アンサンブル・カルマンフィルタ

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データ同化研究チーム

Who am I?

http://data-assimilation.riken.jp/miyoshi/

大学卒業

↓

気象庁企画課 (2年)

↓

気象庁数値予報課 (1年3ヶ月)

↓

メリーランド大学大学院留学

(2年, M.S. and Ph.D.)

↓

気象庁数値予報課 (3年6ヶ月)

↓

メリーランド大学 (4年)

↓

理化学研究所 (3年+)

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Data Assimilation Research Team

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Education

- 2005 Ph.D. in Meteorology, University of Maryland, College Park, Maryland, USA (Dissertation PDF)
- 2004 M.S. in Meteorology, University of Maryland, College Park, Maryland, USA (Scholarly Paper PDF)
- 2000 B.S. in Physics, Faculty of Science, Kyoto University, Kyoto, Japan

データ同化研究チームについて

データ同化研究チームは、理化学研究所・計算科学研究機構に2012年10月に新たに設置されました。 データ同化は、シミュレーションと観測データとを融合し相乗効果を生み出す統計数理に基づいた学際的科学です。計算機が高度化しシミュレーションが精緻になるほど、実際に観測されたデータとシミュレーションとを付きあわせ、これらを融合することの意義・効用が増します。 データ同化研究チームでは、スーパーコンピュータ「京」を生かした大規模シミュレーションのための効率的かつ高精度なデータ同化アルゴリズムを研究開発するとともに、データ同化の先進的な理論研究や、幅広い応用研究を行います。 具体的には、超並列システム「京」に最適な並列化データ同化アルゴリズムを構築し、「京」の威力を発揮して世界最先端のデータ同化研究を行うとともに、「京」の高度利用に資する高速データ同化ソフトウエアを開発します。

RIKEN AICS

Data Assimilation Team

http://data-assimilation.riken.jp/

2016年4月1日　理研AICSにて

データ同化をハブとした数理科学、実験・観測科学、シミュレーション科学の融合研究イノベーションハブの形成

データ同化をハブとして、実験・観測科学、理論・シミュレーション科学を橋渡しする。データ同化が理研内のハブとしての拠点機能を構築することができ、将来の国際社会における融合研究イノベーションハブとなるための下地とする。また、理研の枠にとらわれず幅広いシミュレーション科学、実験・観測科学研究の相互連携を牽引する。国際ハブとしての機能は、我が国では科学を総合的に推進する理研が果たすべき役割であり、今取り組むことで世界のトップ拠点を狙う。

10/14　理研データ同化ワークショップ

様々な応用分野におけるデータ同化研究の課題および展望を共有、議論し、データ同化研究の知の集積、研究者間の交流を促進する。

データ同化をハブとしたイノベーションを生み出す広範なデータ同化研究コミュニティの形成および拡大

9/9-10/24　理研内競争的資金

理研内研究者によるデータ同化をハブとした融合研究に関する新しい着想に対して資金を投じる。
新たな着想を具体的な研究計画にまで練り上げる。

理研内で融合研究を始めるためのシード発掘、研究スタートアップの促進

11/14-18　理研データ同化合宿

データ同化に興味を持つ大学院生や若手研究者等を募り、参加者自身がデータ同化システムを実装する演習を行う。

データ同化の基礎技術を有する人材育成、データ同化コミュニティの裾野拡大

イノベーションハブ

2017/2/27-3/2　理研データ同化国際シンポジウム

研究計画発表

データ同化をハブとした数理科学、実験・観測科学、シミュレーション科学、データ駆動科学の融合に関するシンポジウムを開催する

データ同化の応用範囲を広げ、様々な分野に双方向にフィードバックする数理科学としてのデータ同化をさらに強化
イノベーションを生み出す「国際科学技術ハブ」への布石

研究者招聘

国内外の優秀な研究者が滞在

ハブ化を助長
相互連携を牽引

SPEEDY-LETKFを使った実習

- 2008年ブエノスアイレスで実績あり
  - 約2週間で、3次元変分法とアンサンブルカルマンフィルタの比較
  - 古いバージョンだった
- 今回は正味2日でアンサンブルカルマンフィルタのみを扱う
  - 新しいバージョン

Intensive Course on Data Assimilation
Buenos Aires, Argentina
27 October - 7 November 2008

School of Sciences of the University of Buenos Aires and Center for Atmospheric and Ocean Research CIMA/CONICET

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CONTENIDO

Dr. Eugenia Kalnay - Dr. Celeste Saulo
Organizers

GOALS: Provide participants with a solid foundation to understand current approaches for in situ and remotely sensed data assimilation, with a concentration on basic concepts and developments, and simple computational exercises.
Prepare attendants to participate in the Workshop that will take place the following week on 4D-Var and Ensemble Kalman Filter.
Scholarships: Through WWRP/THORPEX support, there will be grants to support the travel, lodging and per diem of up to 10 Latin American participants. Other regional and local qualified participants can participate in the course, without support, but without additional tuition costs.

OBJETIVOS: Proveer herramientas para comprender como se aborda en la actualidad la problemática de la asimilación de datos -tanto de observaciones in situ como remotas-, concentrándose en los conceptos básicos y en los desarrollos esenciales. Prepara a los cursantes a participar en el Workshop a realizarse la semana siguiente sobre 4D-Var y Ensemble Kalman Filter.
Becas: Mediante el auspicio de la WWRP/THORPEX se contará con becas para financiar viaje y estadia de hasta 10 participantes de Latinoamérica. Otros participantes calificados locales y regionales tambien pueden solicitar asistir al curso, sin apoyo económico, pero sin costos de inscripción.

SPONSOR ORGANIZATIONS

WWRP
THORPEX
A World Weather Research Programme
CIMA
CONICET
UBA

Endorsed by CPTEC (Brazil) and by La Plata Basin Regional Hydroclimate Project (LPB)
Auspiciado por CPTEC (Brasil) y por La Plata Basin Regional Hydroclimate (LPB)
in support of capacity building in Latin America / en apoyo a la formacion de recursos humanos en Latinoamerica

データ同化

観測・実験データ　　　　シミュレーション

データ同化は、シミュレーションと現実世界を結びつけ、相乗効果を生み出す。

双方の情報を最大限に抽出

データ同化

観測・実験データ　　シミュレーション

データ同化

1 + 1

>2

TEDxSannomiyaより

http://tedxsannomiya.com/speakers/takemasa-miyoshi/


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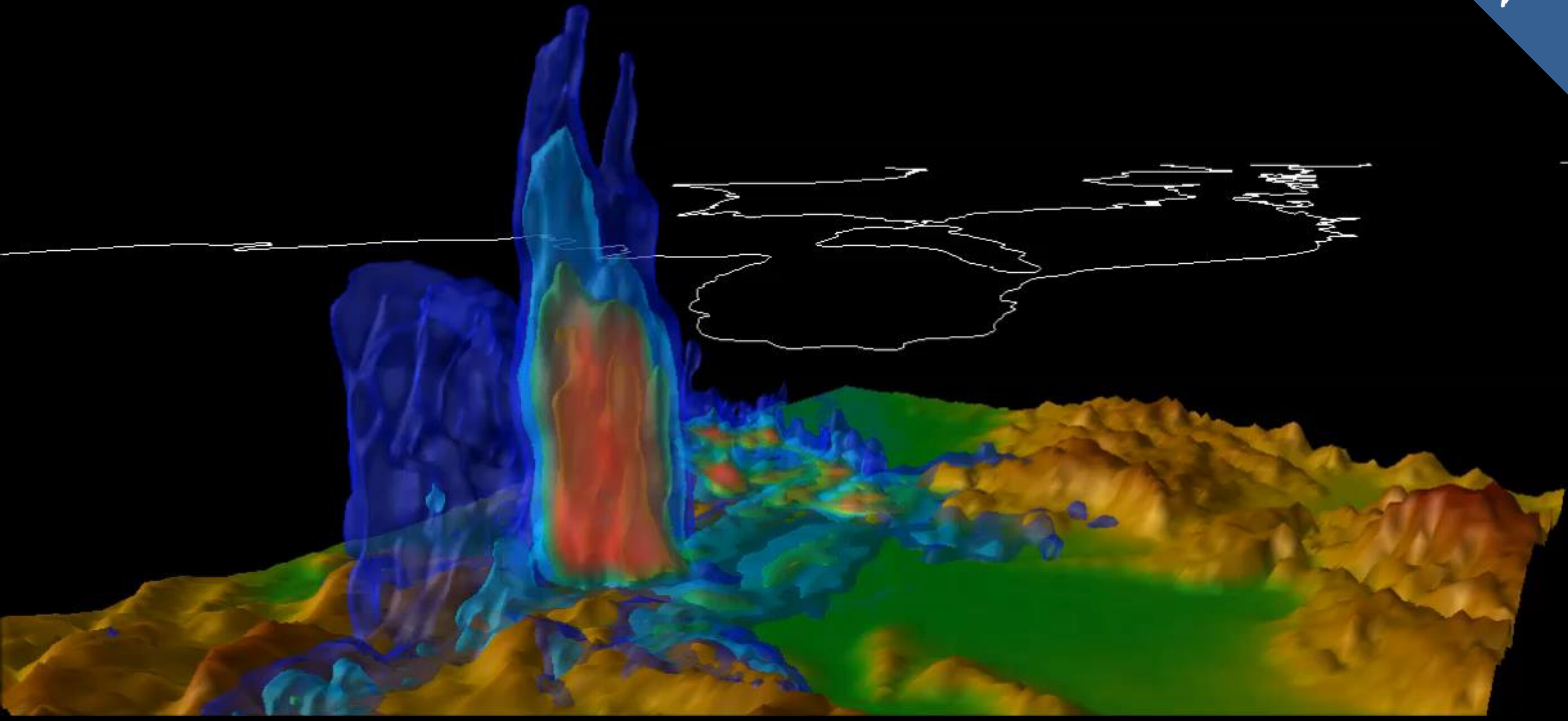
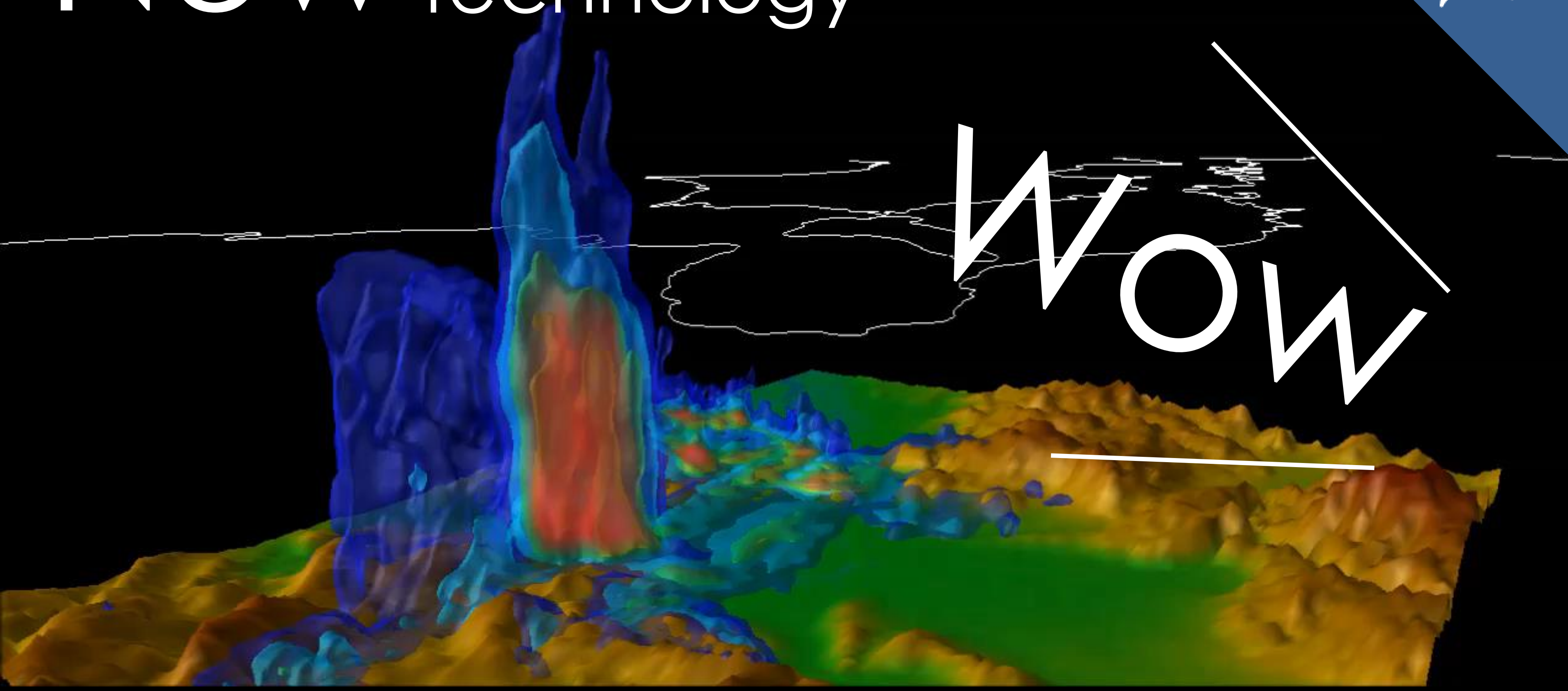
Raindrops in the air



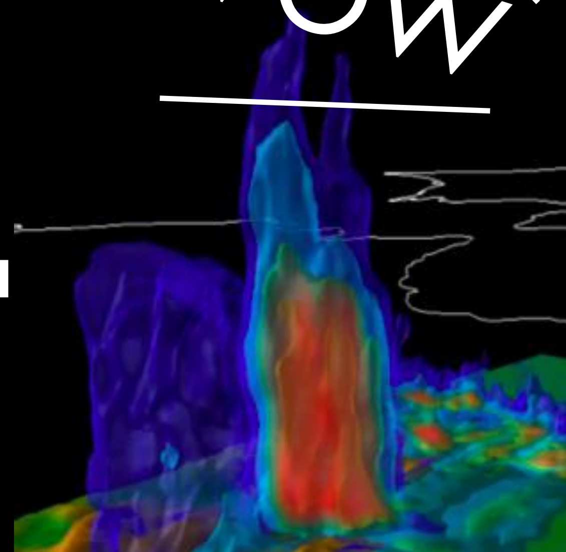
New radar technology



Wow

+

Wow



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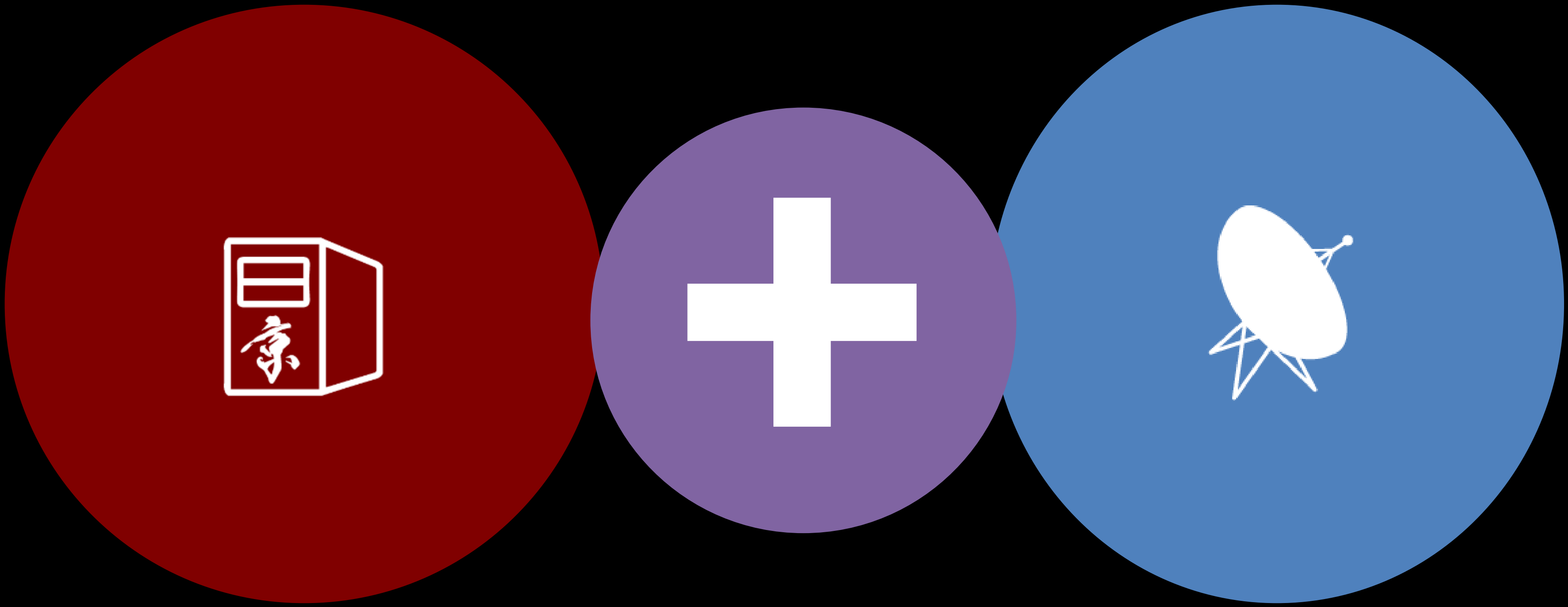
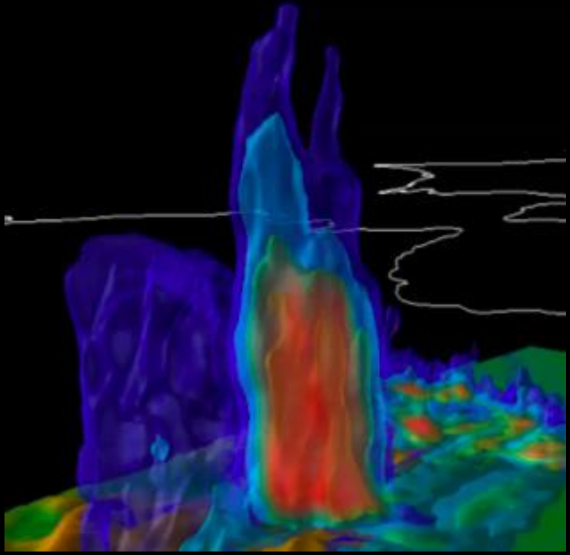
Data Assimilation

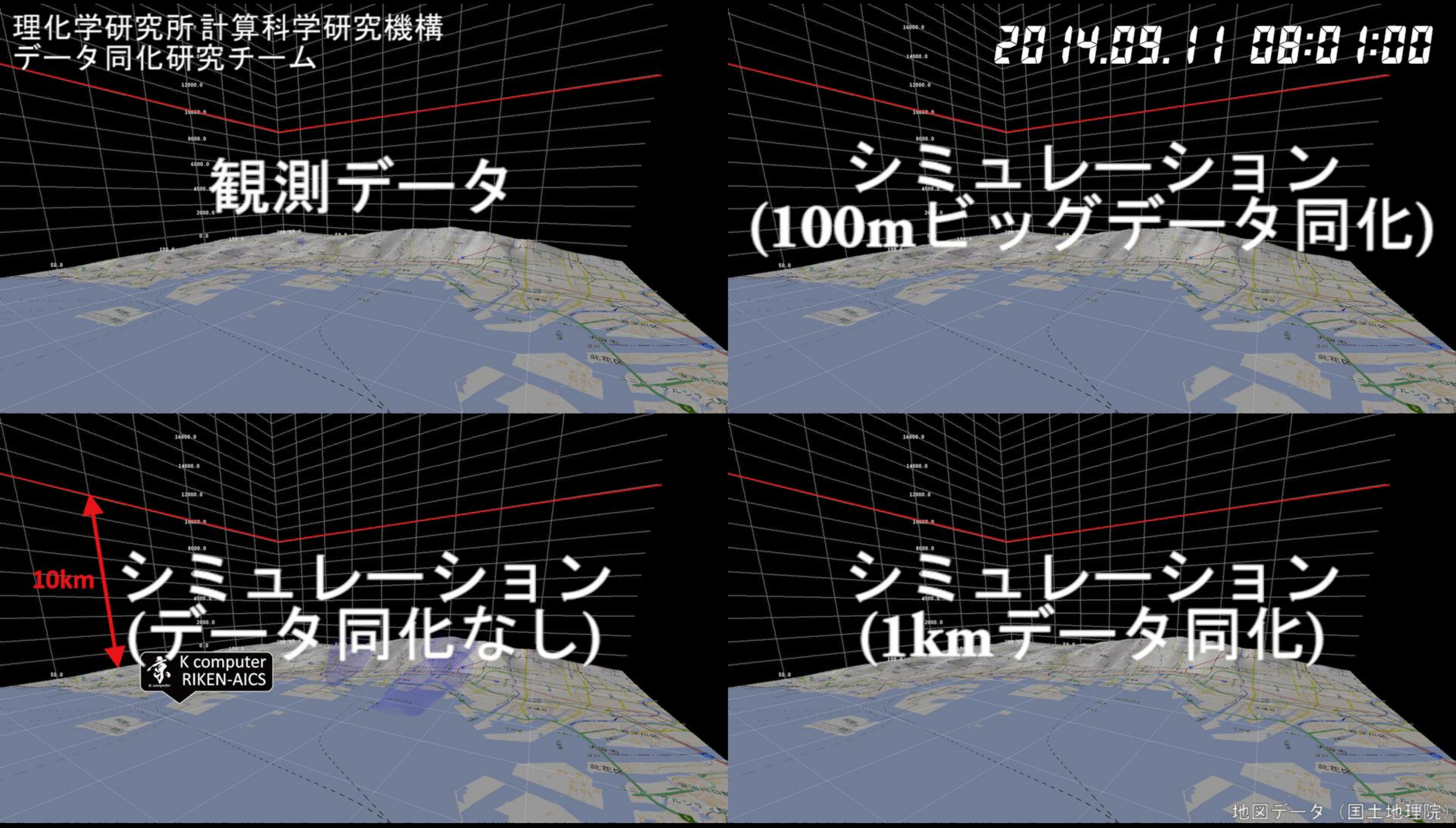




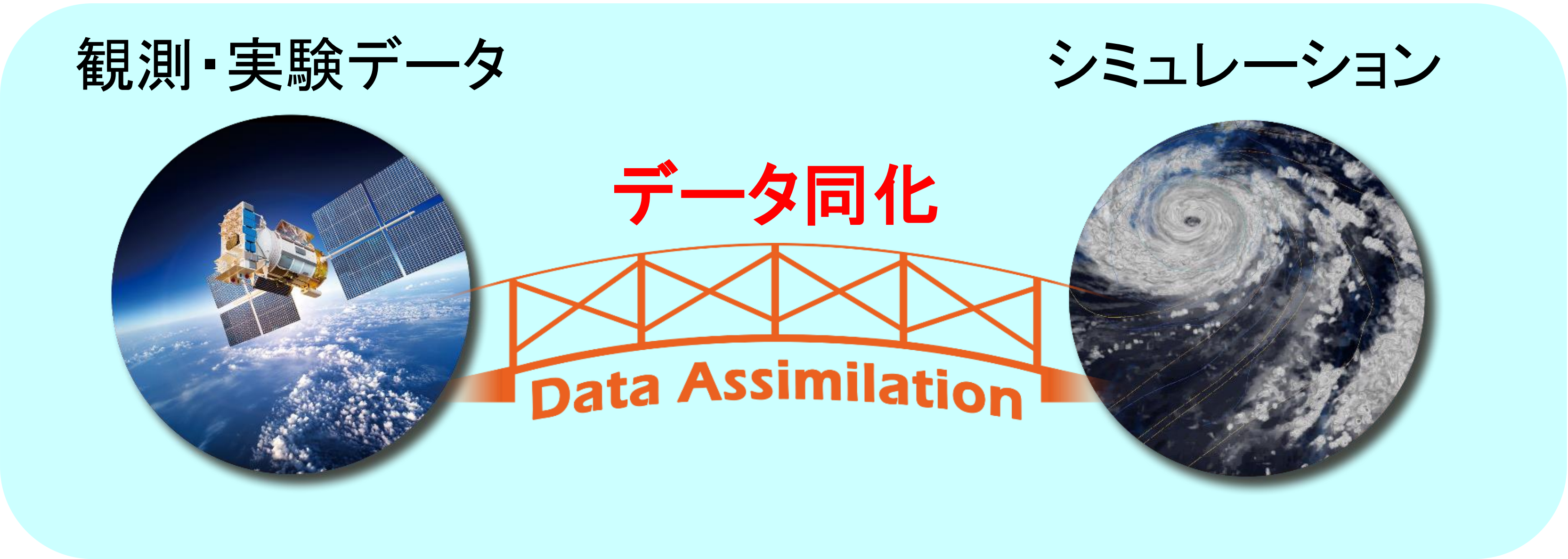
= ~~ゲリラ~~豪雨

2014年9月11日朝、ゲリラ豪雨

2014年9月11日朝、ゲリラ豪雨



データ同化



データ同化は、シミュレーションと現実世界を結びつけ、相乗効果を生み出す。

双方の情報を最大限に抽出

カオス同期　Chaos Synchronization

Master (drive) system

Slave (response) system

自然

観測

何らかの情報伝達

モデル

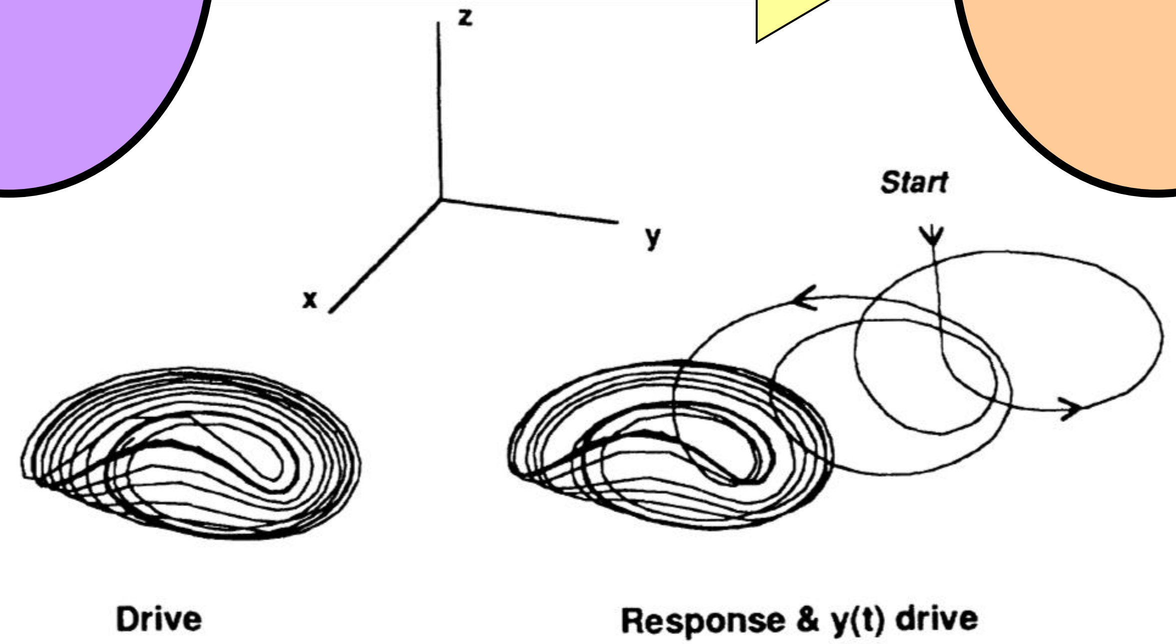


FIG. 1. The attractors for the Rössler drive system and the $(x'$-$z')$ response system and $y(t)$ drive variable.

DA as Chaos Synchronization (*Yang et al. 2006*)

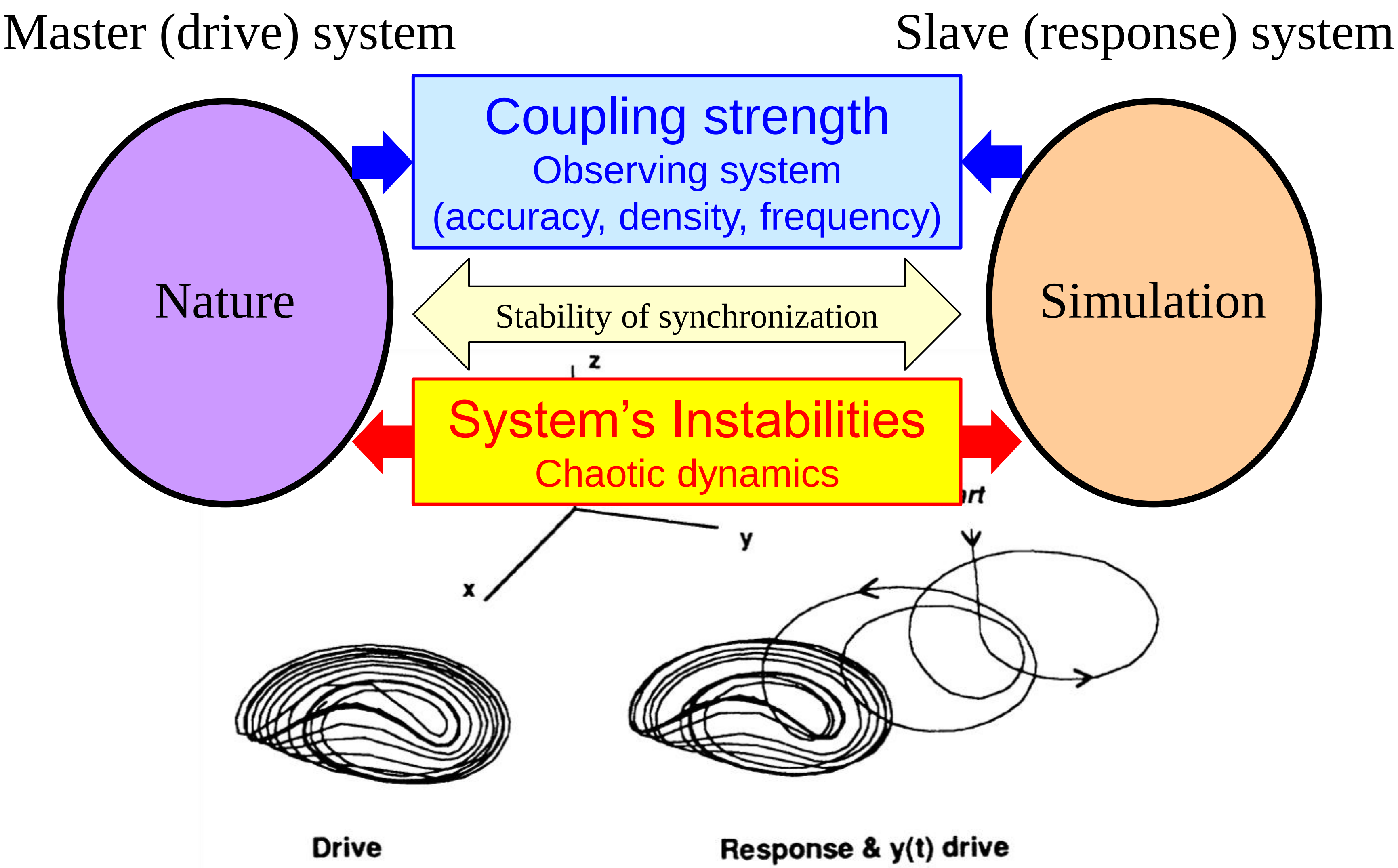
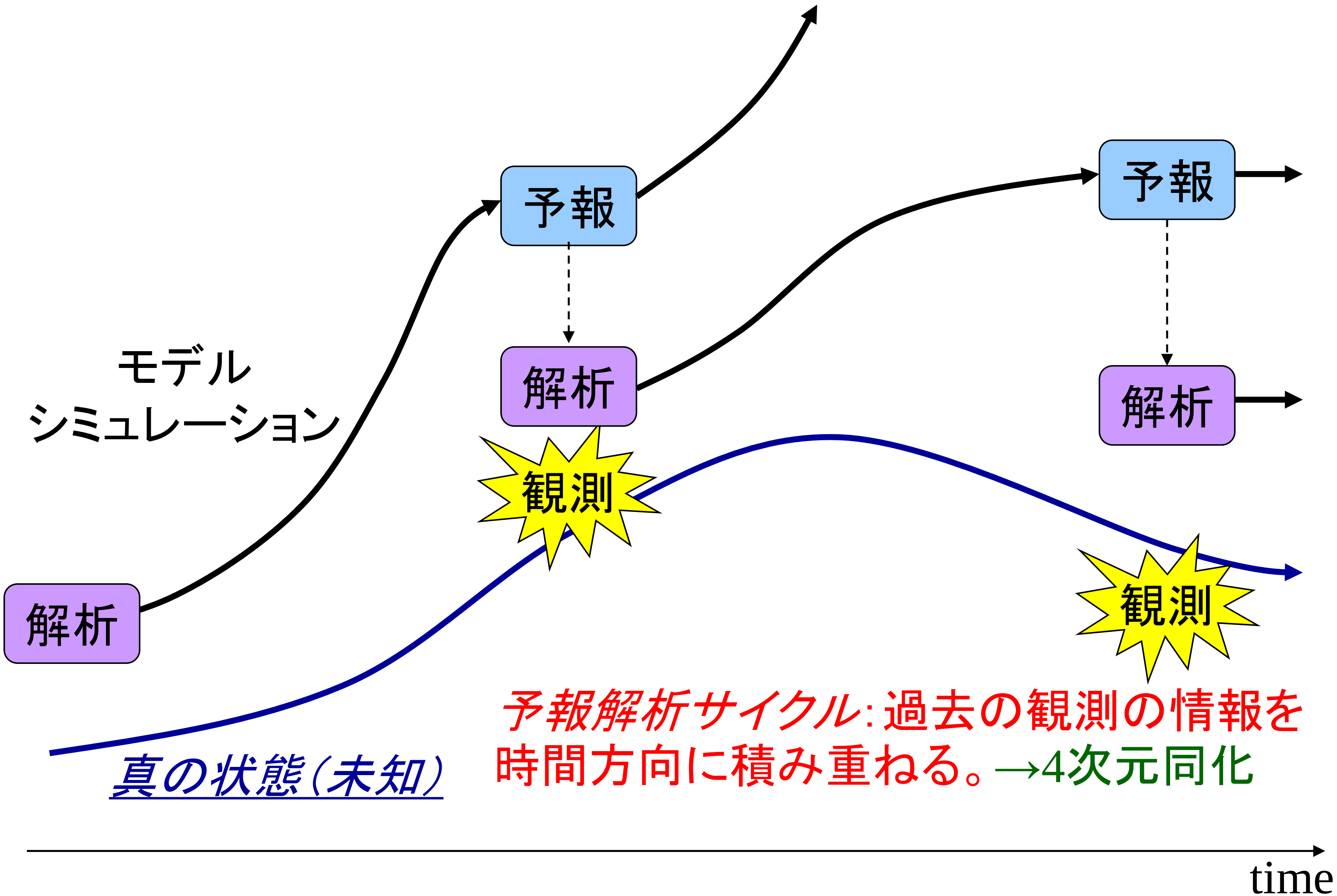
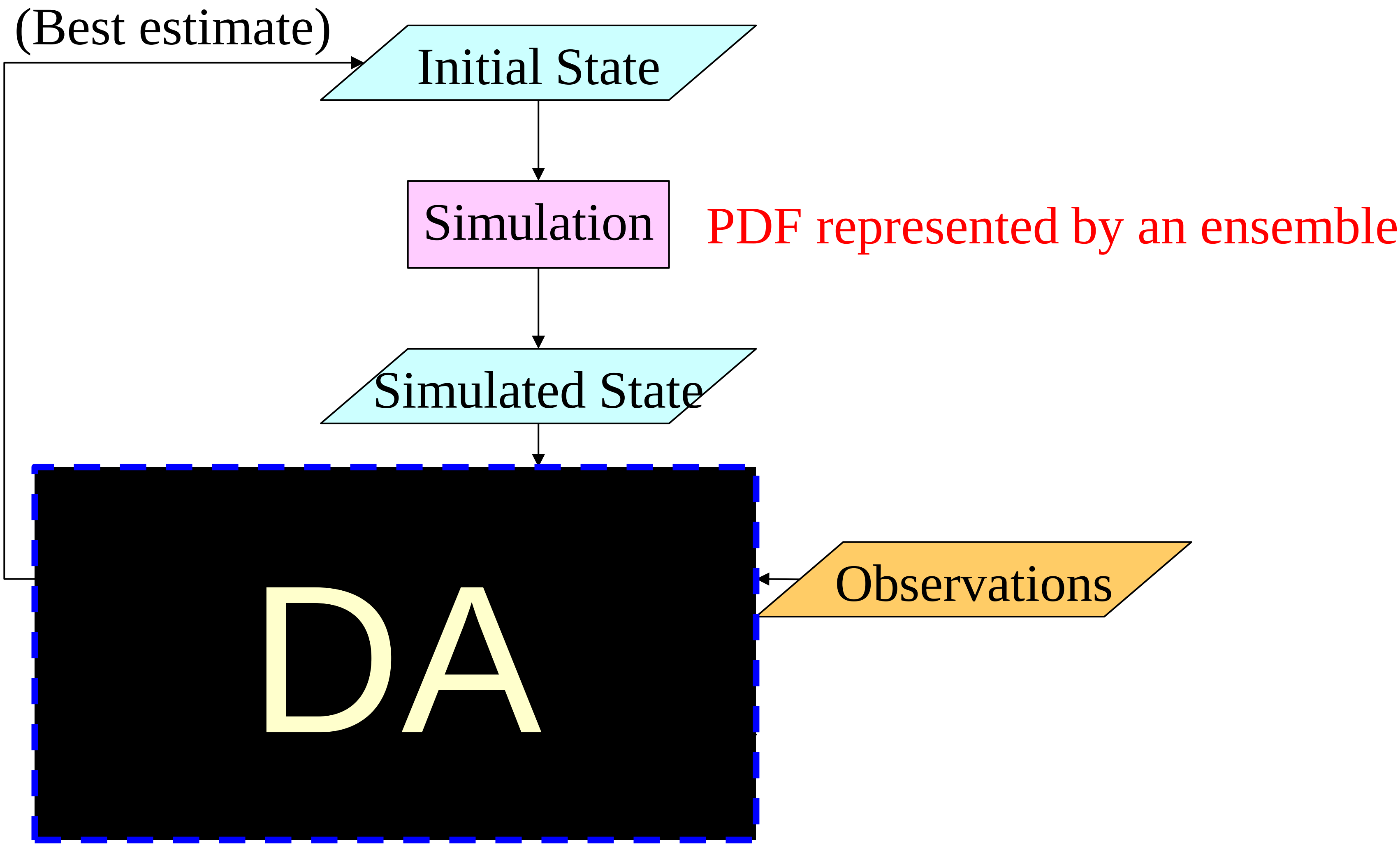


FIG. 1. The attractors for the Rössler drive system and the (x'-z') response system and $y(t)$ drive variable.

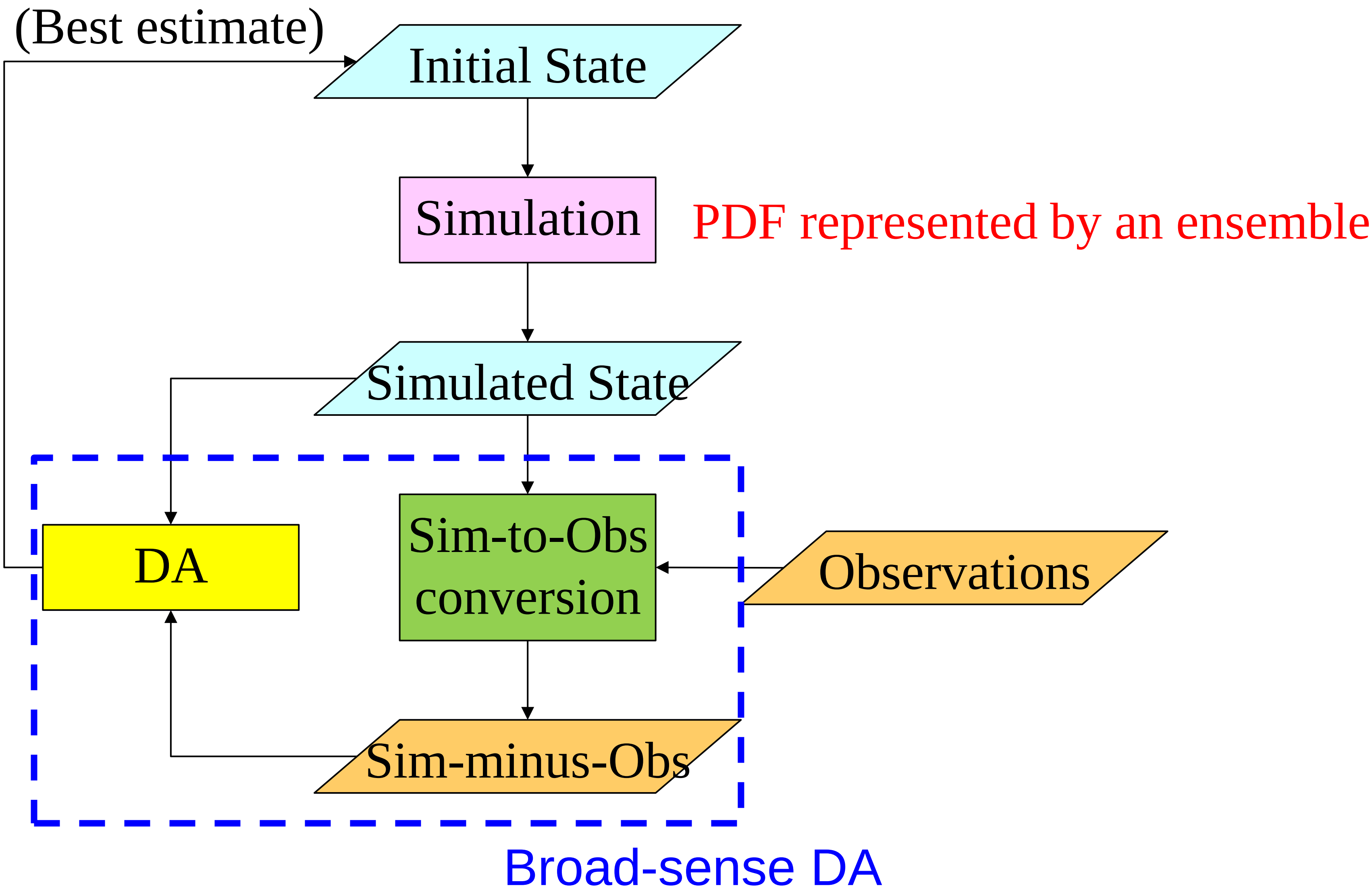
数値天気予報のしくみ


予報
予報
モデル
シミュレーション
解析
解析
解析
観測
観測
真の状態(未知)
予報解析サイクル: 過去の観測の情報を
時間方向に積み重ねる。→4次元同化
time

データ同化（DA）のworkflow



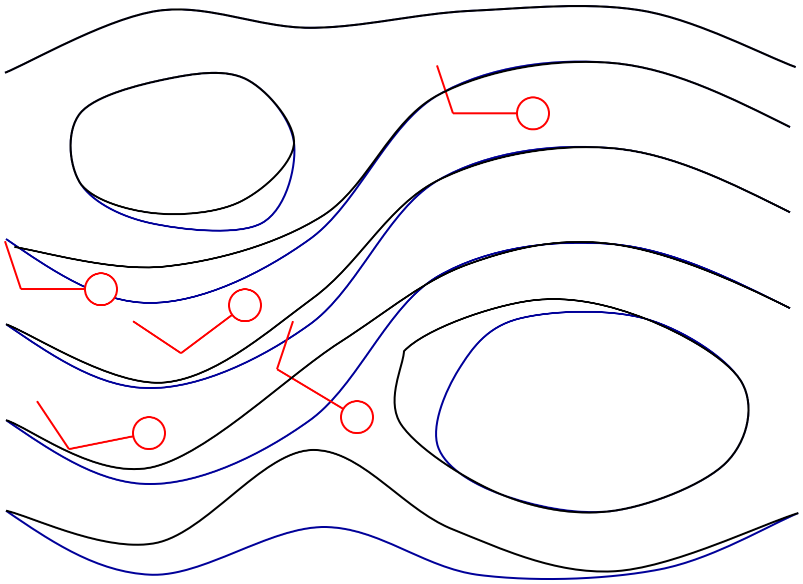
データ同化（DA）のworkflow



Data Assimilation

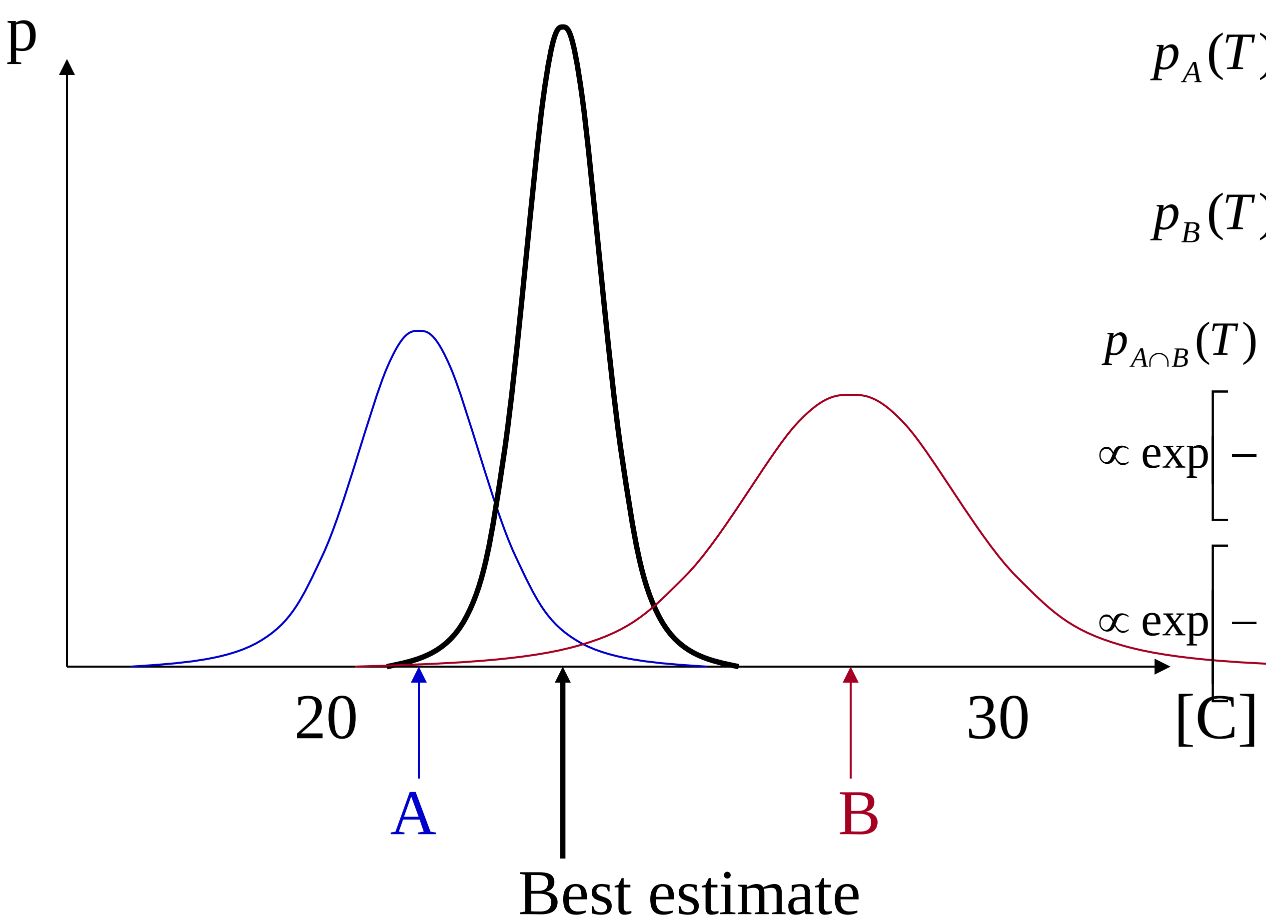
DA corrects forecast fields to fit better with observations.

DA produces *the best estimate* of the current state, which is used as the *initial condition*.



Geopotential height at upper atmosphere is basically parallel to winds.

A simple example: two thermometers



Temperature of this room

$$p_A(T) \propto \exp\left[-\frac{(T-T_A)^2}{2\sigma_A^2}\right]$$

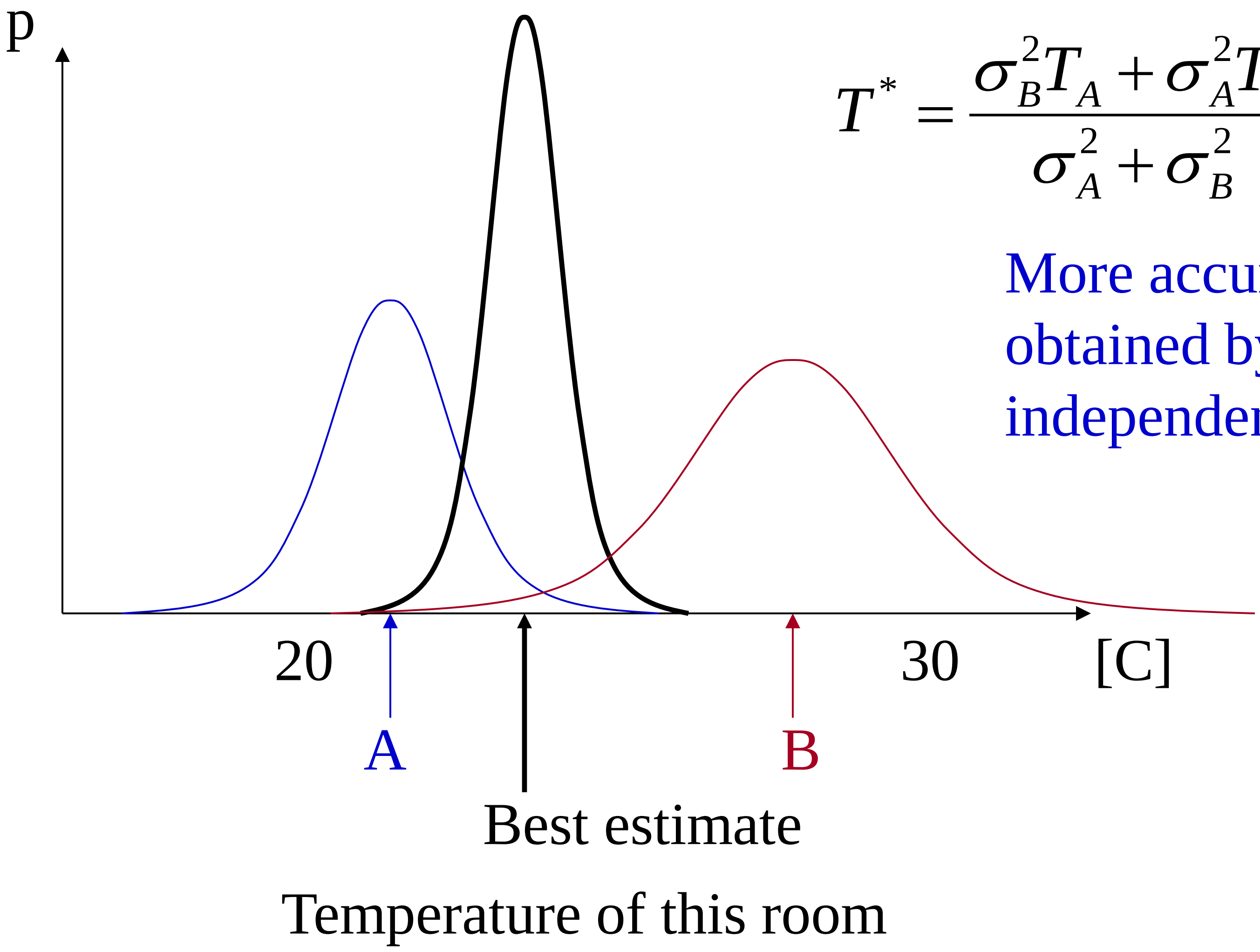
$$p_B(T) \propto \exp\left[-\frac{(T-T_B)^2}{2\sigma_B^2}\right]$$

$$p_{A\cap B}(T) = p_A(T) \bullet p_B(T)$$

$$\propto \exp\left[-\frac{(T-T_A)^2}{2\sigma_A^2} - \frac{(T-T_B)^2}{2\sigma_B^2}\right]$$

$$\propto \exp\left[-\frac{\sigma_A^2+\sigma_B^2}{2\sigma_A^2\sigma_B^2}\left(T - \frac{\sigma_B^2 T_A + \sigma_A^2 T_B}{\sigma_A^2+\sigma_B^2}\right)^2\right]$$

A simple example: two thermometers



$$T^* = \frac{\sigma_B^2 T_A + \sigma_A^2 T_B}{\sigma_A^2 + \sigma_B^2}, \sigma^* = \frac{\sigma_A^2 \sigma_B^2}{\sigma_A^2 + \sigma_B^2}$$

More accurate analysis is obtained by combining two independent information.

Multidimensional generalization

Generalizing to a multidimensional variable

Background error covariance

Background PDF

$$p^f(\mathbf{x}) \propto \exp[-\tfrac{1}{2}(\mathbf{x}-\mathbf{x}^f)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^f)]$$

Observation PDF

$$p^o(\mathbf{x}) \propto \exp[-\tfrac{1}{2}(H\mathbf{x}-\mathbf{y}^o)^T \mathbf{R}^{-1}(H\mathbf{x}-\mathbf{y}^o)]$$

Joint distribution

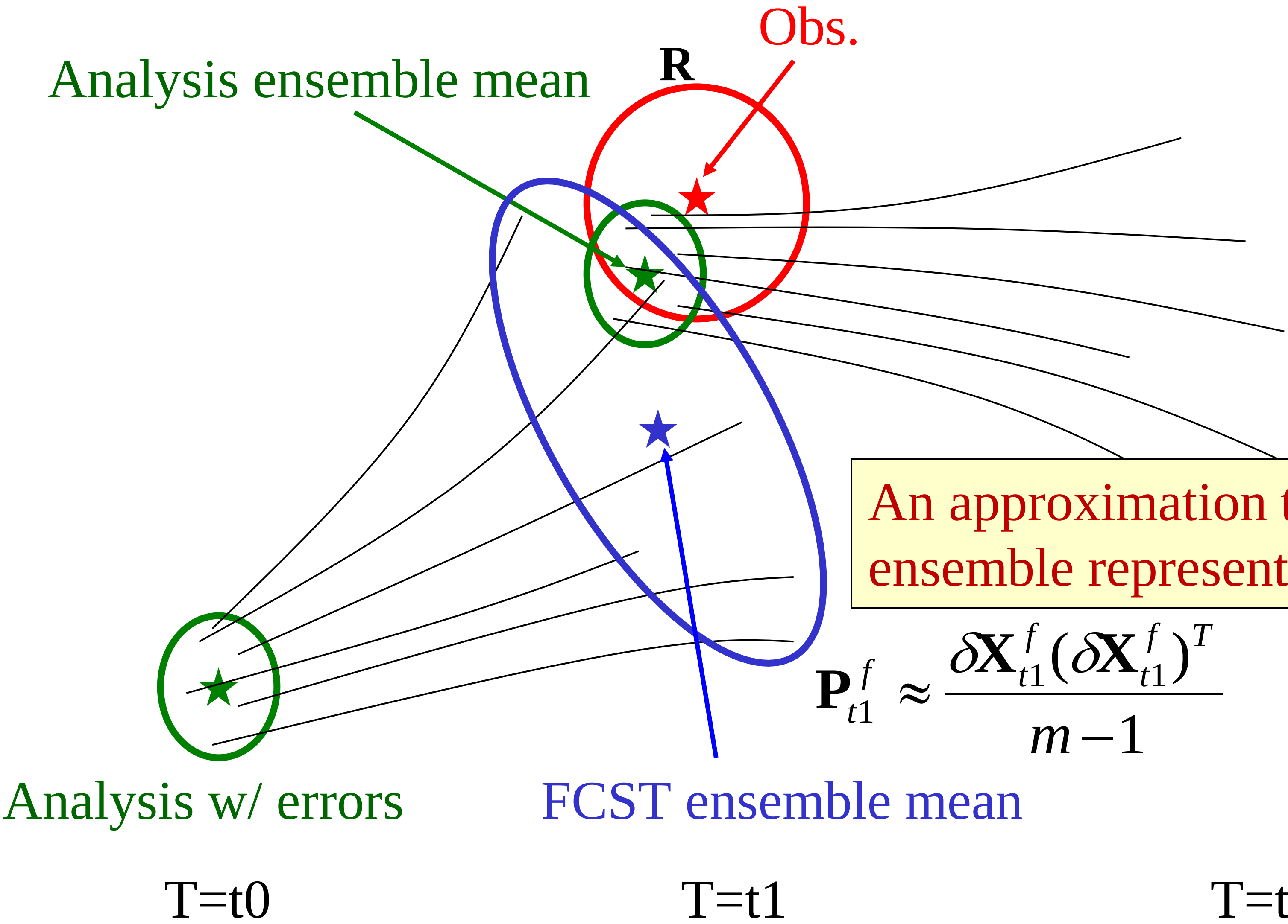
Observation error covariance

$$p^{f\cap o}(\mathbf{x}) = p^f(\mathbf{x}) \bullet p^o(\mathbf{x})$$

$$\propto \exp[-\tfrac{1}{2}\{(\mathbf{x}-\mathbf{x}^f)^T \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^f) + (H\mathbf{x}-\mathbf{y}^o)^T \mathbf{R}^{-1}(H\mathbf{x}-\mathbf{y}^o)\}]$$

Analysis is given by the maximizer **x** (maximum likelihood).

We consider the evolution of PDF



An approximation to KF with ensemble representations

$$\mathbf{P}_{t1}^{f} \approx \frac{\delta \mathbf{X}_{t1}^{f} (\delta \mathbf{X}_{t1}^{f})^{T}}{m-1}$$

LETKF (Local Ensemble Transform Kalman Filter)

Analysis is given by a linear combination of forecast ensemble:

$$\mathbf{X}^a = \overline{\mathbf{x}}^f + \delta\mathbf{X}^f \mathbf{T}$$

Ensemble Transform Matrix

(ETKF, Bishop et al. 2001; LETKF, Hunt et al. 2007)

$$\mathbf{T} = \underbrace{\widetilde{\mathbf{P}}^a (\delta\mathbf{Y})^T \mathbf{R}^{-1} (\mathbf{y}^o - \overline{H(\mathbf{x}^f)})}_{\text{ensemble mean update}} + \underbrace{[(m-1)\widetilde{\mathbf{P}}^a]^{1/2}}_{\text{uncertainty update}}$$

$$\widetilde{\mathbf{P}}^a = [(m-1)\mathbf{I}/\rho + (\delta\mathbf{Y})^T \mathbf{R}^{-1} \delta\mathbf{Y}]^{-1}$$

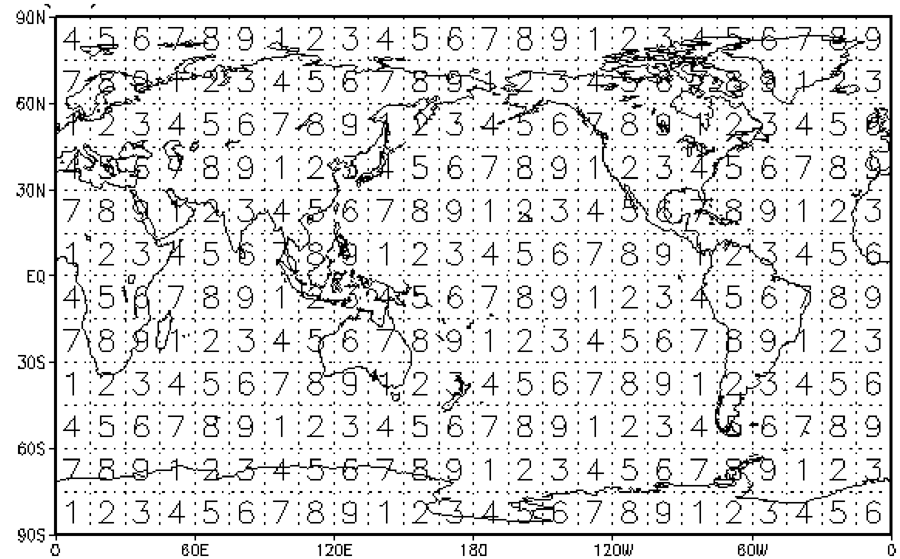
Analysis error covariance in the ensemble subspace

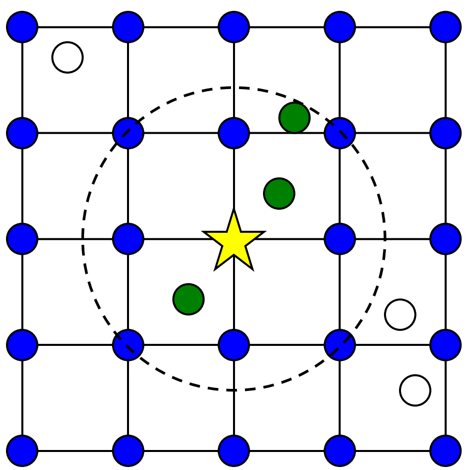
LETKF algorithm (Hunt et al. 2007)

Local Ensemble Transform Kalman Filter

Each grid point is treated independently.

→ *essentially perfectly parallel*



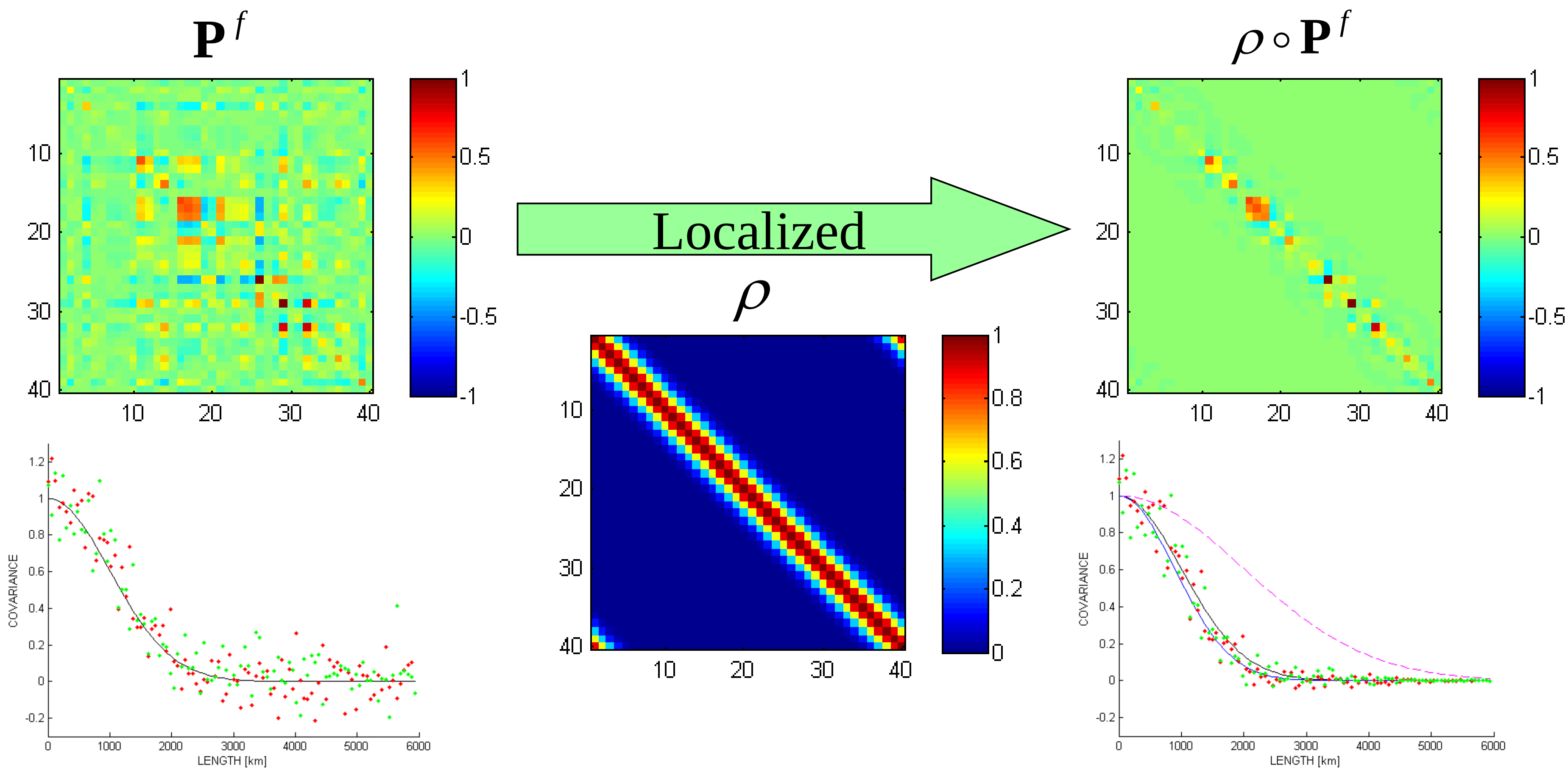


Multiple observations are treated simultaneously.

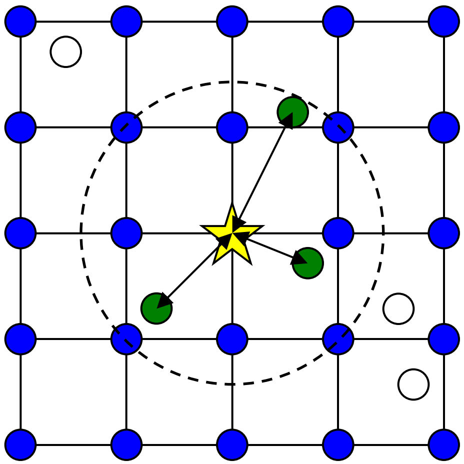
T matrix is computed at each grid point independently.

Covariance localization (e.g., Houtekamer and Mitchell 1998)

Empirical treatment for…
- reducing sampling noise
- increasing the rank



Localization in LETKF



Analysis of the *i*-th variable:

$$\underset{(N\times m)}{\mathbf{x}_i^a} = \bar{\mathbf{x}}_i^f \mathbf{1}_{1\times m} + \underset{(N\times m)}{\delta\mathbf{x}_i^f}\,\underset{(m\times m)}{\mathbf{T}_i}(\underline{\delta\mathbf{Y}_i^f, \mathbf{R}_i, \mathbf{d}_i})$$

Two steps of localization:

1. Selecting a subset of global obs for the *i*-th variable

   $\delta\mathbf{Y}_i^f, \mathbf{R}_i, \mathbf{d}_i$ are composed of only selected local obs.

2. Obs error std. is weighted by the localization factor

   $\mathbf{R}_i \leftarrow \tilde{\rho}_i^{-1} \circ \mathbf{R}_i$ so that far-away obs have large error.

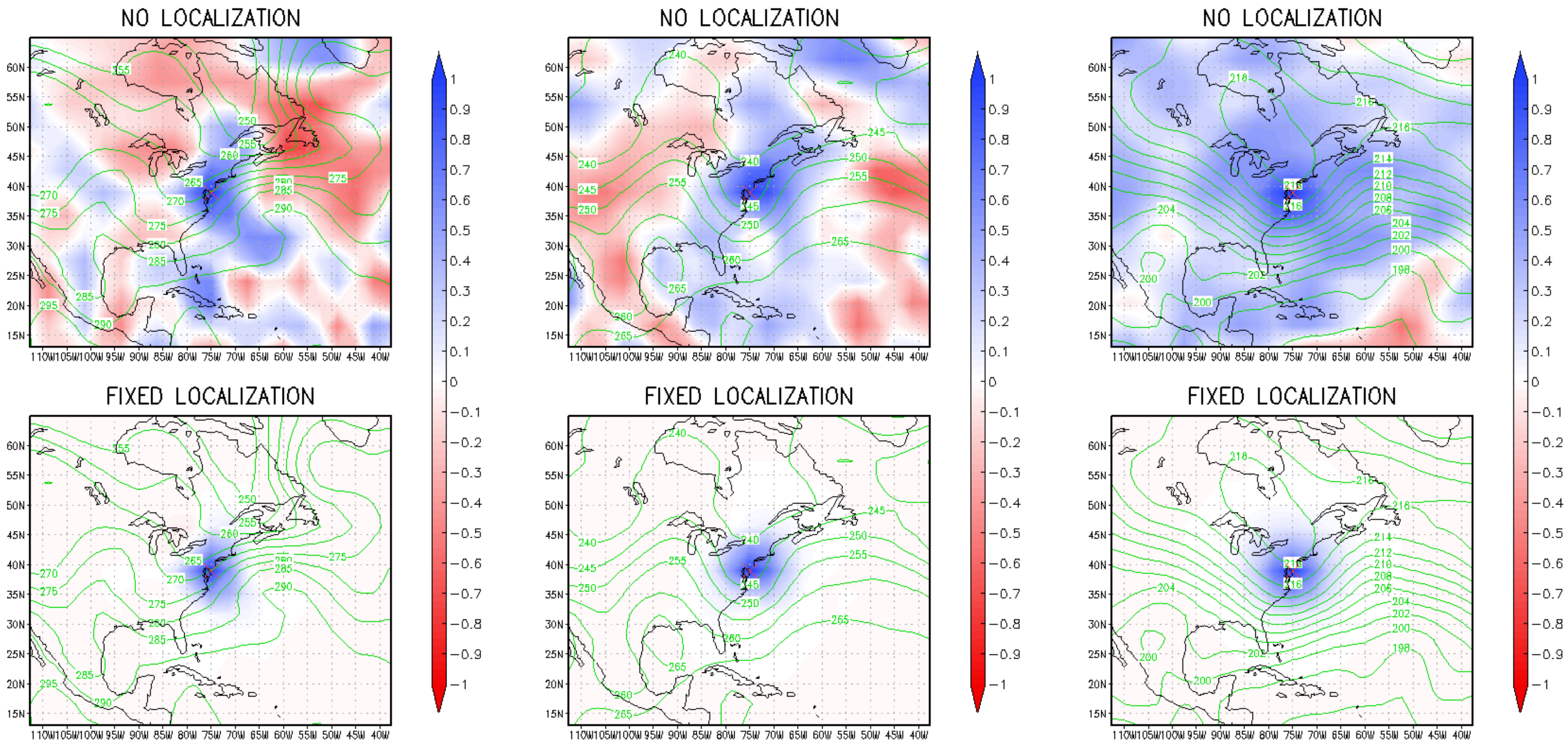
   R-localization, Hunt et al. (2007)

Difficulties of localization

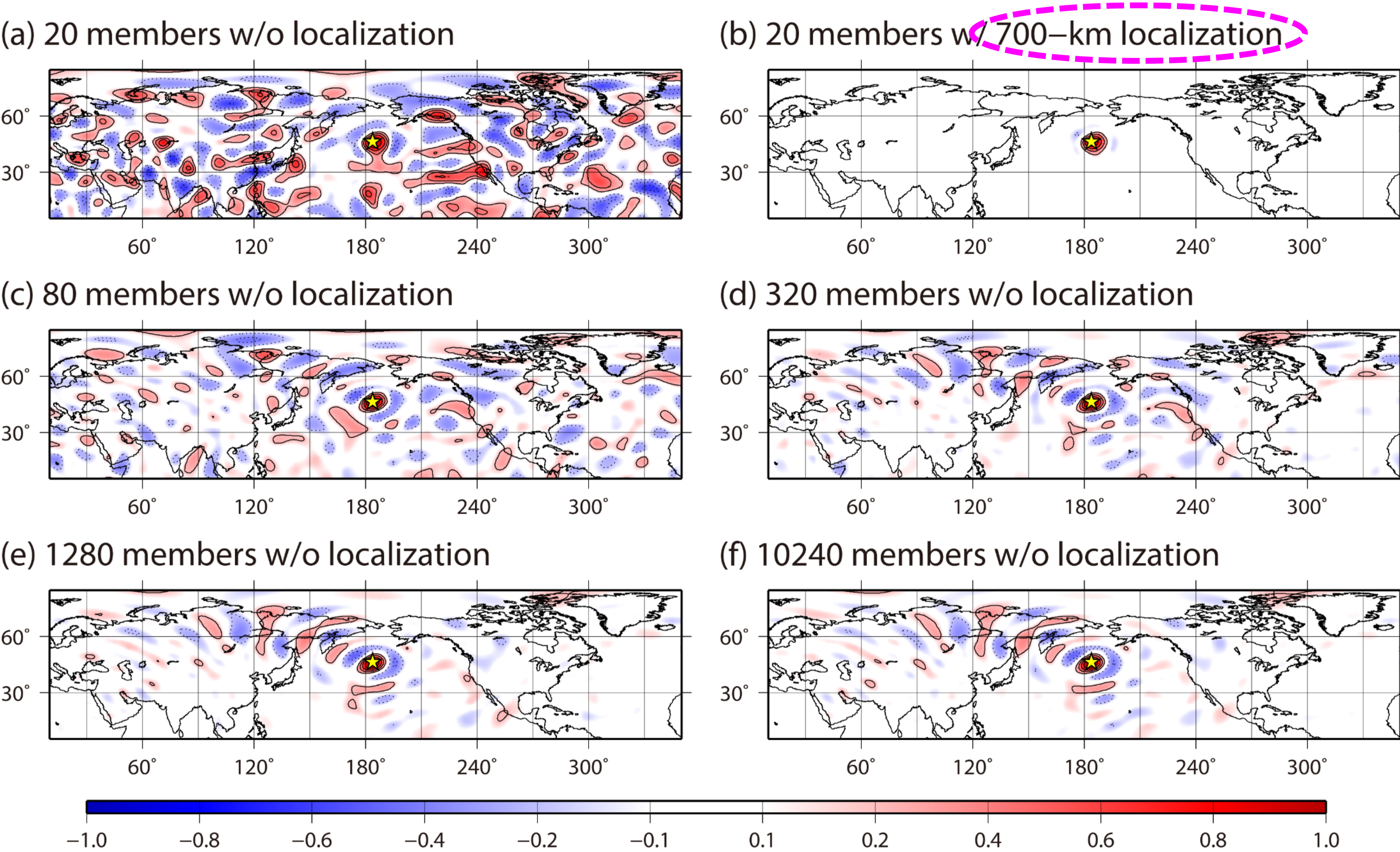
Difficulties include…

- dependence on (x, y, z, t) ➔ loss of flow-dependence
- balance issue

$\sigma = 0.95$ $\sigma = 0.51$ $\sigma = 0.08$



10240-member SPEEDY-LETKF (*Miyoshi and Kondo 2014*)

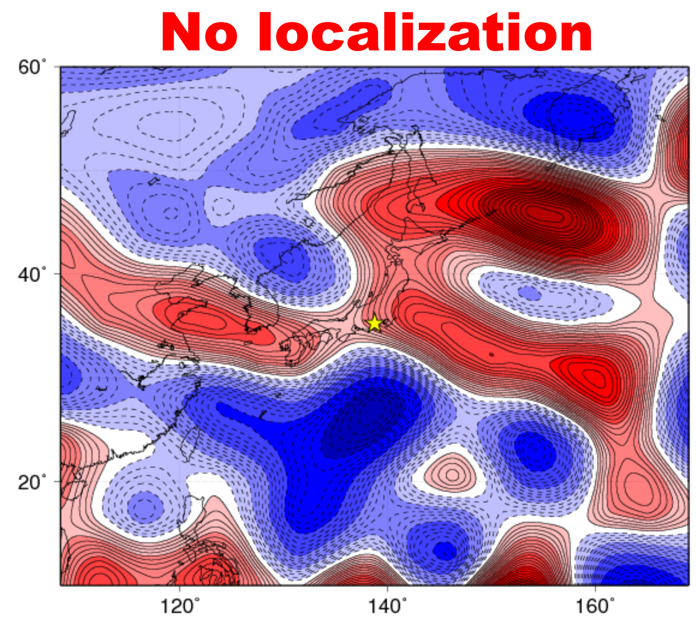


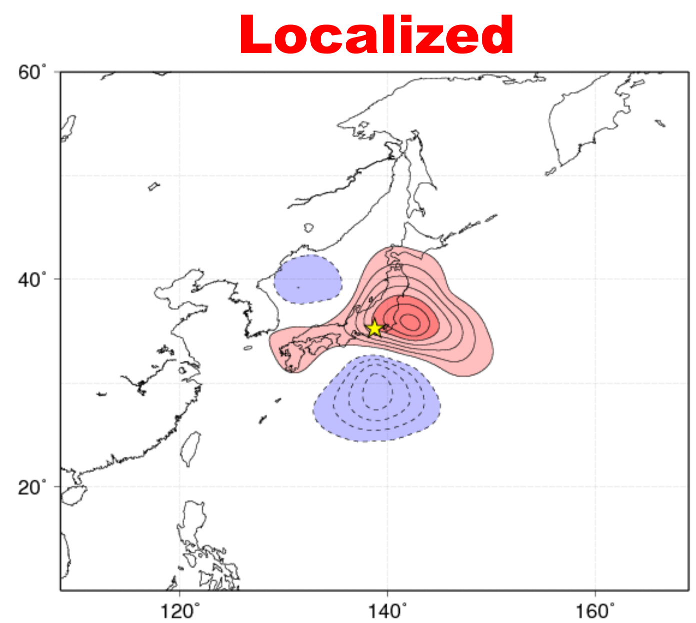
A challenge: multi-scale localization

Localization plays an essential role in an EnKF to cope with limited ensemble size.

Higher resolution requires more localization, limiting the use of observations.

We look for better use of observations by separating the scales.



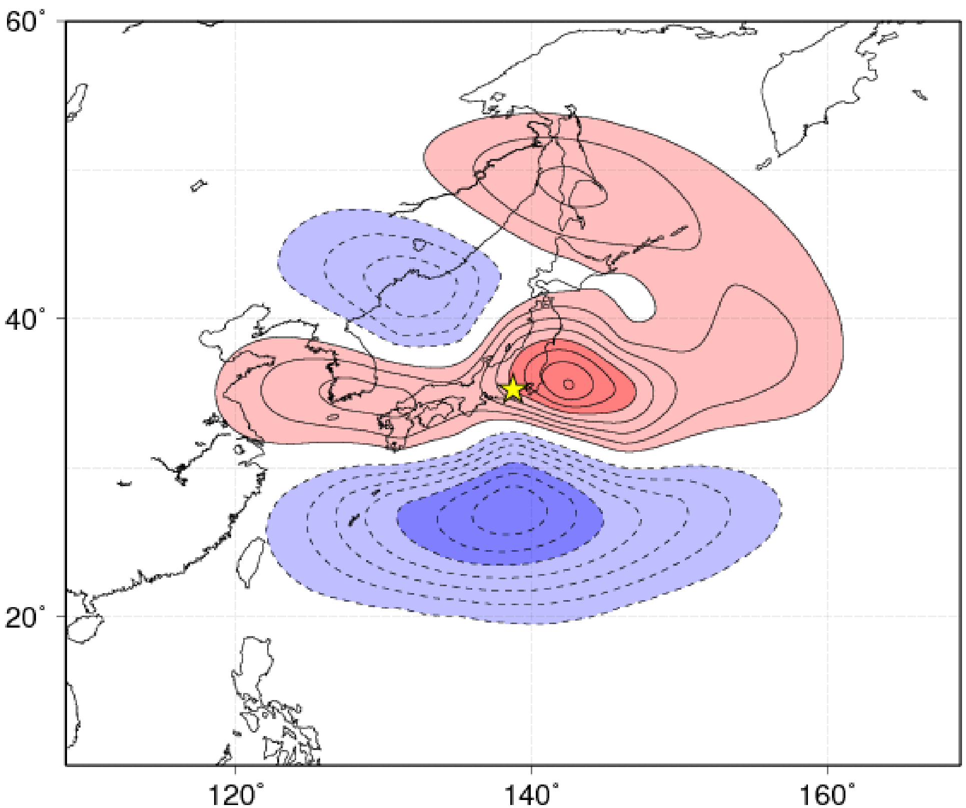


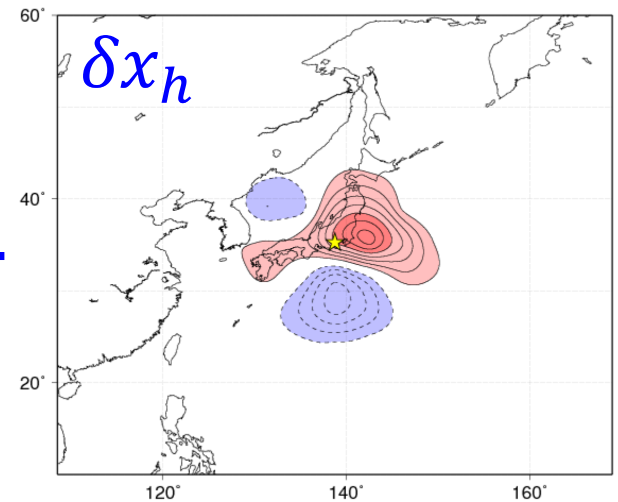
Analysis increment from a single profile observation (20 members)

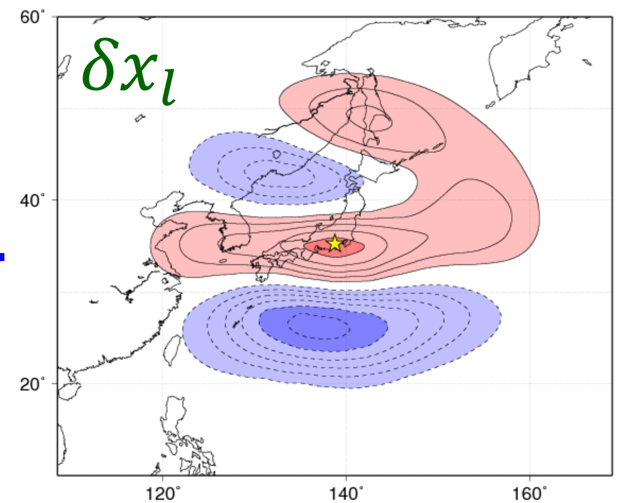
Scale-separated analysis increments

We will construct analysis increments at high (h) and low (l) resolutions separately.

$$\boxed{\delta x = \delta x_h + \delta x_l}$$







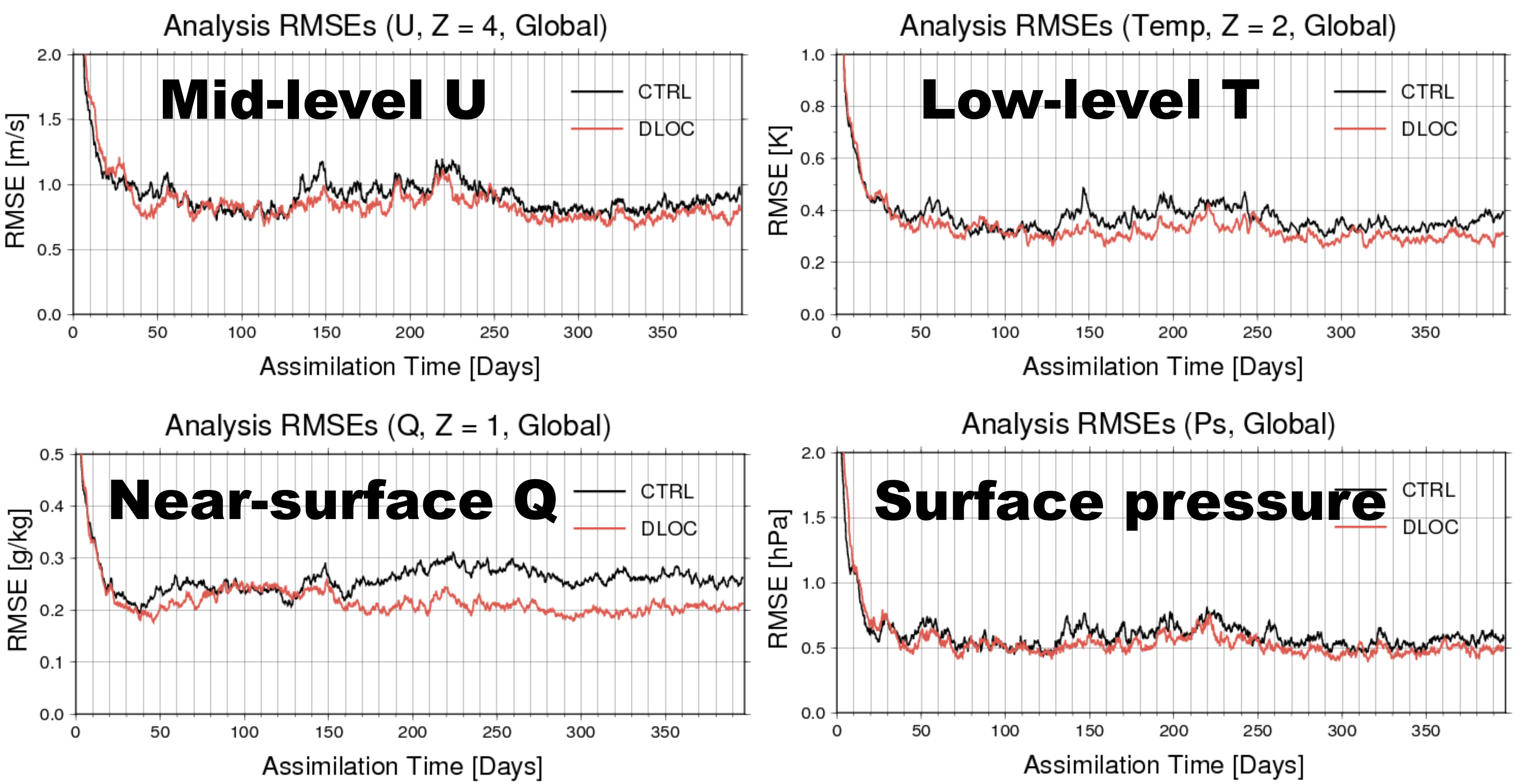
Results are promising.

Experiments with the T30L7 SPEEDY model (***Molteni, 2003***)

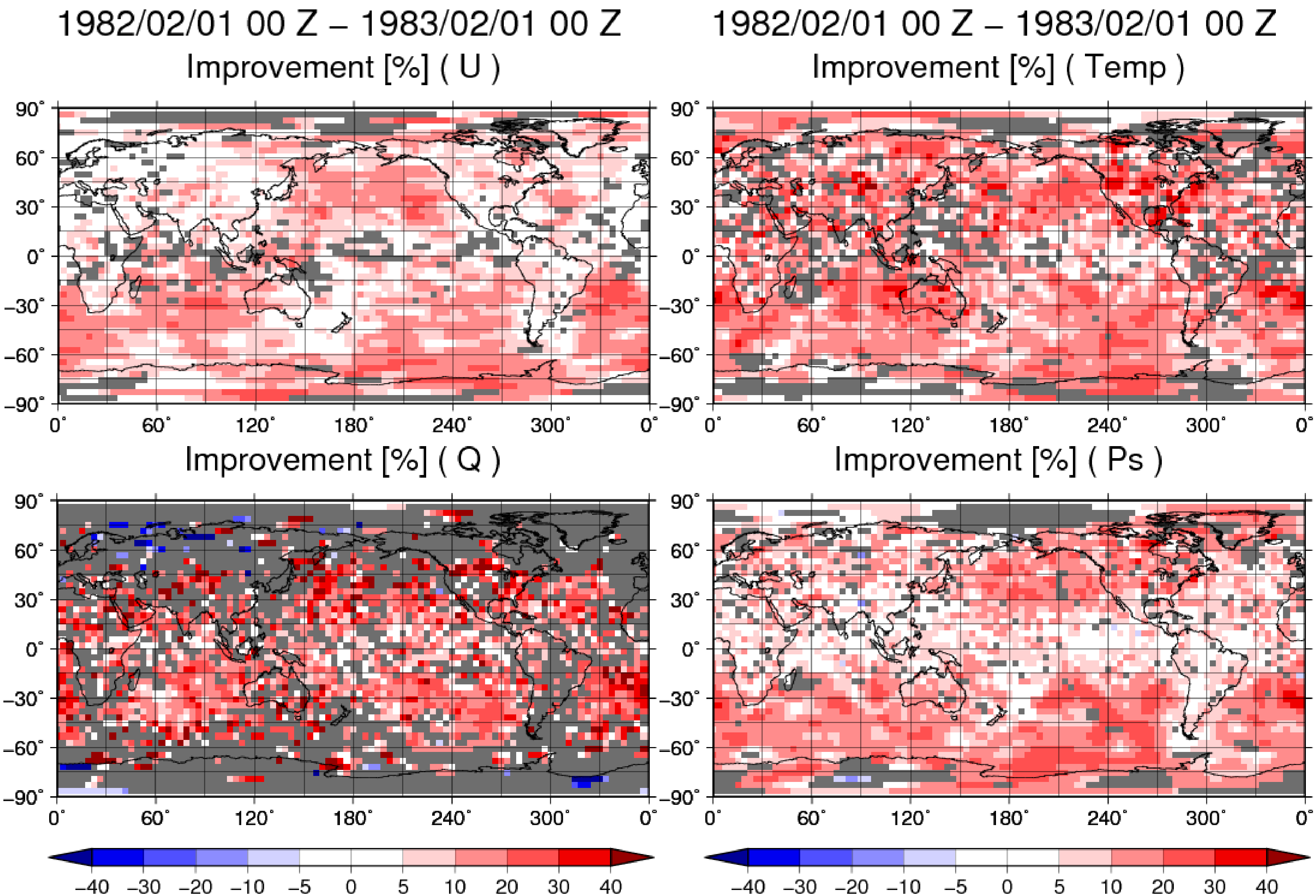
Global-average RMSE

Regular localization (700 km)

Dual localization (600-900 km)



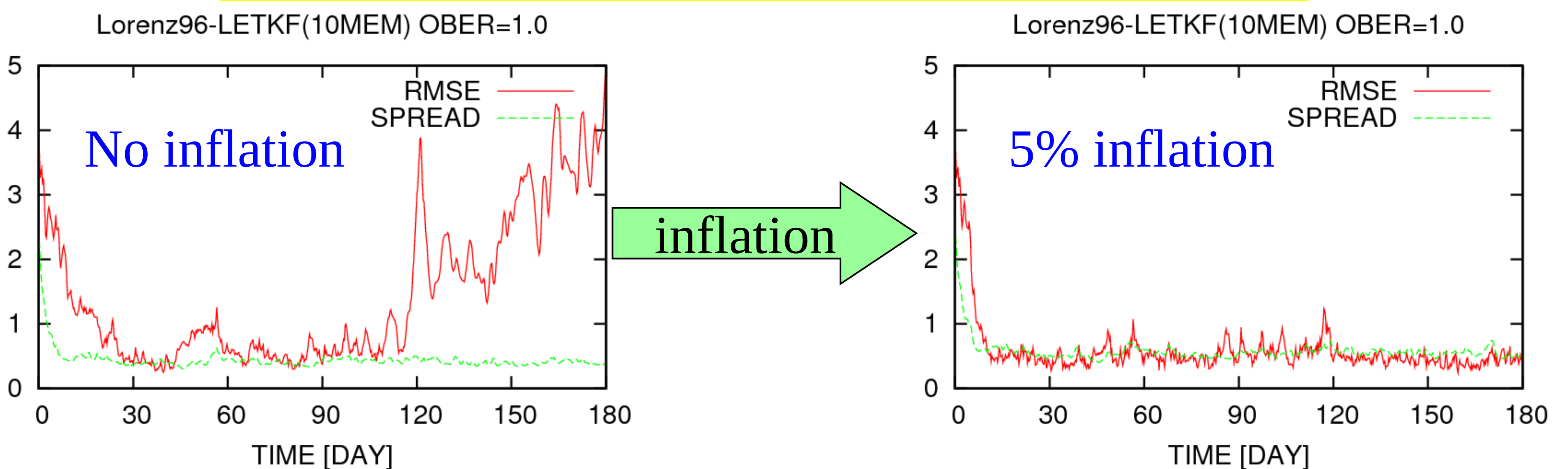
Improved almost everywhere



Covariance inflation (e.g., Houtekamer and Mitchell 1998)

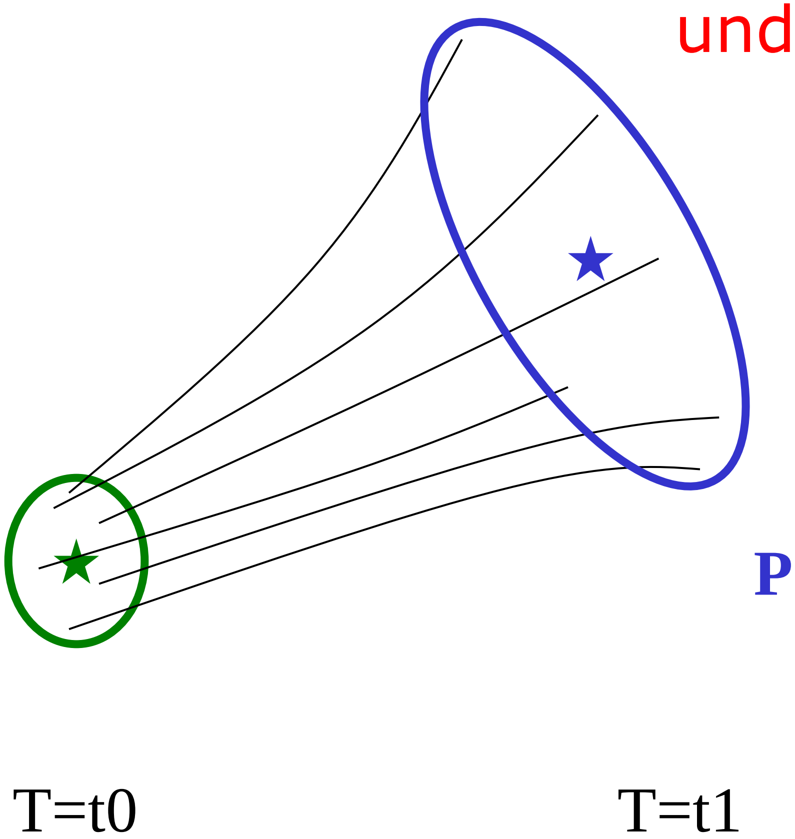
Empirical treatment for…
- variance underestimation

Error variance is underestimated due to *various sources of imperfections*:
- limited ensemble size
- nonlinearity
- model errors



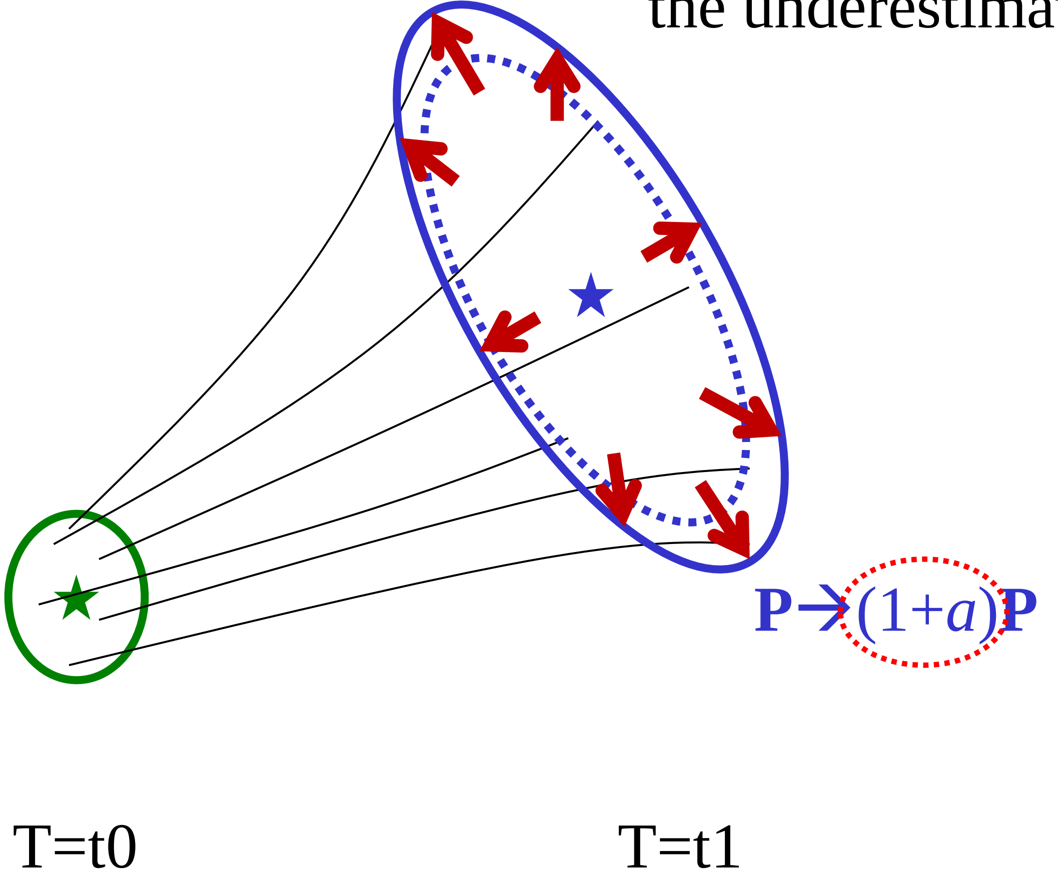
Variance underestimation

Forecast ensemble tends to be under-dispersive.



Covariance inflation

Covariance inflation inflates the underestimated variance.



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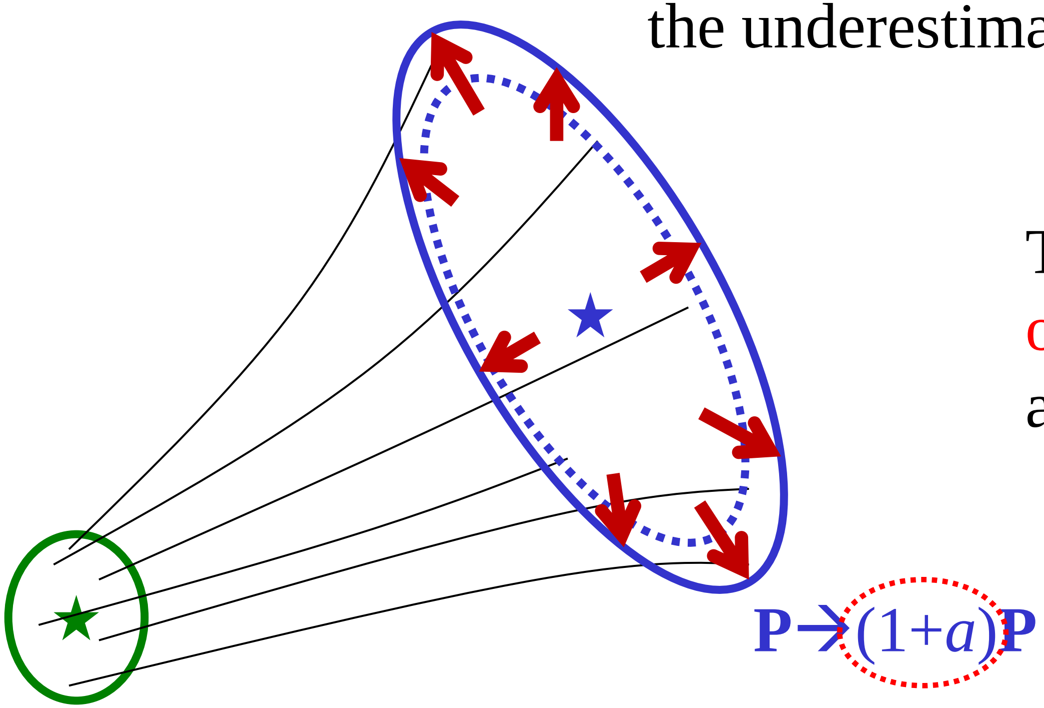
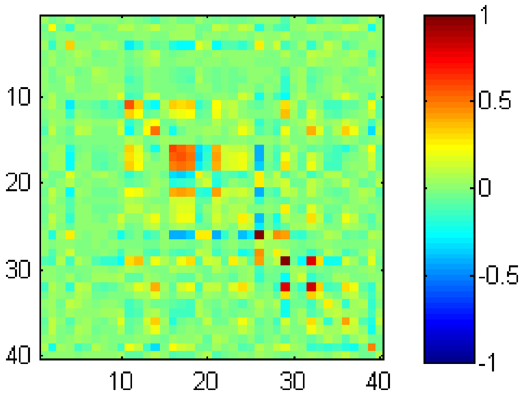


T=t0

T=t1

This also inflates the off-diagonal terms: a side effect.

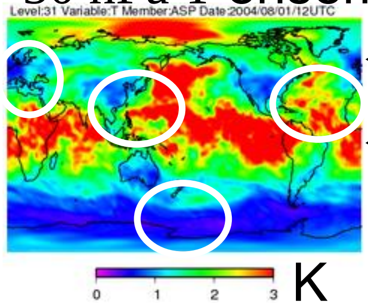


Inflation methods

1. Multiplicative inflation: $\delta x^f \leftarrow \alpha \cdot \delta x^f$

Tuned constant

~50 hPa T ensemble spread



Dense obs → under-dispersive

Sparse obs → over-dispersive

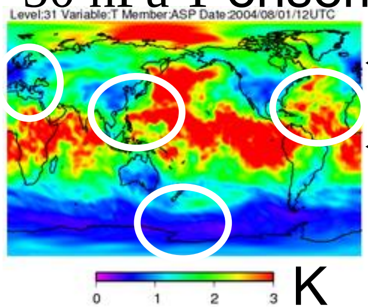
Problematic in real applications

Inflation methods

1. *Multiplicative inflation:* $\delta x^f \leftarrow \alpha \cdot \delta x^f$

Tuned constant

~50 hPa T ensemble spread



K

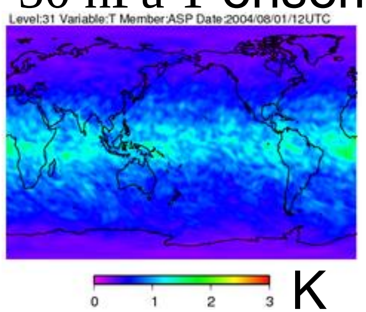
Dense obs → under-dispersive

Sparse obs → over-dispersive

Problematic in real applications

2. *Additive inflation:* $\delta x^a \leftarrow \delta x^a + \delta x^{rnd}$

~50 hPa T ensemble spread



K

This brings new directions to span,
but it is not trivial to have proper random fields.

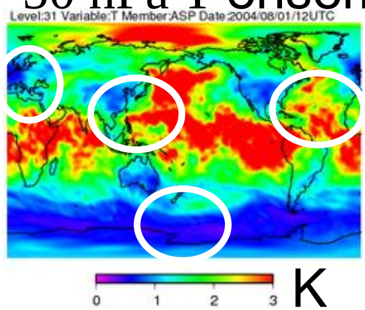
Generally better spread, but an unfavorable high-frequency pattern appears.

Inflation methods

1. *Multiplicative inflation:* $\delta x^f \leftarrow \alpha \cdot \delta x^f$

Tuned constant

~50 hPa T ensemble spread



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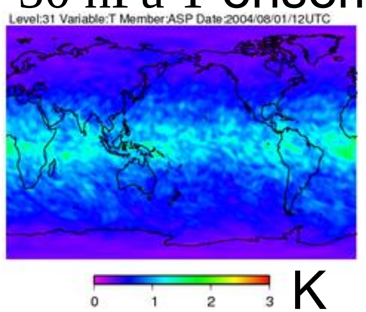
Problematic in real applications

2. *Additive inflation:* $\delta x^a \leftarrow \delta x^a + \delta x^{rnd}$

~50 hPa T ensemble spread



This brings new directions to span,
but it is not trivial to have proper random fields.

Generally better spread, but an unfavorable high-frequency pattern appears.

3. *Relaxation to prior:* $\delta x^a \leftarrow (1-\beta) \cdot \delta x^a + \beta \cdot \delta x^f$ $\beta \sim 0.7$

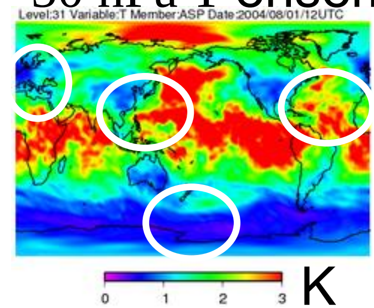
Zhang et al. (2004) showed this worked well.

Inflation methods

1. *Multiplicative inflation:* $\delta x^f \leftarrow \alpha \cdot \delta x^f$

Tuned constant

~50 hPa T ensemble spread



Dense obs → under-dispersive

Sparse obs → over-dispersive

Problematic in real applications

2. *Additive inflation:* $\delta x^a \leftarrow \delta x^a + \delta x^{rnd}$

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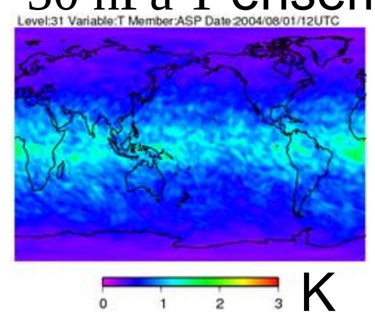

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Zhang et al. (2004) showed this worked well.

4. *Relaxation to prior spread:* $|\delta x^a| \leftarrow (1-\beta)|\delta x^a| + \beta|\delta x^f|$

Whitaker and Hamill (2012), Ying and Zhang (2015)

Adaptive inflation (Anderson’s Bayesian approach)

Anderson (2007; 2009) applied the Bayesian estimation theory to adaptive inflation.

$$\underbrace{\boxed{p(\alpha_i^a)}}_{\text{Posterior}} = \underbrace{\boxed{p(y_i \mid \alpha_i)\, p(y_{i-1} \mid \alpha_i) \cdots p(y_{i-p+1} \mid \alpha_i)}}_{\text{Obs}}\ \underbrace{\boxed{p(\alpha_i^b)}}_{\text{Prior}} / \, norm.$$

Obs PDF is Gaussian w.r.t. obs *y*:

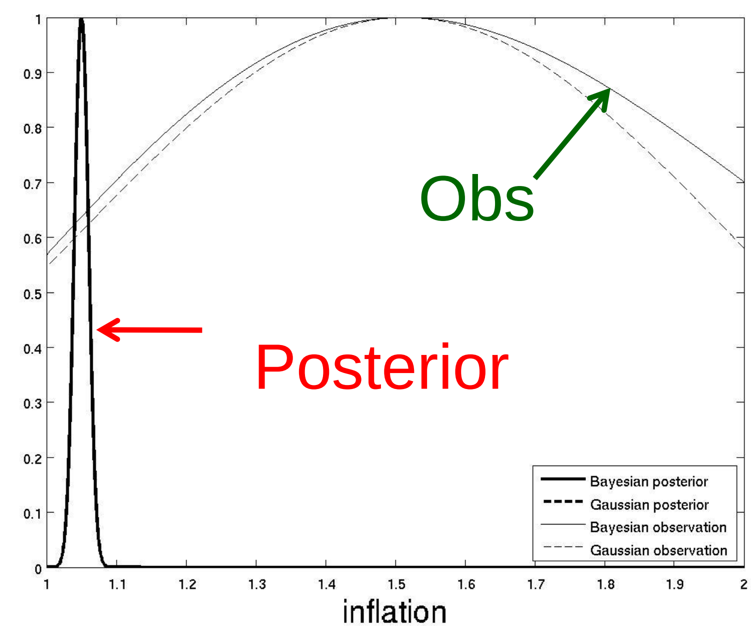
$$p(y_i \mid \alpha_i) = \frac{1}{\sqrt{2\pi(\alpha_i H_i P_i H_i^T + R_i)}} \exp\left(-\frac{(y_i - H_i x_i)^2}{2(\alpha_i H_i P_i H_i^T + R_i)} \right)$$

$$\boxed{\text{This is not Gaussian w.r.t. } \alpha_i}$$

Gaussian prior PDF is assumed:

$$p(\alpha_i^b) = N(\overline{\alpha}_i^b, v_i^b)$$

This is a tuning parameter!!



Adaptive inflation

Anderson (2007; 2009) applied the Bayesian estimation theory to estimate the inflation parameter α **adaptively**.

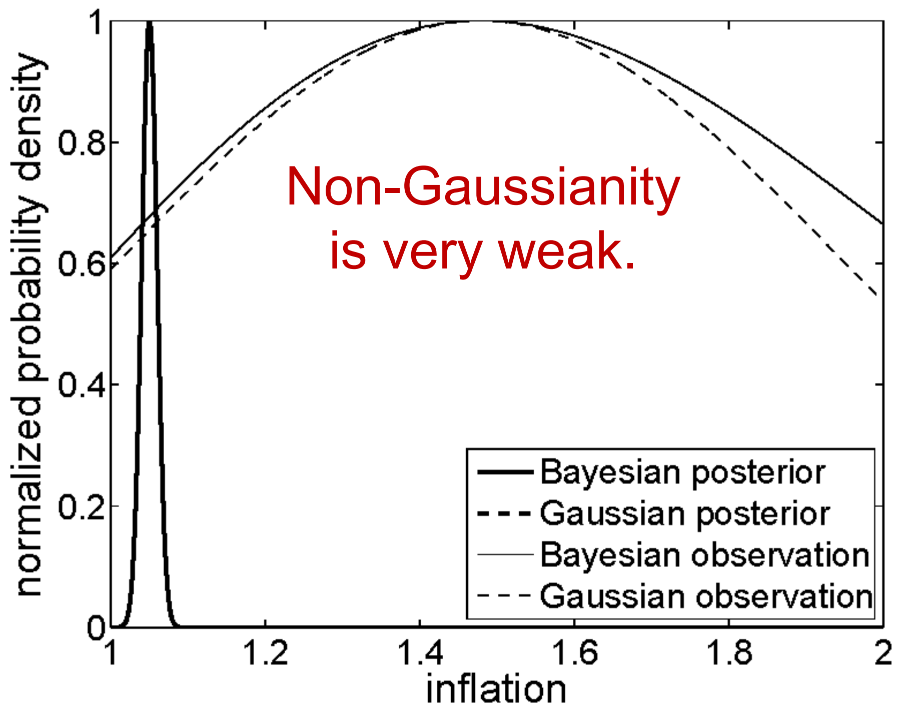
$$\underbrace{\boxed{p(\alpha_i^a)}}_{\text{Posterior}} = \underbrace{\boxed{p(y_i \mid \alpha_i)\, p(y_{i-1} \mid \alpha_i) \cdots p(y_{i-p+1} \mid \alpha_i)}}_{\text{Obs}} \underbrace{\boxed{p(\alpha_i^b)}}_{\text{Prior}} / \mathit{norm}.$$

Li et al. (2009) applied the Gaussian assumption.

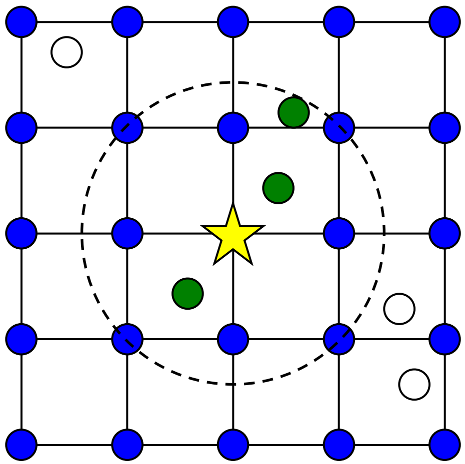
$$\underbrace{\boxed{p(\alpha_i^a)}}_{\text{Posterior}} = \underbrace{\boxed{N(\overline{\alpha}_i^o, v_i^o)}}_{\text{Obs}} \underbrace{\boxed{p(\alpha_i^b)}}_{\text{Prior}} / \mathit{norm}.$$

The Gaussian approach is adopted, with additional enhancements of v_i^o and localization (next slide).

Miyoshi (2011)



Localization of inflation estimates



$\star$: Current grid point

●: Grid points

●: Local observations

○: Remote observations

$$\boxed{p(\alpha_i^a)} = \boxed{N(\overline{\alpha}_i^o, v_i^o)}\boxed{p(\alpha_i^b)} / norm.$$

Posterior   Obs   Prior

Apply the maximum likelihood estimate at each grid point independently.

Miyoshi (2011)

$$\alpha = \alpha(x, y, z, t)$$

First step to test the new idea

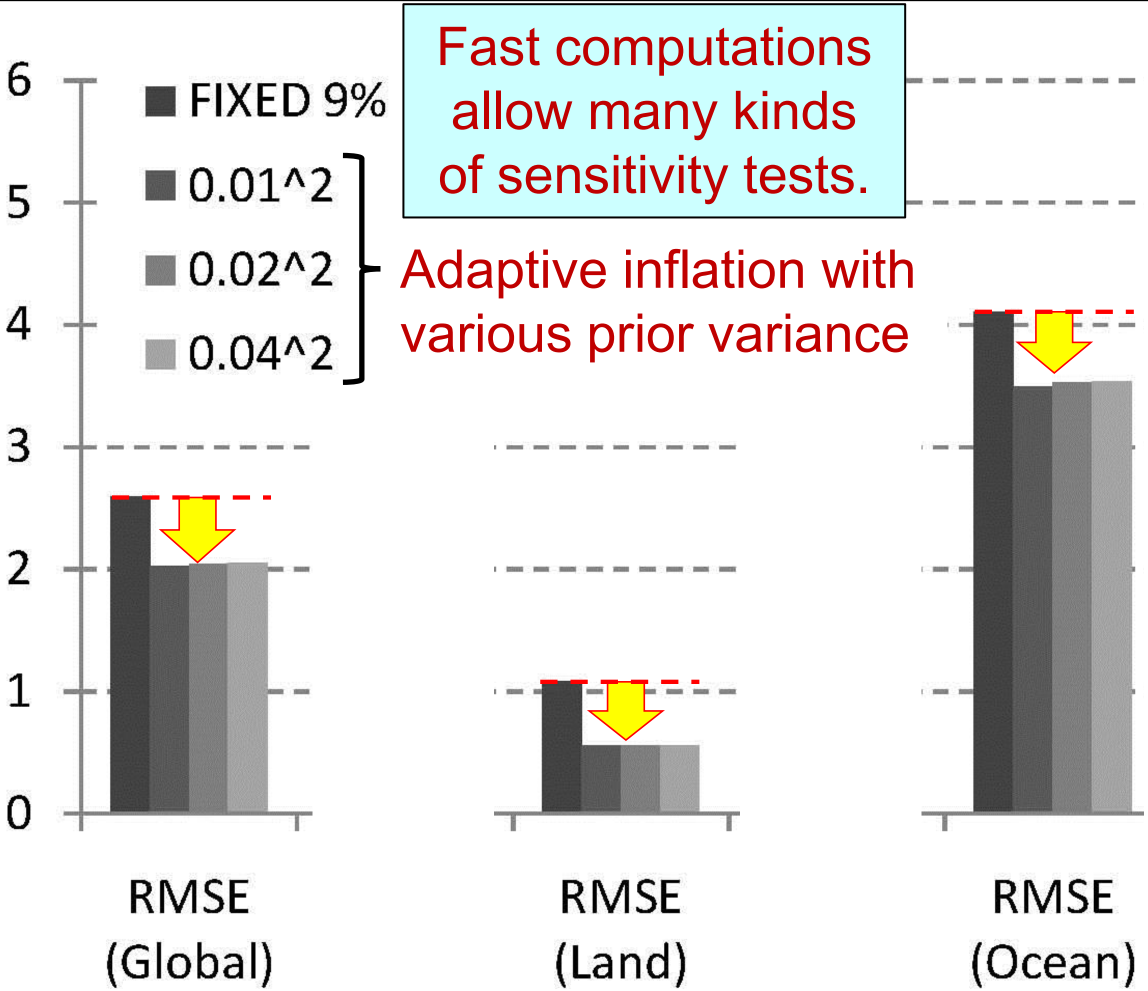
1 Toy models
(e.g., Lorenz model)

2 Intermediate AGCM
(SPEEDY model, Molteni 2003)

3 Real systems
(e.g., operational models)

Easy to implement, fast to run,
accumulating experiences by trial and error

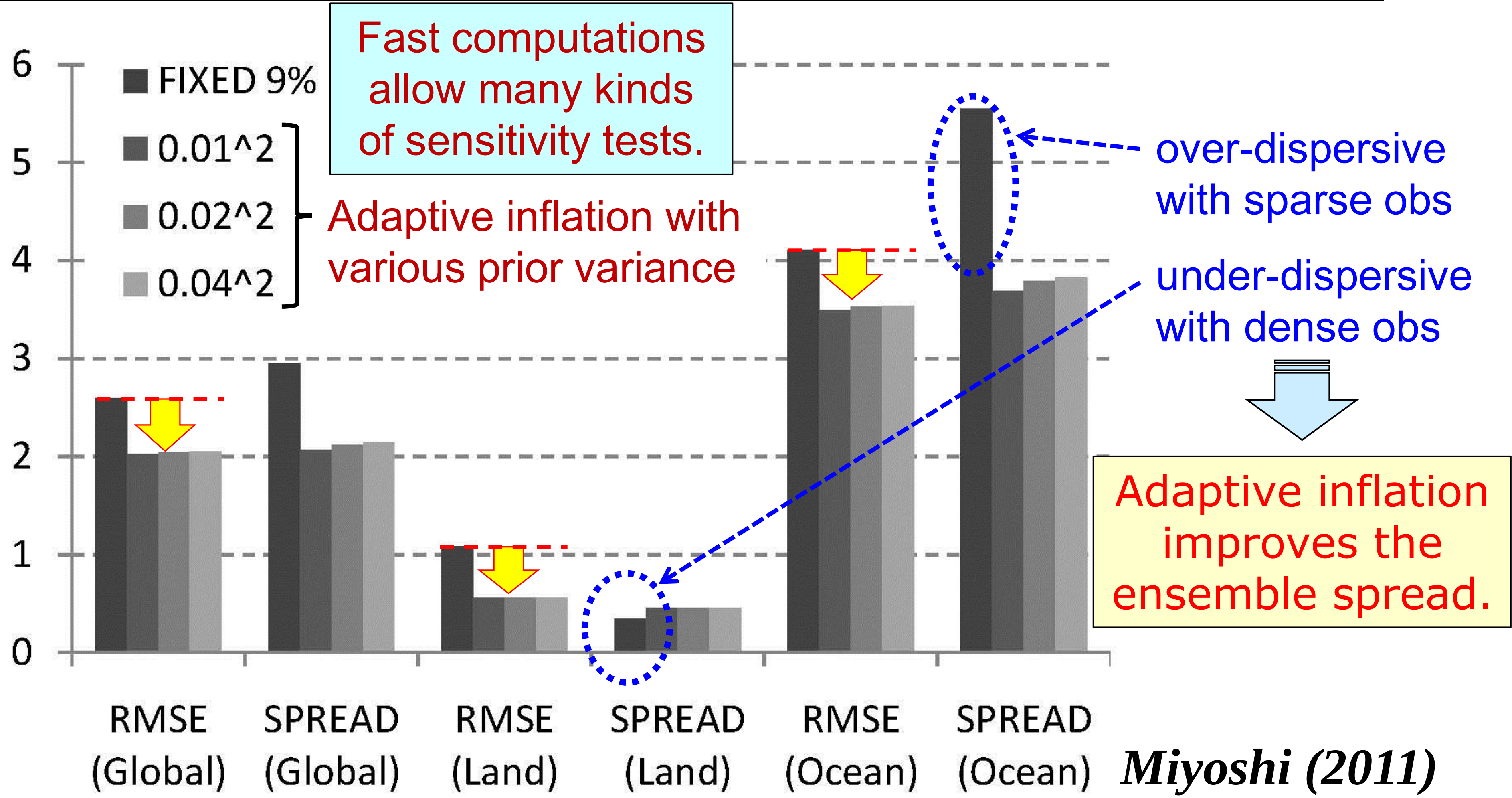
Results with the Lorenz model



Miyoshi (2011)

Adaptive inflation reduces the RMS errors significantly.

Results with the Lorenz model



Adaptive inflation reduces the RMS errors significantly.

Step 2: more realistic testing

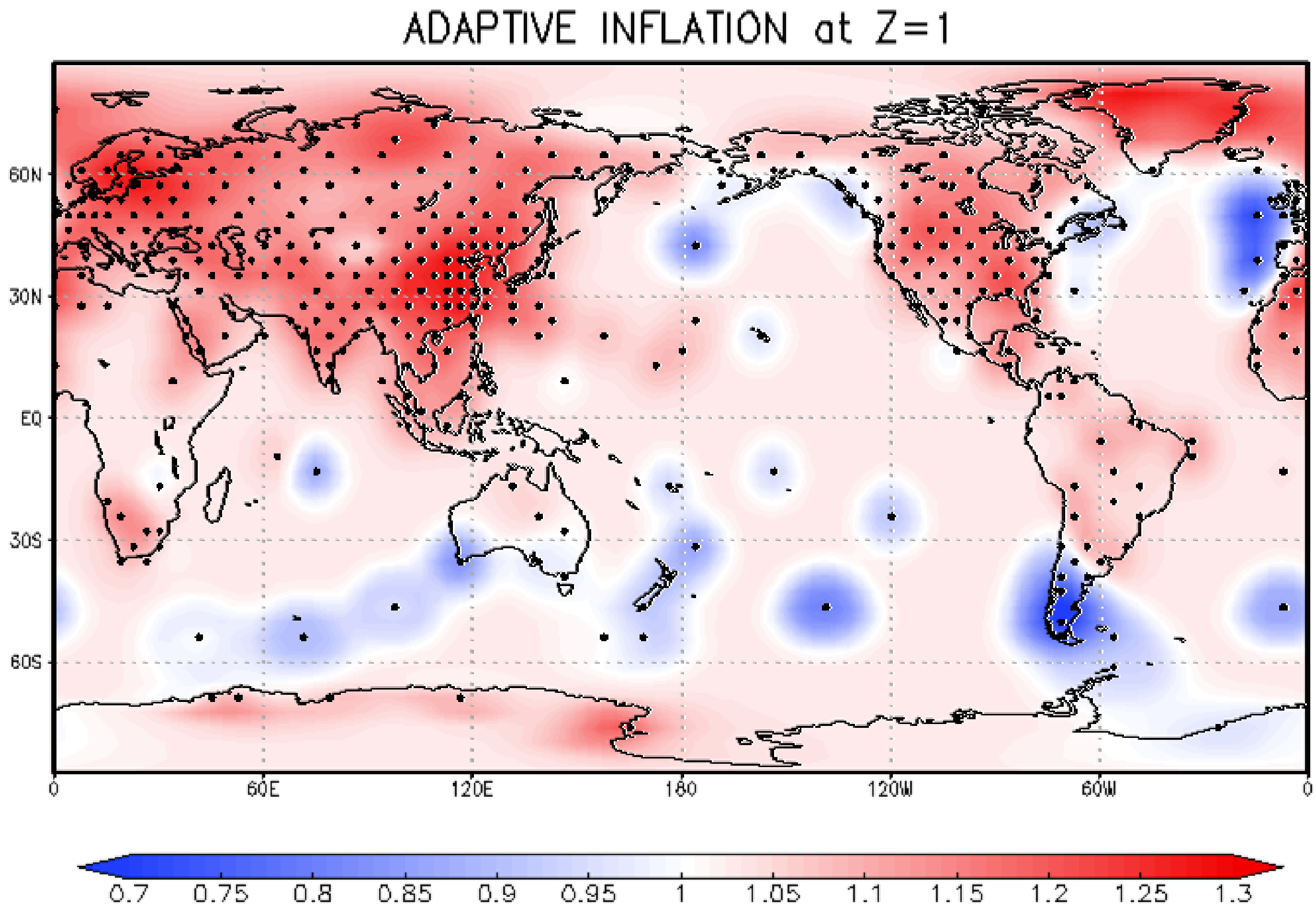
1 Toy models
(e.g., Lorenz model)

2 Intermediate AGCM
(SPEEDY model, Molteni 2003)

3 Real systems
(e.g., operational models)

Testing applicability and feasibility
with a single PC!

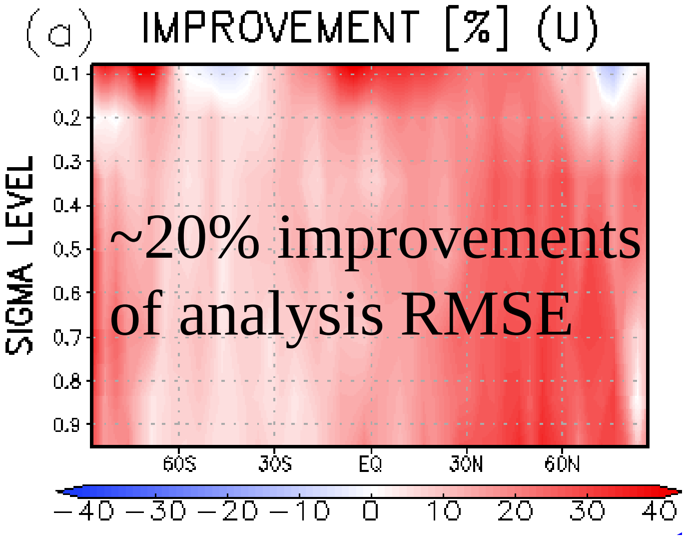
Spatial pattern of inflation



Generally large inflation over densely observed areas

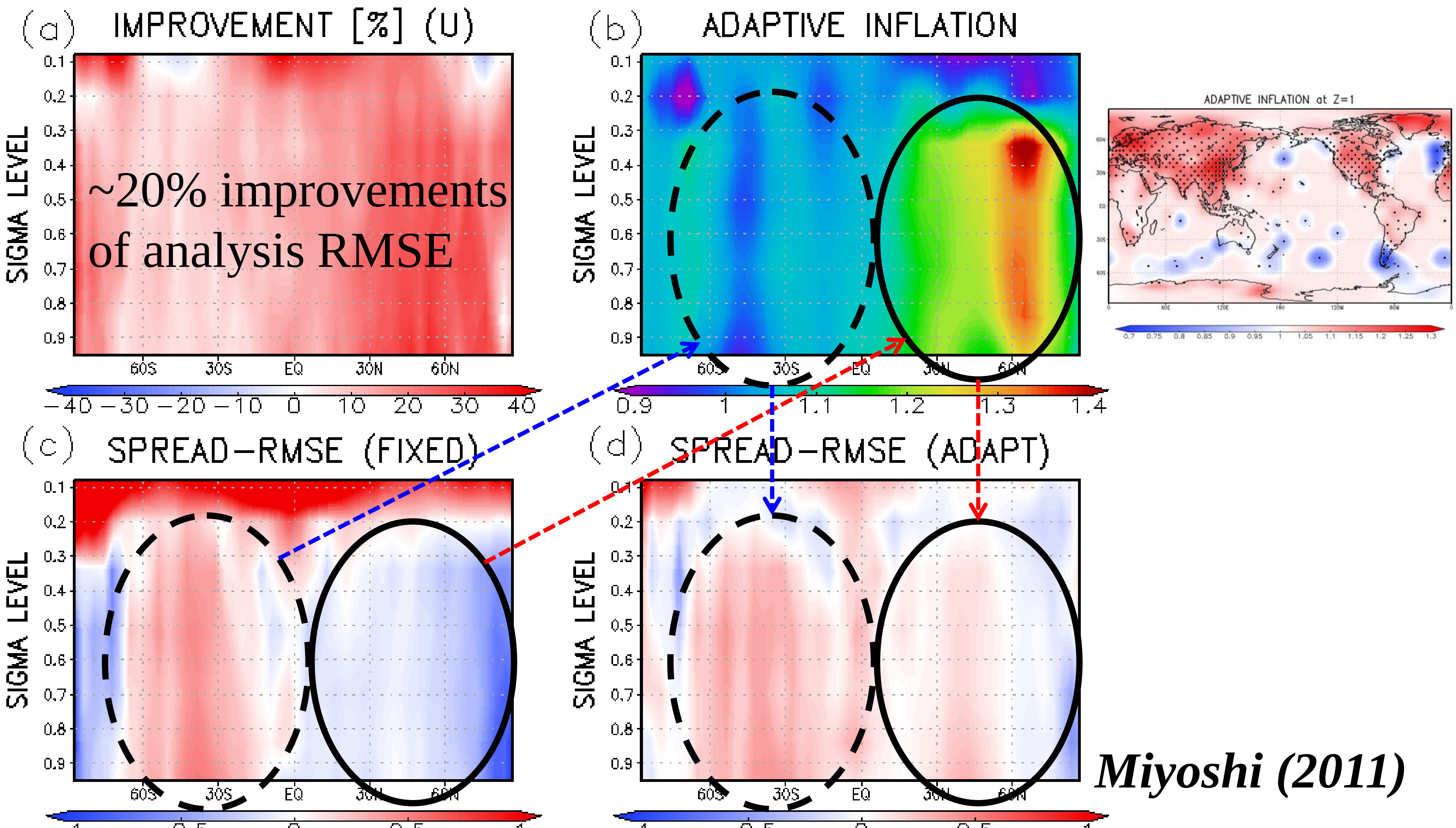
Miyoshi (2011)

Improvements due to adaptive inflation



Miyoshi (2011)

Improvements due to adaptive inflation



Miyoshi (2011)

sparse obs,
large spread

dense obs,
small spread

Adaptive inflation improves
the ensemble spread.

Step 3: real applications

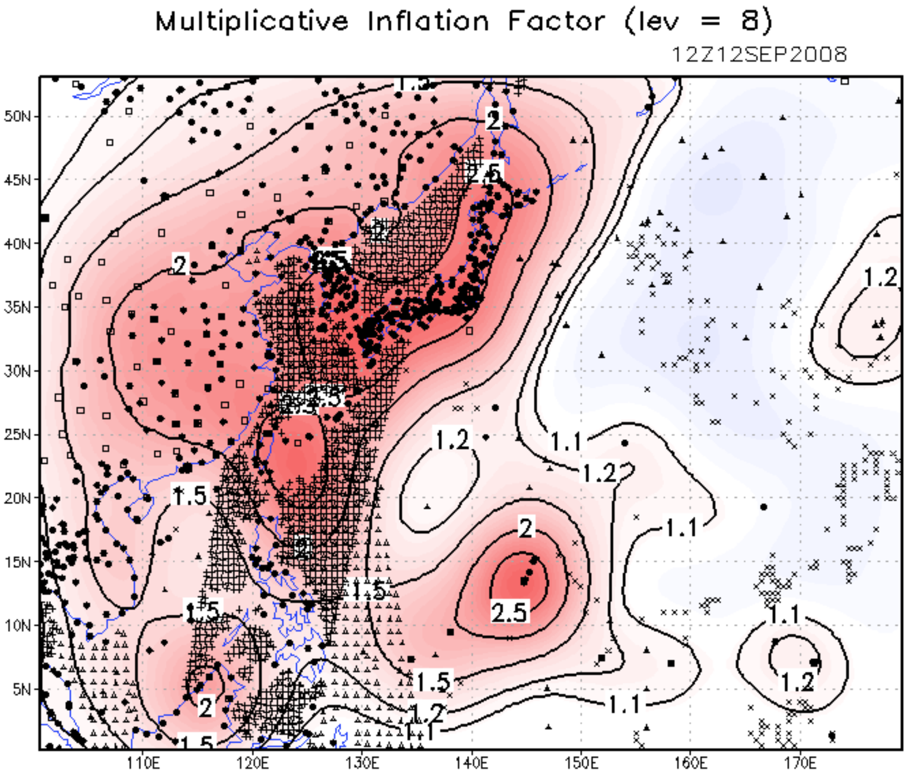
1 Toy models
(e.g., Lorenz model)

2 Intermediate AGCM
(SPEEDY model, Molteni 2003)

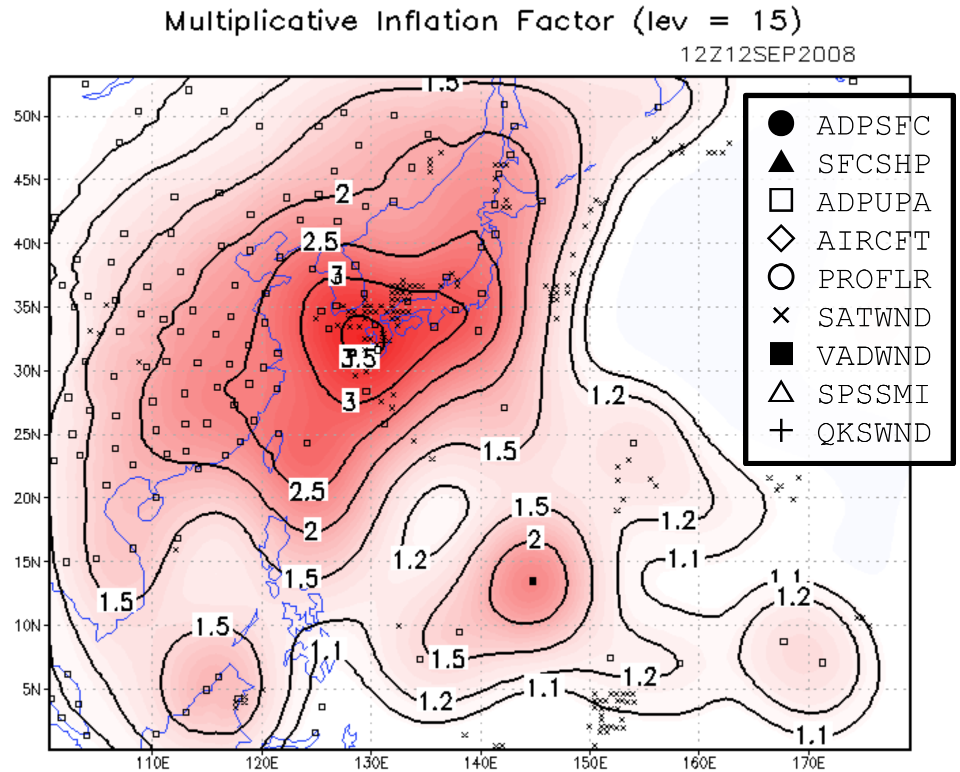
3 Real systems
(e.g., operational models)

Test with real observations

Lower troposphere



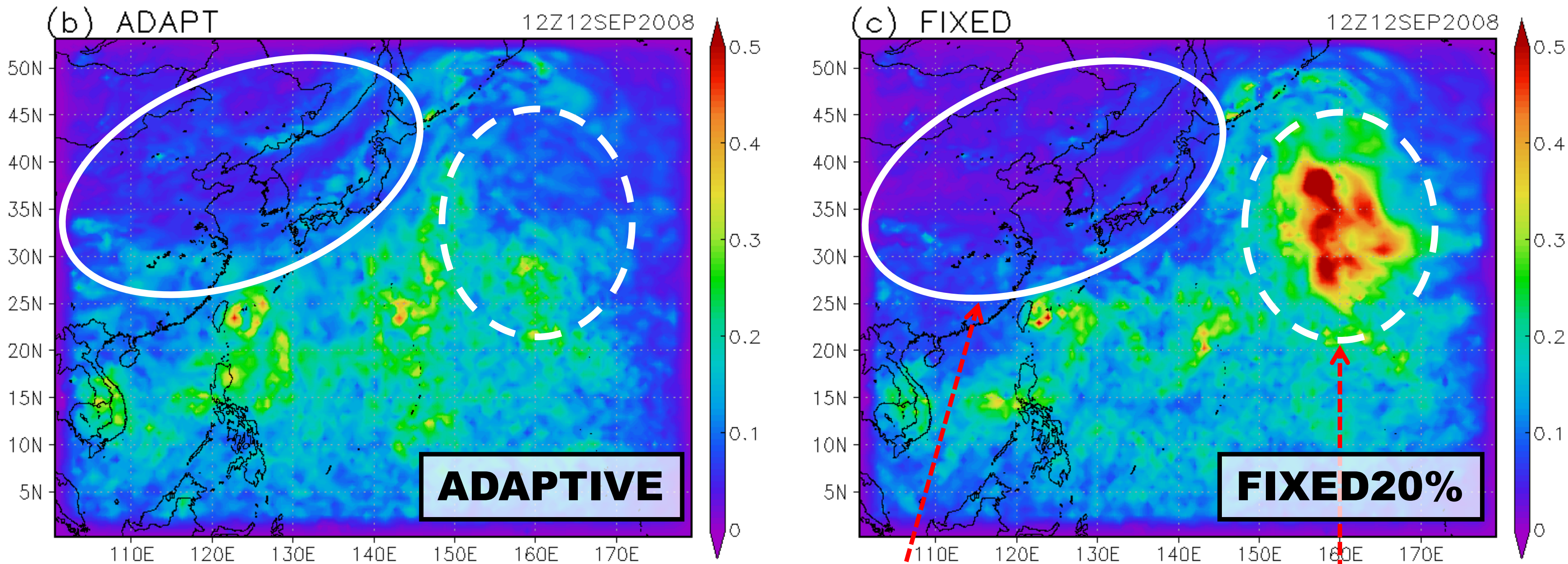
Middle troposphere



- Adaptive inflation accounts for imperfections such as model errors and limited ensemble size.
- Large adaptive inflation > 100 % (2.0) appears occasionally and is appropriate in limited regions.

Miyoshi and Kunii (2011)

Ensemble spread (T500)



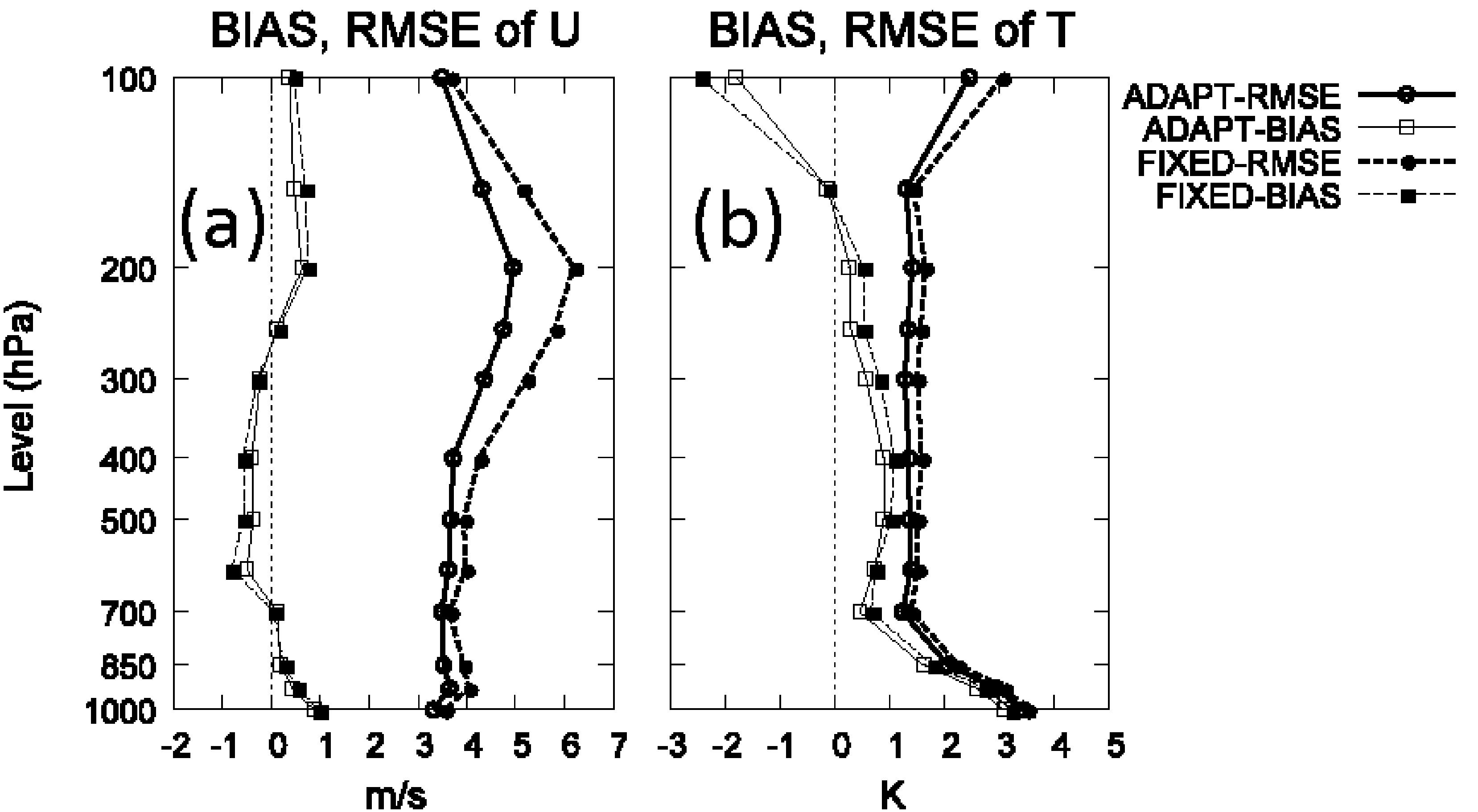
Adaptive inflation improves the ensemble spread.

under-dispersive with dense obs

over-dispersive with sparse obs

Miyoshi and Kunii (2011)

6-hr forecast vs. radiosondes



Adaptive inflation reduces the RMSE and BIAS consistently.

Miyoshi and Kunii (2011)

Benefits to many applications

1 Toy models
(e.g., Lorenz model)

2 Intermediate AGCM
(SPEEDY model, Molteni 2003)

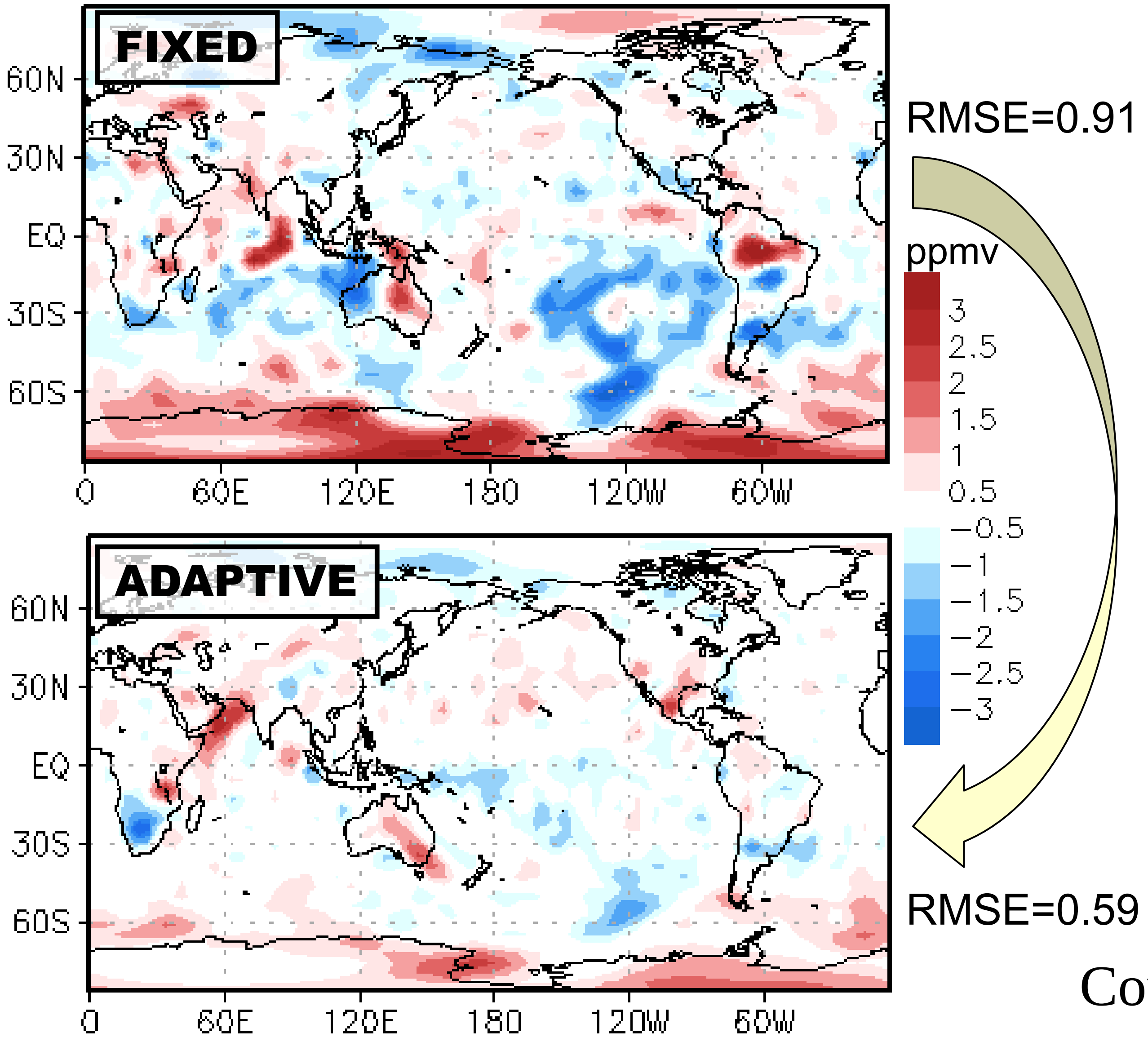
3 Real systems
(e.g., operational models)

Benefits to diverse research,
world-wide users,
and even operations

The LETKF code is available at
http://code.google.com/p/miyoshi/

Application to CO_2 data assimilation

Near-surface CO_2 concentration error

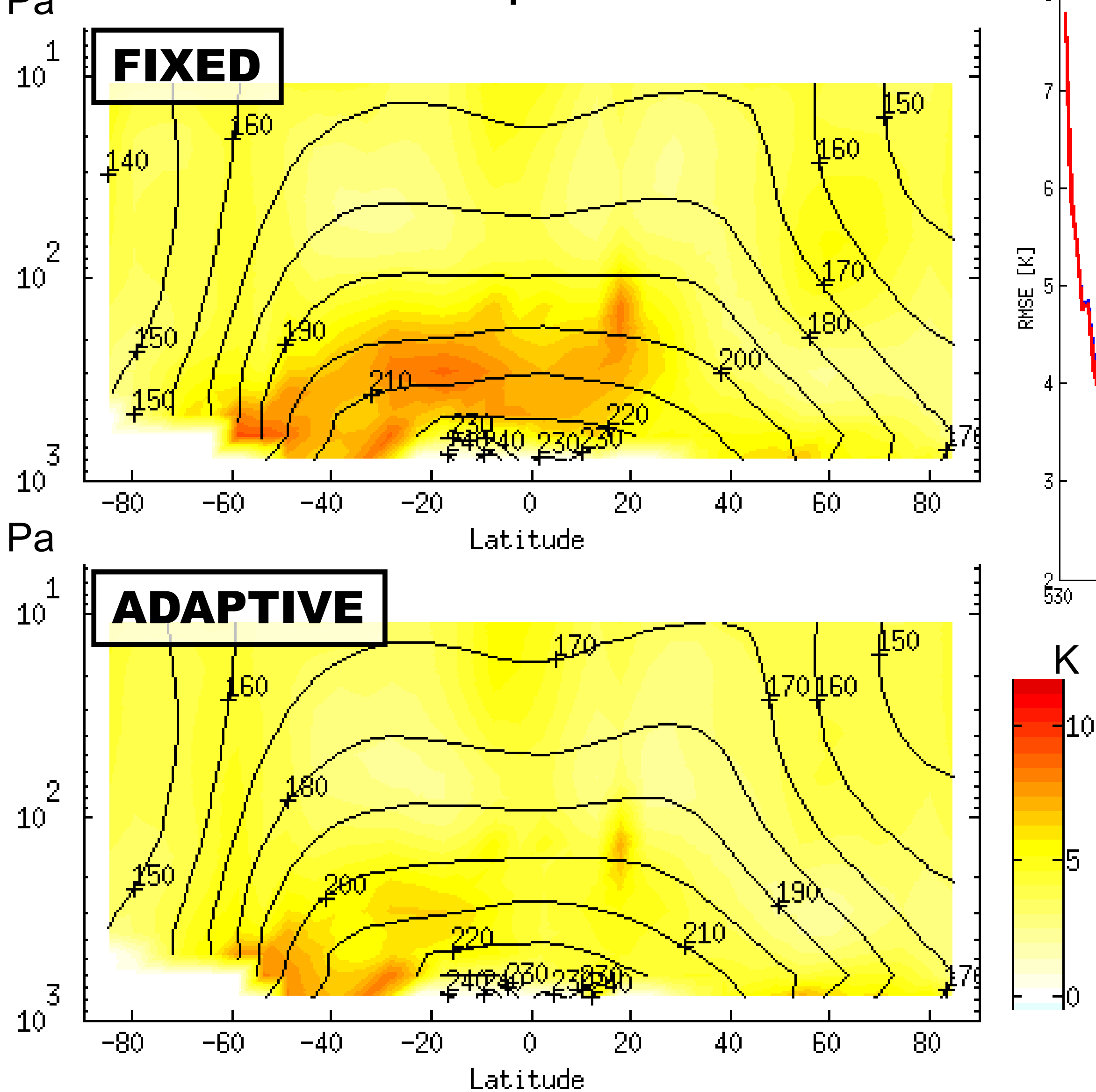


Adaptive inflation improved the CO_2 analysis

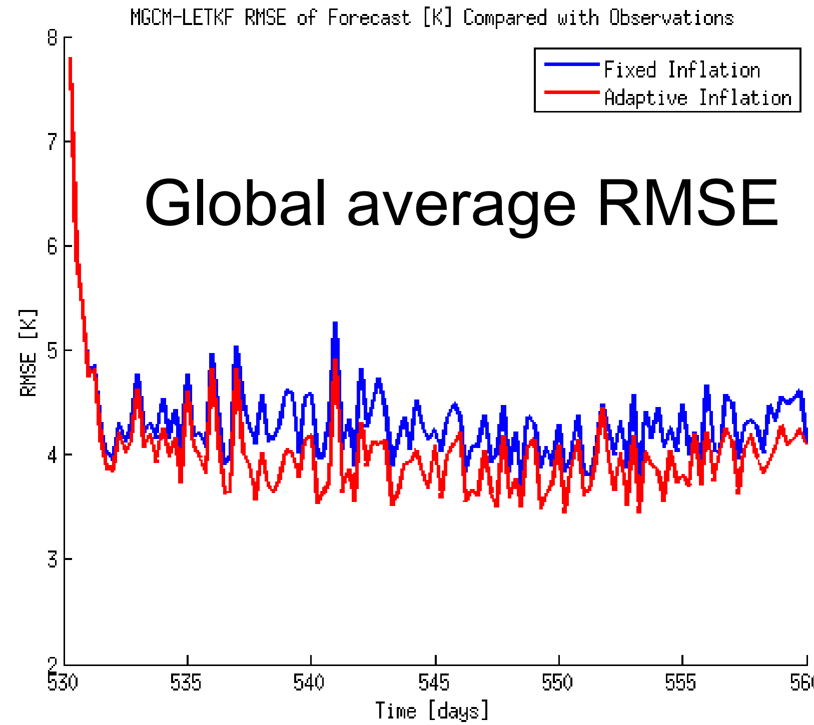
Courtesy of J.-S. Kang

Results of Mars GCM

Zonal mean temperature RMSE



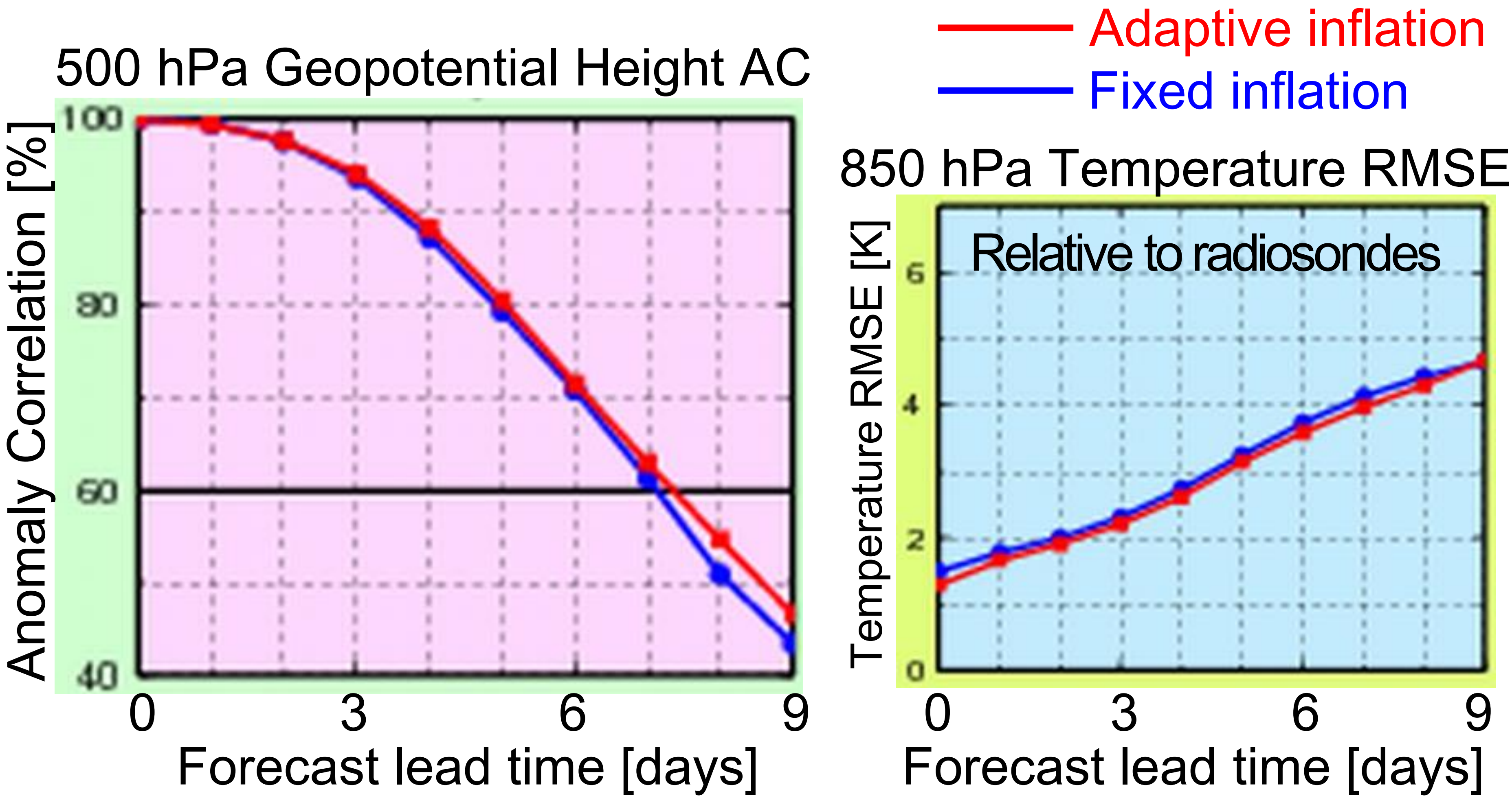
Global average RMSE



Clear advantage of adaptive inflation

Courtesy of S. Greybush

JMA operational NWP system



Adaptive inflation improved the global 9-day forecasts significantly.

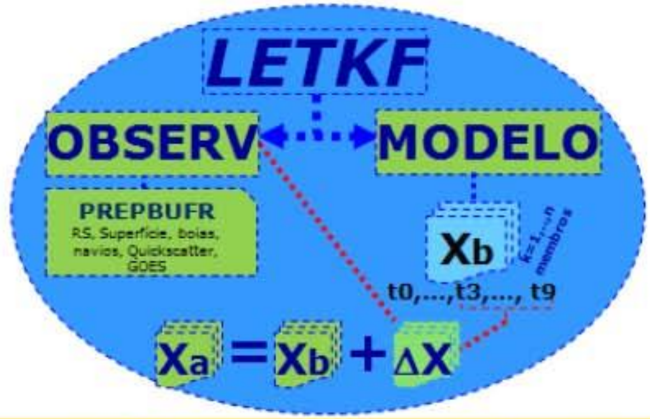
Courtesy of Y. Ota (JMA)

Experience from Brazilian CPTEC

Slide courtesy of J. Aravequia

LETKF_MCGA/CPTEC

Goal : To produce operational analysis and forecast using LETKF - MCGA/CPTEC



Implementation steps:

-LETKF ERIC

✓Interfaces : model MCGA/CPTEC<-> LETKF (It was not easy as we were thinking before to start);

✓Coding resolution changes to be friendly (original T062L28);

✓Coding for use of NCEP PREPBUF observations ;

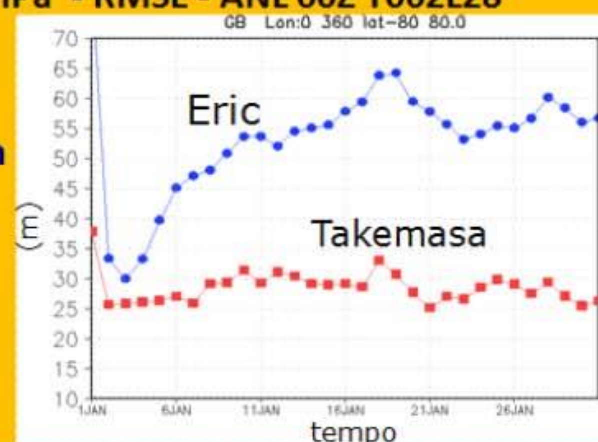
- **LETKF TAKEMASA (parallel version, T062L28)**

- Actual effort : tuning experiments.

ZGEO 250hPa - RMSE - ANL 00Z T062L28

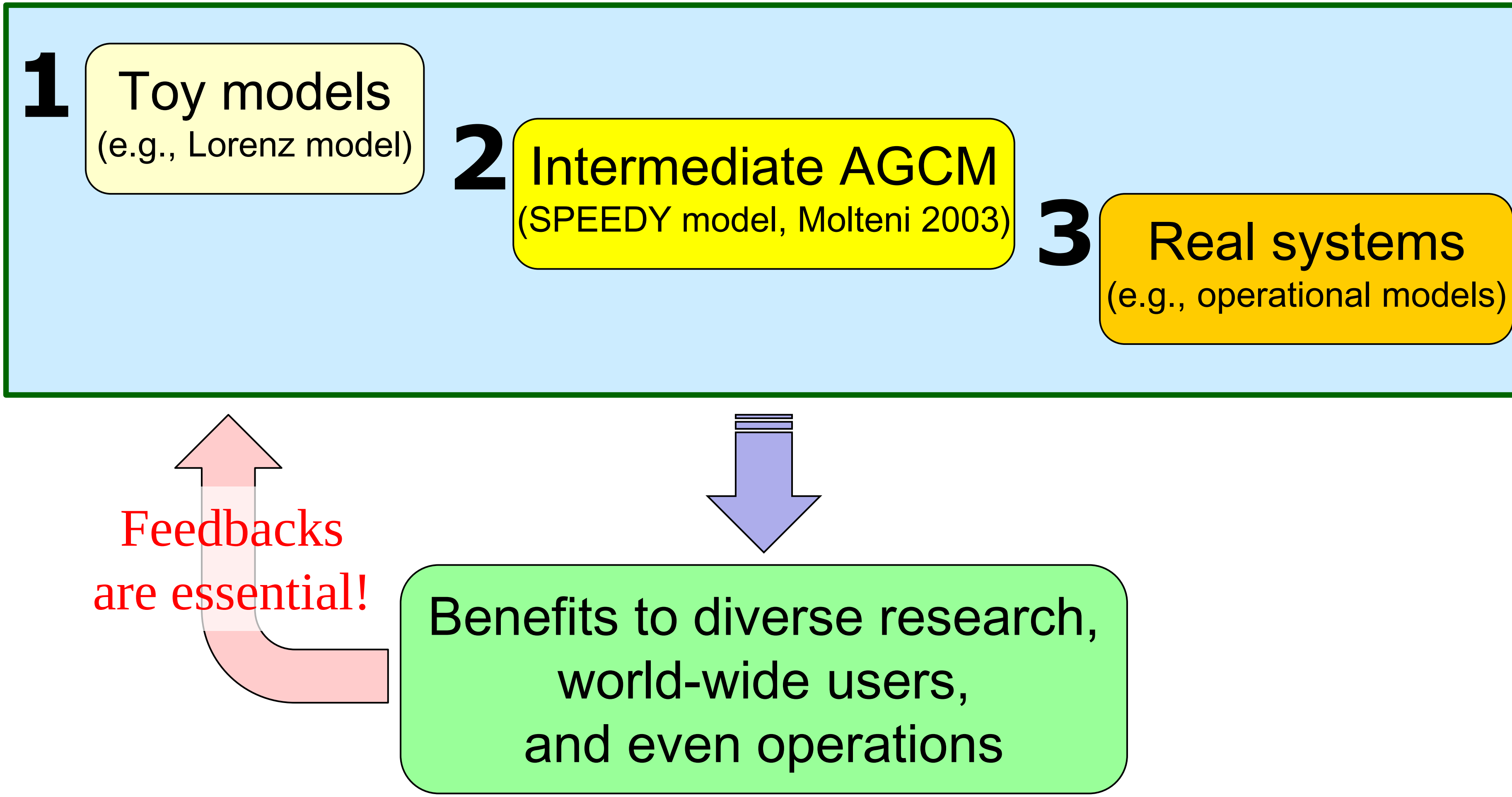
Versão Takemasa reduz erro da análise e o Sistema se estabiliza mais rápido.

ANL REF: NCEP



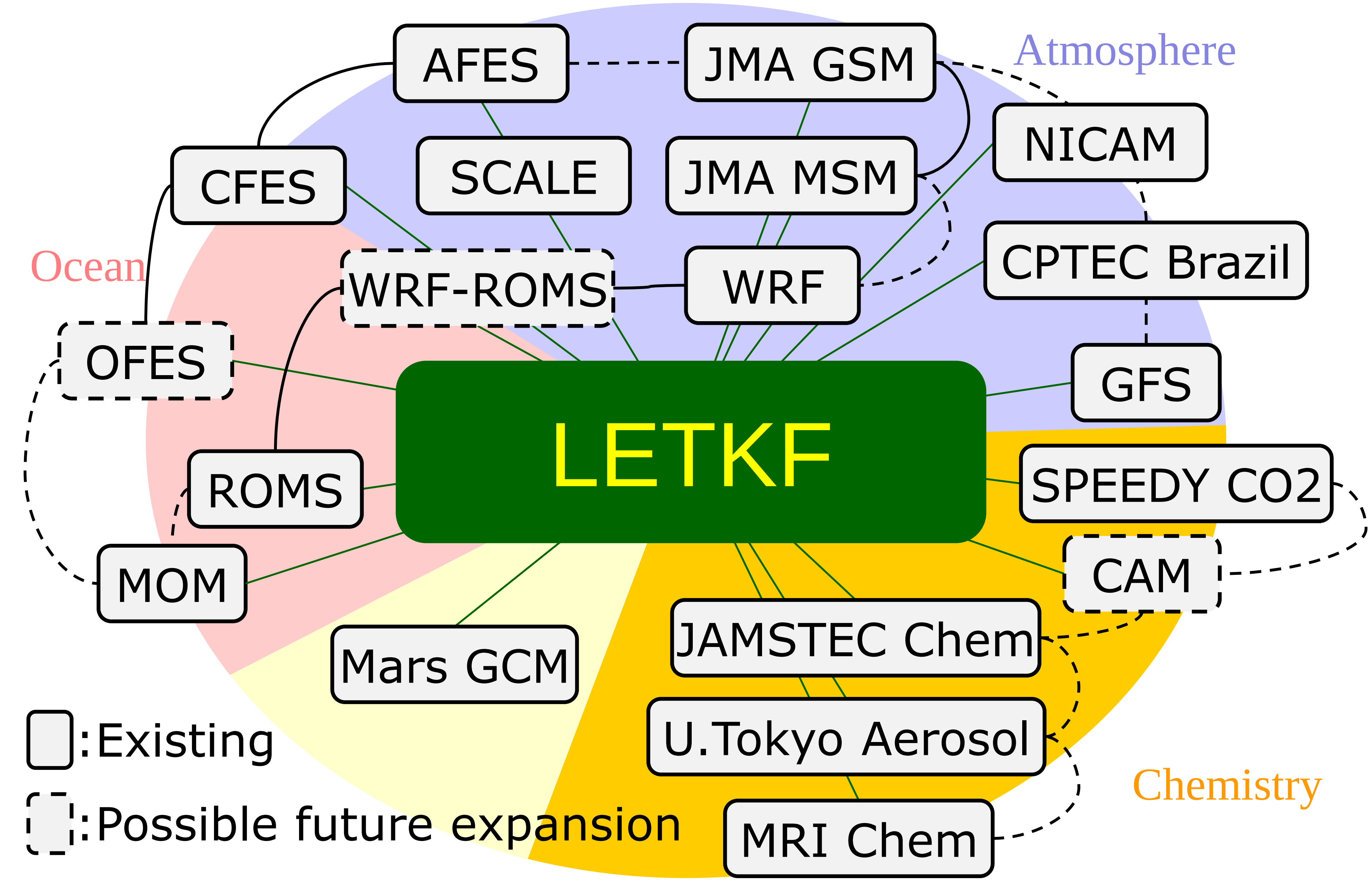
Solange S. de Souza; José A. Aravéquia; Paulo Kubota

Feedbacks inspire future studies

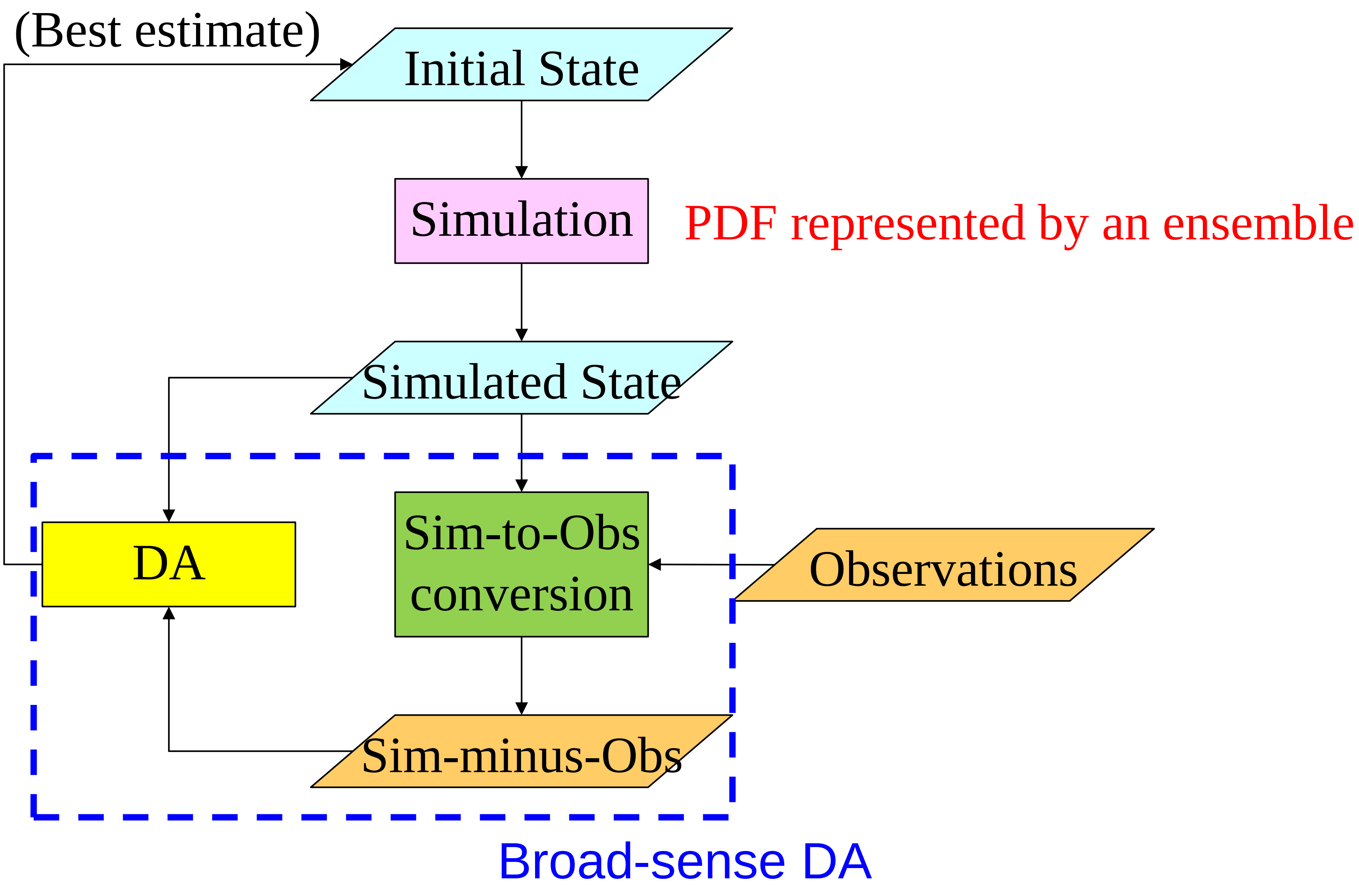


- Inspiring new ideas
- Demands from operations
- Technical improvements

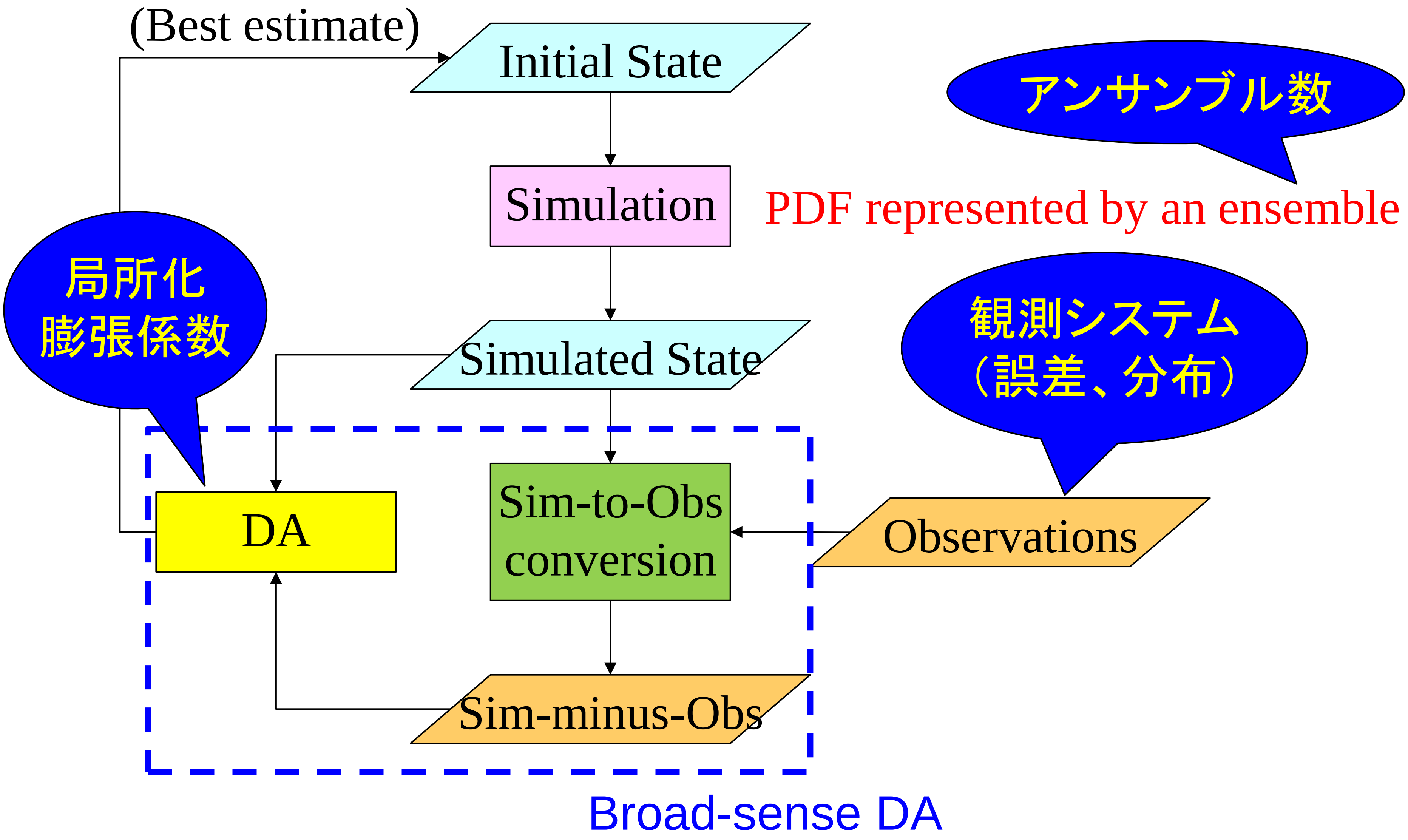
Expanding collaborations



データ同化（DA）のworkflow



今回の実習のテーマ



(Best estimate)
Initial State
Simulation
Simulated State
DA
Sim-to-Obs conversion
Observations
Sim-minus-Obs
Broad-sense DA
アンサンブル数
PDF represented by an ensemble
局所化
膨張係数
観測システム
（誤差、分布）