Assimilation with faster super observation algorithm for meteorological 'Big Data'

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INTRODUCTION

Recent Satellite Observation Data

- Newest generation of satellites have higher spatial and temporal resolution with richer amount of data size

  e. g. Himawari – 8

  → 3 times faster to observe in the world

  → 50 times larger amount of data size (Bessho et al. 2016)

Satellite Observation in Assimilation

- Thinning (Ochotta 2005) or Super-observation (SO; Lorenc 1981) are necessary to avoid correlation between each observation
- Himawari-8 infrared radiances all-sky assimilation case for Typhoon Soundelor used thinning (Honda et al. 2018)
- MetOp-A infrared radiance CO retrieval super-observation data was assimilated (Klonecki et al. 2012)

MOTIVATION

- Develop faster SO system for the peculiar grid model (NICAM; Satoh et al. 2007) to increase computational efficiency
- Compare Thinning and SO assimilation cases, and examine the impact on the assimilation and forecast
- Investigate horizontal correlation distance in both cases

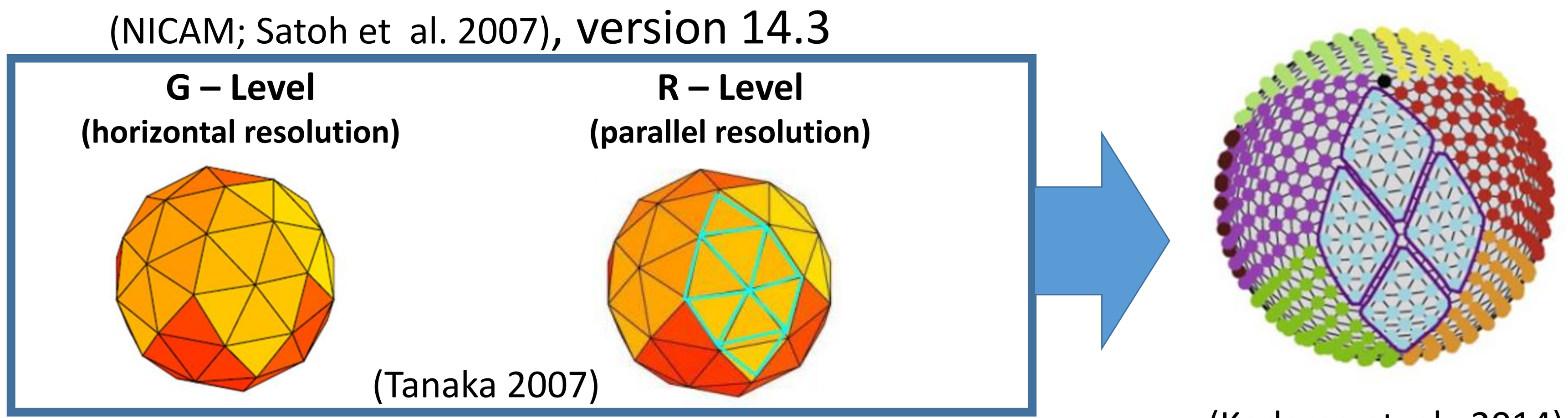
CHALLENGES

- Thinning or SO is still debatable
- Making SO takes a certain amount of computation resources

  (T. Kawabata and K. Okamoto Personal talk)

EXPERIMENT SETTINGS

Model: Nonhydrostatic ICosahedral Atmospheric Model (NICAM; Satoh et al. 2007), version 14.3



Assimilation Method: LETKF (Hunt et al. 2007, Terasaki et al. 2015)

- 00UTC 1st Nov. 2011 One time DA
- Resolution : Gl06-Rl01 (~112km), 38 layers
- **10** Ensemble Members
- Fixed RTPS (Whitaker and Hamill 2012)

  Relaxation Parameter = 0.95
- Horizontal Localization is 400 km

Obs. Settings Table

	SO - DA	Thin-DA
Prepbufr	SO	Thinng
AMSU-A	Thinning	Thinning

ALGORITHM OF FASTER SO

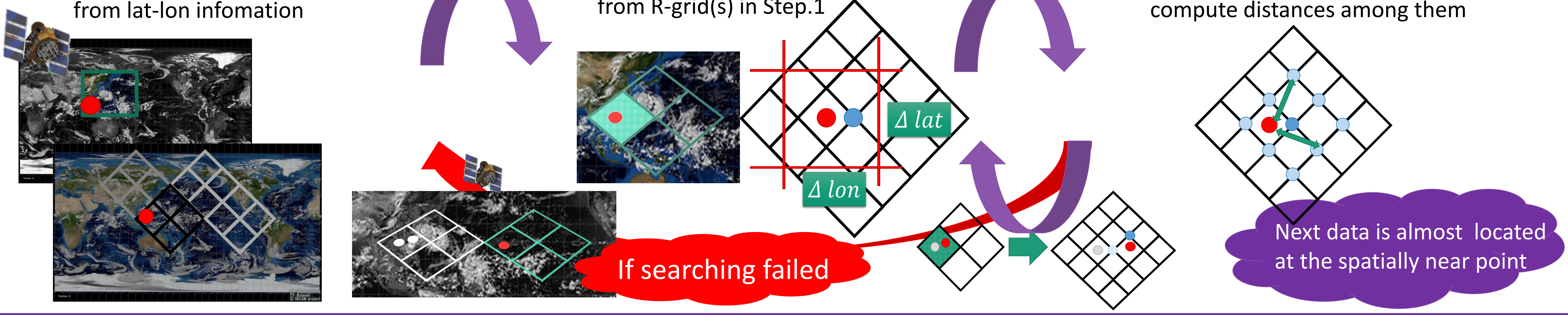
Flow Chart of High Speed Super-observation (HSS)

* Code can be download My **Github** Account : **Kuritaku**

1. Estimate potential R-grid(s) from lat-lon infomation

2. Compute a potential G-grid point from R-grid(s) in Step.1

3. Set Look up table, and then compute distances among them



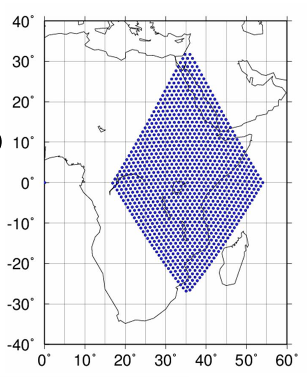
Result

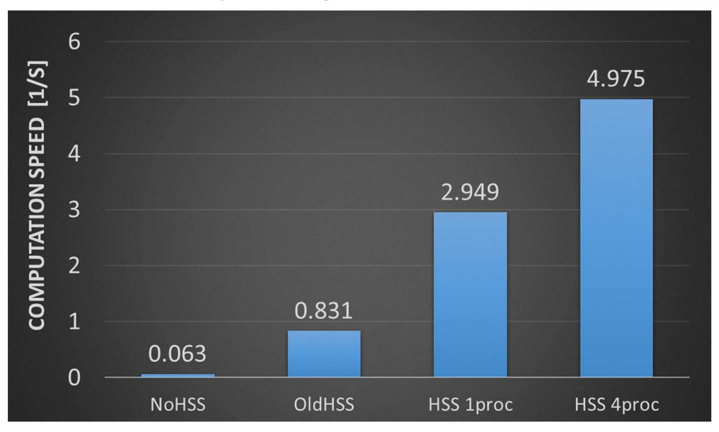
Computation Speed of HSS

Test Case

Compare the speed of algorithm to make super-observation for **1156** data points into each nearest grid points

Test data points which correspond R-grid No.1 →

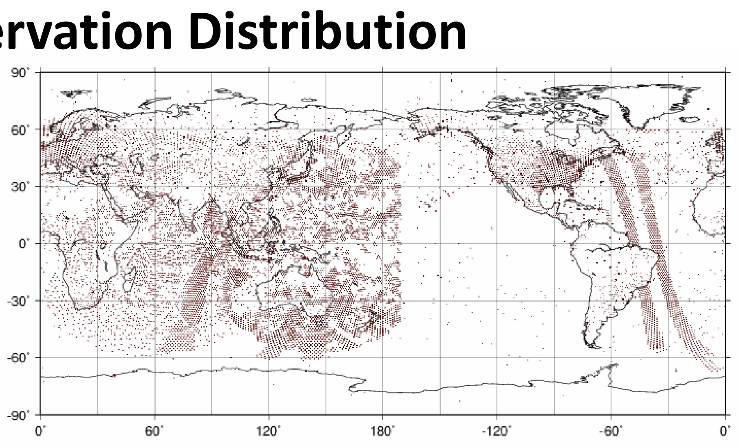




Observation Distribution

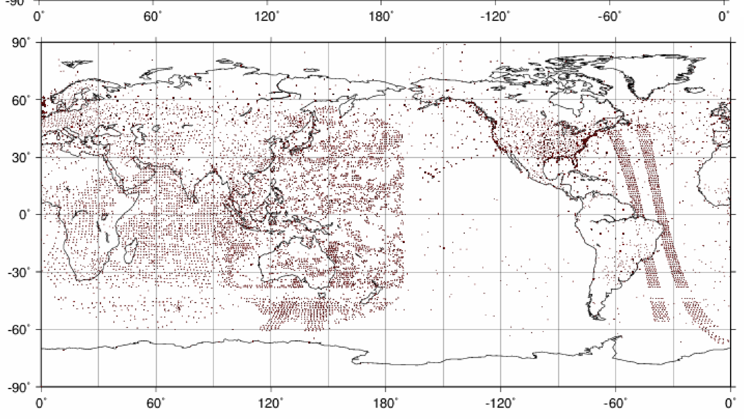
SO

Num. of. Obs. **216,838**



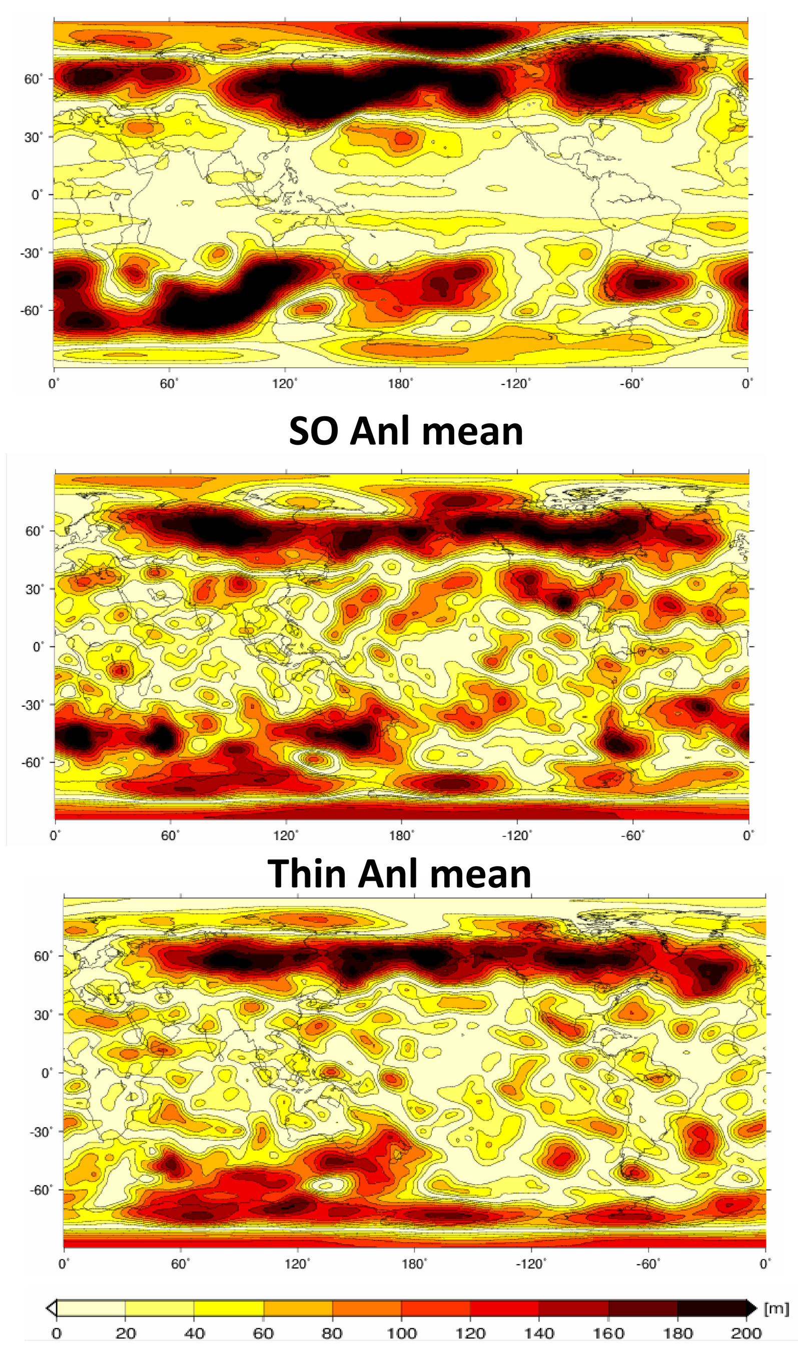
Thin

Num. of. Obs. **183,112**



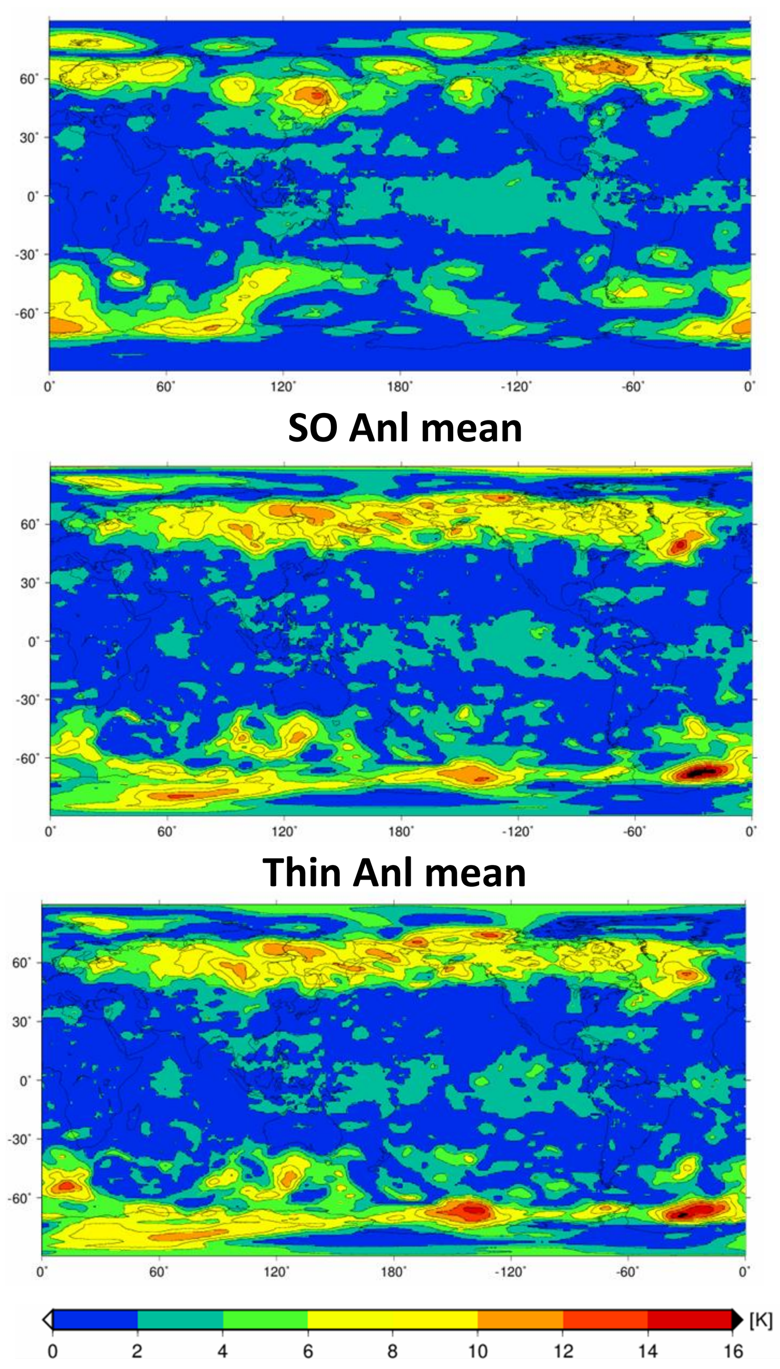
* Thinning distance was almost Grid resolution (~ 112 km)

	Gues mean	Anl mean
SO North	103.2 m	104.6 m
South	78.1 m	81.8 m
Thin North	〃	97.2 m
South	〃	84.1 m



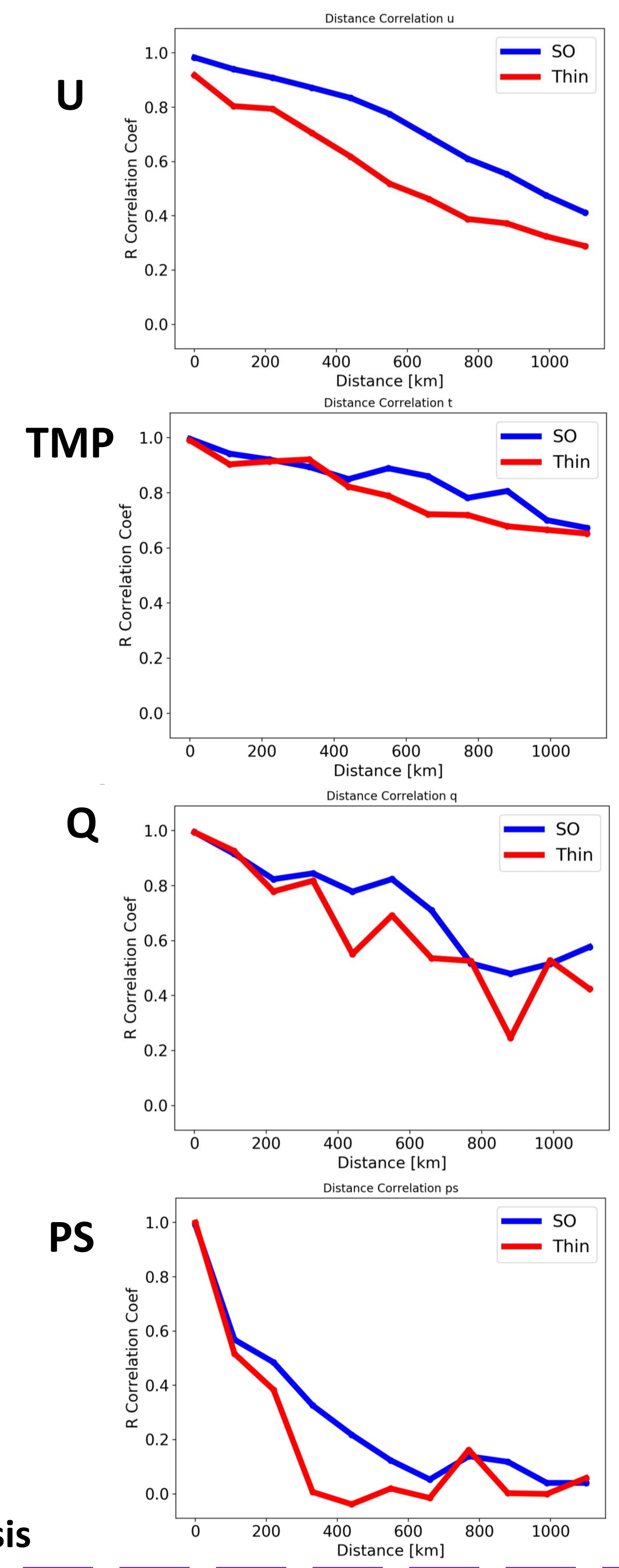
RMSD of HGT at 500 hPa against FNL Reanalysis

	Gues mean	Anl mean
SO North	3.45 K	3.97 K
South	3.04 K	4.08 K
Thin North	〃	4.17 K
South	〃	3.81 K



RMSD of TMP at 500 hPa against FNL Reanalysis

Horizontal Distance Correlation



Discussion

- ✓ Thinning for DA is superior to that of SO. Is this same in the super-observation of AMSU-A ?
- ✓ Why does the analysis get worse result than first guess?
- ✓ Average computation in SO was simple mean. Does weighted average e.g., Gaussian interpolation more represent better ?

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