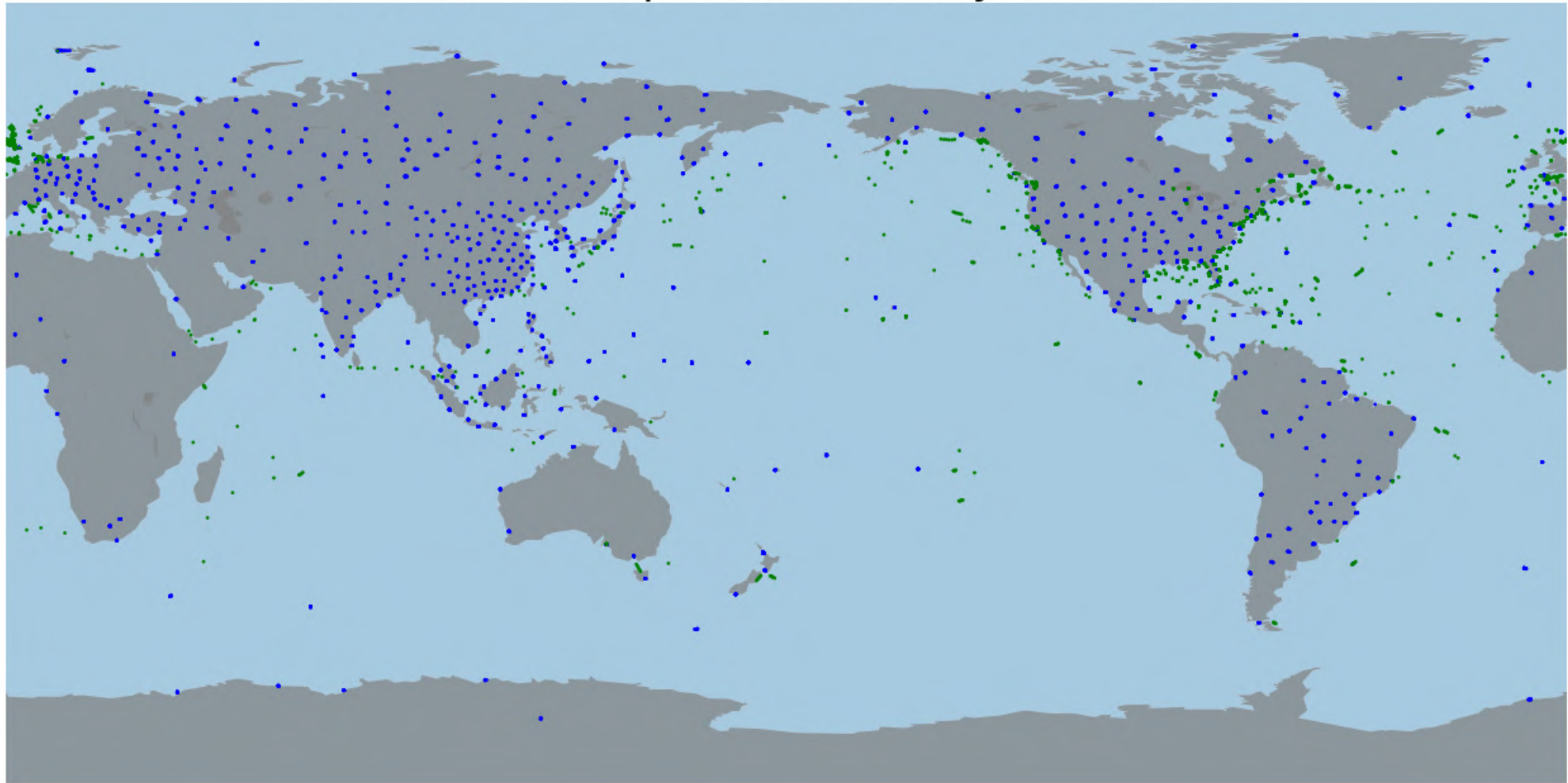
• ADPUPA(220) - 36575	• VADWND(224) - 8557	• PROFLR(229) - 156	• AIRCFT(230) - 805	• SFCSHP(280) - 6972	• SFCSHP(282) - 221	• ASCATW(290) - 11117
• ADPUPA(221) - 745						

2018051312 Temperature Assimilated



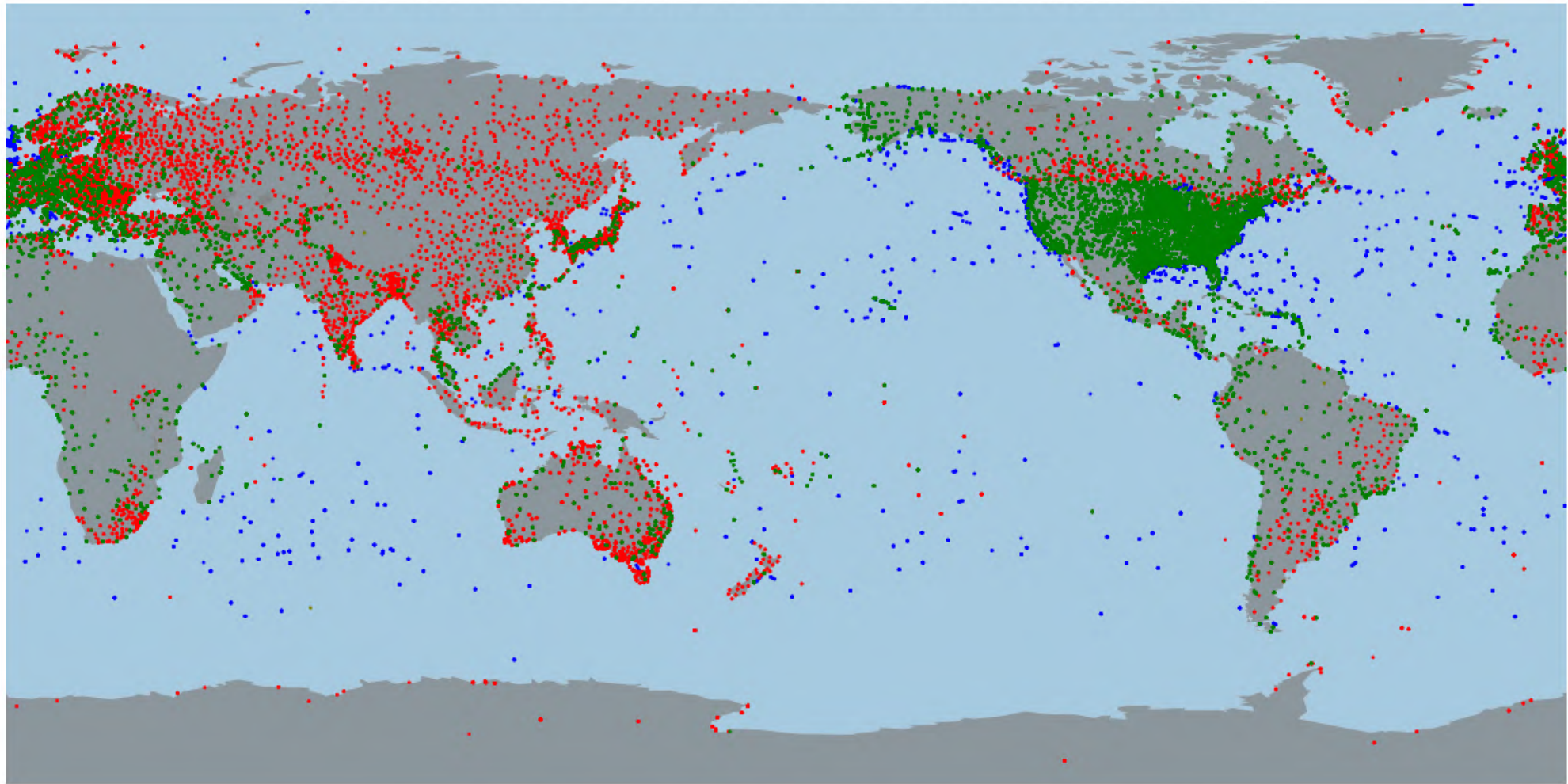
• ADPUPA(120) - 28644 • AIRCFT(130) - 2278 • SFCSHP(180) - 7018

2018051312 Specific Humidity Assimilated



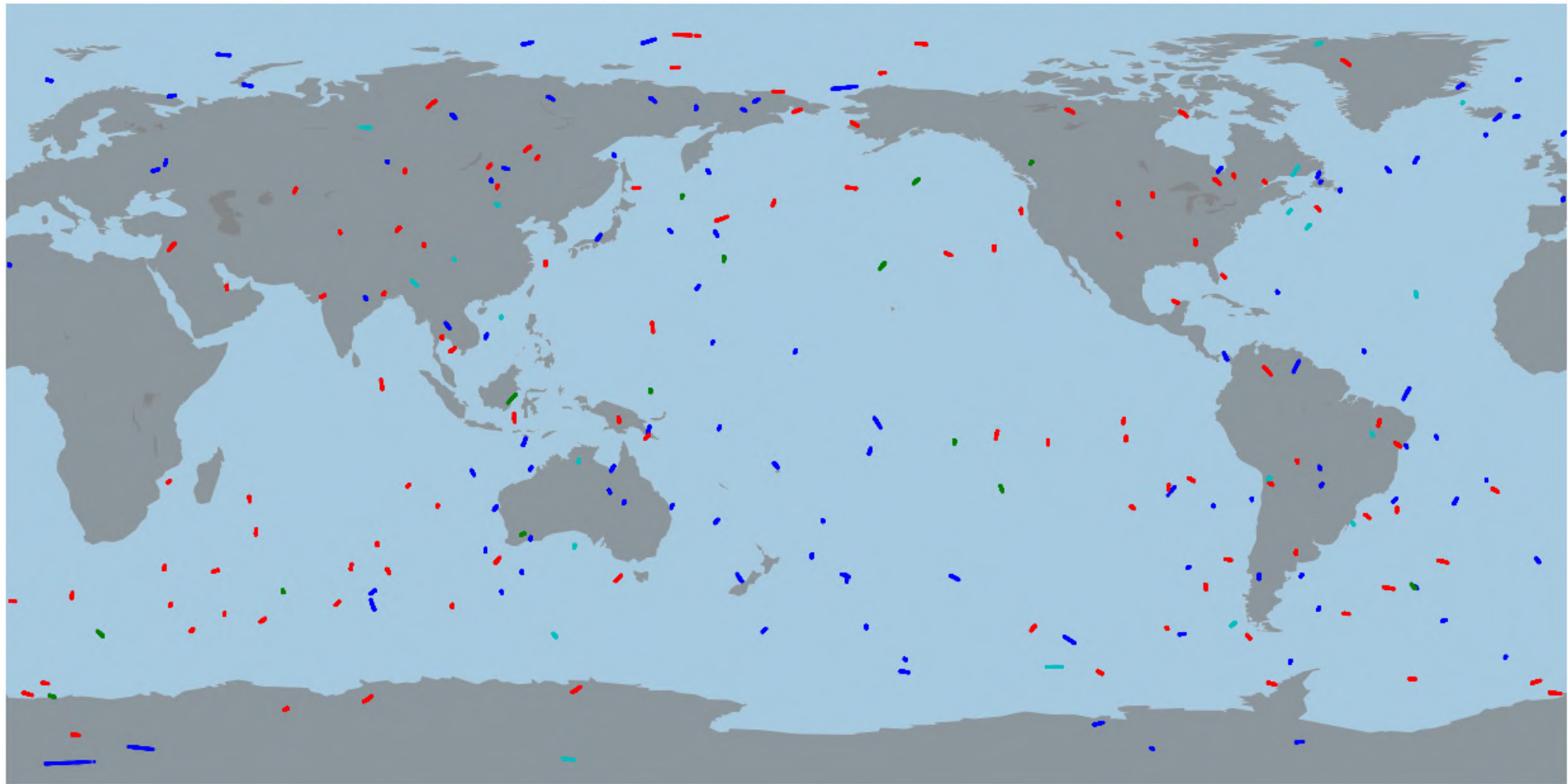
• ADPUPA(120) - 13472 • SFCSHP(180) - 3125

2018051312 Surface Pressure Assimilated



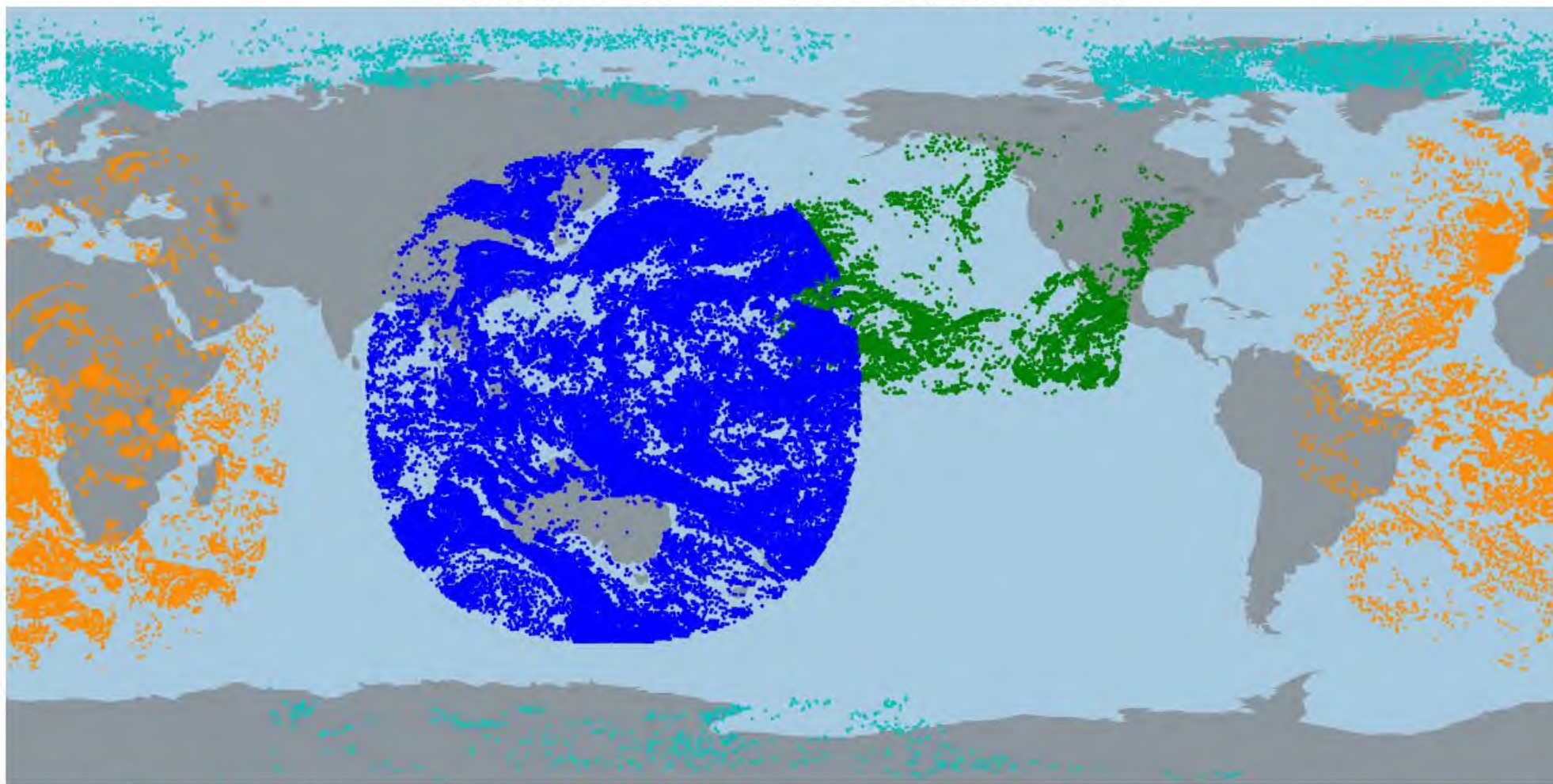
● ADPUPA(120) - 591 ● SFCSHP(180) - 9032 ● ADPSFC(181) - 19111 ● ADPSFC(187) - 46644

2018051312 GPS Radio Occultation Assimilated



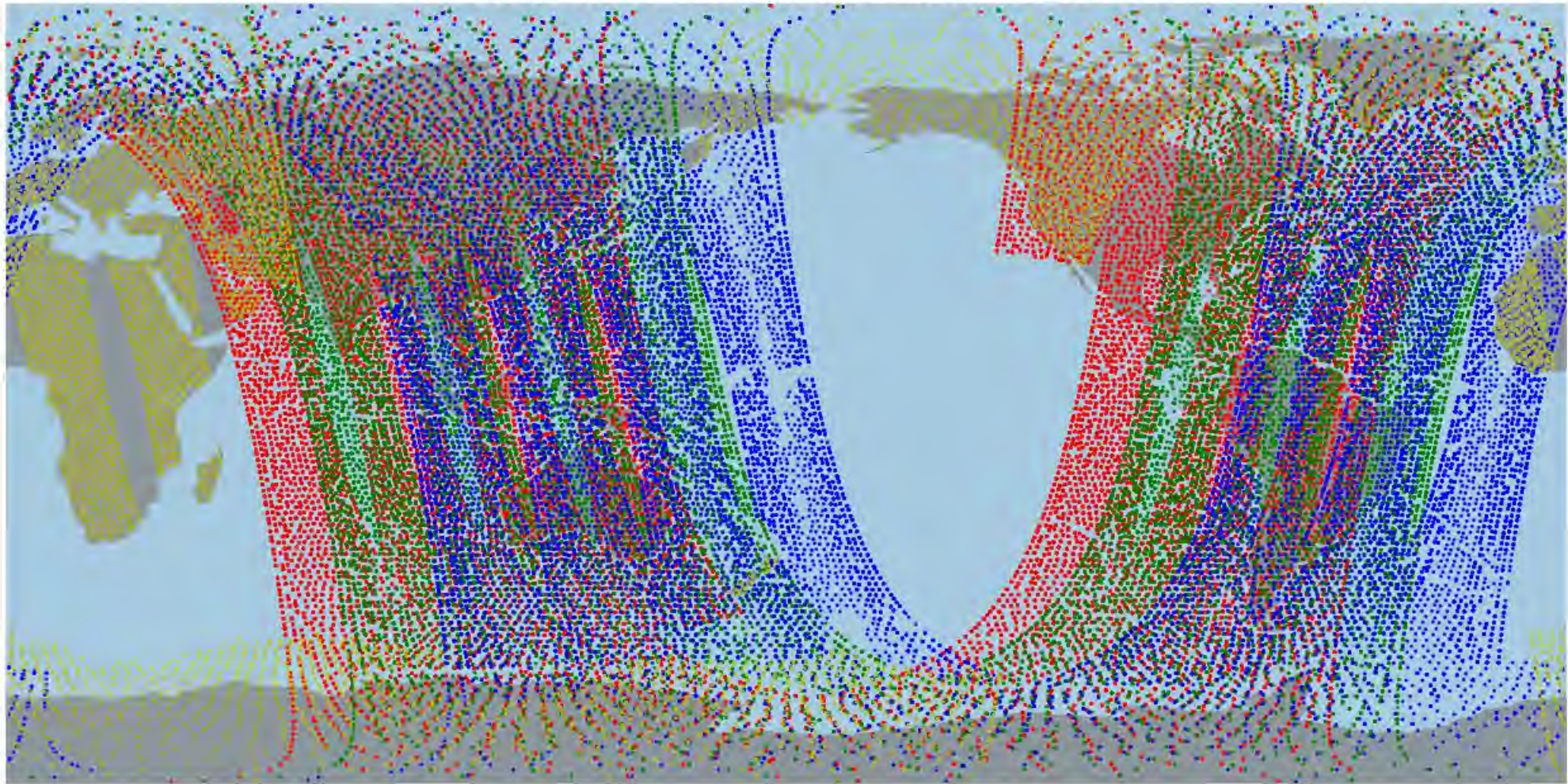
• METOP-A(4) - 12989 • COSMIC-1(740) - 14158 • COSMIC-6(745) - 1924 • TerraSAR-X(42) - 2281

2018051312 AMV Assimilated



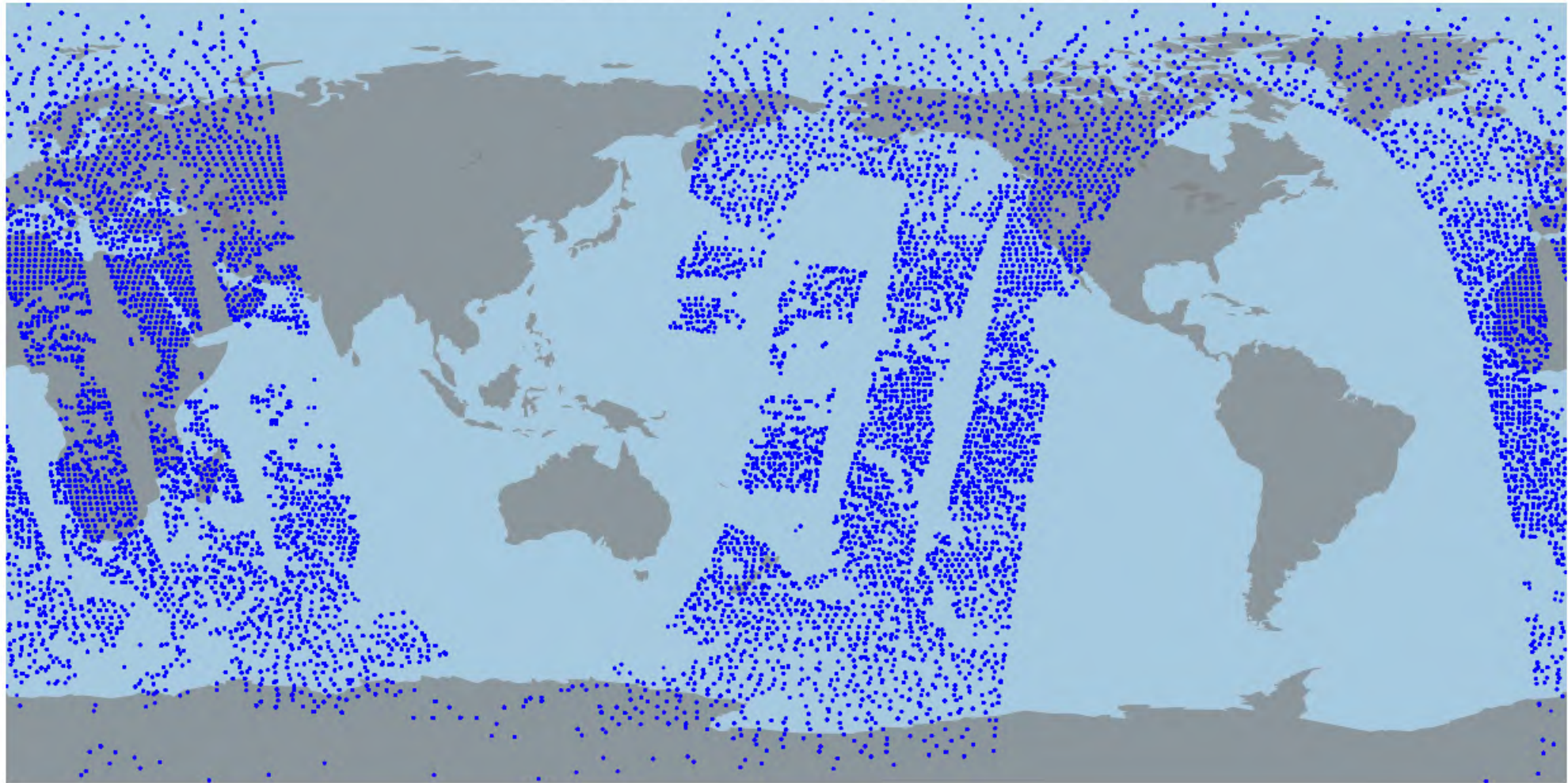
• HIMAWARI(242) - 6764	• GOES(245) - 5538	• HIMAWARI(250) - 43616	• METEOSAT(253) - 2427	• AQUA(257) - 4008	• AQUA(258) - 148	• AQUA(259) - 3063
• METEOSAT(243) - 9862	• GOES(246) - 7087	• HIMAWARI(252) - 24344				

2018051312 AMSU-A Assimilated



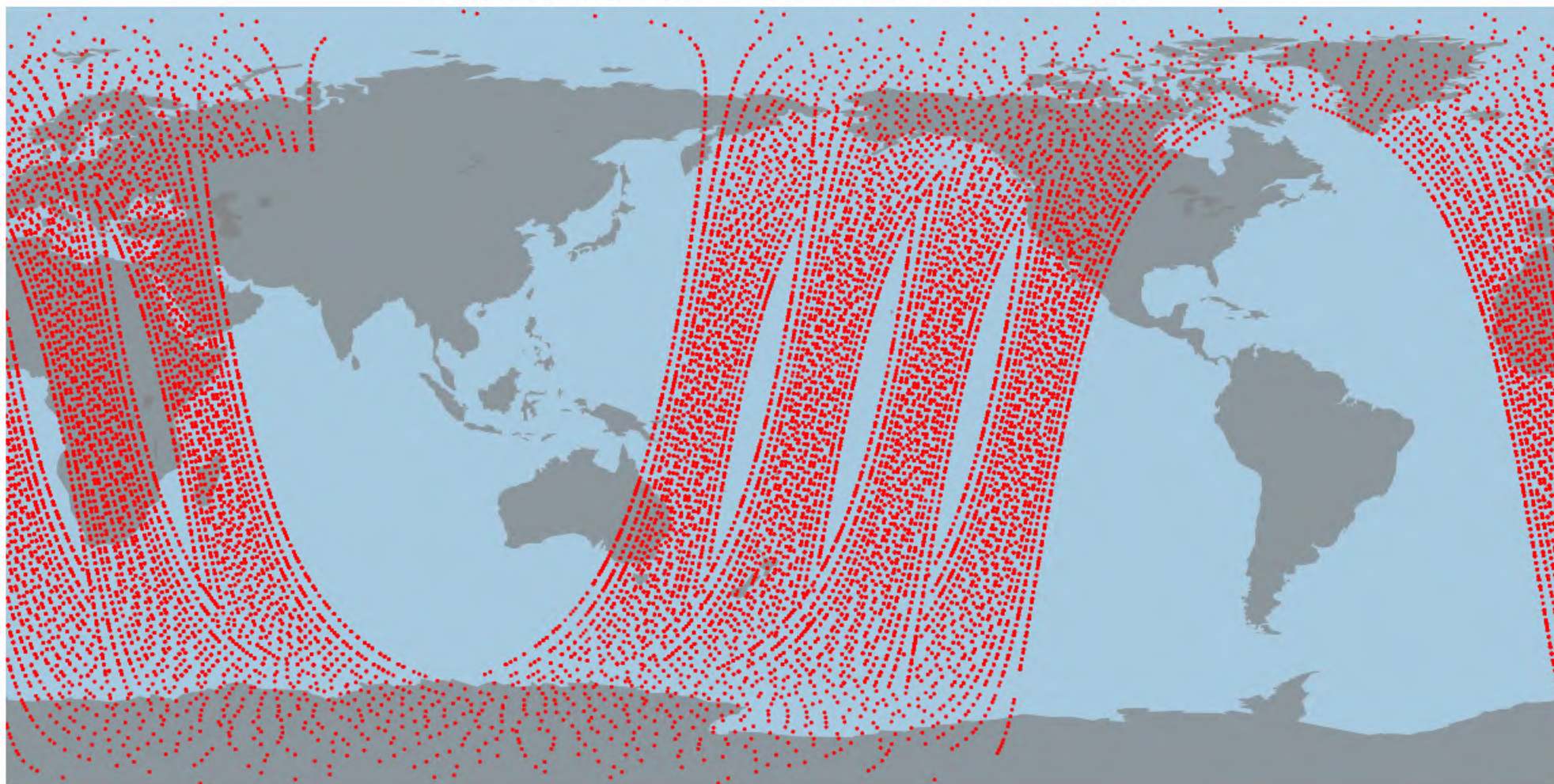
• NOAA-15 - 94077 • NOAA-18 - 71872 • METOP-A - 37806 • AQUA - 6880

2018051312 AIRS Assimilated



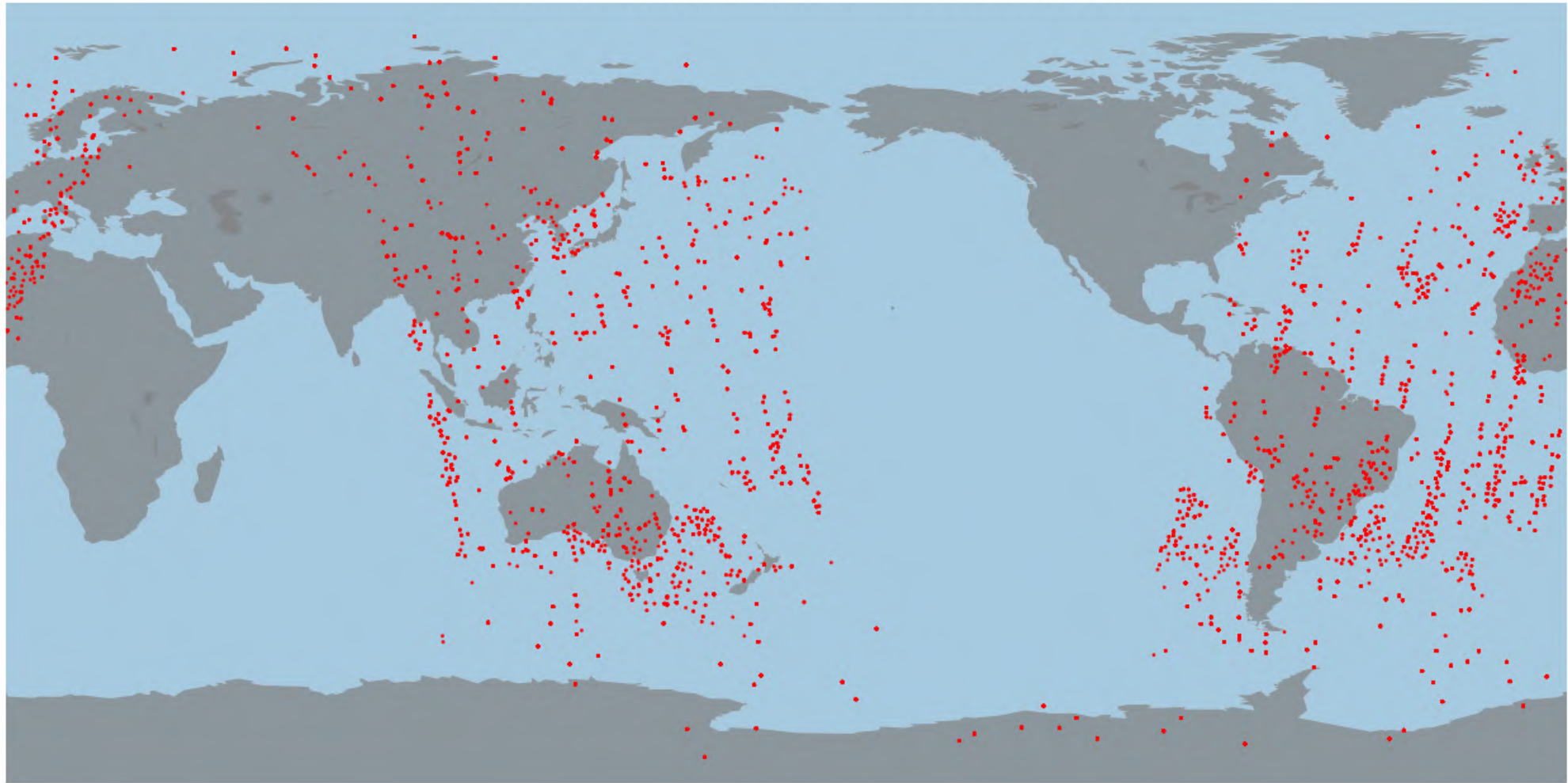
• AQUA - 130862

2018051312 ATMS Assimilated



• Suomi NPP - 57191

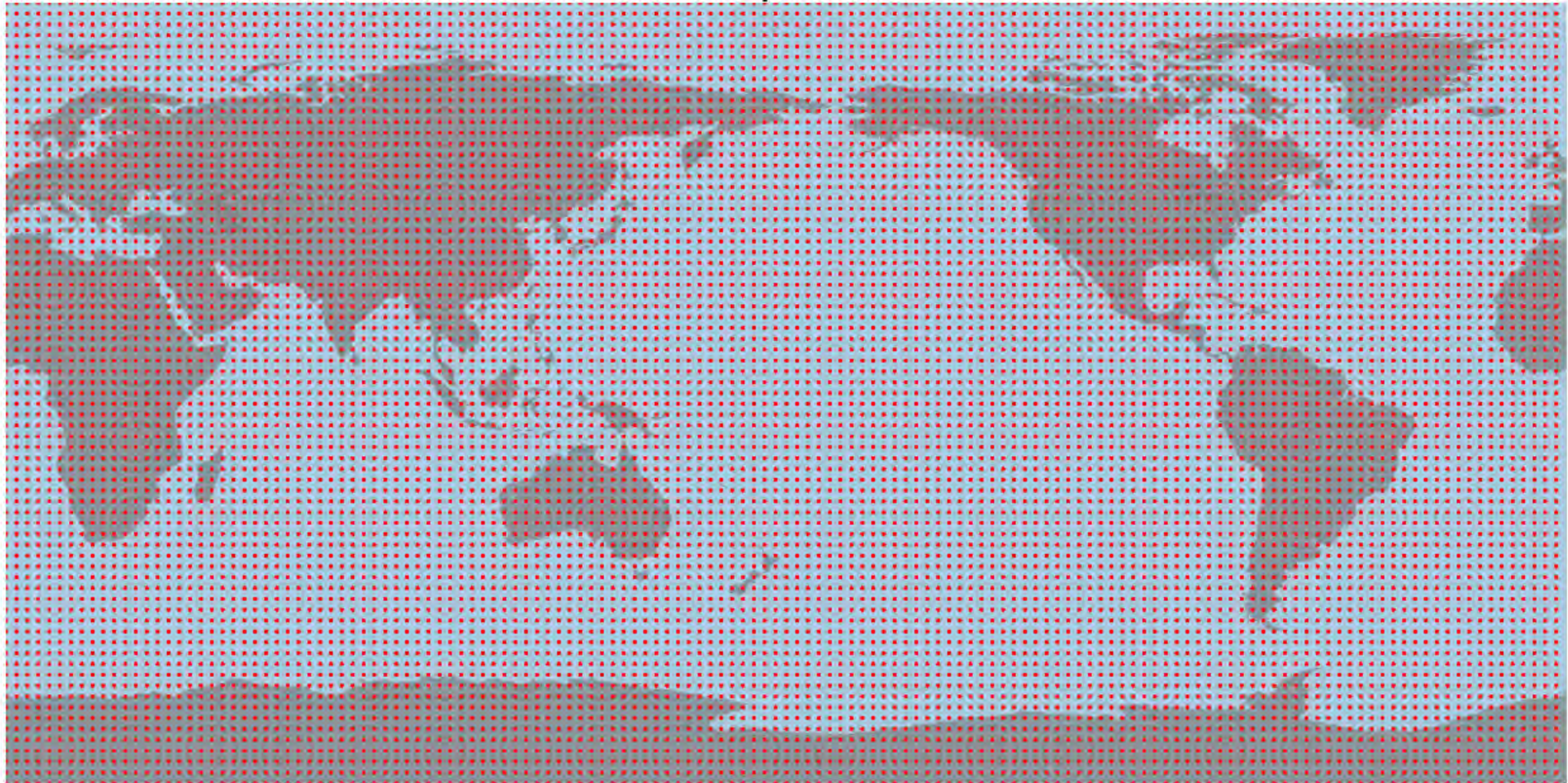
2018051312 IASI Assimilated



• METOP-A - 11267

850 hPa

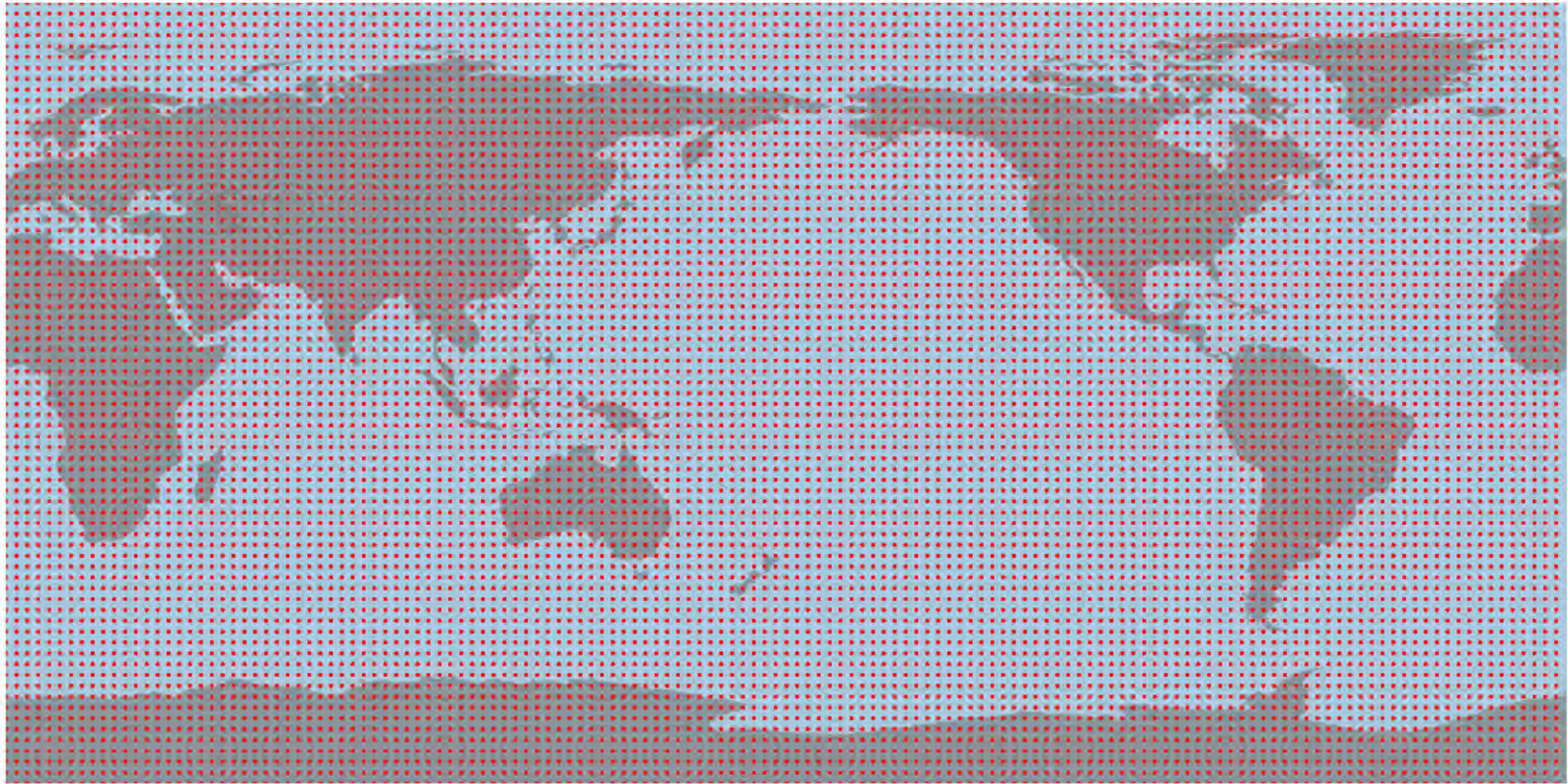
2018051312 Temperature Assimilated



• CWB - 42017

850,700,500,200 hPa

2018051312 U-wind Assimilated

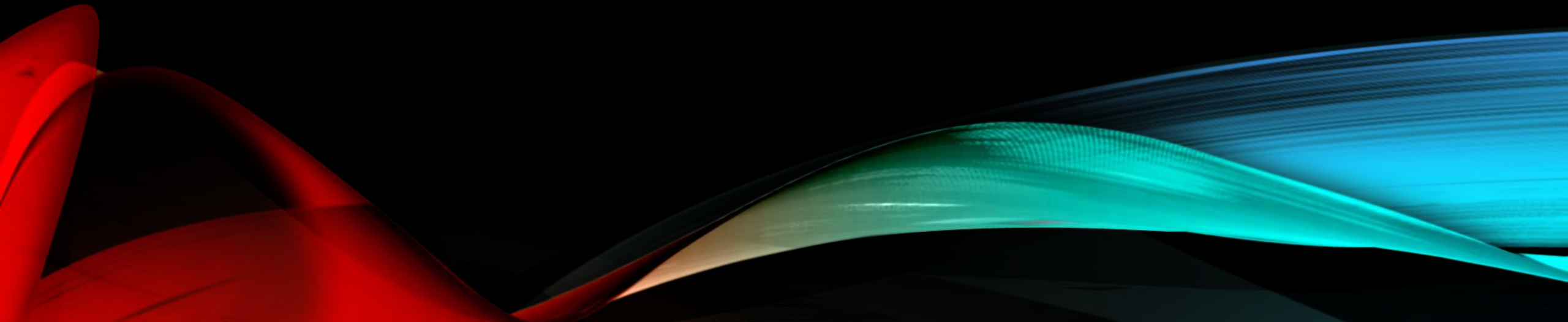


• CWB - 42017



變分資料同化 VARIATIONAL DATA ASSIMILATION

3DVar、4DVar



GS1 3DVAR DATA ASSIMILATION SYSTEM

$$J(\mathbf{x}'_f) = \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \frac{1}{2} (\mathbf{H}\mathbf{x}'_f - \mathbf{d})^T \mathbf{R}^{-1} (\mathbf{H}\mathbf{x}'_f - \mathbf{d})$$

$\mathbf{x}'_f$: ANALYSIS INCREMENT

$\mathbf{d}$: INOVATION AT , ($\mathbf{d} = \mathbf{y} - H(\mathbf{x}^b)$)

$\mathbf{B}$: BACKGROUND ERROR COVARIANCE

$\mathbf{R}$: OBSERVATION ERROR COVARIANCE

$\mathbf{H}$: OBSERVATION OPERATOR

GSI 4DVAR DATA ASSIMILATION SYSTEM

$$J(\mathbf{x}'_f) = \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \frac{1}{2} \sum_{i=0}^K [\mathbf{H}_i \mathbf{L}(t_0, t_i) \mathbf{x}'_f - \mathbf{d}_i]^T \mathbf{R}_i^{-1} [\mathbf{H}_i \mathbf{L}(t_0, t_i) \mathbf{x}'_f - \mathbf{d}_i]$$

$\mathbf{x}'_f$: ANALYSIS INCREMENT

$\mathbf{d}_i$: INOVATION AT TIME i , ($\mathbf{d}_i = \mathbf{y}_i - H(\mathbf{x}_i^b)$)

$\mathbf{L}(t_0, t_i)$: TANGENT LINEAR MODEL, EVOLVE FROM TIME 0 TO i

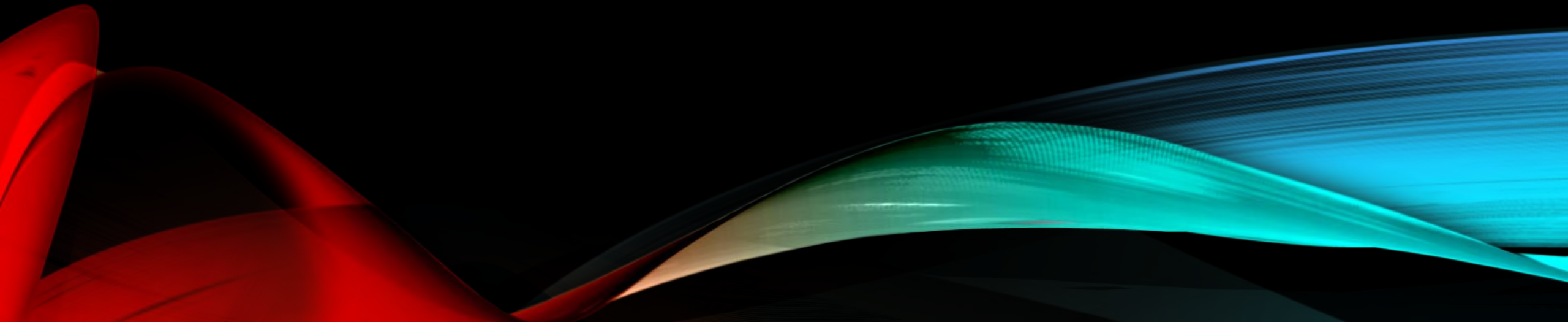
$\mathbf{B}$: BACKGROUND ERROR COVARIANCE

$\mathbf{R}$: OBSERVATION ERROR COVARIANCE

$\mathbf{H}_i$: OBSERVATION OPERATOR AT TIME i

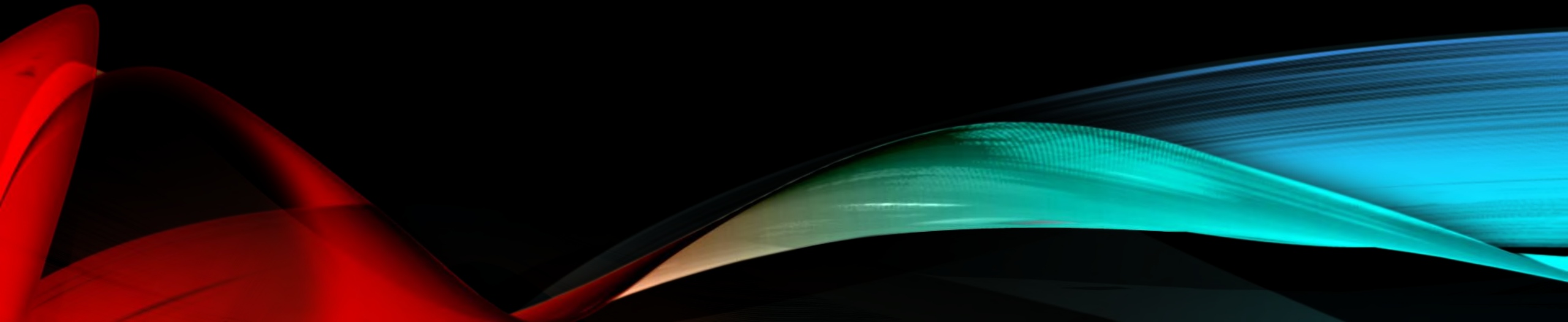
系集資料同化 ENSEMBLE DATA ASSIMILATION

EnKF、EnSRF、EAKF、ETKF、LETKF



混成系集變分資料同化 HYBRID ENSEMBLE-VARIATIONAL DATA ASSIMILATION

3DEnVar、4DEnVar、En4DVar



GSI HYBRID-3DENVAR DATA ASSIMILATION SYSTEM

$$J(\mathbf{x}'_f, \alpha^n) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} \sum_{n=1}^N (\alpha^n)^T \mathbf{A}^{-1} (\alpha^n) + \frac{1}{2} (\mathbf{H} \mathbf{x}'_t - \mathbf{d})^T \mathbf{R}^{-1} (\mathbf{H} \mathbf{x}'_t - \mathbf{d})$$

$$\mathbf{x}'_t = \mathbf{x}'_f + \sum_{n=1}^N (\alpha^n \circ \mathbf{x}_e^n), \quad \frac{1}{\beta_f} + \frac{1}{\beta_e} = 1$$

$\mathbf{x}'_t$: TOTAL ANALYSIS INCREMENT

$\mathbf{x}'_f$: ANALYSIS INCREMENT ESTIMATED BY STATIC ERROR COVARIANCE

β_f : THE WEIGHTING OF STATIC ERROR COVARIANCE

β_e : THE WEIGHTING OF ENSEMBLE ERROR COVARIANCE

α^n : AUGMENTED CONTROL VECTOR (ACV)

$\mathbf{x}_e^n$: ENSEMBLE PERTURBATION

$\mathbf{d}$: INNOVATION AT t , ($\mathbf{d} = \mathbf{y} - \mathbf{H}(\mathbf{x}^b)$)

$\mathbf{A}$: LOCALIZATION MATRIX

$\mathbf{B}$: BACKGROUND ERROR COVARIANCE

$\mathbf{R}$: OBSERVATION ERROR COVARIANCE

$\mathbf{H}$: OBSERVATION OPERATOR

GS HYBRID-EN4DVAR DATA ASSIMILATION SYSTEM

$$J(\mathbf{x}'_f, \alpha^n) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} \sum_{n=1}^N (\alpha^n)^T \mathbf{A}^{-1} (\alpha^n) + \frac{1}{2} \sum_{i=0}^K [\mathbf{H}_i \mathbf{L}(t_0, t_i) \mathbf{x}'_t - \mathbf{d}_i]^T \mathbf{R}_i^{-1} [\mathbf{H}_i \mathbf{L}(t_0, t_i) \mathbf{x}'_t - \mathbf{d}_i]$$

$$\mathbf{x}'_t = \mathbf{x}'_f + \sum_{n=1}^N (\alpha^n \circ \mathbf{x}_e^n), \quad \frac{1}{\beta_f} + \frac{1}{\beta_e} = 1$$

$\mathbf{x}'_t$: TOTAL ANALYSIS INCREMENT

$\mathbf{x}'_f$: ANALYSIS INCREMENT ESTIMATED BY STATIC ERROR COVARIANCE

β_f : THE WEIGHTING OF STATIC ERROR COVARIANCE

β_e : THE WEIGHTING OF ENSEMBLE ERROR COVARIANCE

α^n : AUGMENTED CONTROL VECTOR (ACV)

$\mathbf{x}_e^n$: ENSEMBLE PERTURBATION

$\mathbf{d}_i$: INNOVATION AT TIME i , ($\mathbf{d}_i = \mathbf{y}_i - H(\mathbf{x}_i^b)$)

$\mathbf{A}$: LOCALIZATION MATRIX

$\mathbf{B}$: BACKGROUND ERROR COVARIANCE

$\mathbf{R}$: OBSERVATION ERROR COVARIANCE

$\mathbf{H}$: OBSERVATION OPERATOR

GSI HYBRID-4DENVAR DATA ASSIMILATION SYSTEM

$$J(\mathbf{x}'_f, \alpha^n) = \beta_f \frac{1}{2} (\mathbf{x}'_f)^T \mathbf{B}^{-1} (\mathbf{x}'_f) + \beta_e \frac{1}{2} \sum_{n=1}^N (\alpha^n)^T \mathbf{A}^{-1} (\alpha^n) + \frac{1}{2} \sum_{i=0}^K [\mathbf{H}_i \mathbf{x}'_i - \mathbf{d}_i]^T \mathbf{R}_i^{-1} [\mathbf{H}_i \mathbf{x}'_i - \mathbf{d}_i]$$

$$\mathbf{x}'_i = \mathbf{x}'_f + \sum_{n=1}^N (\alpha^n \circ (\mathbf{x}_e^n)_i), \quad \frac{1}{\beta_f} + \frac{1}{\beta_e} = 1$$

$\mathbf{x}'_i$: TOTAL ANALYSIS INCREMENT AT TIME i

$\mathbf{x}'_f$: ANALYSIS INCREMENT ESTIMATED BY STATIC ERROR COVARIANCE

β_f : THE WEIGHTING OF STATIC ERROR COVARIANCE

β_e : THE WEIGHTING OF ENSEMBLE ERROR COVARIANCE

α^n : AUGMENTED CONTROL VECTOR (ACV)

$\mathbf{x}_e^n$: ENSEMBLE PERTURBATION

$\mathbf{d}_i$: INNOVATION AT TIME i , ($\mathbf{d}_i = \mathbf{y}_i - H(\mathbf{x}_i^b)$)

$\mathbf{A}$: LOCALIZATION MATRIX

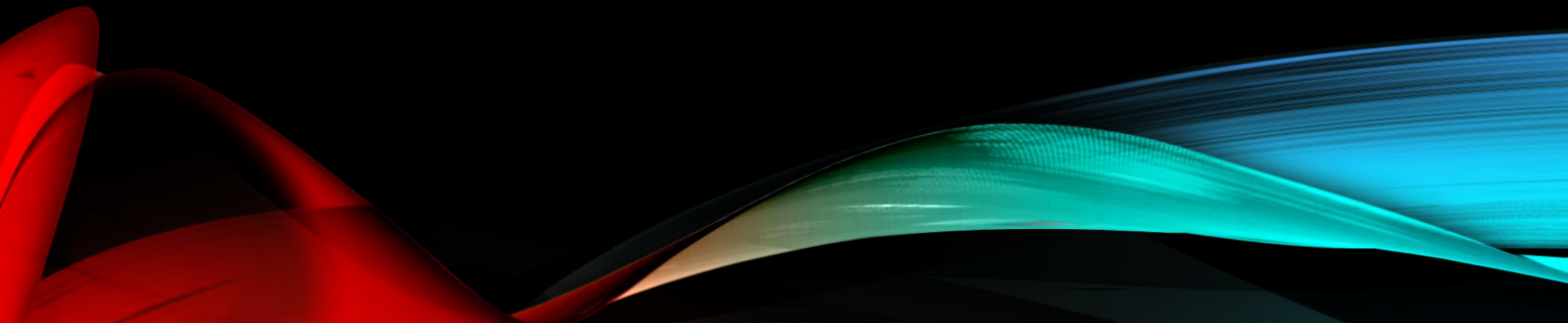
$\mathbf{B}$: BACKGROUND ERROR COVARIANCE

$\mathbf{R}$: OBSERVATION ERROR COVARIANCE

$\mathbf{H}$: OBSERVATION OPERATOR

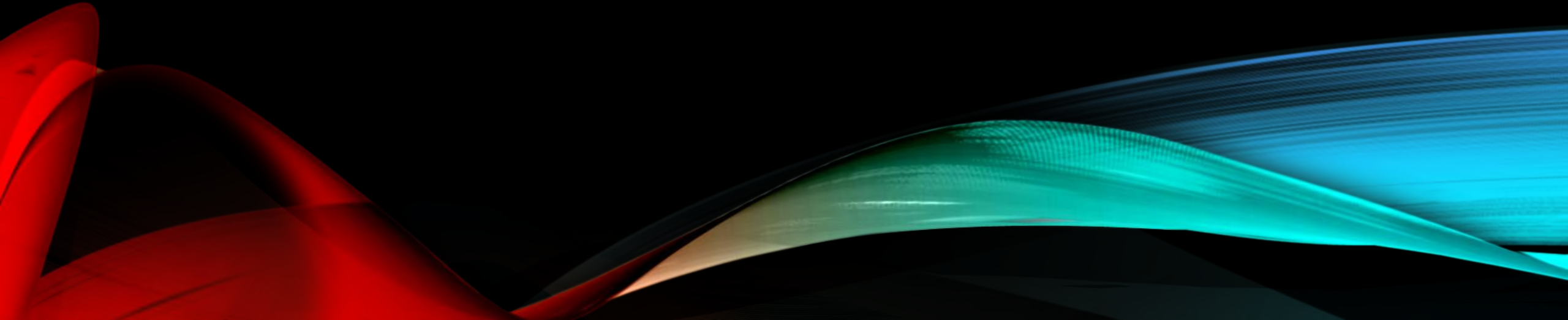
增益混成資料同化 GAIN HYBRID DATA ASSIMILATION

HG-EnDA

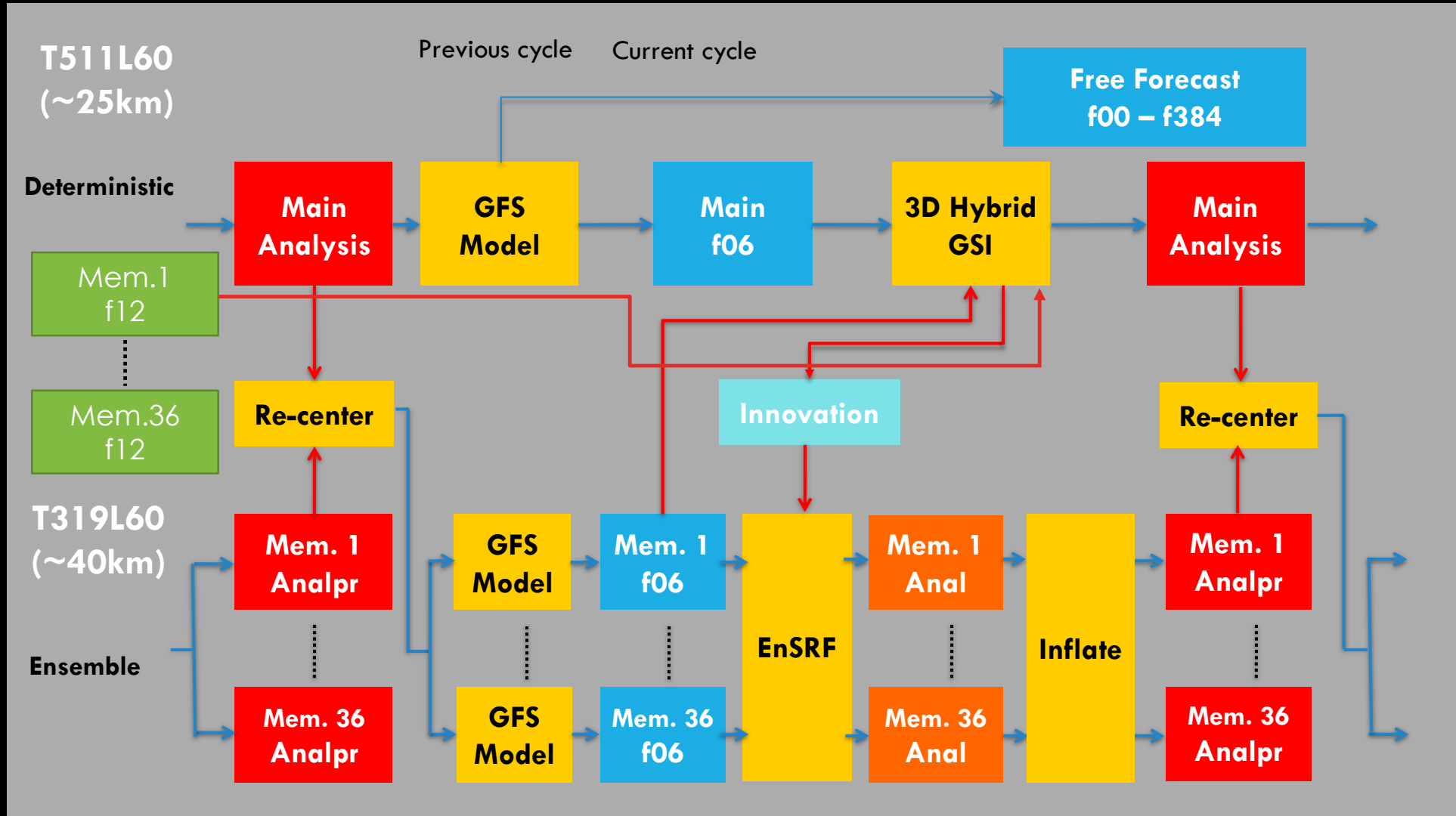


- 全球預報系統
- 資料同化系統
- 觀測資料
- 資料同化分組規劃

中央氣象局資料同化系統



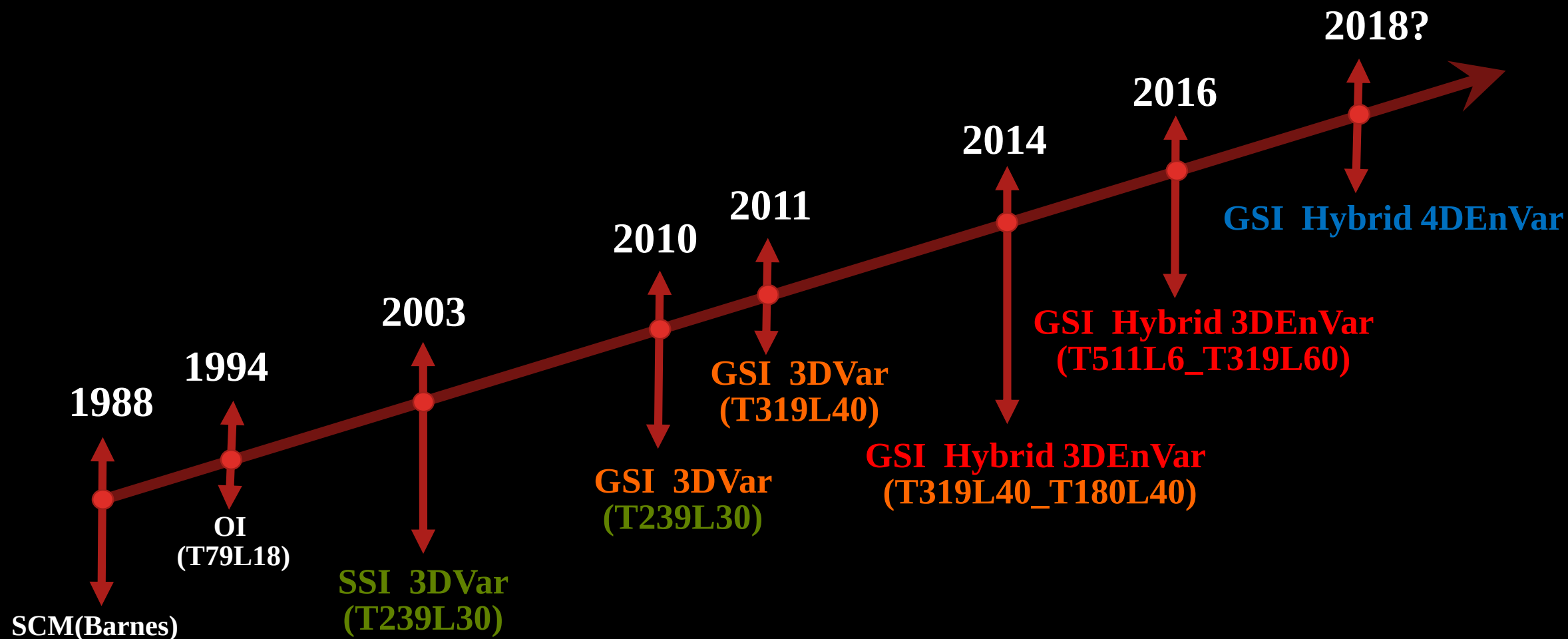
中央氣象局全球預報系統架構



中央氣象局全球資料同化系統

Variational Data Assimilation	GSI Hybrid 3D-EnVar (Wang, 2010 ; Kleist 2016)
Ensemble Data Assimilation	EnSRF (Jeff Whitaker, 2002)
Resolution	T511L60 (~25km)
Ens. Resolution	T319L60 (~40km)
Beta Static Weights	0.25
Beta Ensemble Weights	0.75
Ensemble Member size	72 (36 EnKF + 36 Time lagging)
Additive Inflation	NMC Method
Recentering	Yes
TC and EC bogus data	Yes
Observations from	NCEP and GTS
Horizontal localization	800 km

中央氣象局資料同化系統的發展



傳統觀測、衛星觀測、掩星觀測、雷達觀測、氣膠觀測、臭氧觀測

觀測資料使用現況與未來規劃

Cases	Operational	Operational + Rest	Operational + Rest + Extra
No. of Bufr Files	6	10	17
List of Bufr Files	prepbuf amsuabuf gpsrobuf airsbufr iasibuf Atmsbuf	prepbuf amsuabuf gpsrobuf airsbufr iasibuf atmsbuf hirs4buf mhsbuf gsnd1buf sbuvbuf	prepbuf amsuabuf gpsrobuf airsbufr iasibuf atmsbuf hirs4buf mhsbuf gsnd1buf sbuvbuf crisbuf hirs3buf gomebuf satwndbuf seviribuf ssmisbuf gingrbuf

資料同化分組

