

沖合観測網を活用した津波データ同化による 津波予測

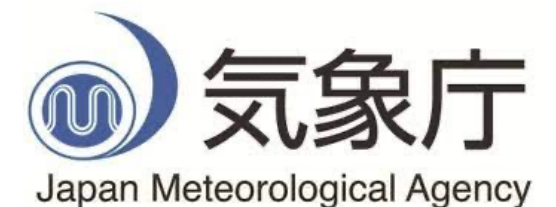
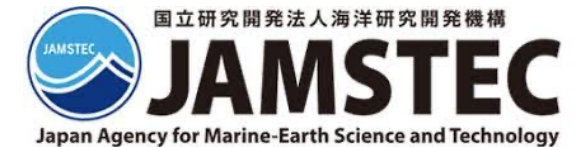
王 宇晨 (Yuchen WANG), 今井 健太郎 (Kentaro IMAI),
楠本 聡 (Satoshi KUSUMOTO), 高橋 成実 (Narumi TAKAHASHI)



2022 Dec 08

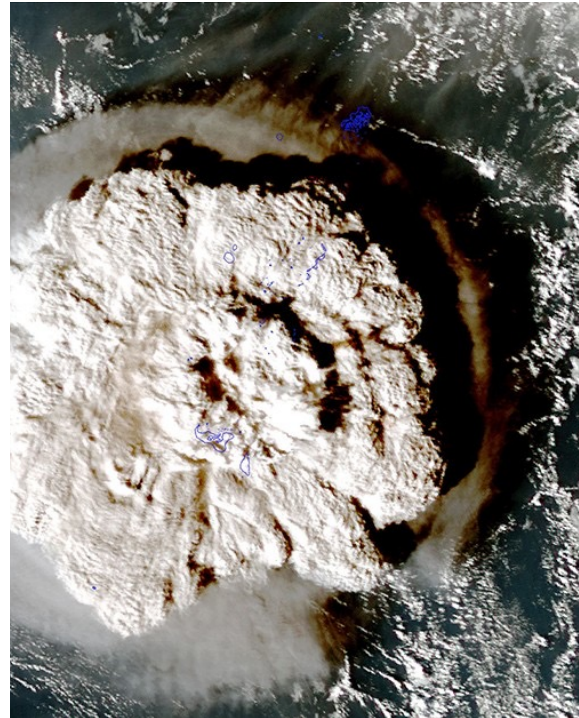
Acknowledgements

- I appreciate the help of my co-authors that contributed to this work.
- I thank the funding of JAMSTEC Young Research Fellow.
- The data used in this study were obtained from the Japan Agency for Marine-Earth Science and Technology, National Research Institute for Earth Science and Disaster Resilience, Japan Meteorological Agency, and Geospatial Information Authority of Japan.



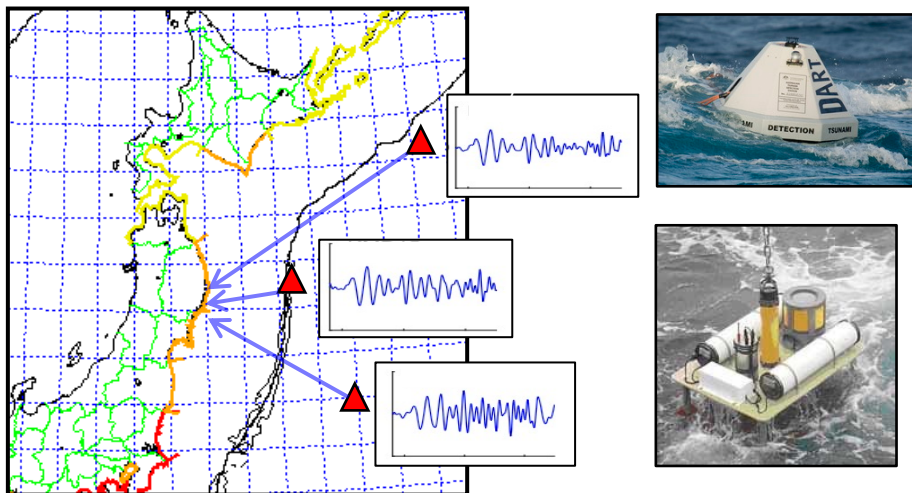
Introduction – Tsunami from 2022 Tonga Volcanic Eruption

- Hunga Tonga-Hunga Ha'apai volcano
- Large eruption: 04:14:45 (UTC), January 15, 2022.
- The tsunami event had a **complex generating mechanism**, making it difficult to use traditional tsunami early warning method based on source inversion.

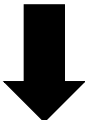


(Witze, [2022 Nature](#); SCMP, [2022](#))

Tsunami Data Assimilation Approach



Offshore Tsunami Observation



Tsunami Forecasting

Do not need source information!

$$x_n = (h(n\Delta t, x, y), M(n\Delta t, x, y), N(n\Delta t, x, y))^T$$

Height

X-Velocity

Y-Velocity

$$x_n^f = F x_{n-1}^a$$

$$x_n^a = x_n^f + W (y_n - H x_n^f)$$

I. Forecasting Step

II. Assimilating Step

x_n^f : Forward Tsunami Wavefield

y_n : Observation

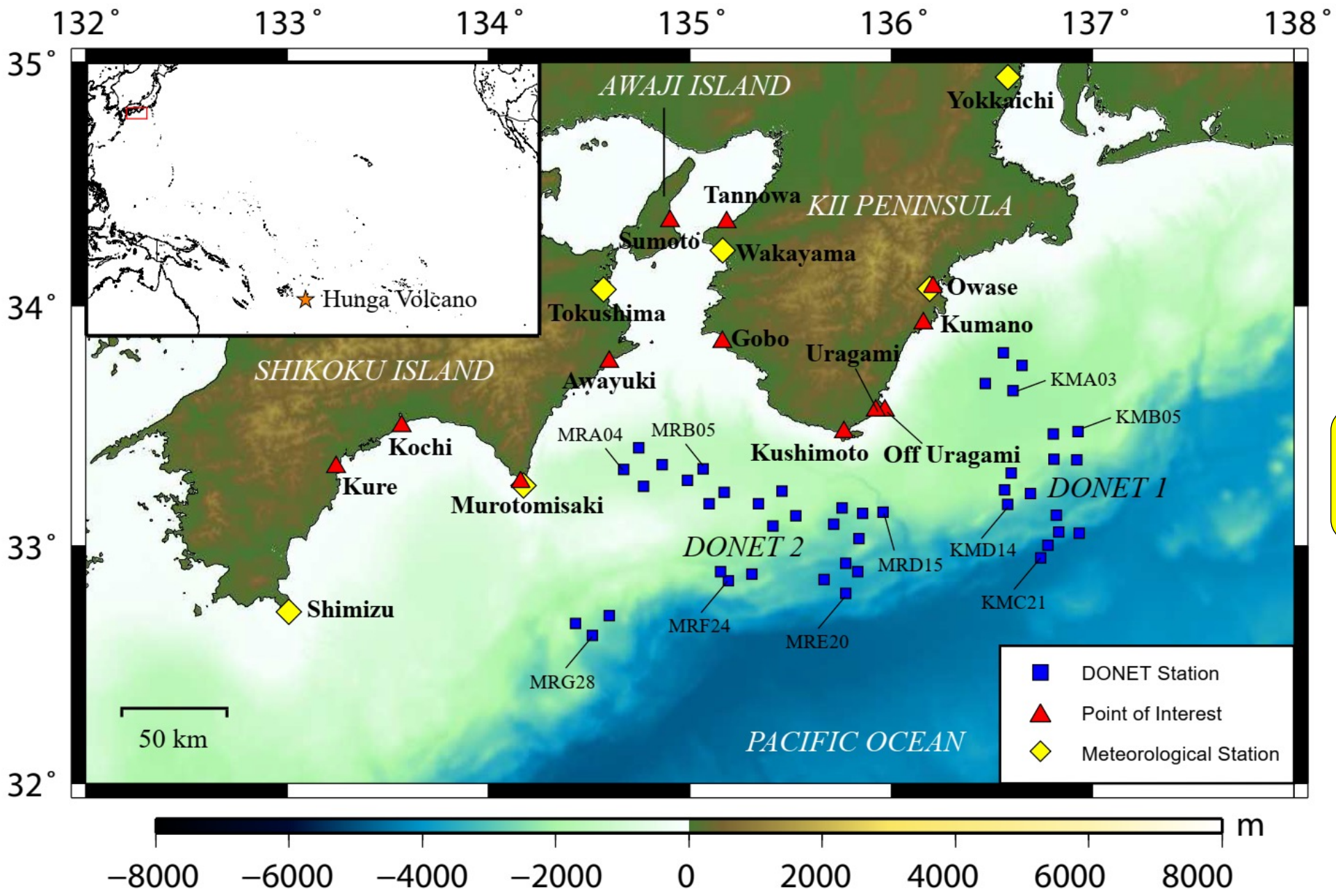
x_n^a : Assimilated Tsunami Wavefield

W : Weight Matrix

H : Sparse Linear Observation Matrix

F : Propagation Matrix

(Maeda et al., 2015 GRL; Gusman et al., 2016 GRL)



Observation at 44 DONET stations



Data Assimilation

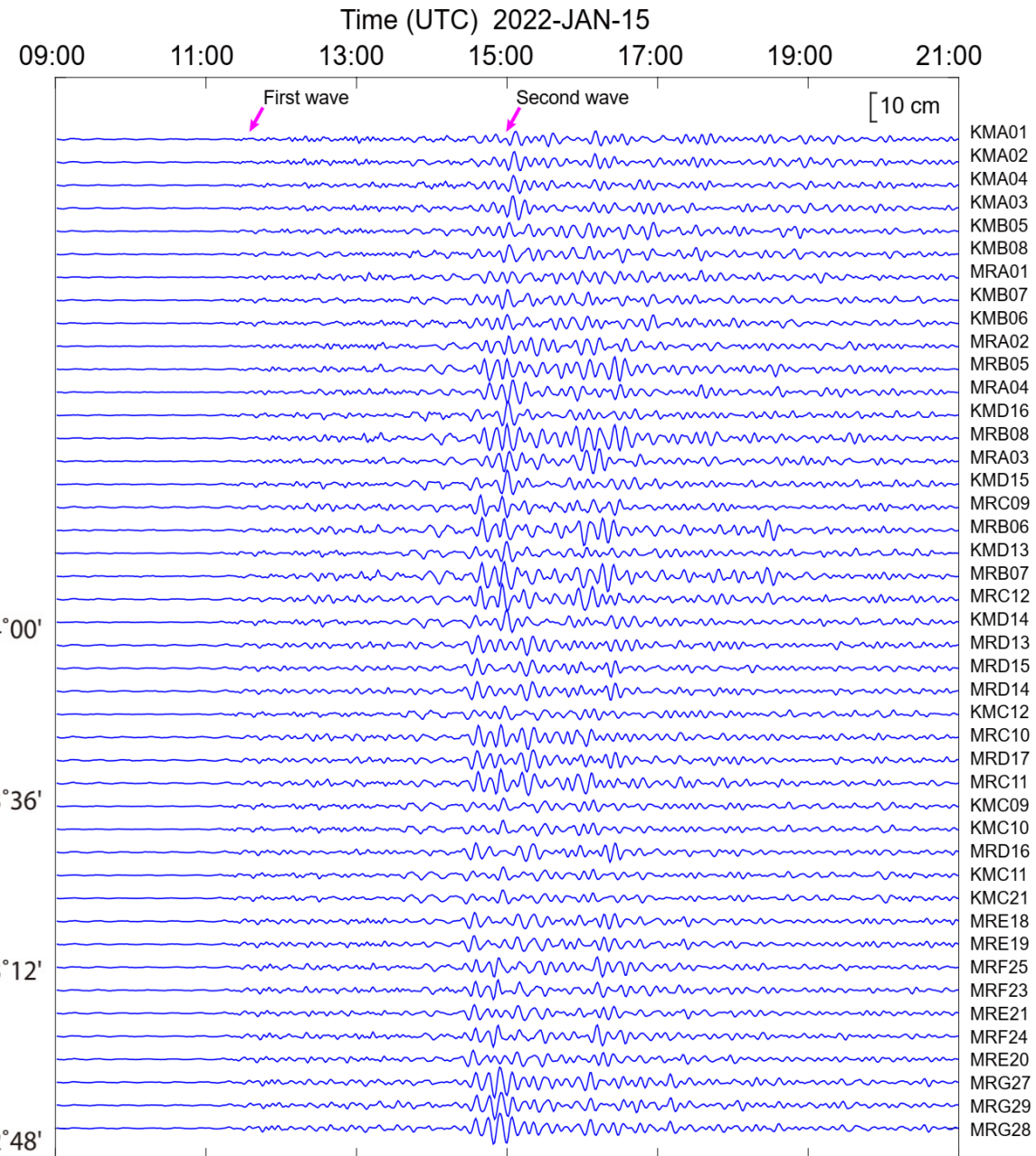
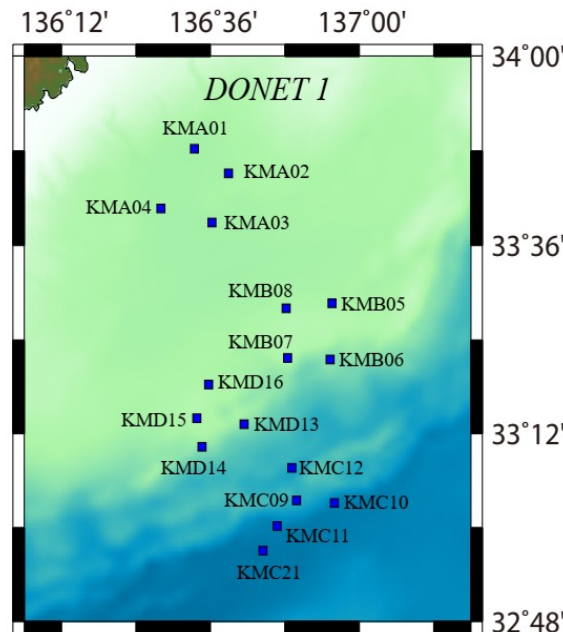
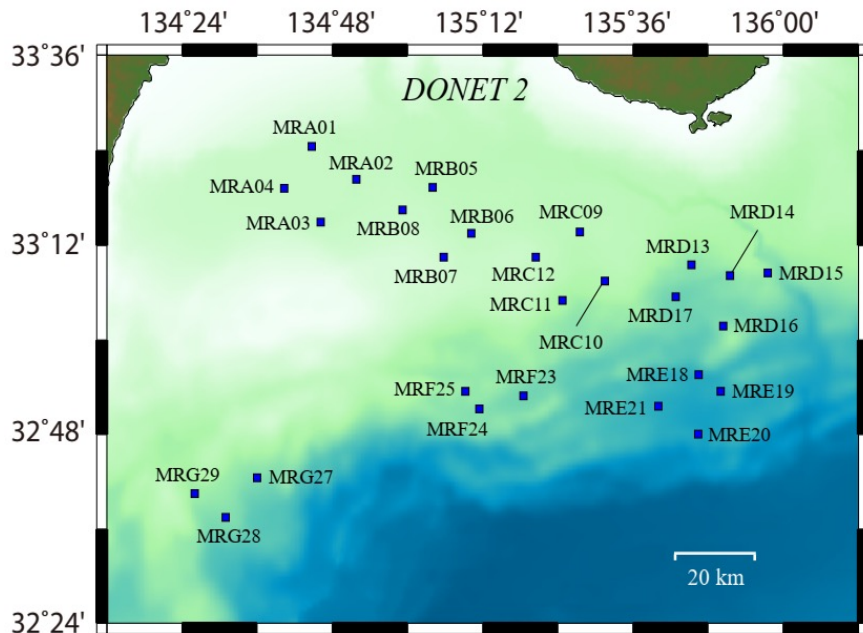
Tsunami forecasting at 12 points of interest

DONET data available at [doi:10.17598/nied.0008](https://doi.org/10.17598/nied.0008)



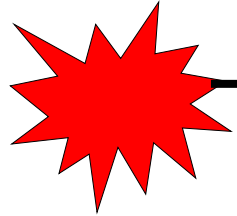
DONET Data Processing

1. Basic quality control
2. Convert pressure to water height
3. Linear interpolation
4. Band-pass filtering (200–1200 s)



Assimilation Setting

Volcanic eruption



04:15

Assimilation starts

09:00

Forecasting 1

14:00

Forecasting 2

15:00

Assimilation continues

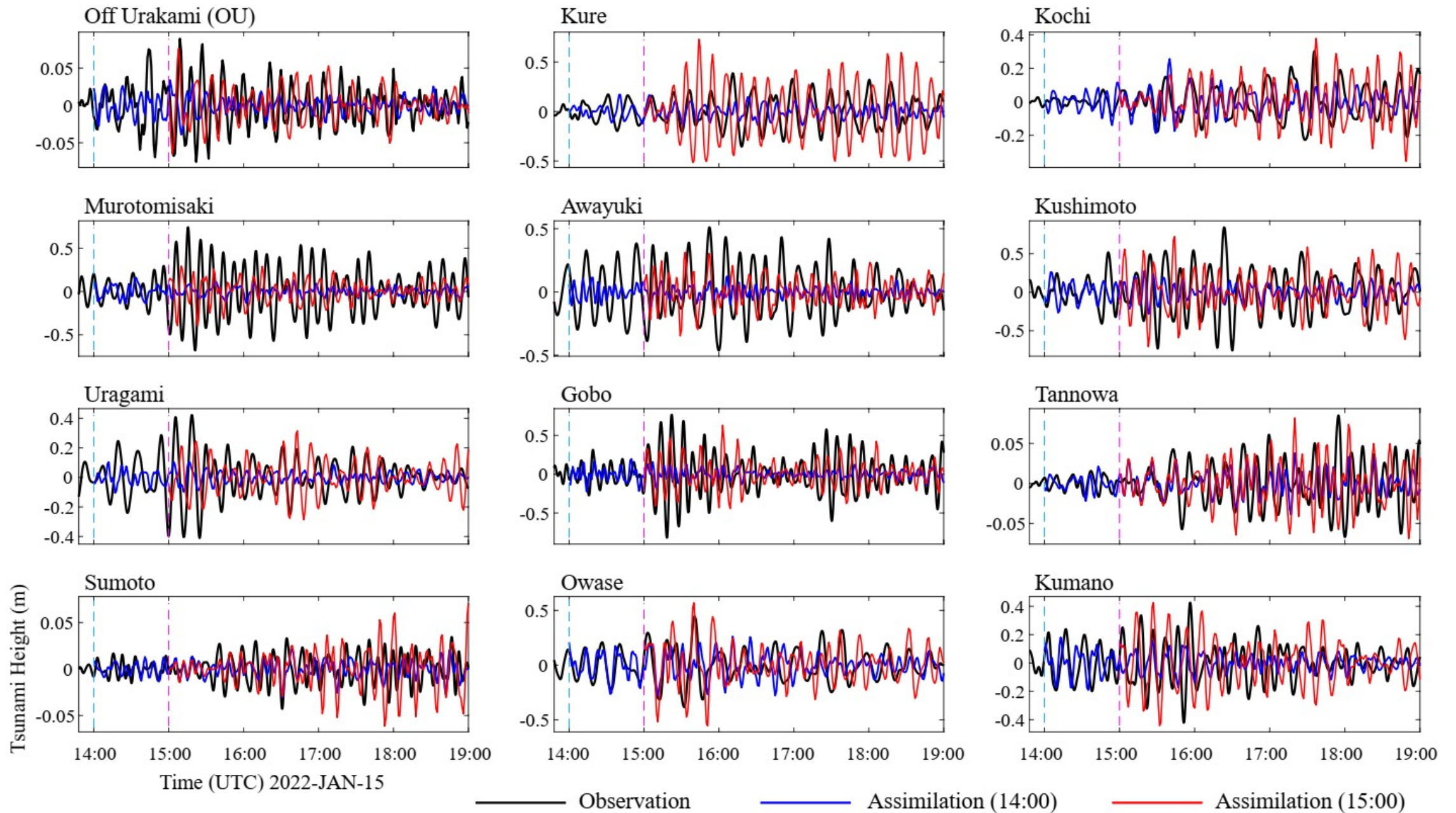
Computational parameters

Time step: 1 s

Grid size: 0.3 arc min (~ 500 m)

Grid range: 132–138° E and 32–35° N

Propagation model: Linear dispersive model



Accuracy Analysis

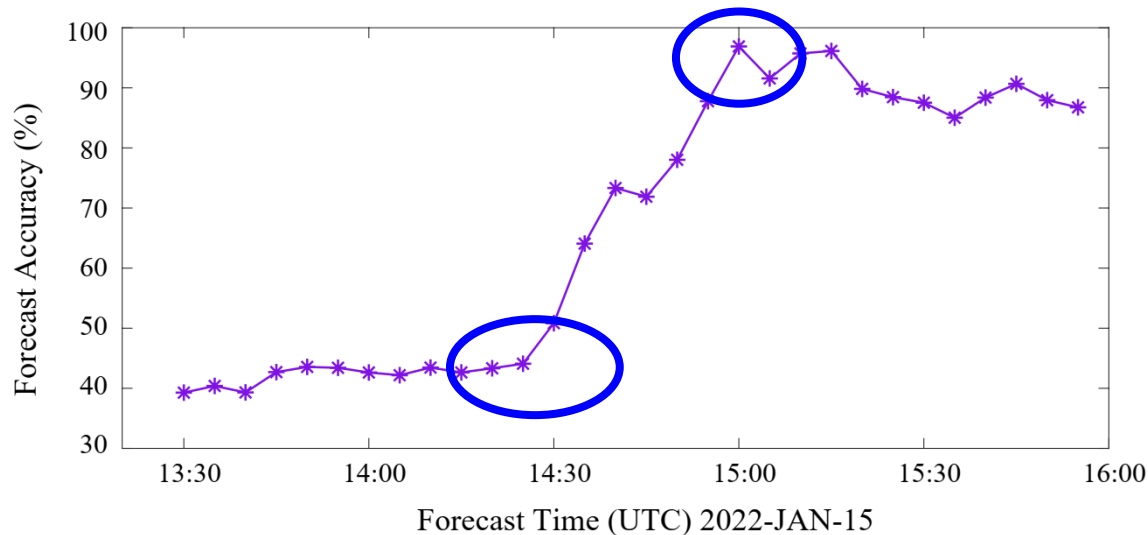
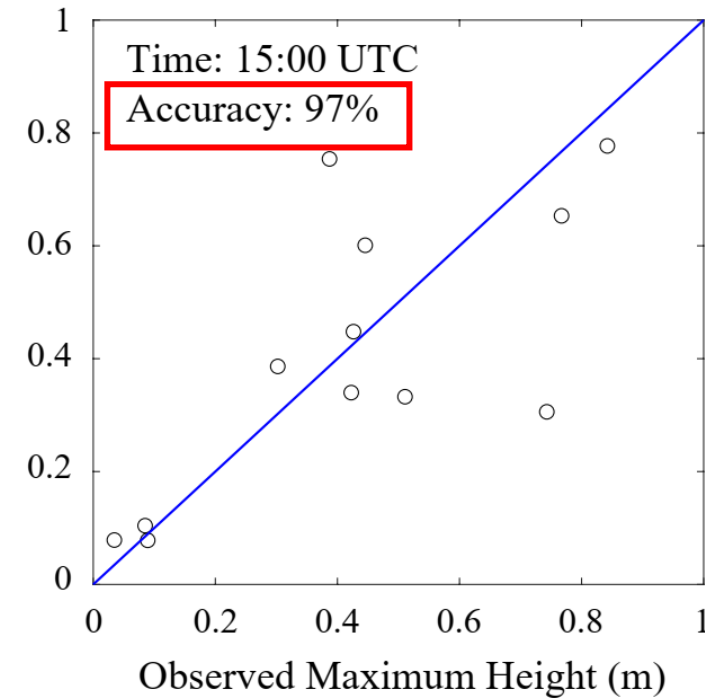
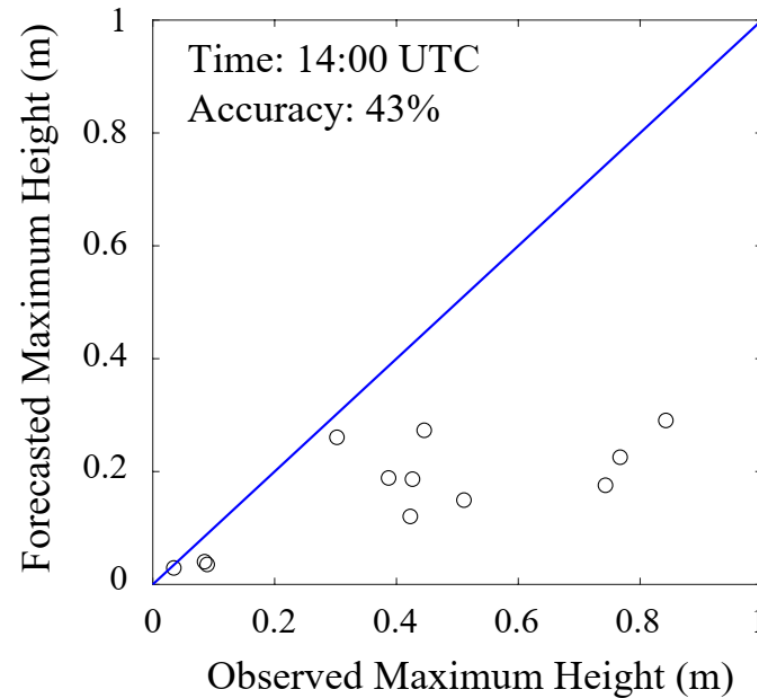
$$\log(K) = \frac{1}{N} \sum_{j=1}^N \log\left(\frac{A_j^{obs}}{A_j^{pred}}\right)$$

Accuracy = $1/K * 100\%$ ($K \geq 1$)

or $K * 100\%$ ($K < 1$)

A_j^{obs} : Observed maximum amplitude at j -th station

A_j^{pred} : Predicted maximum amplitude at j -th station

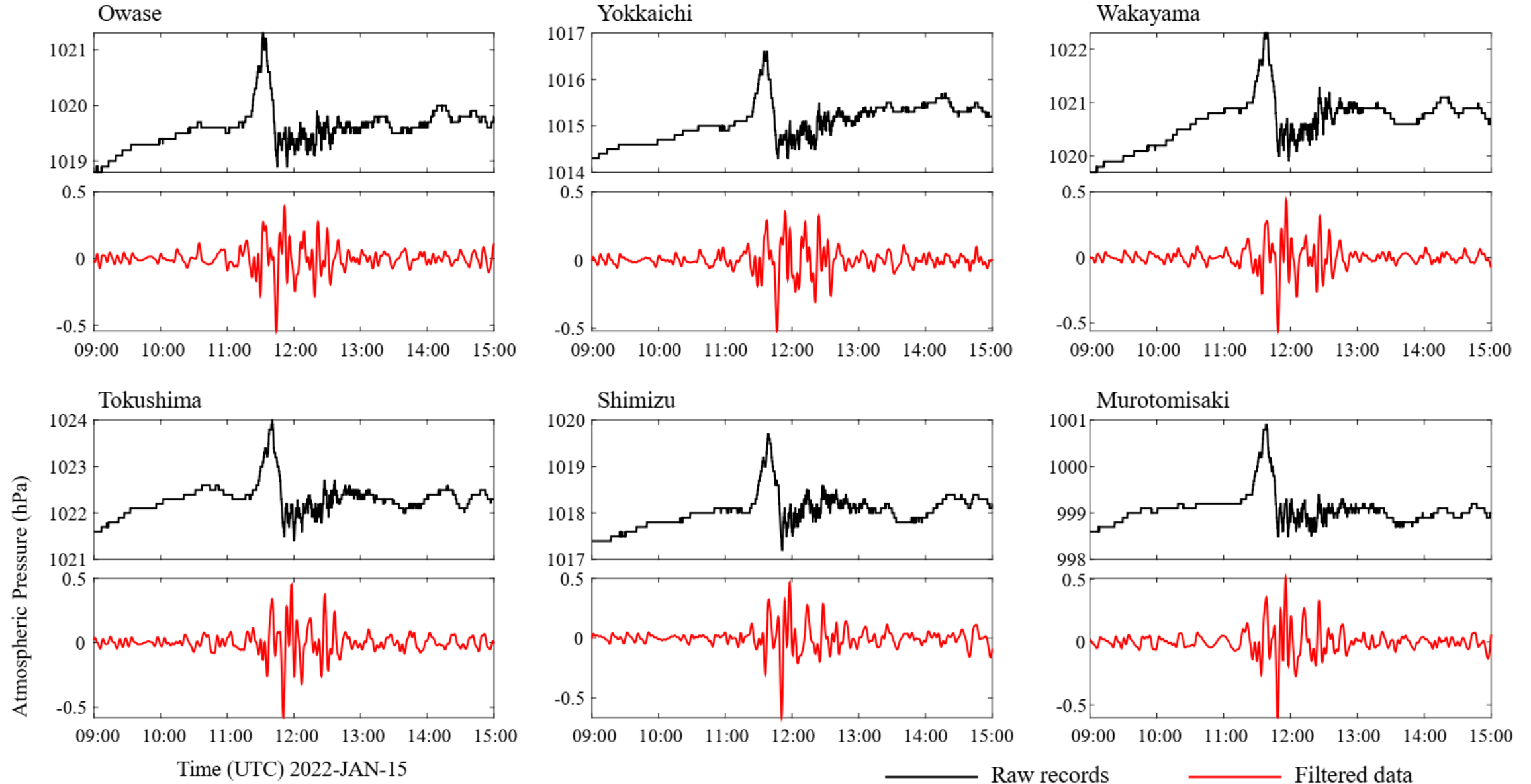


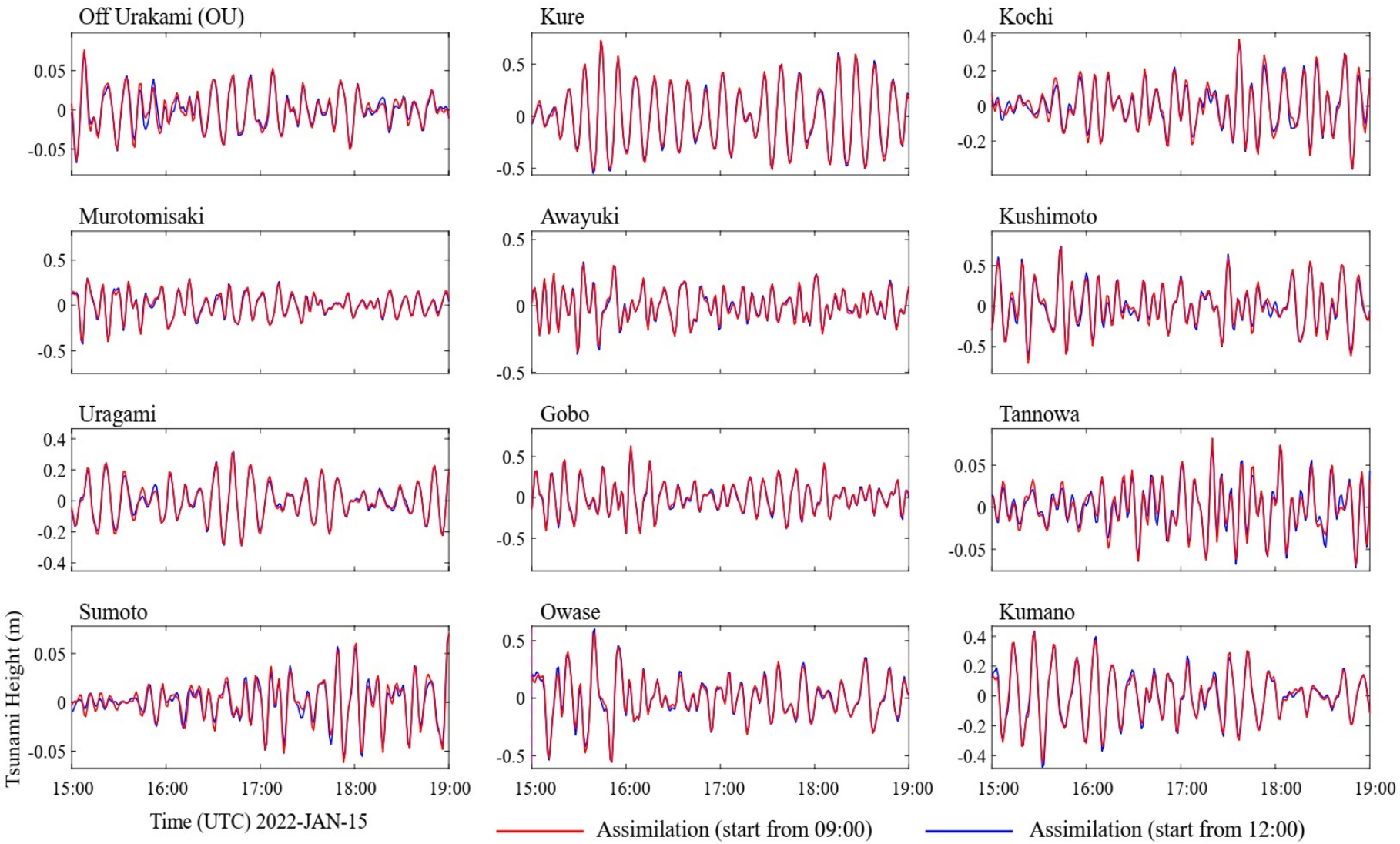
Low accuracy: Before 14:25

Accuracy increase: 14:30 – 14:55

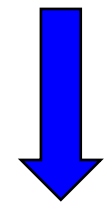
High accuracy: After 15:00

Effects of Air-Pressure Change on Data Assimilation





Almost same results of different starting time (09:00 & 12:00).



Very limited effects from initial air-pressure change.

Reason: Data assimilation is a **self-corrective** process (Wang & Satake, 2021 SRL)

Conclusion

- First time to conduct data assimilation for a non-seismic tsunami
- Predicting coastal tsunami waveforms using DONET observations
- A forecast accuracy of 97% at 15:00 (UTC)
- Little effects on data assimilation from air-pressure variations

Next step:

Use radar observations (tsunami velocity) for data assimilation

Thank you for your attention!