Oceanic iron distribution of the global ocean estimated by data assimilation approach

海洋溶存鉄の Green 関数法を応用した
3次元分布再現について

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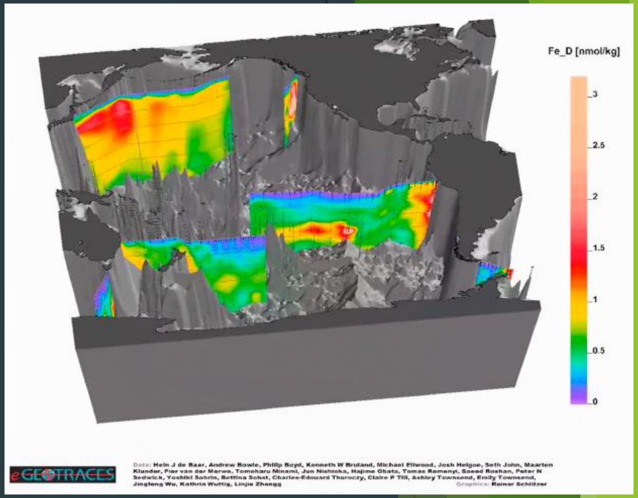
Introduction

Oceanic iron is considered as one of the restriction factors of the primary production.

Recently, we can identify the iron distribution along some observational sections covering a basin scale.



We constructed a useful gridded three-dimensional dissolved iron data by applying data assimilation approach.

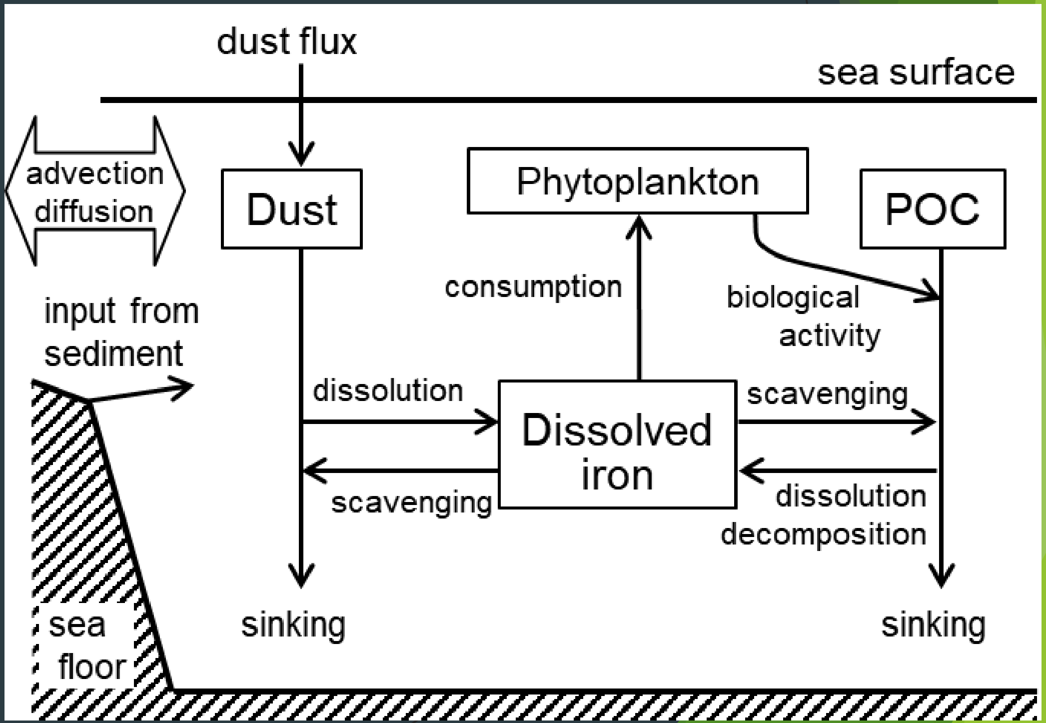
The obtained gridded dissolved iron data is the dynamically consistent interpolated data in the spatially and temporally.

Model

A simplified oceanic iron cycle model

$$\frac{\partial dFe}{\partial t} = ADV(dFe) + DIFF(dFe) + SMS(dFe)$$

dFe : dissolved iron



Referencing Moor *et al.* (2008) and Tagliabue *et al.* (2017)

Model

Physical field

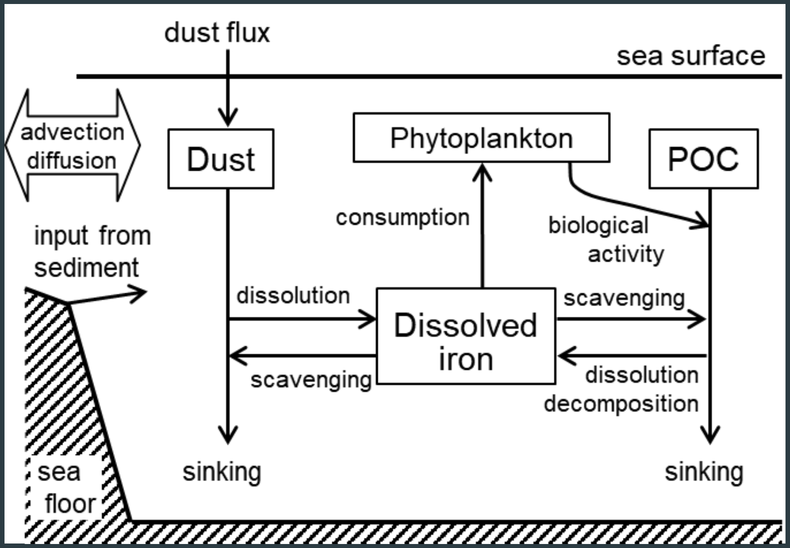
ESTOC (Estimated State of Global Ocean
for Climate Research)

The dataset of 4-dimensional dynamical ocean state.
Estimated by the ocean data assimilation system (4DVAR).

Region : quasi Global Ocean from 75°S to 80°N
Horizontal Resolution : 1° × 1°
Vertical Resolution : full depth range of 46 layer (45 layer + BBL)
Dataset : monthly mean data from Jan. 1957 to Dec. 2011

Monthly mean u, v, T, and S data
from Jan. to Dec. in 1980
was employed as the off-line model.

Model



dissolution

$$Ds_p = Rd_p \times Fe_p \quad : \text{for POC}$$

$$Ds_d = Rd_d \times Fe_d \quad : \text{for Dust}$$

Ds : amount of dissolution
Rd : dissolution rate
Fe : iron concentration in particulate

consumption

$$Cs = v_{chl} \times C_{chl}$$

Cs : amount of dissolution
v_{chl} : consumption rate
C_{chl} : phytoplankton biomass

scavenging

$$scav = Sc \times dFe \qquad \textit{Moor et al.}\ [2008]$$

$$Sc = Sc_b \qquad (dFe < LC)$$

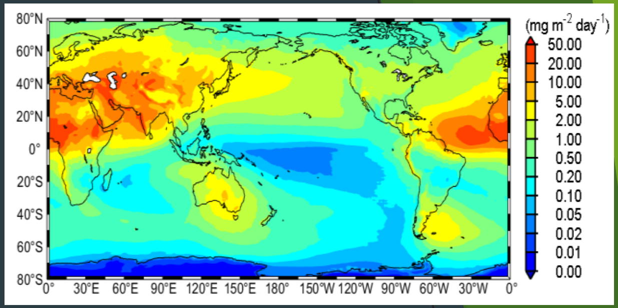
$$Sc = Sc_b + (dFe - LC) \times C_{high} \qquad (dFe \geq LC)$$

$$Sc_b = Sc_p \times POC + Sc_d \times Dust$$

Model

◆ Atmospheric dust data

MERRA-2 (The Modern-Era Retrospective analysis for Research and Applications, Version 2; Gelaro *et al.*, 2017)



Annual mean Dust Deposition from MERRA-2 data

10 years averaged (1980～1989) monthly mean dust flux at sea-surface

◆ POC data

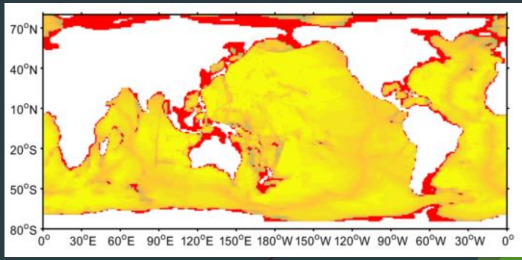
SeaWiFS climatological monthly mean POC data.

◆ Phytoplankton data

SeaWiFS climatological monthly mean chlorophyll-a data.

◆ Iron source from sea floor

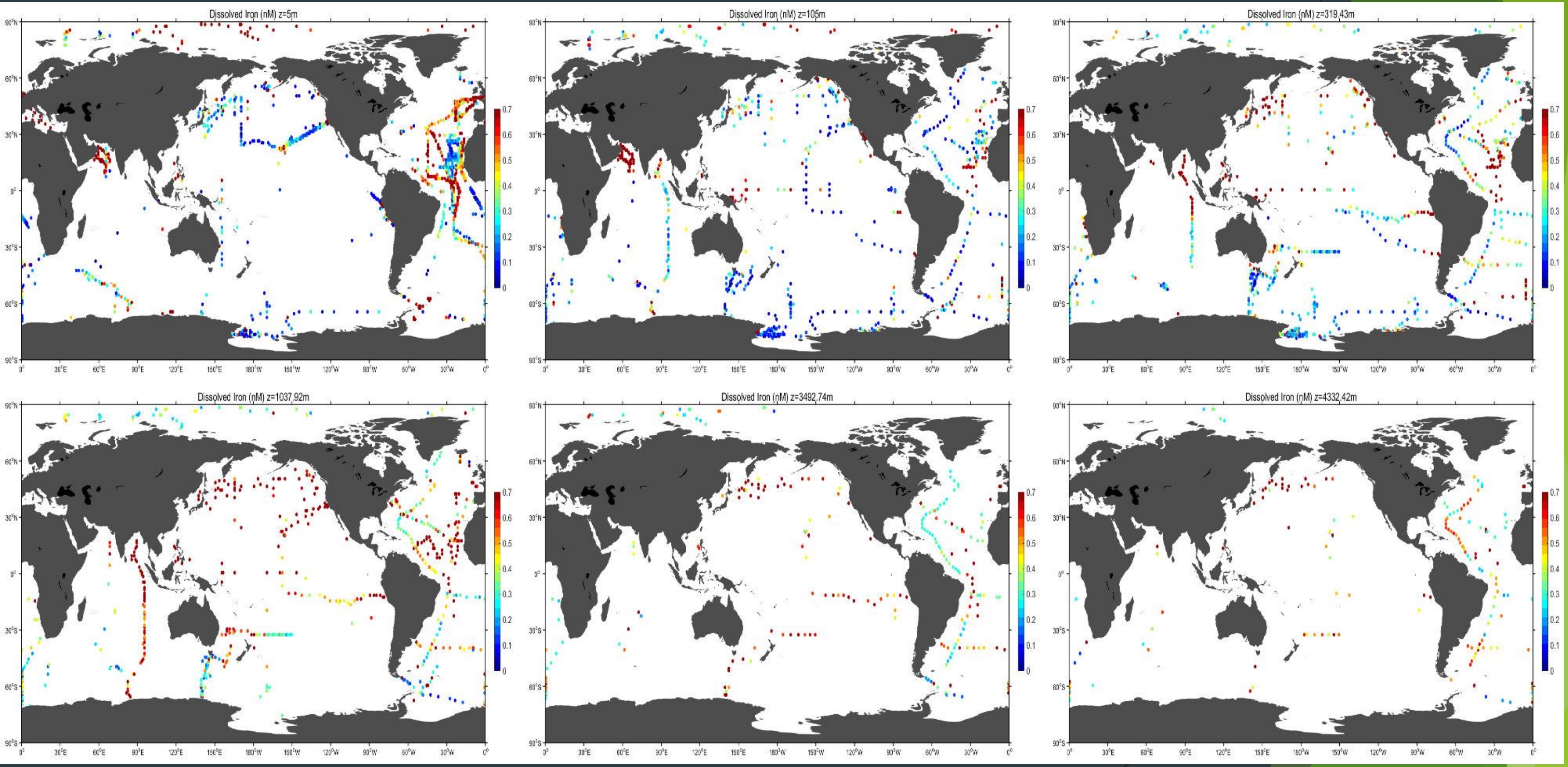
The region of the shelf was assumed at the sea floor up to 1000m.



◆ Iron source from abyssal hydrothermal vent was omitted.

Observational Data

- GEOTRACES Intermediate Data Product 2017 Version 2 (Schlitzer *et al*., 2018)
- Compiled data by Tagliabue *et al*. (2015)



Horizontal map of the dissolved iron observational data (nmol L^{-1}) which was constructed by merge of the observational databases in the 1 degree model grid.

Data assimilation

Green's function approach

Integrate the observation to iron cycle model

Cost Function : $J(\boldsymbol{x}) = \frac{1}{2}[H(\boldsymbol{x}) - \boldsymbol{y}]^T R^{-1}[H(\boldsymbol{x}) - \boldsymbol{y}]$

$\boldsymbol{x}$: control variable

$\boldsymbol{y}$: observation

H : observation operator (including the model time integration)

R : observation error covariance matrices

$$\hat{x} = \boldsymbol{x}_b - (\boldsymbol{DH}^T\boldsymbol{R}^{-1}\boldsymbol{DH})^{-1} \times (\boldsymbol{DH}^T\boldsymbol{R}^{-1}[H(\boldsymbol{x}_b) - \boldsymbol{y}])$$

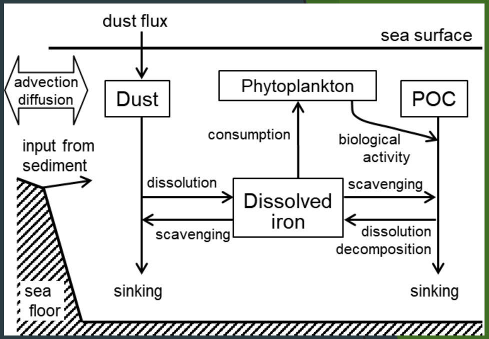
$$(\boldsymbol{DH})_j \cong \frac{H(\boldsymbol{x}_b + \boldsymbol{e}_j) - H(\boldsymbol{x}_b)}{\boldsymbol{e}_j}$$

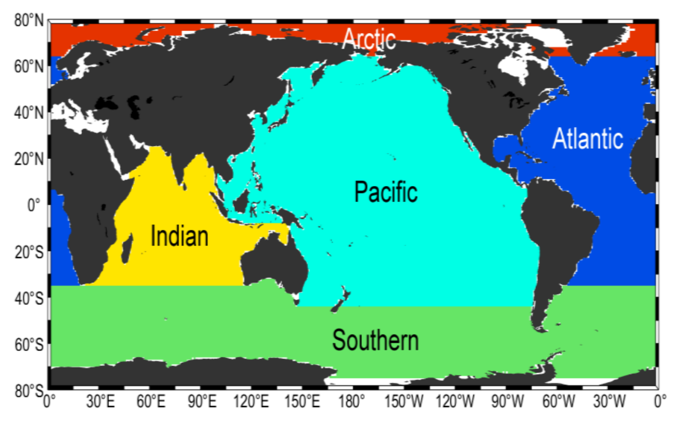
$\boldsymbol{x}_b$: first guess

$\boldsymbol{e}_j$: perturbation of the j-th parameter

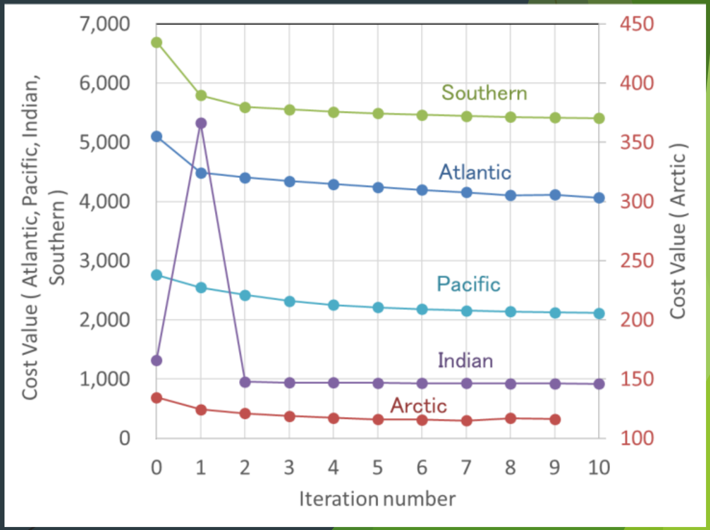
Data assimilation

	Control variables
1	Desorption or dissolution rate from POC (%/day)
2	Desorption or dissolution rate from aeolian dust (%/day)
3	Sinking velosity of POC (m/day)
4	Sinking velosity of dust (m/day)
5	Scavenging rate by POC (L/μgC/day)
6	Scavenging rate by dust (L/μg/day)
7	Ligand concentration (nmol/L)
8	Proportional coefficient (L/nmol/day)
9	Consumption rate by phytoplankton (nmol/mgChl/day)
10	Supply rate from sea floor (nmol/m^2/day)

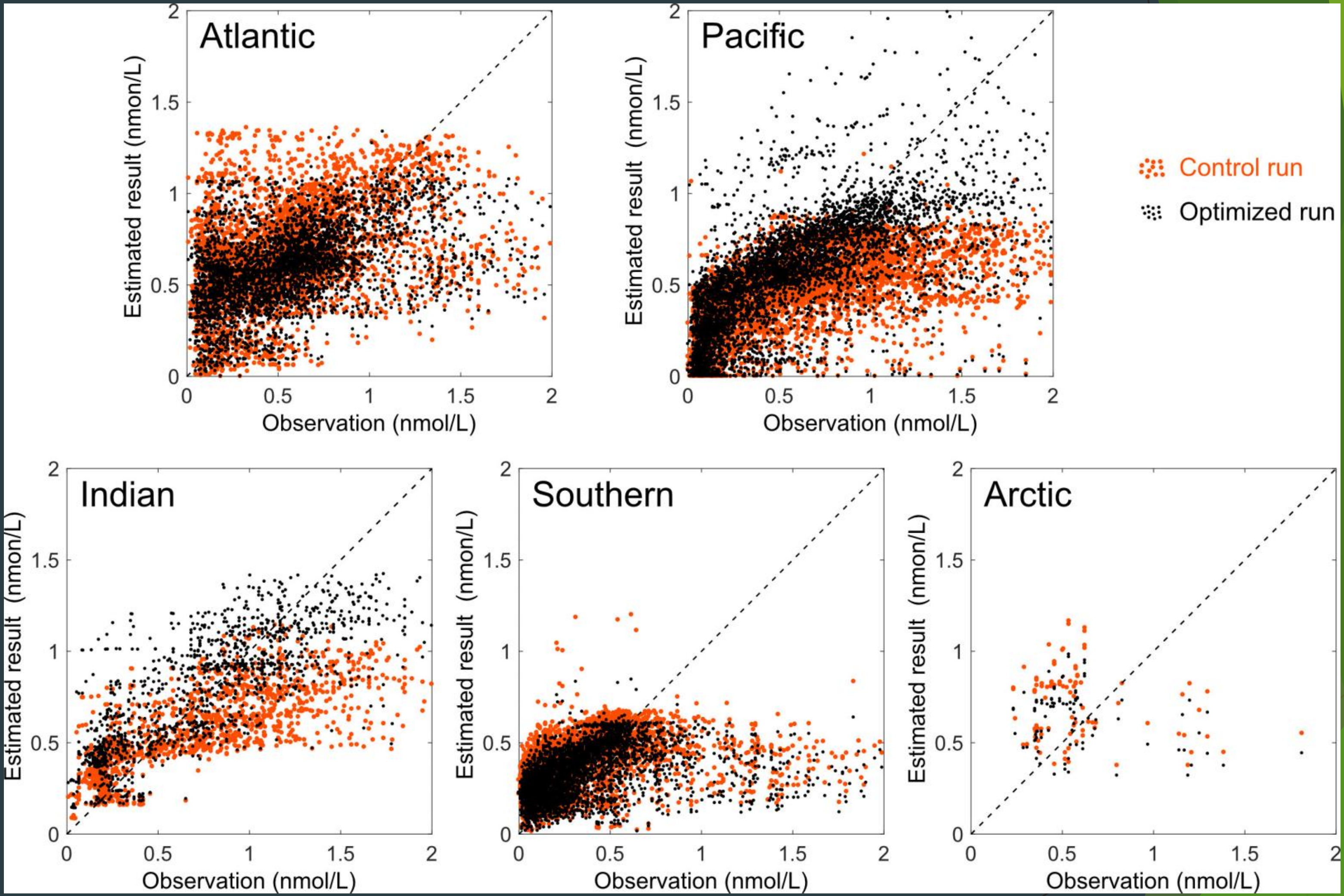




- Executing control run and some perturbation experiments.
- Searching for an optimal set of model parameter values by minimizing the cost function.
- Conducting iterative procedure until stationary value of the cost.



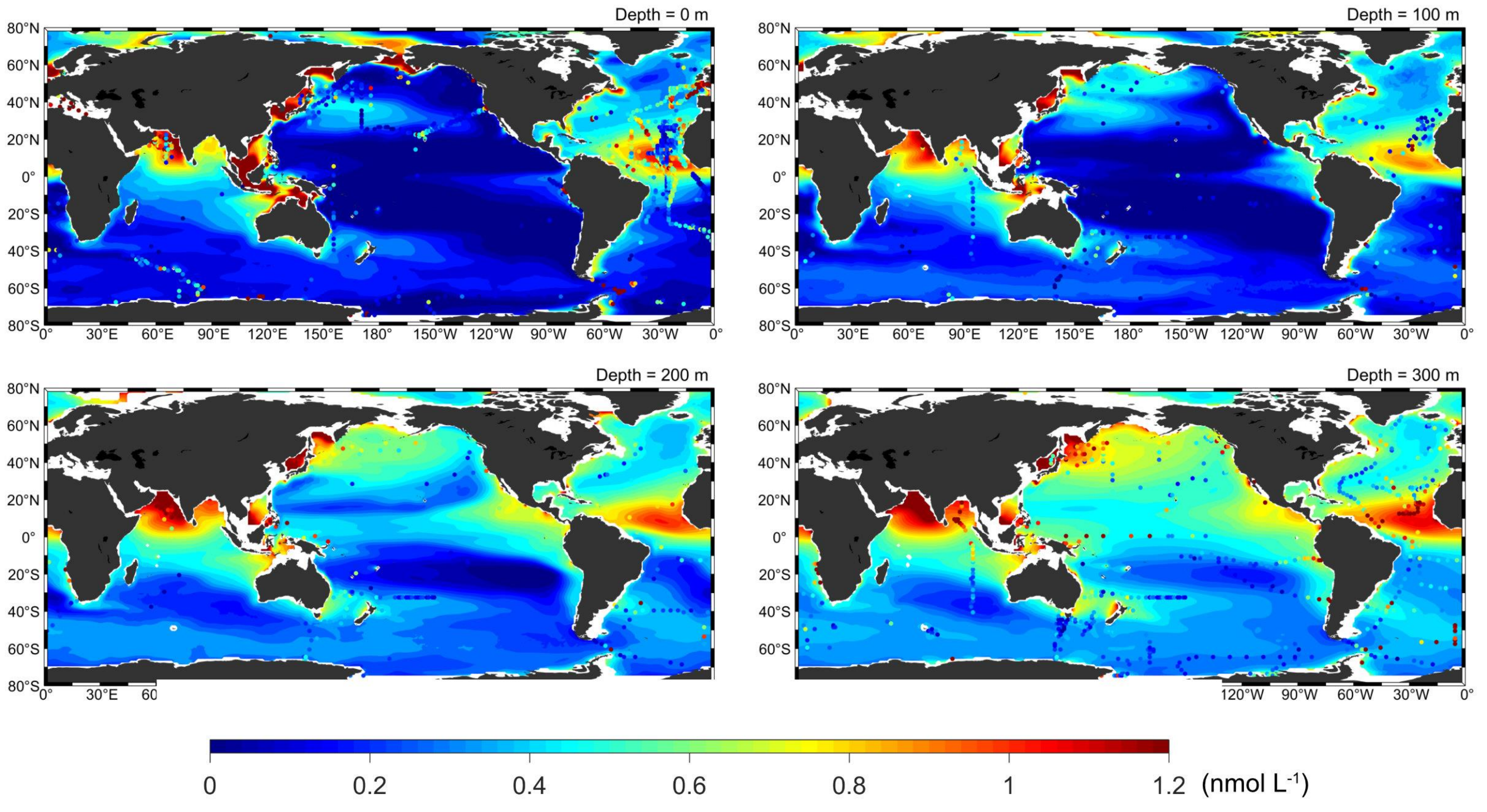
Data assimilation



Scatter diagrams for the comparison between the result of optimized run and control run.

Estimated result

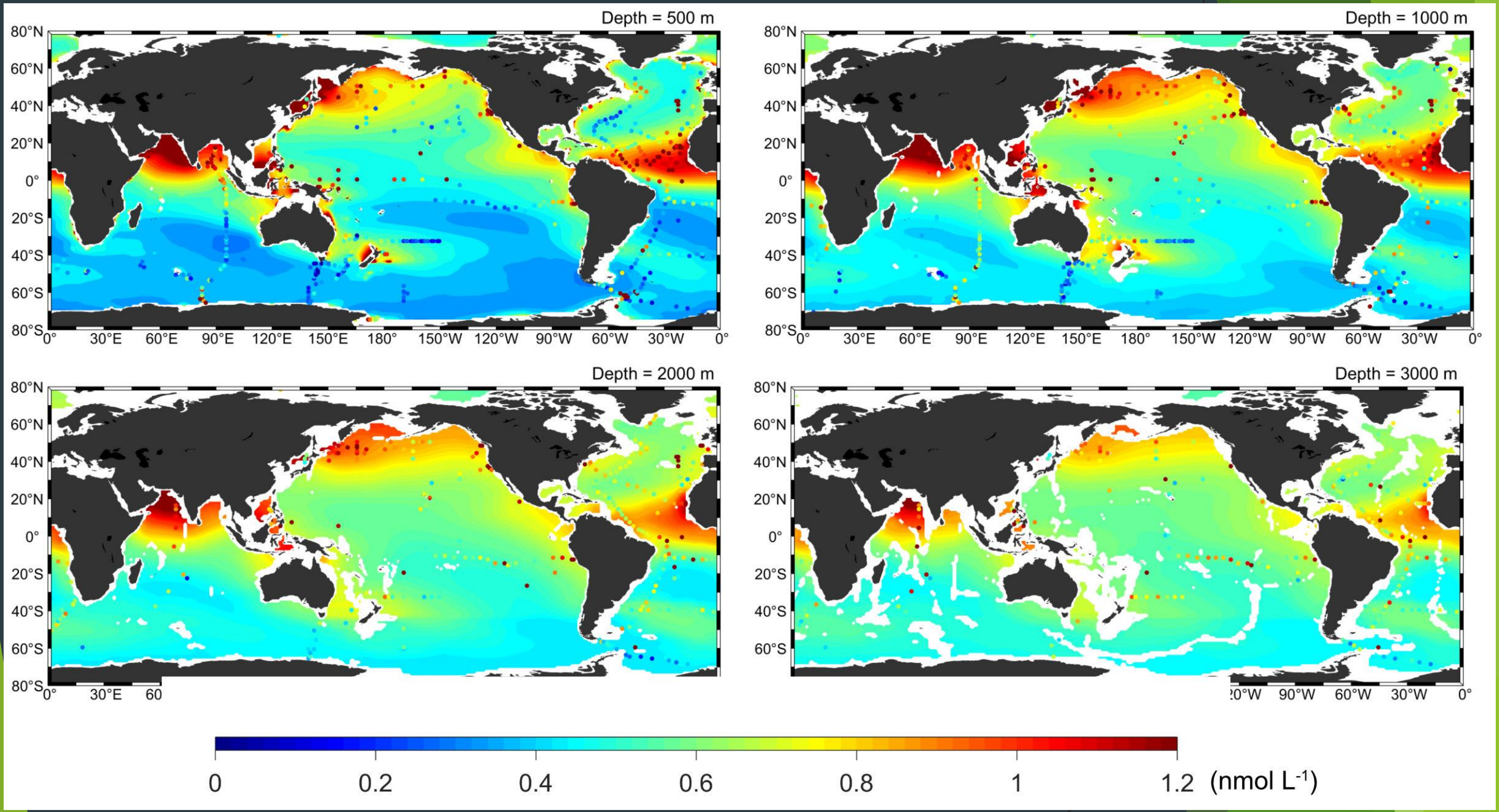
Horizontal map



Horizontal distribution of the dissolved iron concentration.
The observations are shown by circle plot using the same color range.

Estimated result

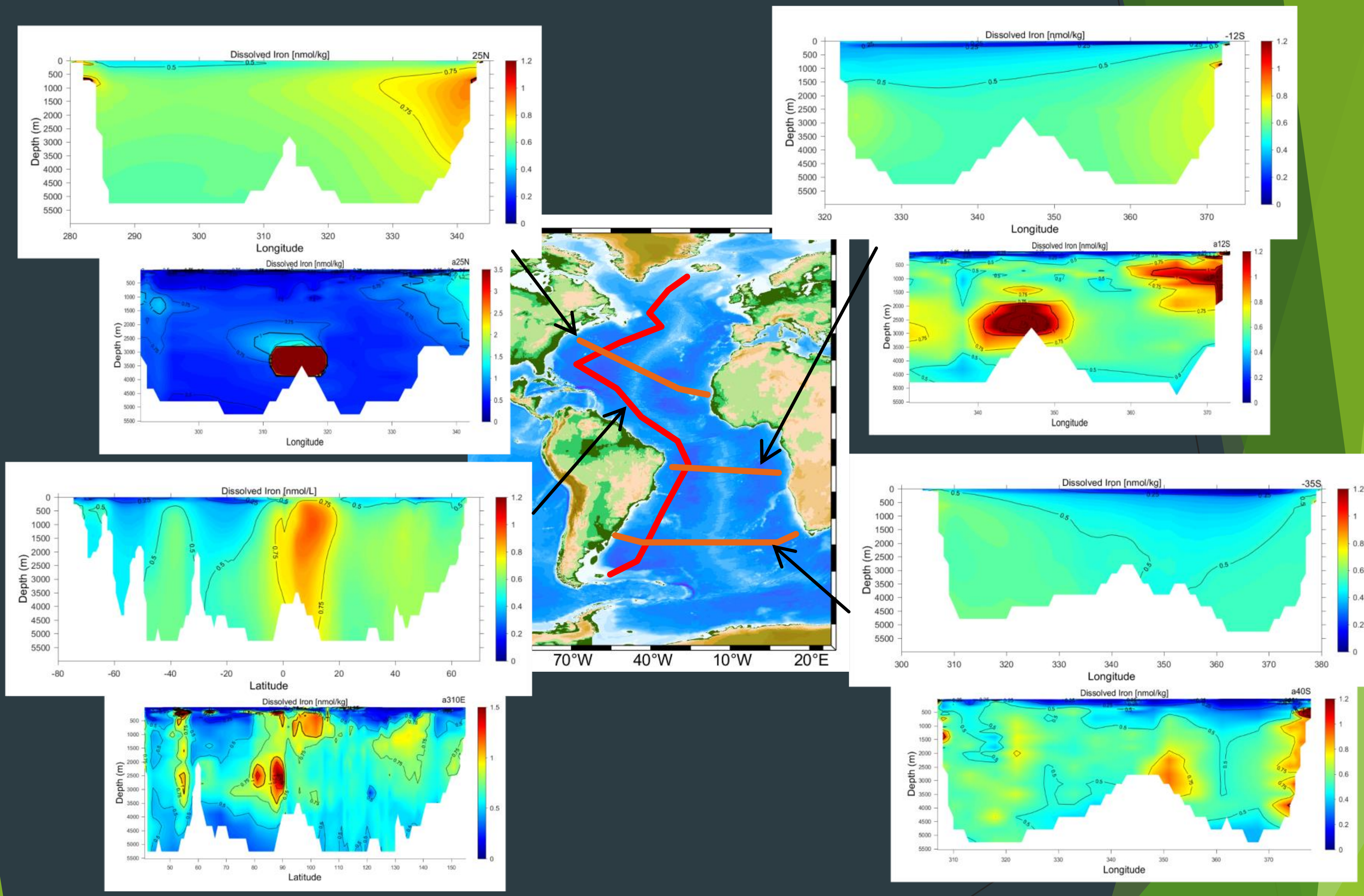
Horizontal map



Horizontal distribution of the dissolved iron concentration.
The observations are shown by circle plot using the same color range.

Estimated result

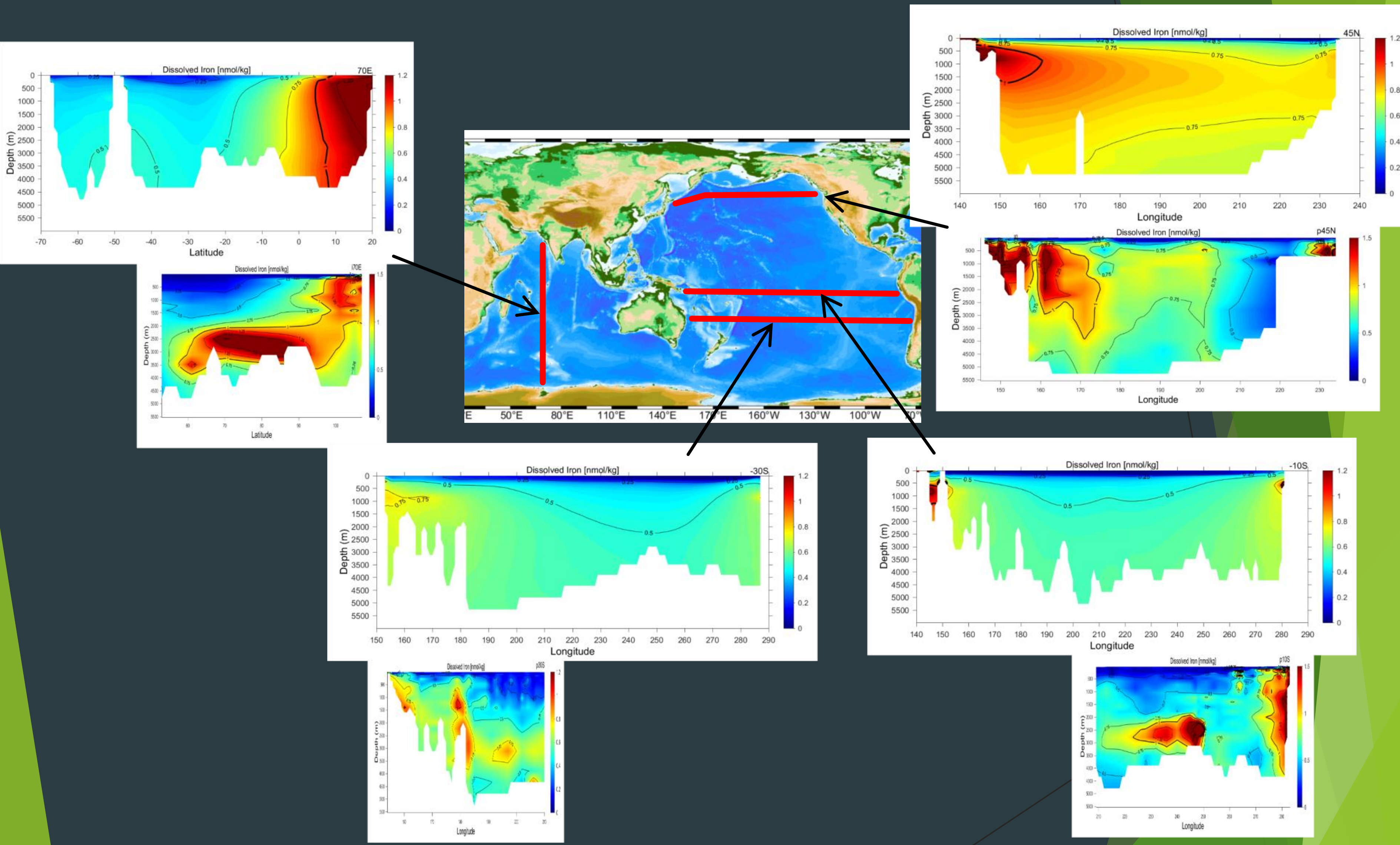
Vertical section



Vertical section plots of the dissolved iron distribution (nmol L^{-1}) for estimated result (upper) and observation (lower).

Estimated result

Vertical section



Vertical section plots of the dissolved iron distribution (nmol L^{-1}) for estimated result (upper) and observation (lower).

Concluding Remarks

- We constructed a useful gridded three-dimensional dissolved iron dataset in the global ocean by using both available observations and model.
- The observations are assimilated to a global oceanic iron cycle model by using a Green's function.
- Our estimation considerably succeeded in capturing the prominent features of each basin.
- We expect that analyzing these simple processes will help to solve the more realistic and more detailed processes to enhance the accuracy of the estimation for primary production and so on.