

ABICに基づくインバージョン解析手法の発展

Development of the method of inversion analyses  
using ABIC

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*Bad modelling leads to a bad inversion result.*

*A bad inversion result suggests bad modeling.*

悪いインバージョン結果には何か理由がある

# Contents

0. Framework of inversion analysis using ABIC
1. More than one sort of prior information  
[Fukahata *et al.* 2004, 2003]
2. More than one sort of data (Joint inversion)  
[Fuuning, Fukahata, Yagi & Parsons 2014]
3. Weak non-linear inversion [Fukahata & Wright 2008]
4. Covariance components due to observation error  
[Fukahata & Wright 2008]
5. Covariance components due to modeling error
  - 1. Discretization error [Yagi & Fukahata 2008]
  - 2. Errors of Green's function [Yagi & Fukahata 2011]

Reference: 地震学におけるABICを用いたインバージョン解析研究の進展,  
深畑, 地震 2, S103-S113, 2009.

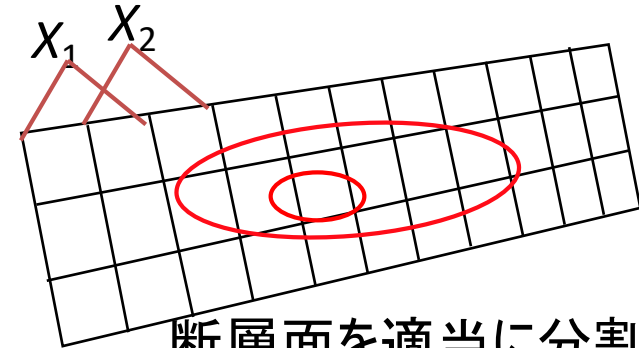
# Inversion Algorithm Using ABIC for slip inversion (1)

(Based on Yabuki & Matsu'ura, 1992)

## 1. Parametric Expansion

$$u(x, y) = \sum_{k=1}^m \sum_{l=1}^L a_{kl} X_k(x) Y_l(y)$$

$a_{kl}$ : model parameter,  $u$ : slip distribution,  
 $X_k(x)$ ,  $Y_l(y)$ : basis function



断層面を適当に分割して  
滑り分布を基底関数展開

## 2. Observation Equation

$$\mathbf{d} = \mathbf{H}\mathbf{a} + \mathbf{e} \quad \mathbf{d}: \text{data}, \mathbf{e}: \text{error}, \mathbf{e} \sim N(\mathbf{0}, \sigma^2 \mathbf{E})$$

$$p(\mathbf{d} | \mathbf{a}; \sigma^2) = (2\pi\sigma^2)^{-\frac{n}{2}} |\mathbf{E}|^{-\frac{1}{2}} \exp\left[-\frac{1}{2\sigma^2} (\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}\mathbf{a})\right]$$

断層運動による地表の変形応答(e.g., Okada, 1985)が必要

## 3. Prior Information (smoothness condition)

$$\int_{XY} \left[ \left( \frac{\partial u}{\partial x} \right)^2 + \left( \frac{\partial u}{\partial y} \right)^2 \right] dx dy = \mathbf{a}^T \mathbf{G} \mathbf{a} \quad \rightarrow \quad \text{small}$$

$$p(\mathbf{a}; \rho^2) = (2\pi\rho^2)^{-\frac{m}{2}} |\mathbf{G}|^{\frac{1}{2}} \exp\left[-\frac{1}{2\rho^2} \mathbf{a}^T \mathbf{G} \mathbf{a}\right]$$

## Inversion Algorithm Using ABIC for slip inversion (2)

(Based on Yabuki & Matsu'ura, 1992)

### 4. Bayes' Theorem (観測からの情報と先験的情報を統合)

$$p(\mathbf{a}; \sigma^2, \rho^2 \mid \mathbf{d}) = c p(\mathbf{d} \mid \mathbf{a}; \sigma^2) p(\mathbf{a}; \rho^2)$$

$$= c (2\pi\sigma^2)^{-(n+m)/2} (\alpha^2)^{P/2} |\mathbf{E}|^{-1/2} |\mathbf{G}|^{1/2} \times \exp\left[-\frac{1}{2\sigma^2} s(\mathbf{a}; \alpha^2)\right]$$

with

$$s(\mathbf{a}; \alpha^2) = (\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}\mathbf{a}) + \alpha^2 \mathbf{a}^T \mathbf{G}\mathbf{a} \quad (\alpha^2 = \sigma^2 / \rho^2 : \text{hyperparameter})$$

### 5. ABIC Minimum (ABIC: Akaike's Bayesian Information Criterion)

$$\text{ABIC}(\sigma^2, \alpha^2) = -2 \log \int p(\mathbf{a}; \sigma^2, \alpha^2 \mid \mathbf{d}) d\mathbf{a} + C$$

The criterion of ABIC minimum  $\rightarrow \hat{\sigma}^2, \hat{\alpha}^2$

Given  $\sigma^2, \alpha^2$ , based on maximum likelihood method

$$\rightarrow \hat{\mathbf{a}} = [\mathbf{H}^T \mathbf{E}^{-1} \mathbf{H} + \hat{\alpha}^2 \mathbf{G}]^{-1} \mathbf{H}^T \mathbf{E}^{-1} \mathbf{d}$$

$$\hat{\mathbf{C}} = \hat{\sigma}^2 (\mathbf{H}^T \mathbf{E}^{-1} \mathbf{H} + \hat{\alpha}^2 \mathbf{G})^{-1}$$

Observation eq.  
 $\mathbf{d} = \mathbf{H}\mathbf{a} + \mathbf{e}; \quad p(\mathbf{d} | \mathbf{a}; \sigma^2)$

Prior information  
 $r = \mathbf{a}^T \mathbf{G}\mathbf{a}; \quad p(\mathbf{a}; \rho^2)$

*Bayes Theorem*

$$p(\mathbf{a}; \sigma^2, \rho^2 | \mathbf{d}) = c p(\mathbf{d} | \mathbf{a}; \sigma^2) p(\mathbf{a}; \rho^2)$$

$$= c (2\pi\sigma^2)^{-(n+m)/2} (\alpha^2)^{P/2} |\mathbf{E}|^{-1/2} |\mathbf{G}|^{1/2} \times \exp\left[-\frac{1}{2\sigma^2} s(\mathbf{a}; \alpha^2)\right]$$

with  $s(\mathbf{a}) = (\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}\mathbf{a}) + \frac{\sigma^2}{\rho^2} \mathbf{a}^T \mathbf{G}\mathbf{a}$

$$\text{ABIC}(\sigma^2, \rho^2) \equiv -2 \log \left[ \int p(\mathbf{a}; \sigma^2, \rho^2 | \mathbf{d}) d\mathbf{a} \right] + C \quad (\text{Akaike 1980})$$

minimum ABIC  Optimal  $\sigma^2, \rho^2$  (hyperparameter)

ABIC enables us to determine the relative weight between observed data and prior information objectively.

# ABIC determines the relative weight based on statistics

## Characteristic of ABIC

Observed data

Prior infor.

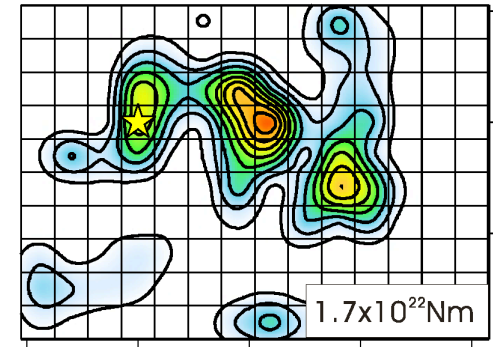
ABIC

Observed data: accurate, sufficient

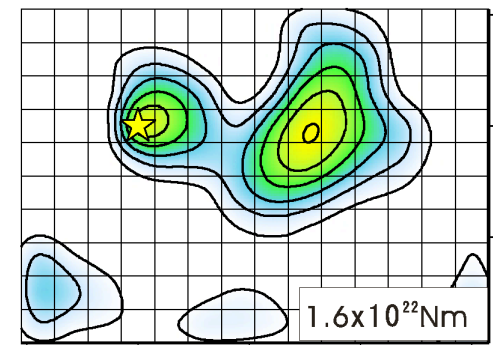
→ the model that fits to the data

Observed data: inaccurate, insufficient

→ the model that follows prior



far + near



far only

Fukahata, Yagi, &  
Matsu'ura (2003)

# Extension of inversion methods using ABIC

# CASE1: More than one sort of prior information

Prior Information

$$\begin{cases} \int_T \int_X \left[ \frac{\partial^2 u(x,t)}{\partial x^2} \right] dx dt = \mathbf{a}^T \mathbf{G}_1 \mathbf{a} \\ \int_T \int_X \left[ \frac{\partial^2 u(x,t)}{\partial t^2} \right] dx dt = \mathbf{a}^T \mathbf{G}_2 \mathbf{a} \end{cases}$$

probability density function

$$\begin{cases} p(\mathbf{a}; \rho_1^2) = (2\pi)^{-\frac{m}{2}} \left| \frac{\mathbf{G}_1}{\rho_1^2} \right|^{\frac{1}{2}} \exp \left[ -\frac{1}{2\rho_1^2} \mathbf{a}^T \mathbf{G}_1 \mathbf{a} \right] \\ p(\mathbf{a}; \rho_2^2) = (2\pi)^{-\frac{m}{2}} \left| \frac{\mathbf{G}_2}{\rho_2^2} \right|^{\frac{1}{2}} \exp \left[ -\frac{1}{2\rho_2^2} \mathbf{a}^T \mathbf{G}_2 \mathbf{a} \right] \end{cases}$$



$$p(\mathbf{a}; \rho_1^2, \rho_2^2) = (2\pi)^{-m} \left| \frac{\mathbf{G}_1}{\rho_1^2} \right|^{\frac{1}{2}} \left| \frac{\mathbf{G}_2}{\rho_2^2} \right|^{\frac{1}{2}} \exp \left[ -\frac{1}{2} \mathbf{a}^T \left( \frac{\mathbf{G}_1}{\rho_1^2} + \frac{\mathbf{G}_2}{\rho_2^2} \right) \mathbf{a} \right] \quad (\text{ex, Yoshida, 1989})$$

Ide et al. 1996)

$$\int p(\mathbf{a}; \rho_1^2, \rho_2^2) d\mathbf{a} \neq 1 \quad \Leftarrow \quad P(A \cap B) \neq P(A)P(B)$$

$$\Rightarrow p(\mathbf{a}; \rho_1^2, \rho_2^2) = (2\pi)^{-\frac{m}{2}} \left| \frac{\mathbf{G}_1}{\rho_1^2} + \frac{\mathbf{G}_2}{\rho_2^2} \right|^{\frac{1}{2}} \exp \left[ -\frac{1}{2} \mathbf{a}^T \left( \frac{\mathbf{G}_1}{\rho_1^2} + \frac{\mathbf{G}_2}{\rho_2^2} \right) \mathbf{a} \right]$$

規格化定数  
の重要性

(Fukahata et al., 2004, 2003)



# Expression of ABIC

## Proper

$$\begin{aligned} \text{ABIC}(\alpha^2, \beta^2) &= N \log s(\mathbf{a}^*) - \log \|\alpha^2 \mathbf{G}_1 + \beta^2 \mathbf{G}_2\| \\ &\quad + \log \|\mathbf{H}^T \mathbf{H} + \alpha^2 \mathbf{G}_1 + \beta^2 \mathbf{G}_2\| + C' \end{aligned}$$

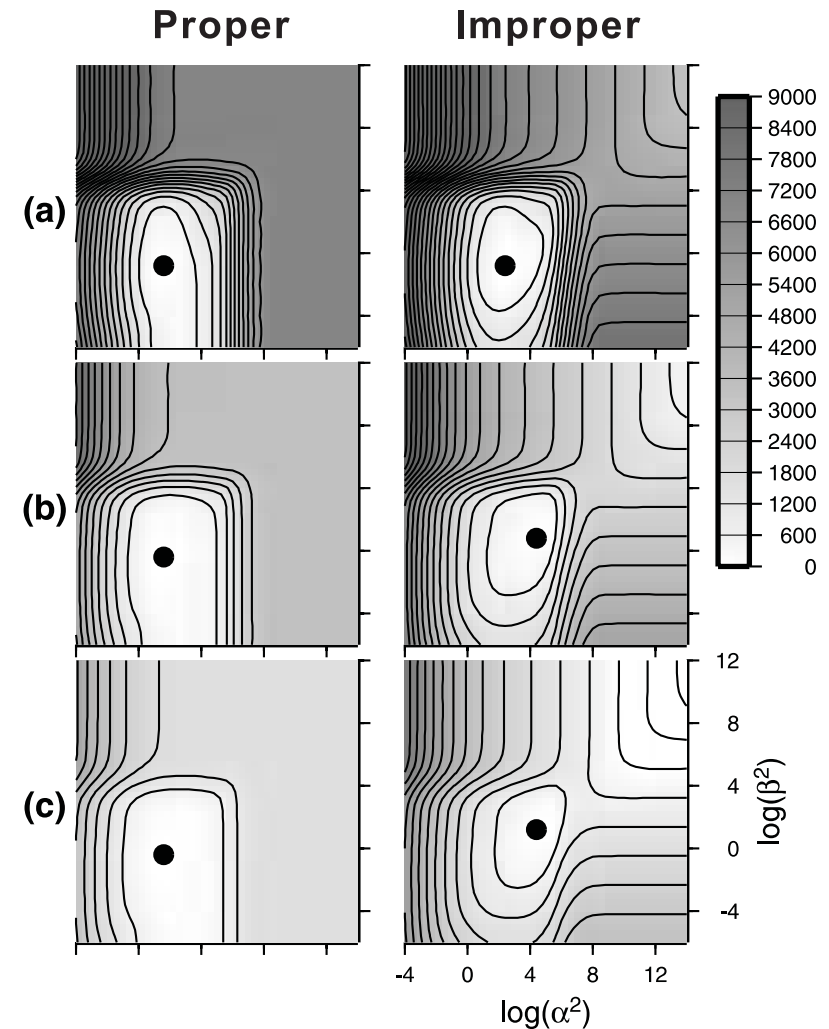
## Improper

$$\begin{aligned} \text{ABIC}(\alpha^2, \beta^2) &= (N + P_1 + P_2 - M) \log s(\mathbf{a}^*) - \log \alpha^{2P_1} \beta^{2P_2} \\ &\quad + \log \|\mathbf{H}^T \mathbf{H} + \alpha^2 \mathbf{G}_1 + \beta^2 \mathbf{G}_2\| + C'' \end{aligned}$$

$(\alpha \rightarrow \text{大}; \beta \rightarrow \text{大}) \Rightarrow \text{ABIC} \rightarrow \text{マイナス無限大}$

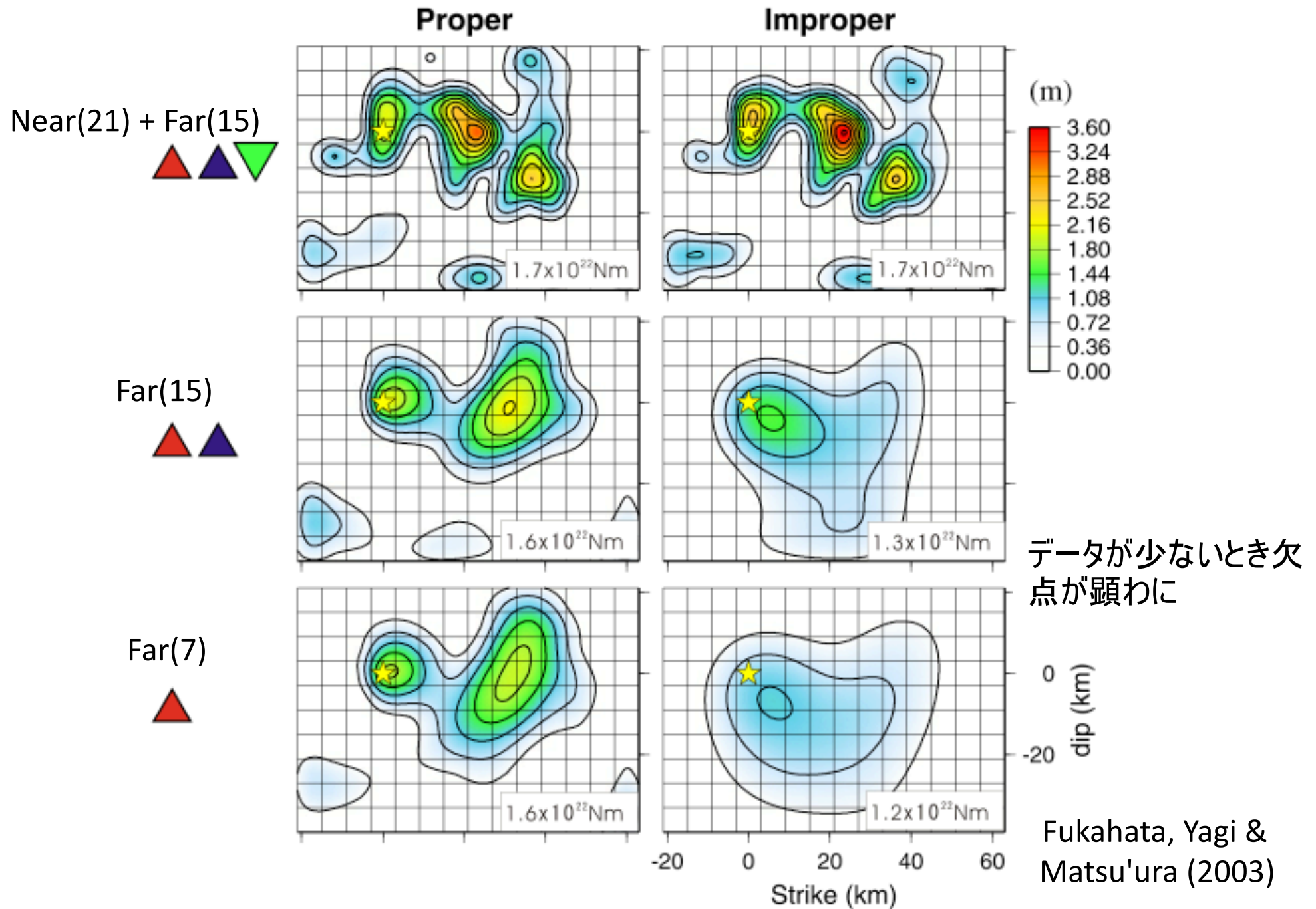
$$\left( \alpha^2 = \frac{\sigma^2}{\rho_1^2}, \beta^2 = \frac{\sigma^2}{\rho_2^2} \right)$$

## ABICコンター



Fukahata, Yagi & Matsu'ura (2003)

# Inverted Slip Distribution



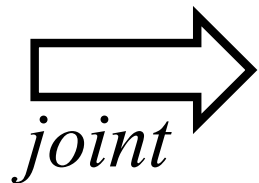
## CASE2: More than one sort of data (Joint inversion)

### Expression of observation equation

$$\text{InSAR: } \mathbf{d}_I = \mathbf{H}_I \mathbf{a} + \mathbf{e}_I, \quad \mathbf{e}_I \sim N(0, \sigma_I^2 \mathbf{E}_I)$$

$$\text{seismic: } \mathbf{d}_s = \mathbf{H}_s \mathbf{a} + \mathbf{e}_s, \quad \mathbf{e}_s \sim N(0, \sigma_s^2 \mathbf{E}_s)$$

$$p(\mathbf{d}_s | \mathbf{a}; \sigma_s^2) = (2\pi\sigma_s^2)^{-\frac{N_s}{2}} |\mathbf{E}_s|^{-\frac{1}{2}} \exp\left[-\frac{1}{2\sigma_s^2} (\mathbf{d}_s - \mathbf{H}_s \mathbf{a})^T \mathbf{E}_s^{-1} (\mathbf{d}_s - \mathbf{H}_s \mathbf{a})\right]$$



$$\mathbf{d} = \mathbf{H}\mathbf{a} + \mathbf{e}, \quad \mathbf{e}_I \sim N(0, \sigma_I^2 \mathbf{E})$$

$$\begin{pmatrix} \mathbf{d}_I \\ \mathbf{d}_s \end{pmatrix} = \begin{pmatrix} \mathbf{H}_I \\ \mathbf{H}_s \end{pmatrix} \mathbf{a} + \begin{pmatrix} \mathbf{e}_I \\ \mathbf{e}_s \end{pmatrix} \quad \sigma_I^2 \mathbf{E} = \begin{pmatrix} \mathbf{E}_I & 0 \\ 0 & \eta^2 \mathbf{E}_s \end{pmatrix}$$

$$p(\mathbf{d} | \mathbf{a}; \sigma_I^2, \eta^2) = (2\pi\sigma_I^2)^{-\frac{N}{2}} |\mathbf{E}(\eta^2)|^{-\frac{1}{2}} \exp\left[-\frac{1}{2\sigma_I^2} (\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1}(\eta^2) (\mathbf{d} - \mathbf{H}\mathbf{a})\right]$$

$\eta^2 (= \sigma_s^2 / \sigma_I^2)$ : relative weight of data sets  $\sim$  new hyperparameter

## CASE2: Joint inversion

### Expression of ABIC

- Prior Information:  $p(\mathbf{a}; \rho_1^2, \rho_2^2) = (2\pi)^{-M/2} \left| \frac{\mathbf{G}_1}{\rho_1^2} + \frac{\mathbf{G}_2}{\rho_2^2} \right|^{1/2} \exp\left(-\frac{1}{2} \mathbf{a}^T \left( \frac{\mathbf{G}_1}{\rho_1^2} + \frac{\mathbf{G}_2}{\rho_2^2} \right) \mathbf{a}\right)$   
(Fukahata *et al.*, 2003, 2004)

- Bayes' Theorem

$$p(\mathbf{a}; \sigma_I^2, \eta^2, \rho_1^2, \rho_2^2 | \mathbf{d}) = c p(\mathbf{d} | \mathbf{a}; \sigma_I^2, \eta^2) p(\mathbf{a}; \rho_1^2, \rho_2^2)$$

- Derivation of ABIC

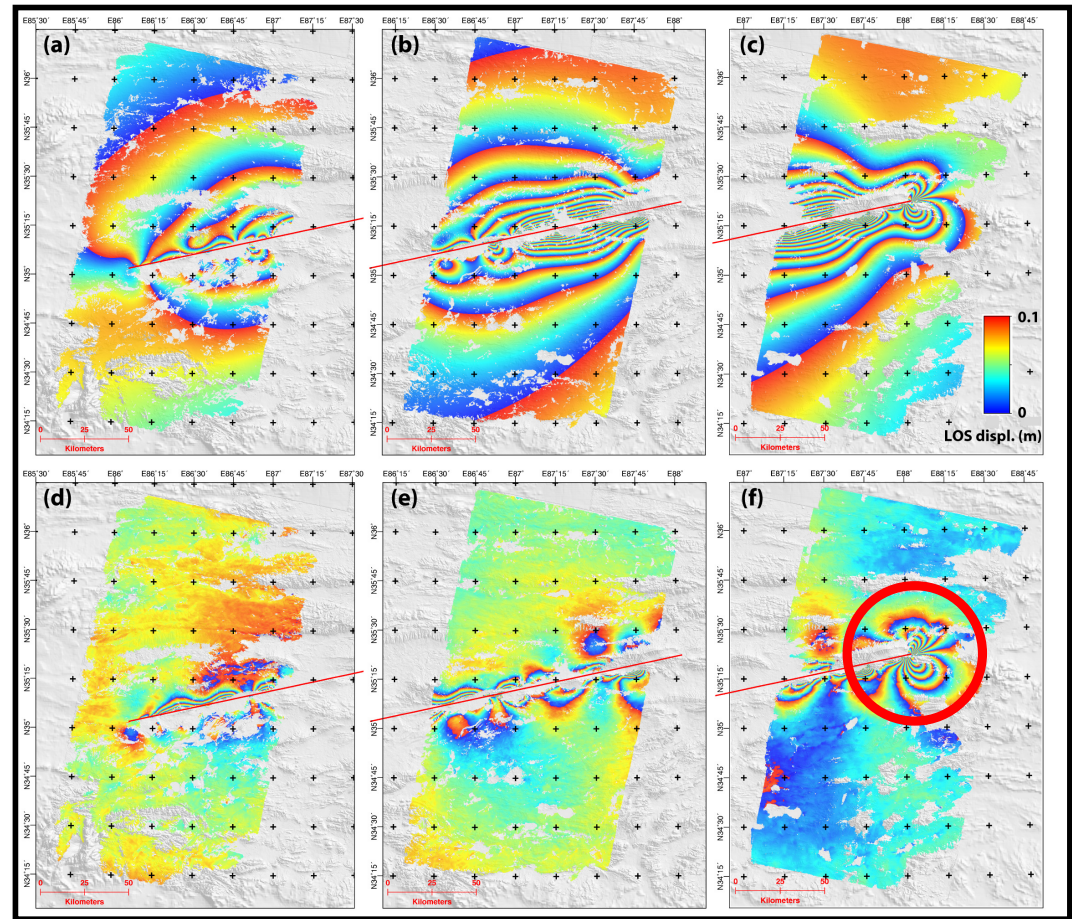
$$\begin{aligned} \text{ABIC}(\alpha^2, \beta^2, \eta^2) &= N \log s(\mathbf{a}^*) - \log |\alpha^2 \mathbf{G}_1 + \beta^2 \mathbf{G}_2| \\ &\quad + \log |\mathbf{H}^T \mathbf{E}^{-1}(\eta^2) \mathbf{H} + \alpha^2 \mathbf{G}_1 + \beta^2 \mathbf{G}_2| + \log |\mathbf{E}(\eta^2)| + C \end{aligned}$$

$$(\alpha^2 = \sigma_I^2 / \rho_1^2, \beta^2 = \sigma_I^2 / \rho_2^2)$$

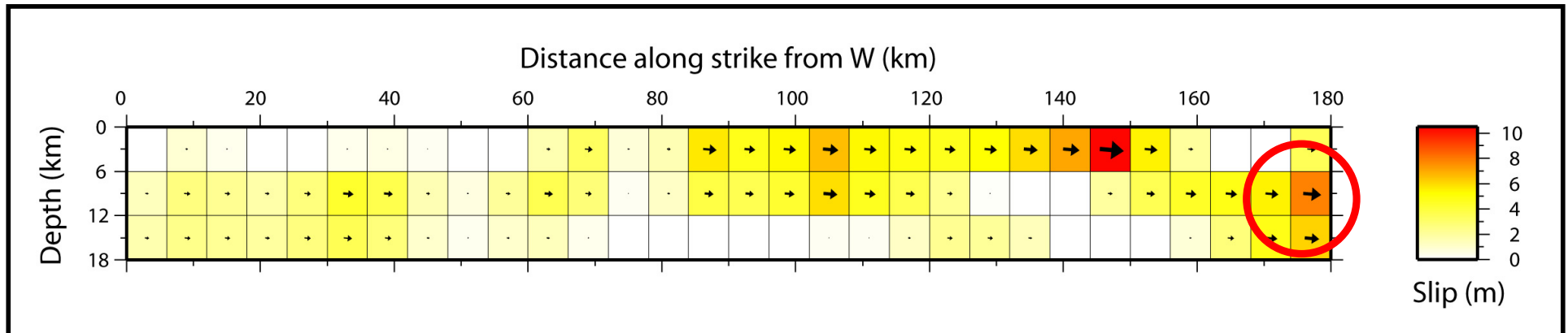
ABIC min  $\rightarrow$  optimum values of  $\alpha^2, \beta^2, \eta^2 \rightarrow \mathbf{a}$

# Results for only InSAR data

データとの比較

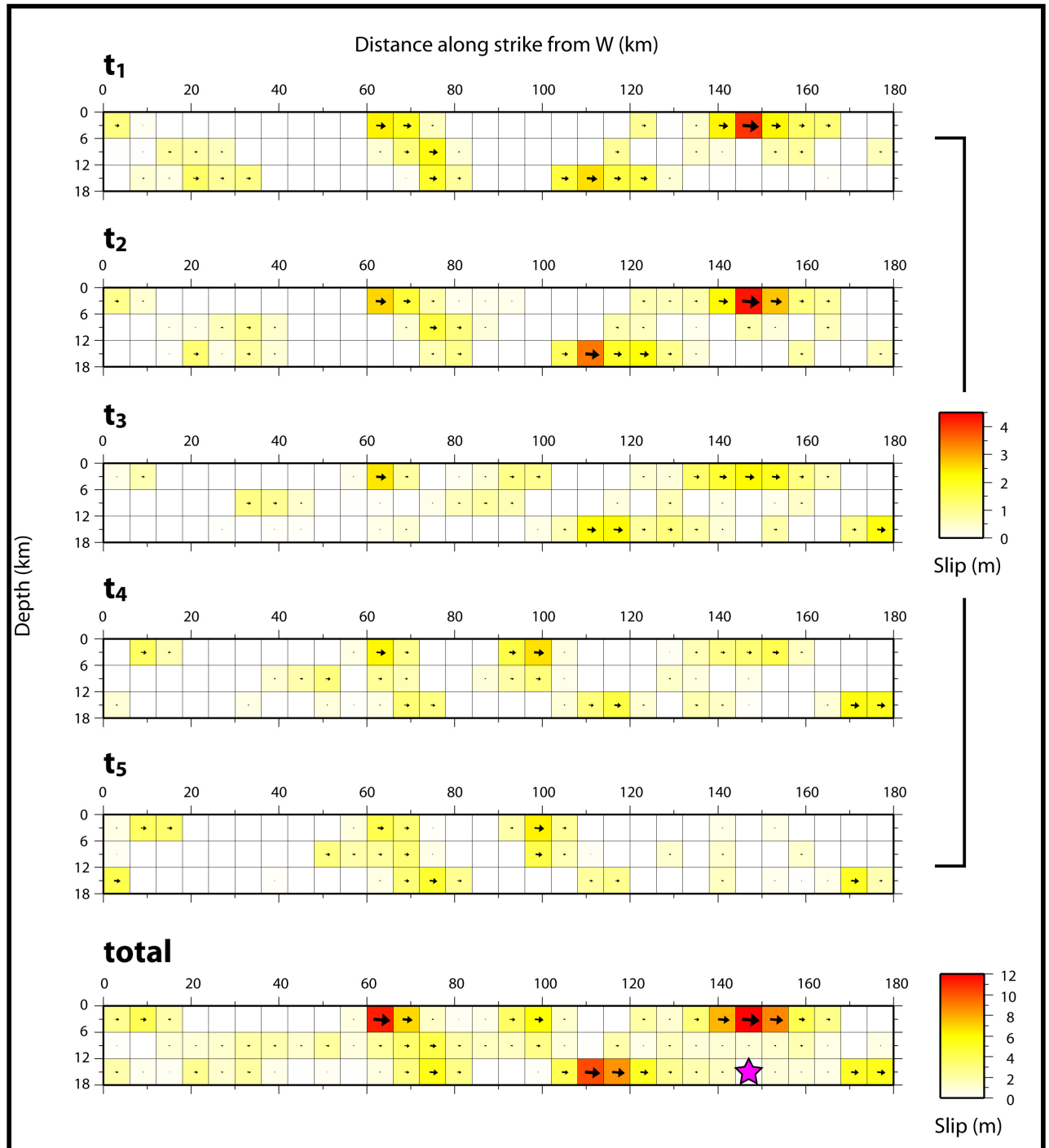


Slip Distribution

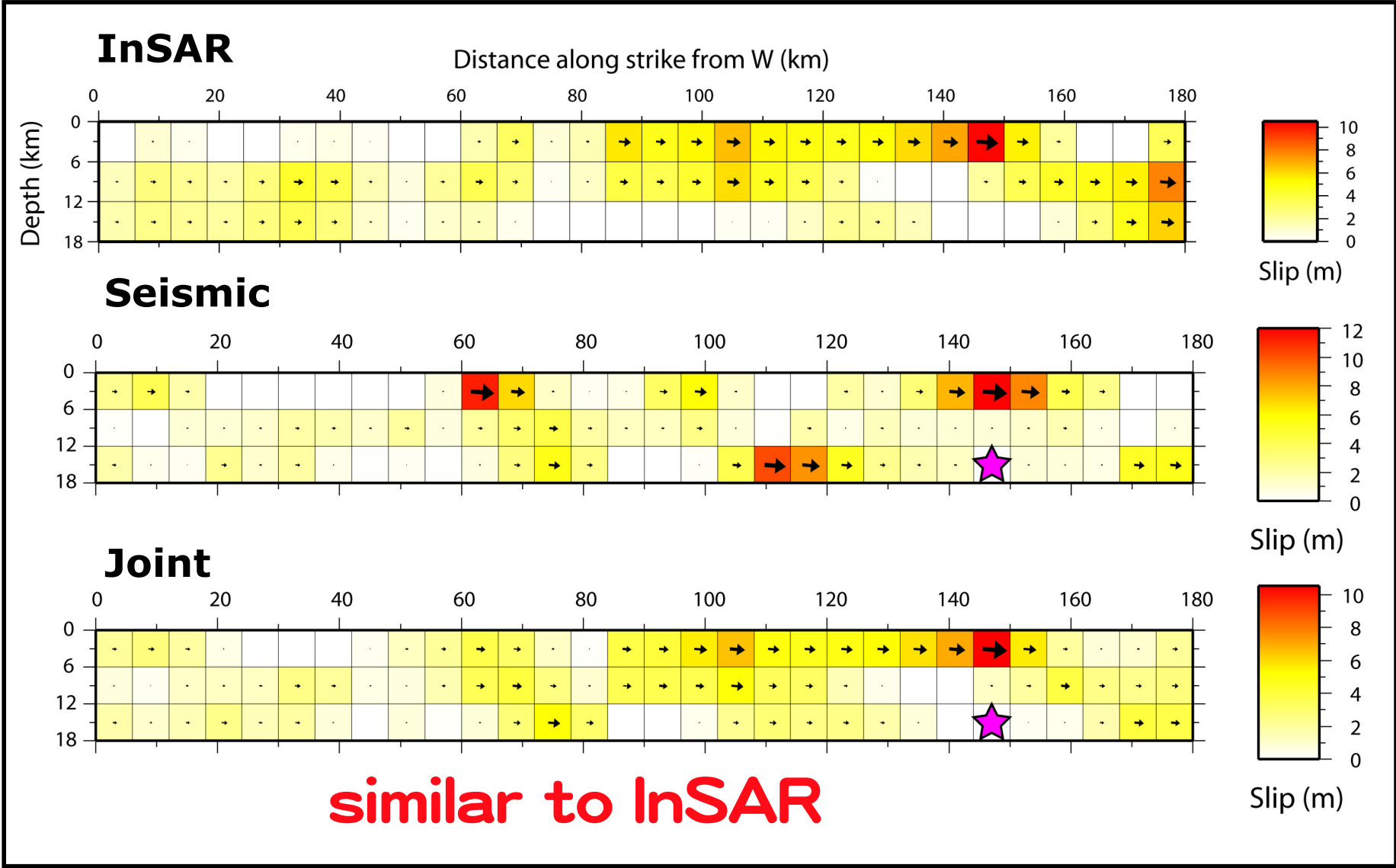


Funning, Fukahata, Yagi & Parsons (2014, GJI)

# Results for Seismic Data



# Result of Joint inversion

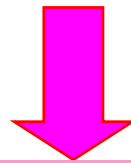


Funning, Fukahata, Yagi & Parsons (2014, GJI)

## CASE3: Weak Non-linear Inversion

### Expression of observation equation

*Non-linear:*  $\mathbf{d} = f(\mathbf{a}, \mathbf{f}) + \mathbf{e}$  ( $f$ : non-linear function)



*no approximation*

*Pseudo linearization:*  $\mathbf{d} = \mathbf{H}(\mathbf{f})\mathbf{a} + \mathbf{e}$  ( $\mathbf{H}$ : matrix)

*The parameters responsible for non-linearity is separated from model parameters  $\mathbf{a}$  that express slip distribution*

where  $\mathbf{f}$  : fault parameters (dip, strike, location)

$$u(x, z; \delta) = \sum_{k=1}^K \sum_{l=1}^L a_{kl} X_k(x) Z_l(z) : \text{slip distribution}$$

$a_{kl}$  : model parameters

$X_k(x), Z_l(z)$  : basis functions



## Determination of the non-linear parameters $\mathbf{f}$ with ABIC

- Residual sum of squares with prior (smoothness constraint)

$$s(\mathbf{a}; \alpha^2, \mathbf{f}) = (\mathbf{d} - \mathbf{H}(\mathbf{f})\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}(\mathbf{f})\mathbf{a}) + \alpha^2 \mathbf{a}^T \mathbf{G} \mathbf{a}$$

cf.  $s(\mathbf{a}; \alpha^2) = (\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}\mathbf{a}) + \alpha^2 \mathbf{a}^T \mathbf{G} \mathbf{a}$  : linear case

$\alpha^2$  : weight between observation and prior

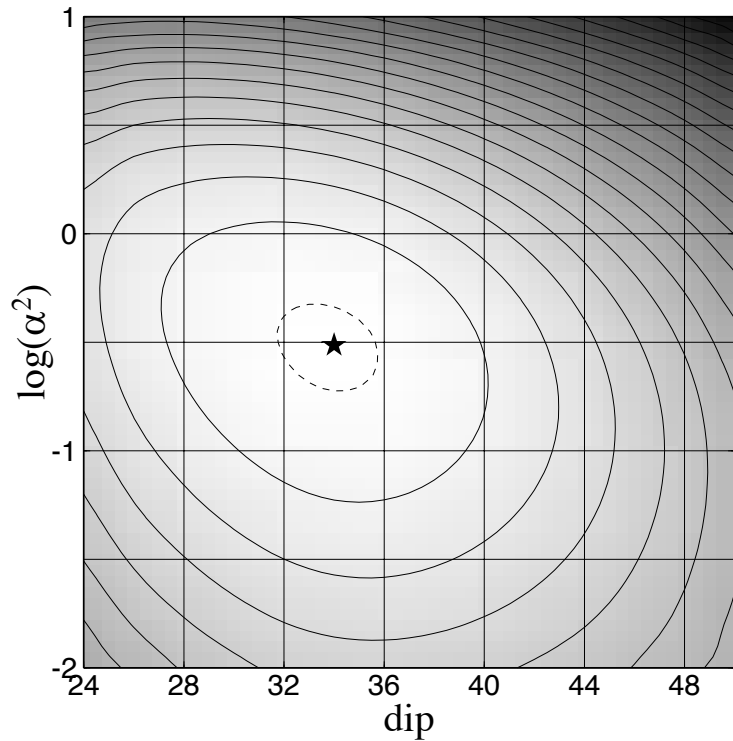
*Non-linear term*

↑  
ABIC min (Yabuki & Matsu'ura, 1992)

*In the same way,*

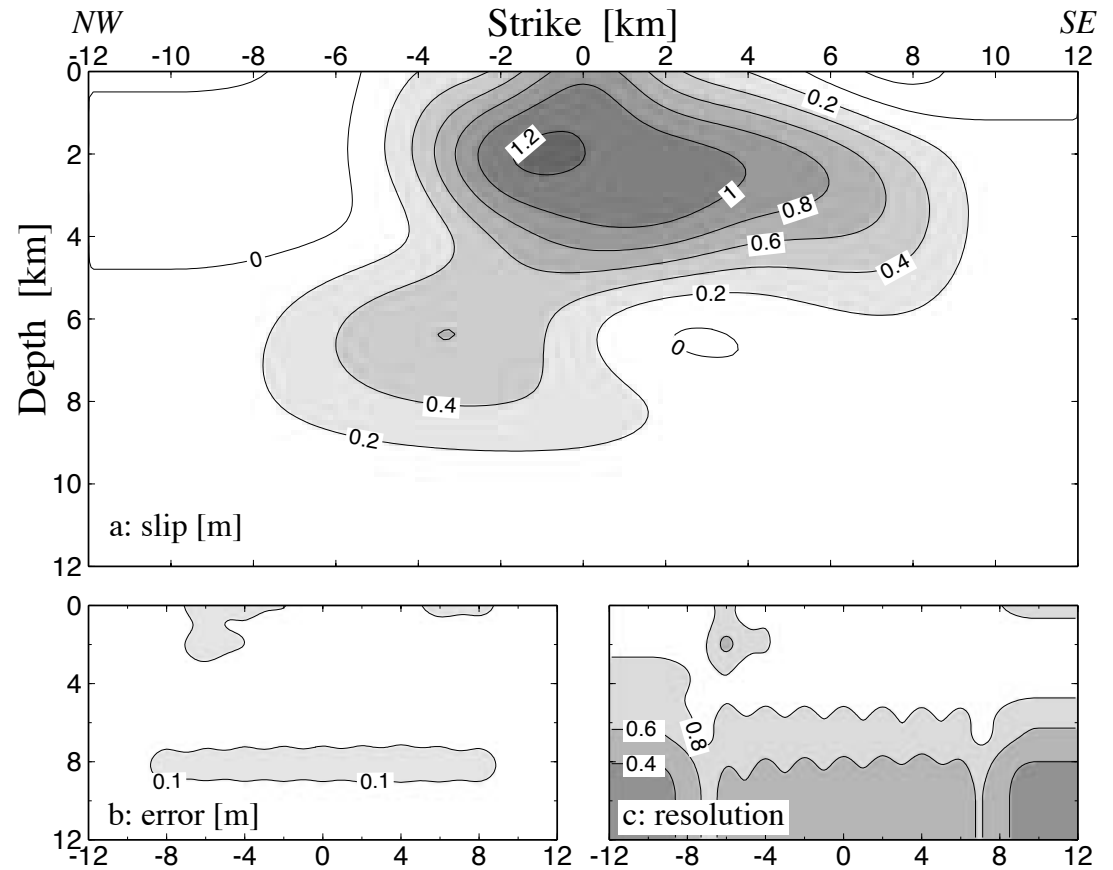
$\mathbf{f}$  ← ABIC min

## 最適傾斜角の推定



実線は20毎のABICコンター.  
点線は最小値から2のコンターで  
誤差範囲に相当.

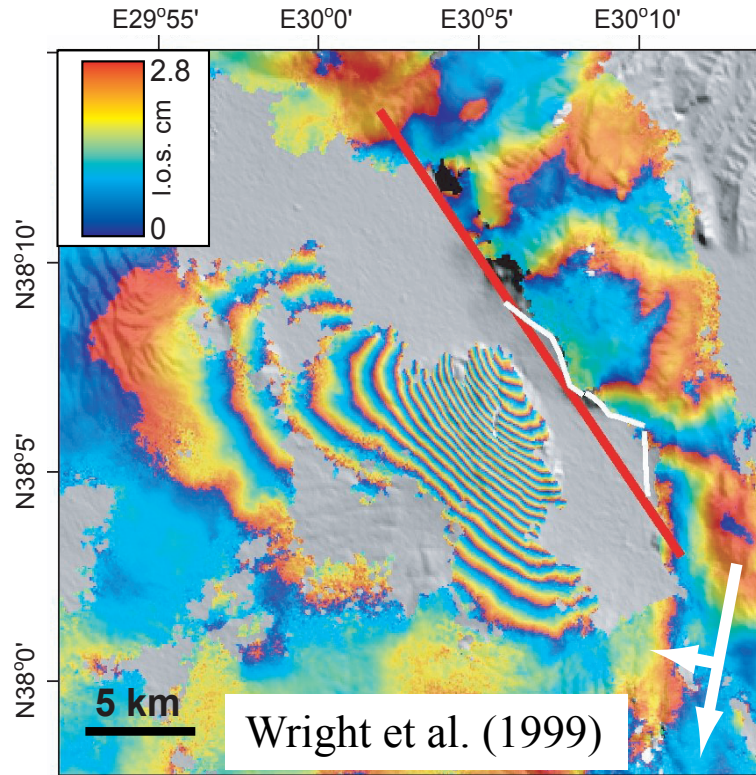
## 誤差付きの滑り分布推定



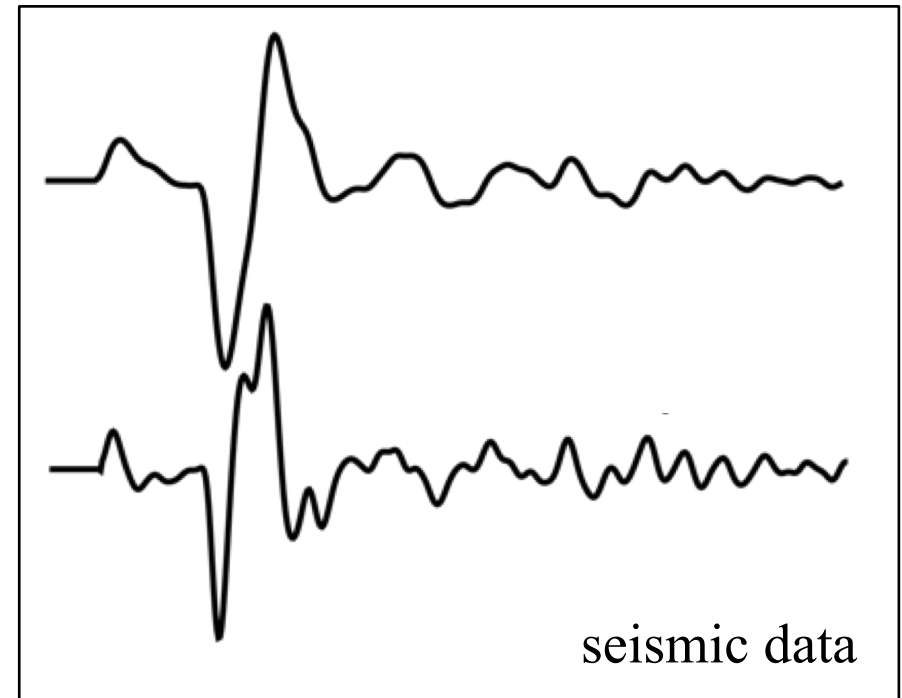
Fukahata & Wright (2008, GJI)

## 4. Covariance components due to observation error

*We have nominally continuous observed data*

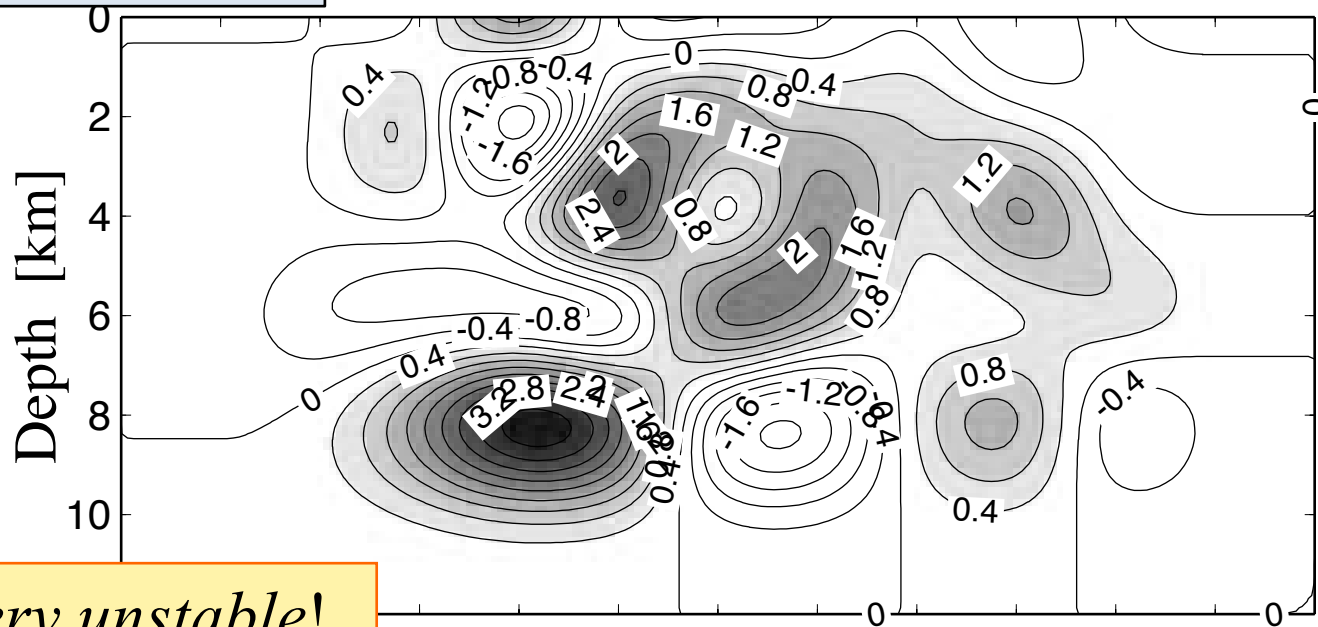


InSAR: one-million data



*How should we sample and invert such data?*

## An inverted result

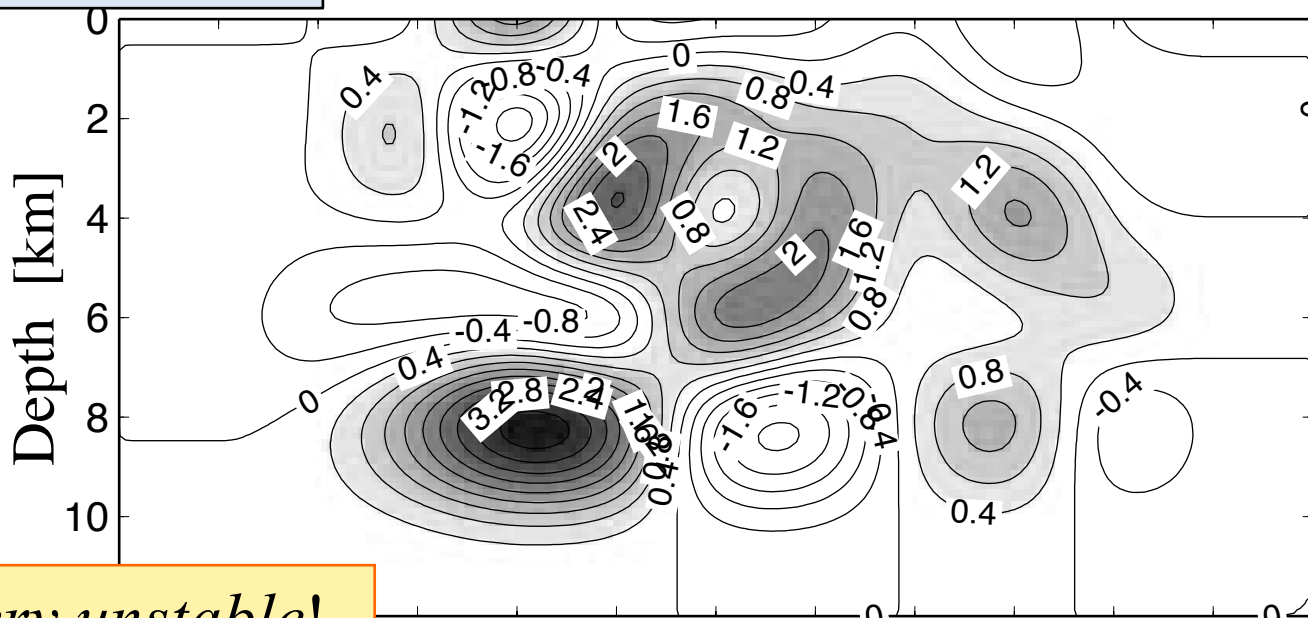


*very unstable!*

Slip distribution of Dinar earthquake

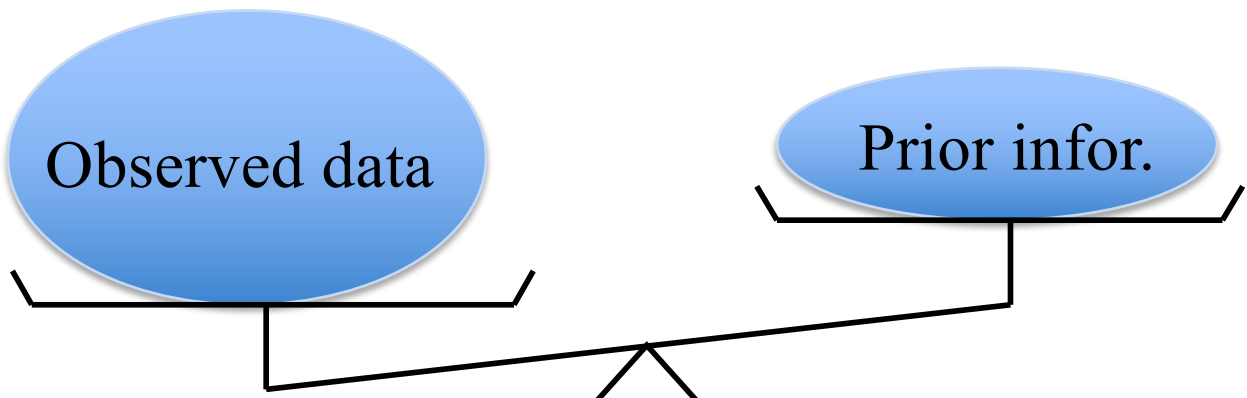
I reviewed the computation program,  
tried various settings, etc,  
but the situation didn't improve.

An inverted result



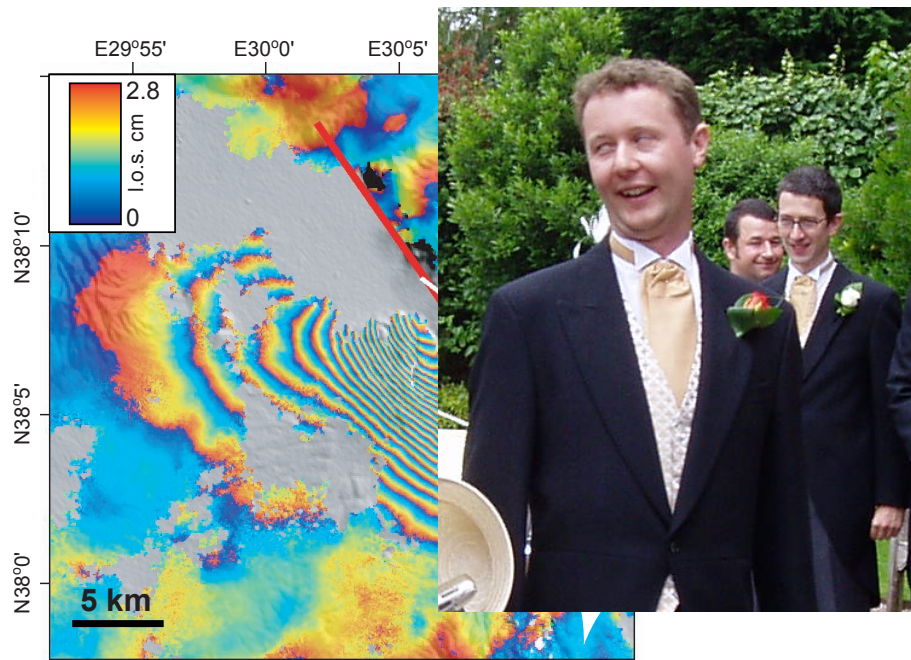
*very unstable!*

Slip distribution of Dinar earthquake



ABIC

Overfitting seemed to occur.



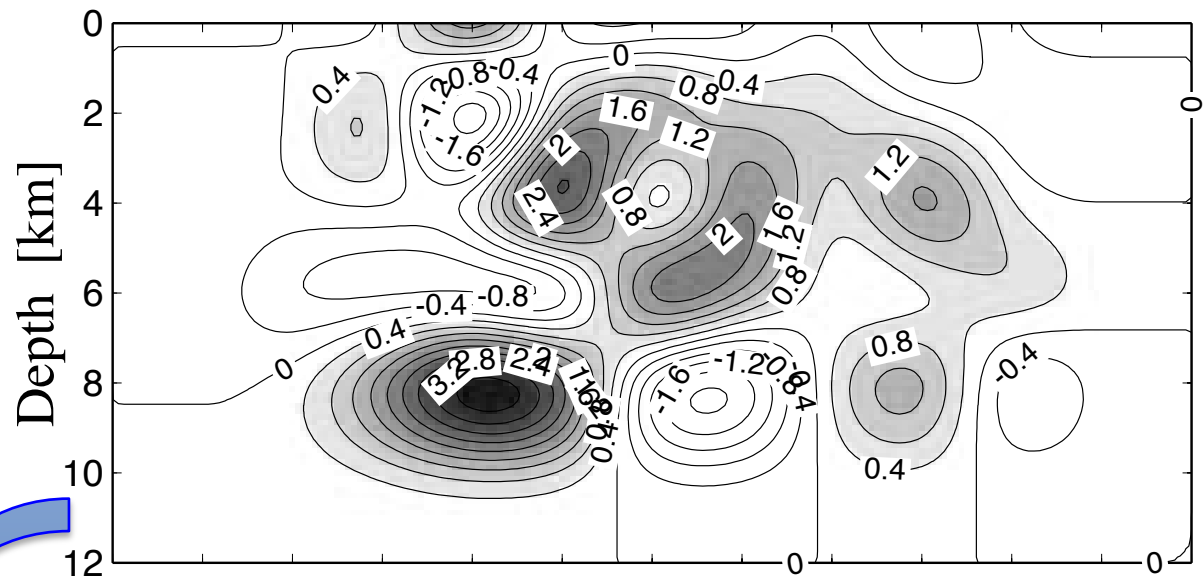
At a coffee time, July 2005  
 me “I wonder 100 m might be too short  
 for the correlation distance.”  
 Tim “Yes, it’s about ten kilometer”  
 me “Oh, really?”

Observation Eq.:  $\mathbf{d} = \mathbf{H}\mathbf{a} + \mathbf{e}, \quad \mathbf{e} \sim N(\mathbf{0}, \sigma^2 \mathbf{E})$

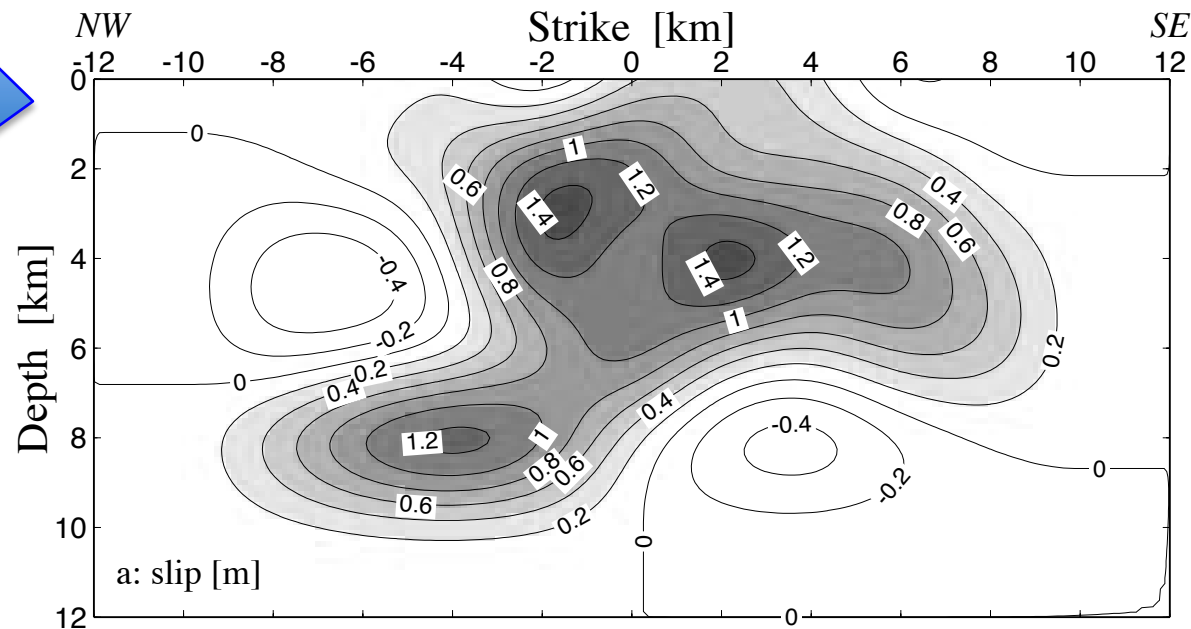
$$s(\mathbf{a}; \alpha^2) = \underbrace{(\mathbf{d} - \mathbf{H}\mathbf{a})^T \mathbf{E}^{-1} (\mathbf{d} - \mathbf{H}\mathbf{a})}_{\text{square of residual}} + \underbrace{\alpha^2 \mathbf{a}^T \mathbf{G}\mathbf{a}}_{\text{smoothness}}$$

$$\mathbf{E} = \mathbf{I} \quad \longrightarrow \quad E_{ij} = \exp\left(-r_{ij}/s\right)$$

$r_{ij}$ : distance between data  $i$  and  $j$   
 $s$ : typical correlation length ( $\sim 10\text{km}$ )

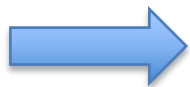


*Introduction of covariance of observation errors*



Fukahata & Wright (2008)

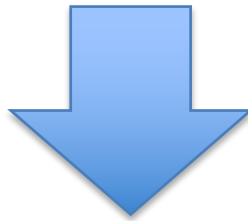
**Important lesson: Bad modelling leads to a bad result.**



A bad result strongly suggests bad modelling.

## Another important lesson

It was possible to manually adjust the hyperparameter to obtain a good-looking result. But, if I did so, probably I didn't realize the importance of covariance components.



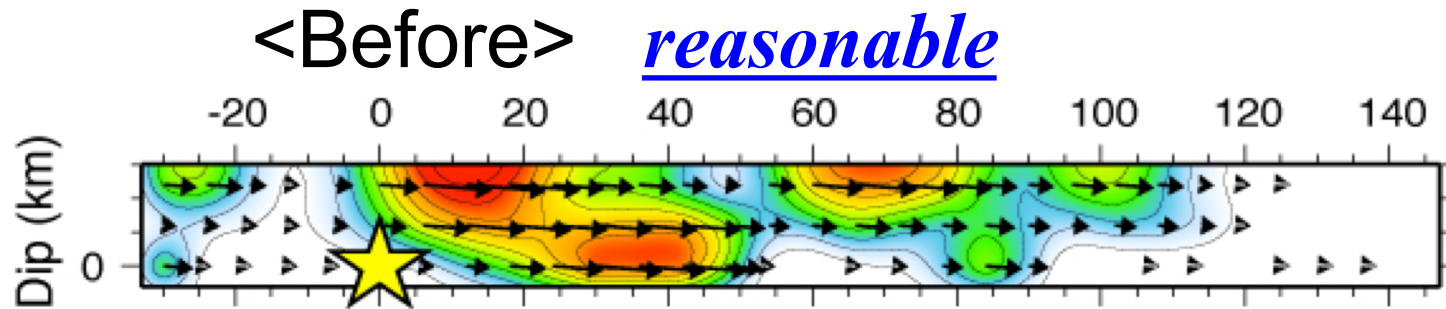
The hyperparameters should be determined statistically (objectively).



## 5. Covariance components due to modeling error

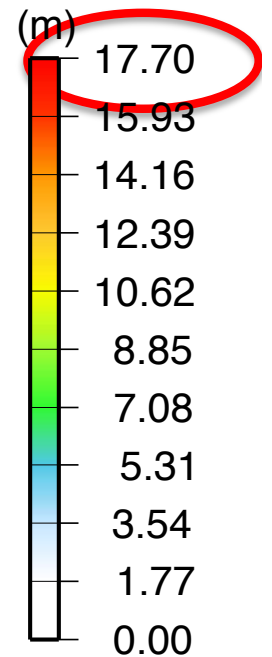
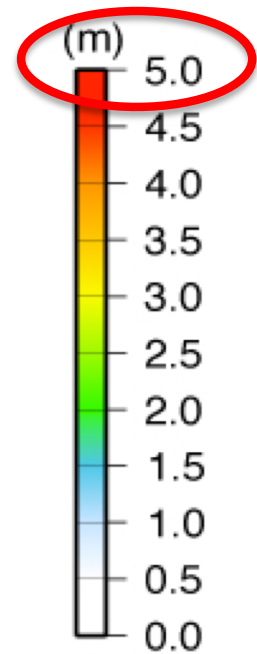
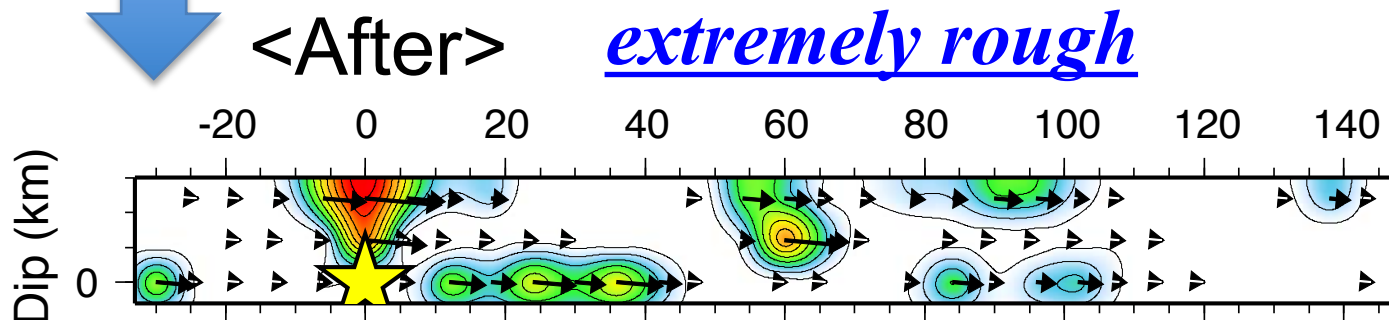
For the case of waveform inversion

Tibet, Manyi earthquake (Mw 7.6) (by Yagi on behalf of G. Funning)



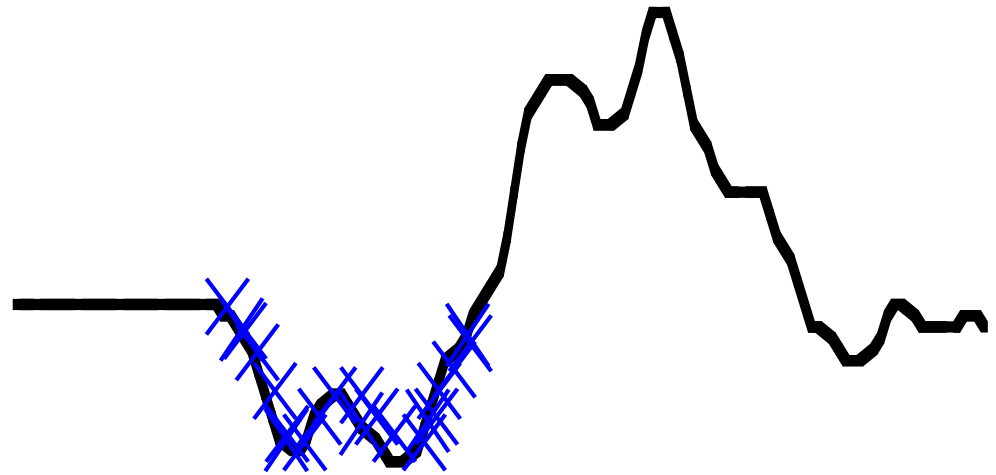
Yagi said,

- improved P-wave picks
- etc, etc,
- *made a sampling rate higher*



Waveform data are basically accurate,  
so observation errors are small.

But if we densely sample,  
data include common error.



Mathematically, covariance matrix  $\mathbf{E}$  becomes

$$\mathbf{E} = \begin{pmatrix} \sigma^2 & 0 & 0 \\ 0 & \sigma^2 & 0 \\ 0 & 0 & \sigma^2 \end{pmatrix} \rightarrow \begin{pmatrix} \sigma^2 & * & \dots & 0 \\ * & \sigma^2 & * & * \\ \vdots & * & \ddots & * \\ 0 & * & * & \sigma^2 \end{pmatrix}$$

We introduced **modeling error** (discretization error),  
which leads to covariance components.

$$u(\mathbf{x}, t) = \sum_k \sum_l a_{kl} X_k(\mathbf{x}) T_l(t) + \underline{\delta u(\mathbf{x}, t)}$$

$X_k(\mathbf{x}), T_l(t)$  : Basis functions (Yagi & Fukahata, 2008)

Introduction of covariance components due to modeling error  
(discretization error) (Yagi & Fukahata, 2008)

discretization error:  $u(\tau) = \sum_{k=1}^K a_k T_k(\tau) + \delta u(\tau)$

$T_k(t)$  : basis function

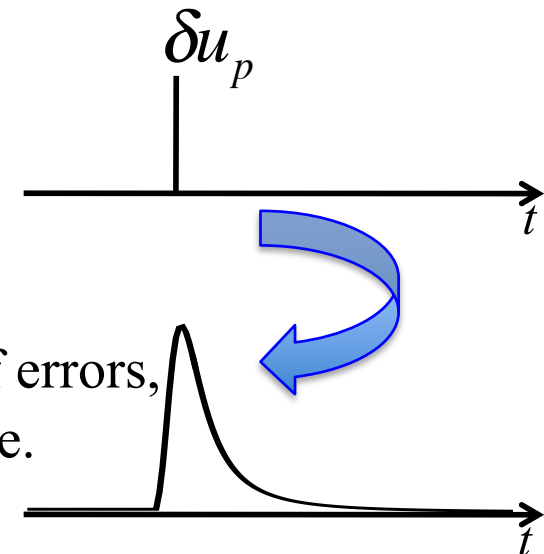
*When parameterizing the problem, discretization error inevitably emerges*

Relation between data and model:  $d_i(t) = \int_s G_i(t;\tau)u(\tau)d\tau$

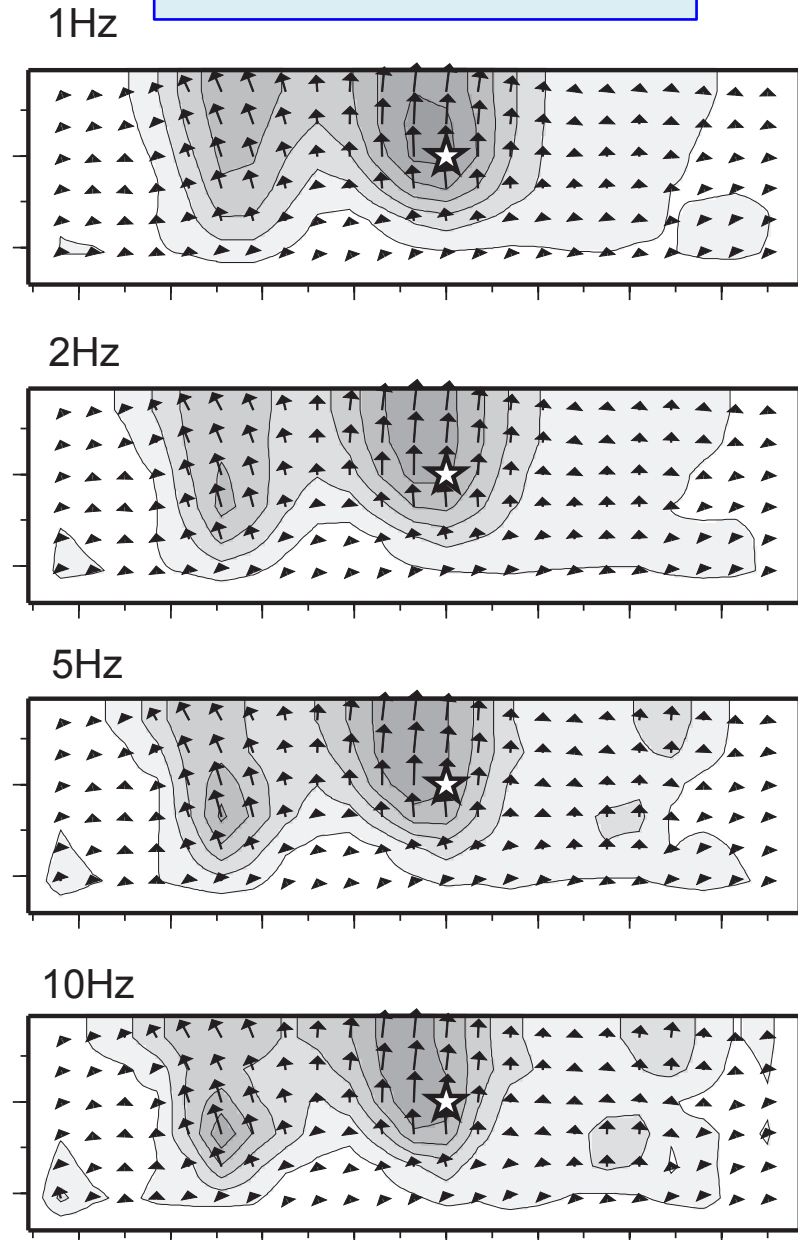
Expression of the error in the observation eq.:

$$e_i^{discr}(t) = \int_s G_i(t;\tau)\delta u(\tau)d\tau$$

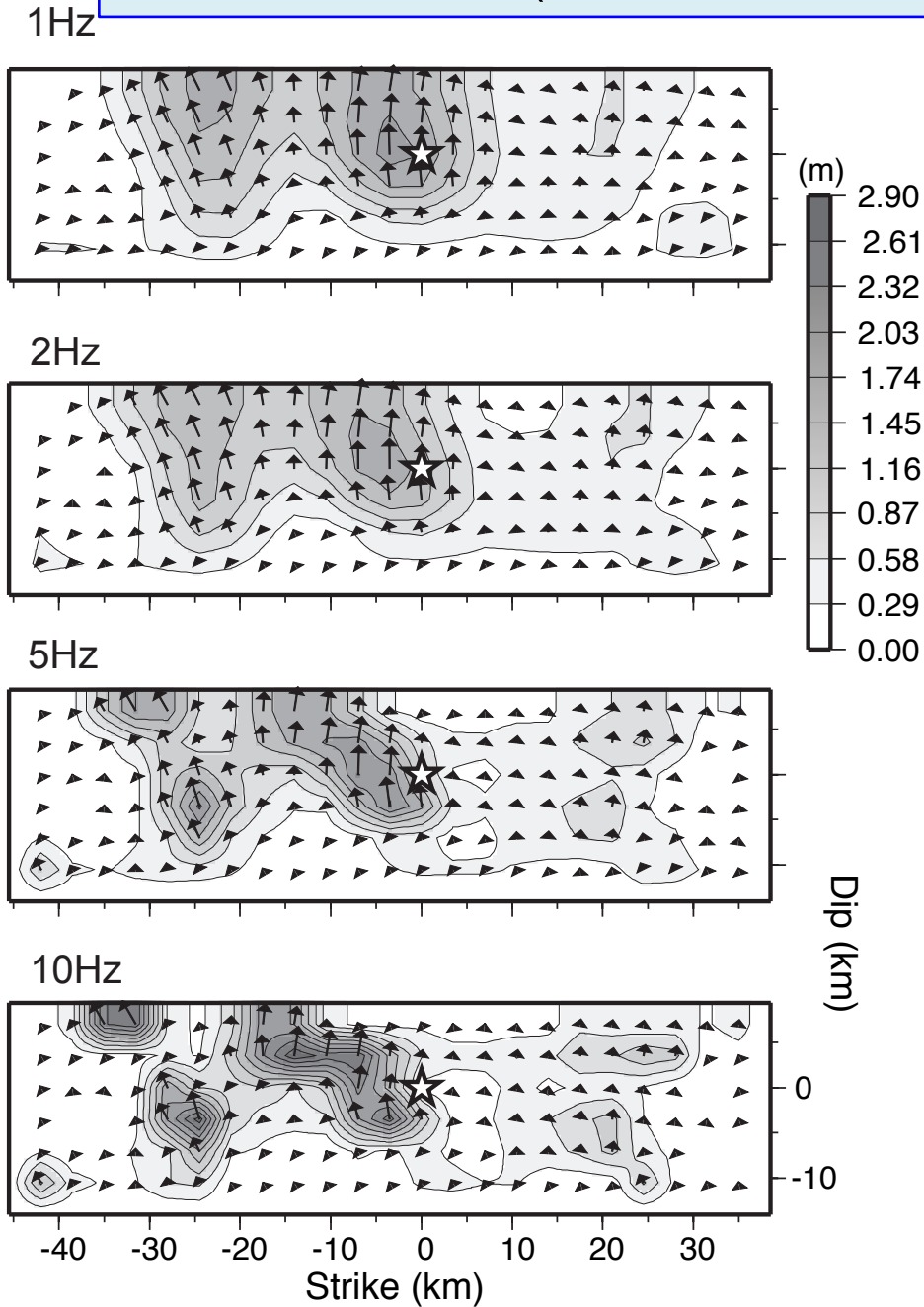
Following the law of propagation of errors,  
covariance components emerge.



# With Covariance

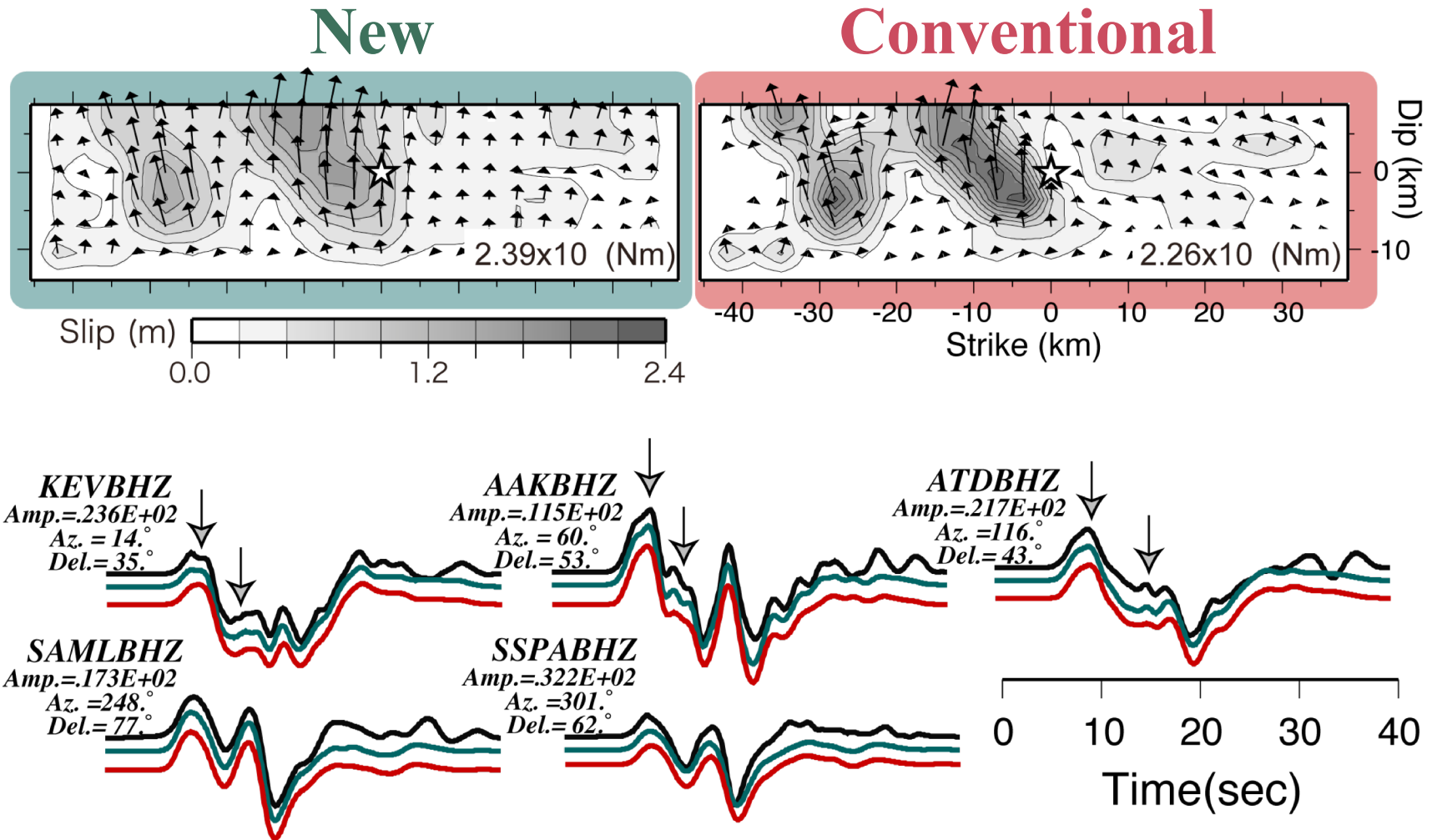


# Conventional (Without Covariance)



(Yagi & Fukahata, 2008)

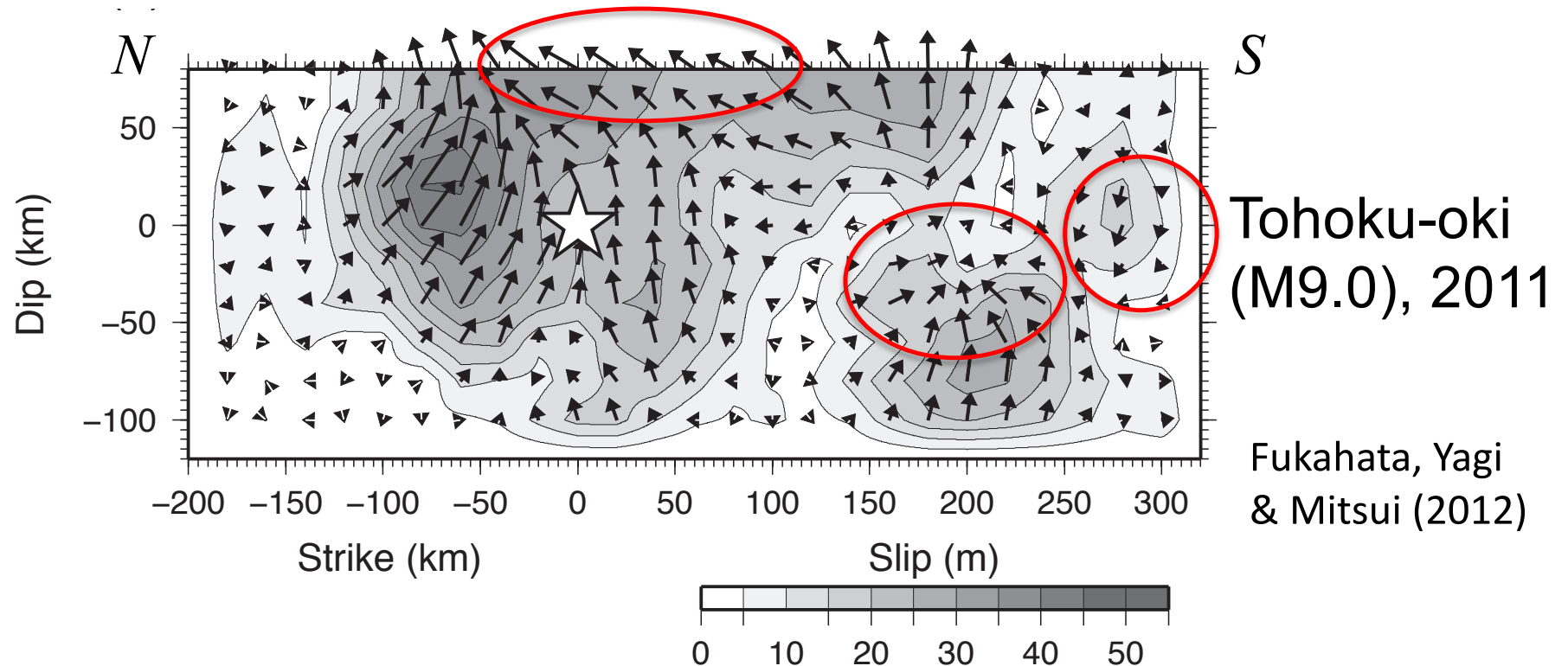
# Reproduction of high frequency components



Note that the residual mean square is *less* in the conventional

## 5-2. Covariance due to uncertainty of Green's function

### Another Example of unrealistic result



Large negative & strike slips

*which also tells us something is wrong in the inversion scheme*

(We should be very careful to apply non-negative condition)

## <Non-negative Condition>

Non-negative condition is commonly considered to be *physically reasonable*. However, the non-negative condition always leads to biased estimates, i.e.,

$$E(u(\mathbf{x})) = 0 \quad \xrightarrow{\text{non-negative}} \quad E(u(\mathbf{x})) > 0$$

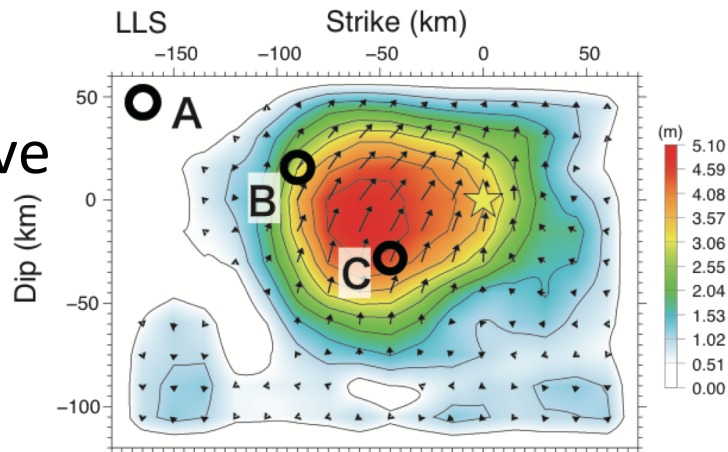
$E$ : expectation

$u$ : slip

$\mathbf{x}$ : a far distance  
from the source

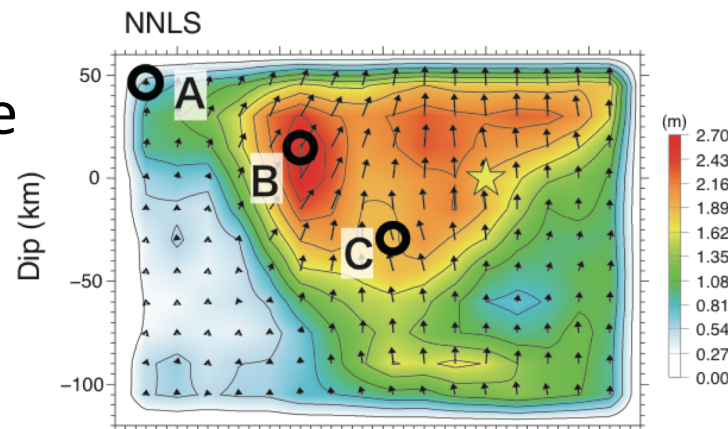
“Unbiased” is one of the most important criterion in statistical inference.

without Non-Negative Condition (LLS)



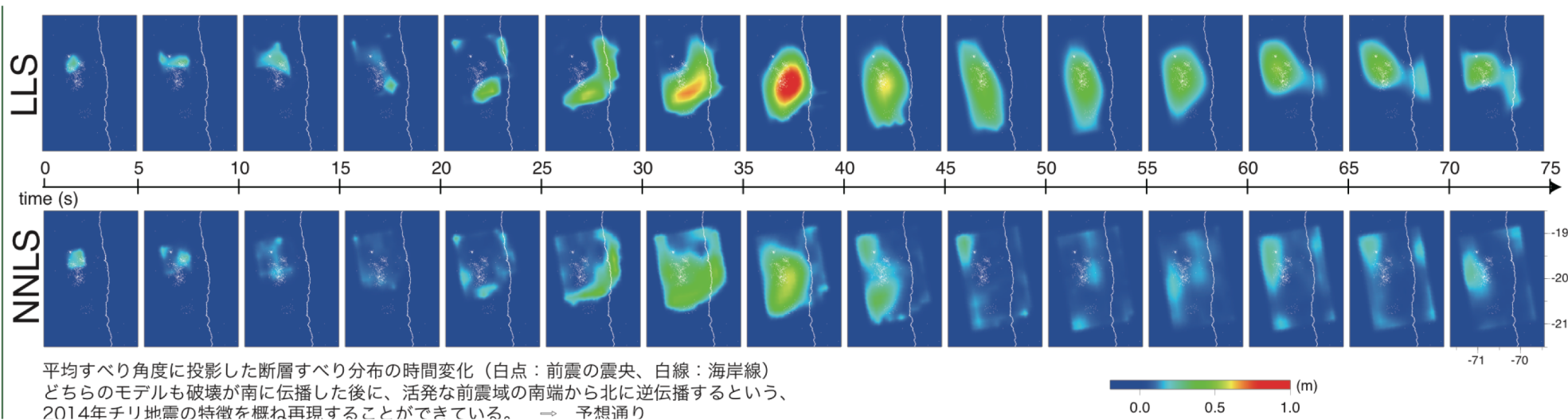
[Max slip]  
5.0 m

with Non-Negative Condition (NNLS)



2.5 m

Yagi & Fukahata  
(2014, SSJ)





# Introduction of uncertainty of Green's function

(Yagi & Fukahata, 2011; GJI)

$$\mathbf{e} = \mathbf{e}^{obs} + \mathbf{e}^{model}$$

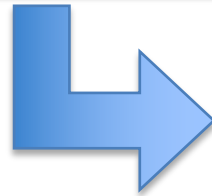
Observation equation :

$$\mathbf{d} = \mathbf{G}\mathbf{a} + \mathbf{e}^{obs}$$



Introduction of uncertainty  
of Green's function

$$\mathbf{d} = (\mathbf{G} + \delta\mathbf{G})\mathbf{a} + \mathbf{e}^{obs}$$



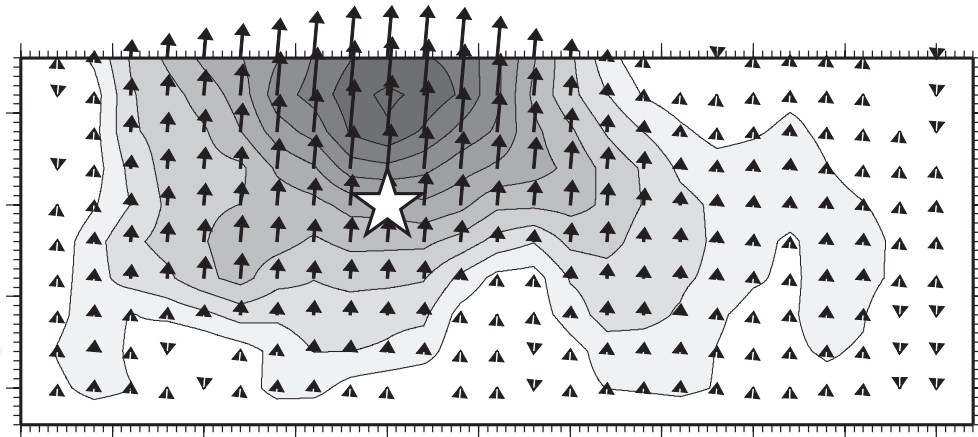
$$\mathbf{d} = \mathbf{G}\mathbf{a} + (\underline{\delta\mathbf{G}\mathbf{a} + \mathbf{e}^{obs}})$$

**New error term**

$\delta\mathbf{G}$  is assumed to be Gaussian for simplicity.

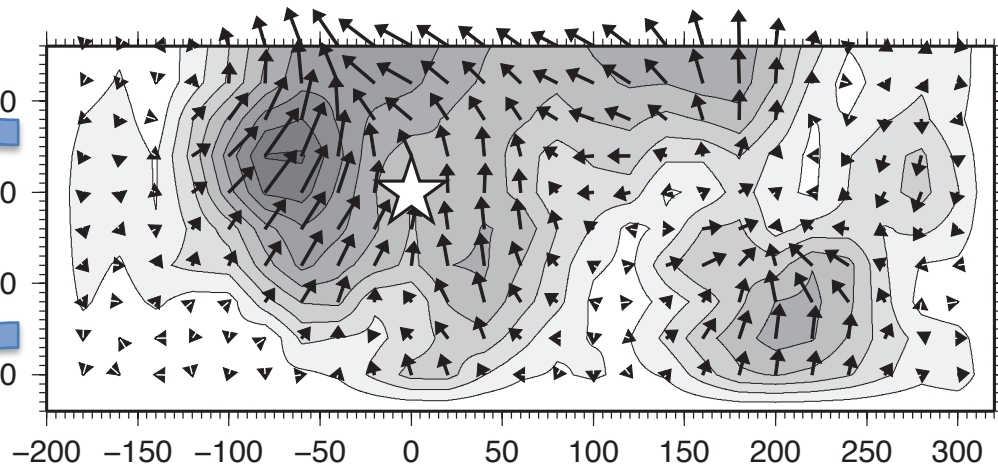
Slip Distribution  
of Tohoku eq.

New (with error of  
Green's function)

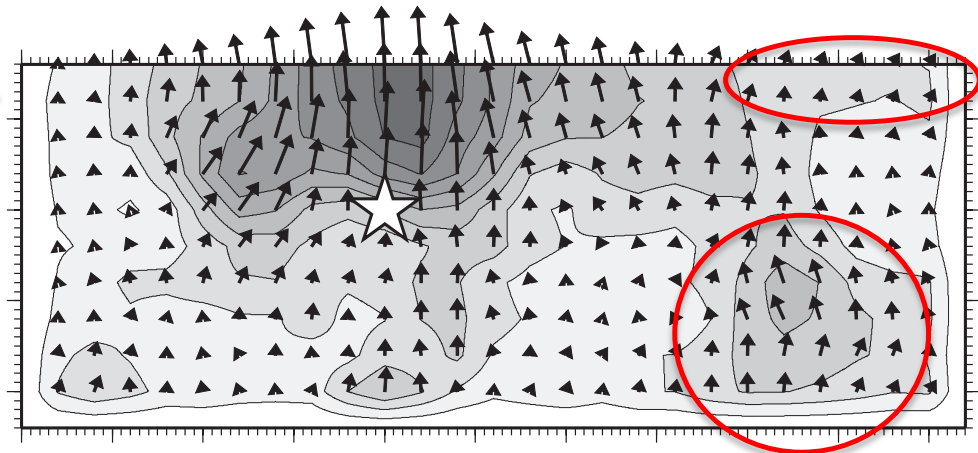


Conventional

Dip (km)

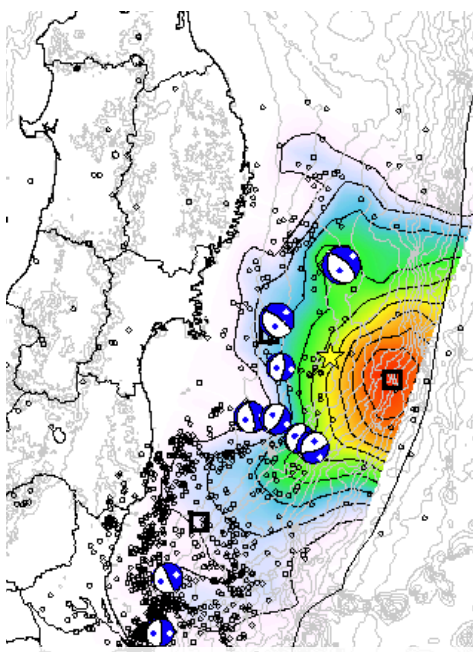


Non-negative  
(without error of  
Green's function)

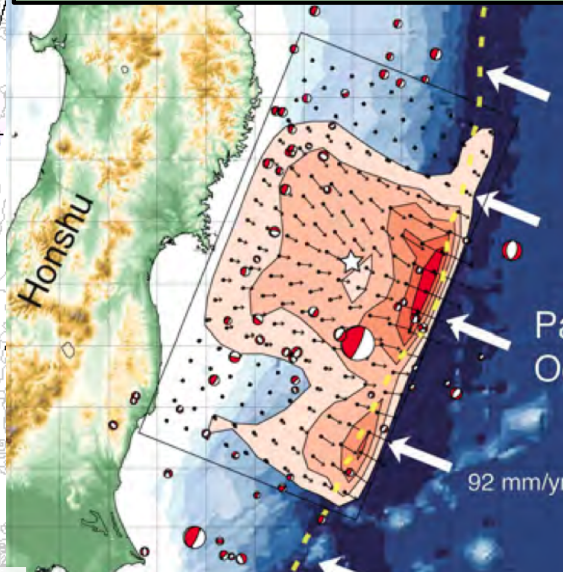


*likely to be  
artificial*

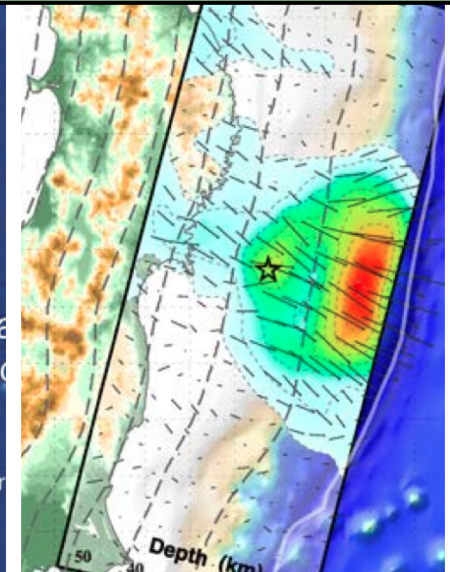
# Inversion results of the Tohoku-oki earthquake



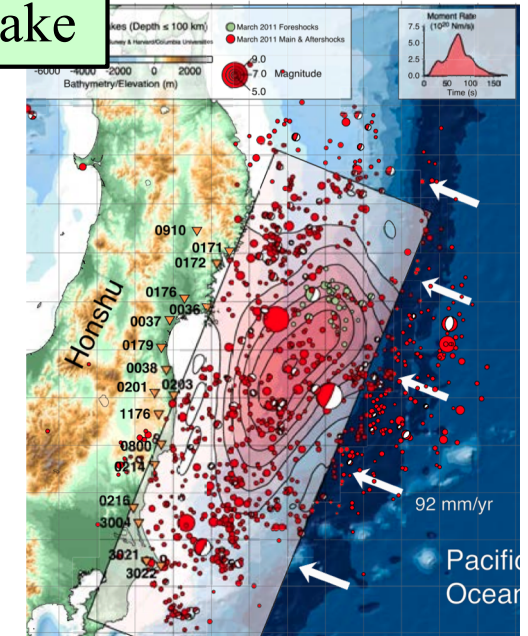
Yagi & Fukahata (2011)



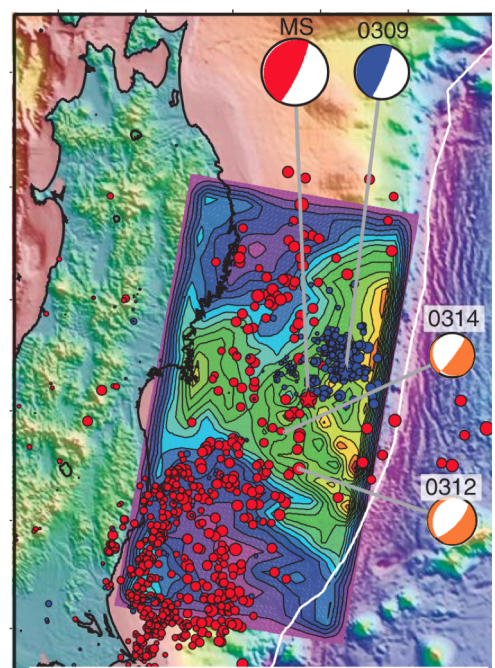
Lay et al. (2011)



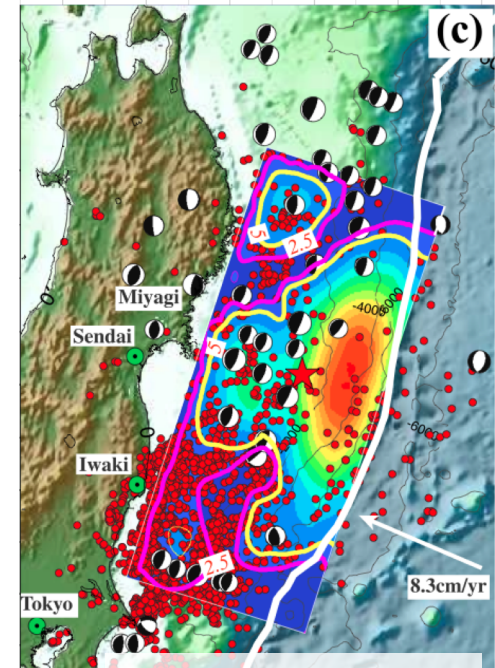
Hayes (2011)



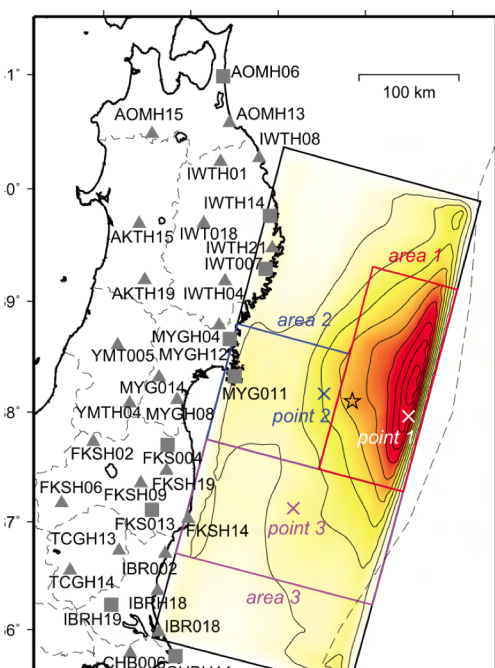
Ammon (2011)



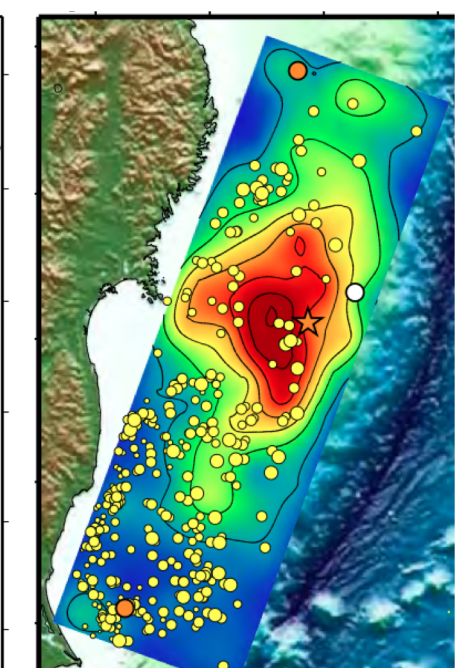
Ide et al. (2011)



Shao et al. (2011)

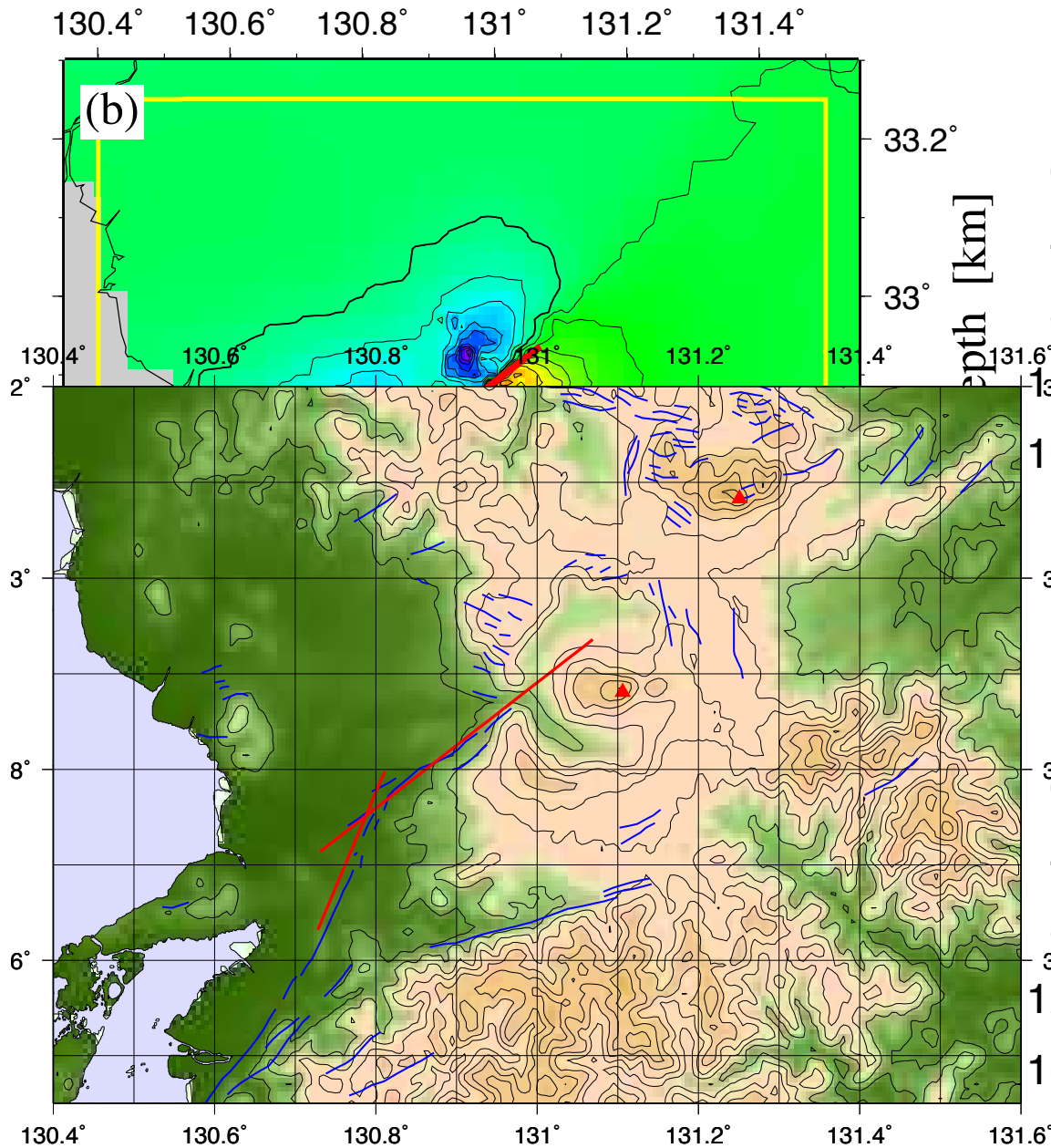


Suzuki et al. (2011)



Koketsu et al. (2011)

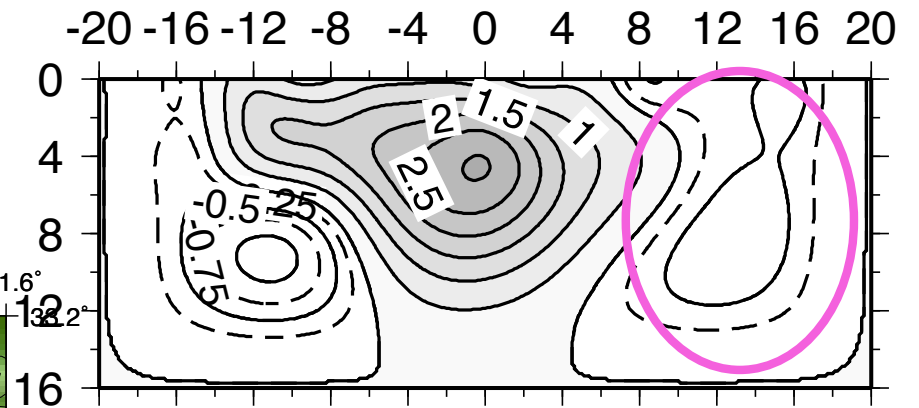
# Error due to setting of a fault model



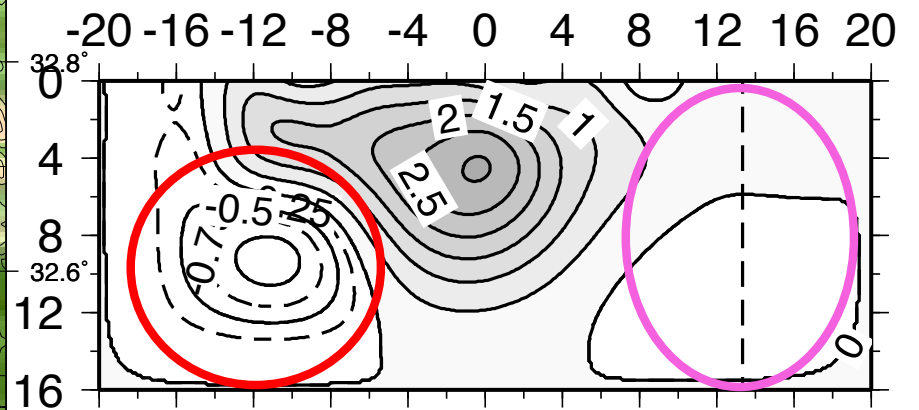
Fukahata & Hashimoto (2016, EPS)

## 2016 Kumamoto earthquake

### 1 Fault Model



### 2 Faults Model



***Negative slip diminishes!***

## Summary

In order to obtain apparently good looking results, we shouldn't adjust the smoothing parameter and/or apply non-negative condition.

Physically unrealistic results strongly suggest that something is wrong in the setting of the inversion analysis.

By seeking the reason for unrealistic results, we can develop a better inversion method

*“Bad modelling leads to a bad result.  
A bad result suggests bad modelling.”*