Real-time Tsunami Detection
by Acoustic-Gravity Waves

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TOWS-WG TT TWO
(Virtual Meeting)

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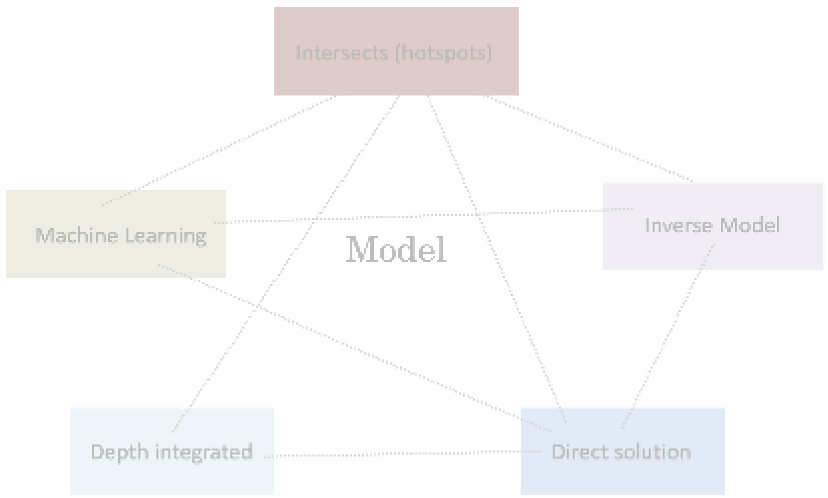
Content

- Brief intro on Acoustic-Gravity Waves
- Early detection model (technical material enclosed)
- Example: real-time analysis
- Summary & future plans



Any sudden disturbance in time & space in a substance (fluid or solid) generates compression-type waves:

Acoustic-Gravity Waves (AGWs)

Sources:

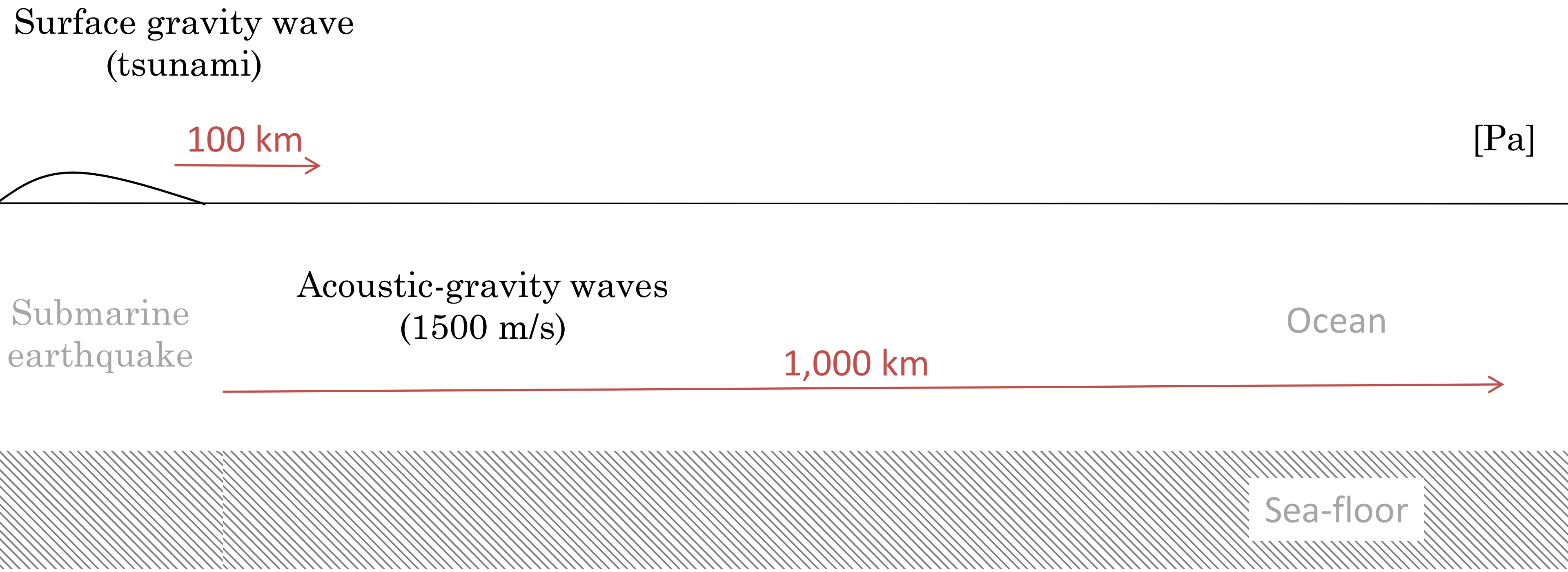
Earthquakes, landslides, explosions, volcanic eruptions, nonlinear wave interaction, meteorite impacts

Main properties:

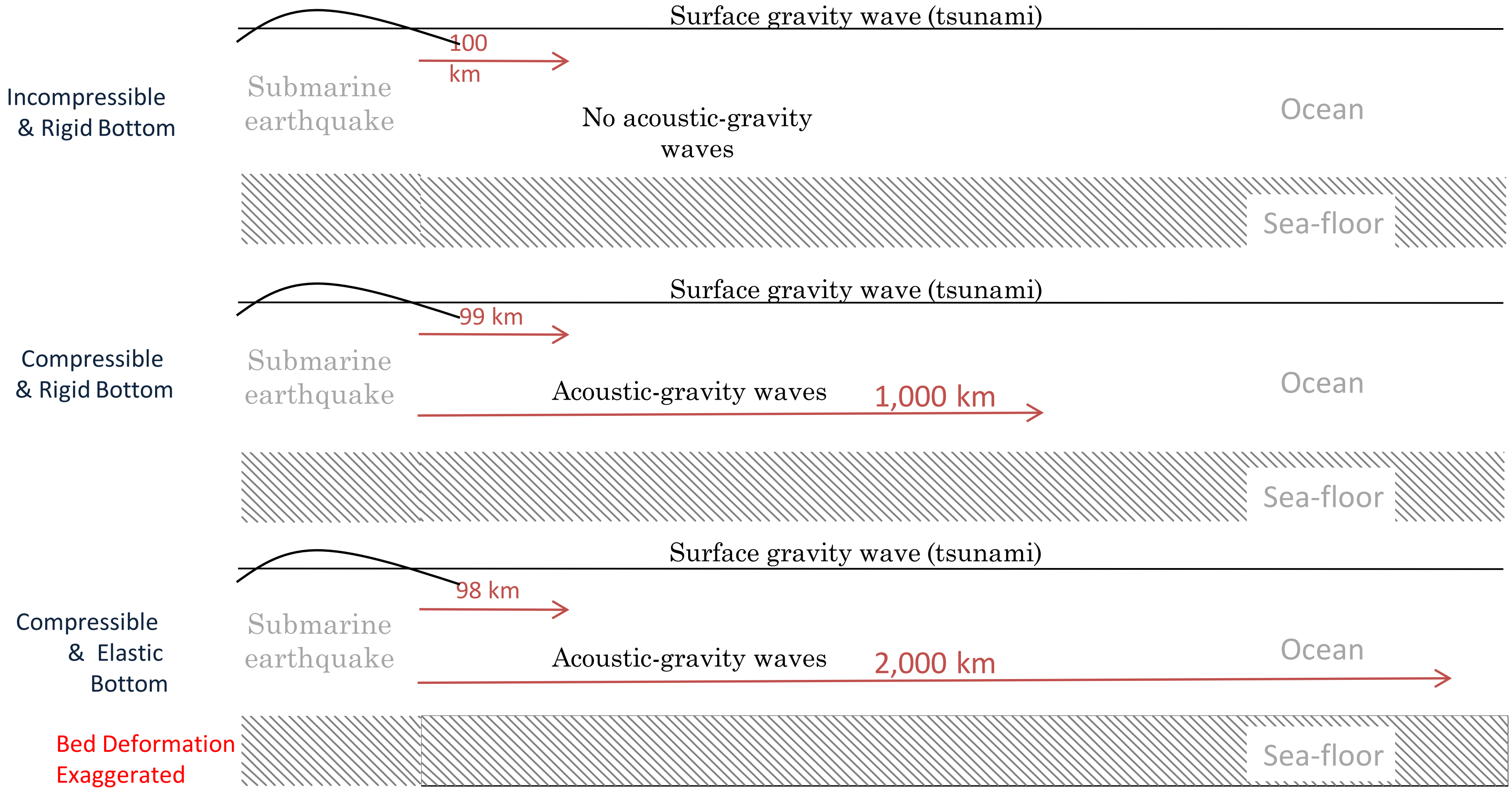
- Low frequency
- High travelling speed (of sound in medium)
- Carry information on the source

Objective: learn about the source by "listening" to AGWs

ACOUSTIC-GRAVITY vs TSUNAMI



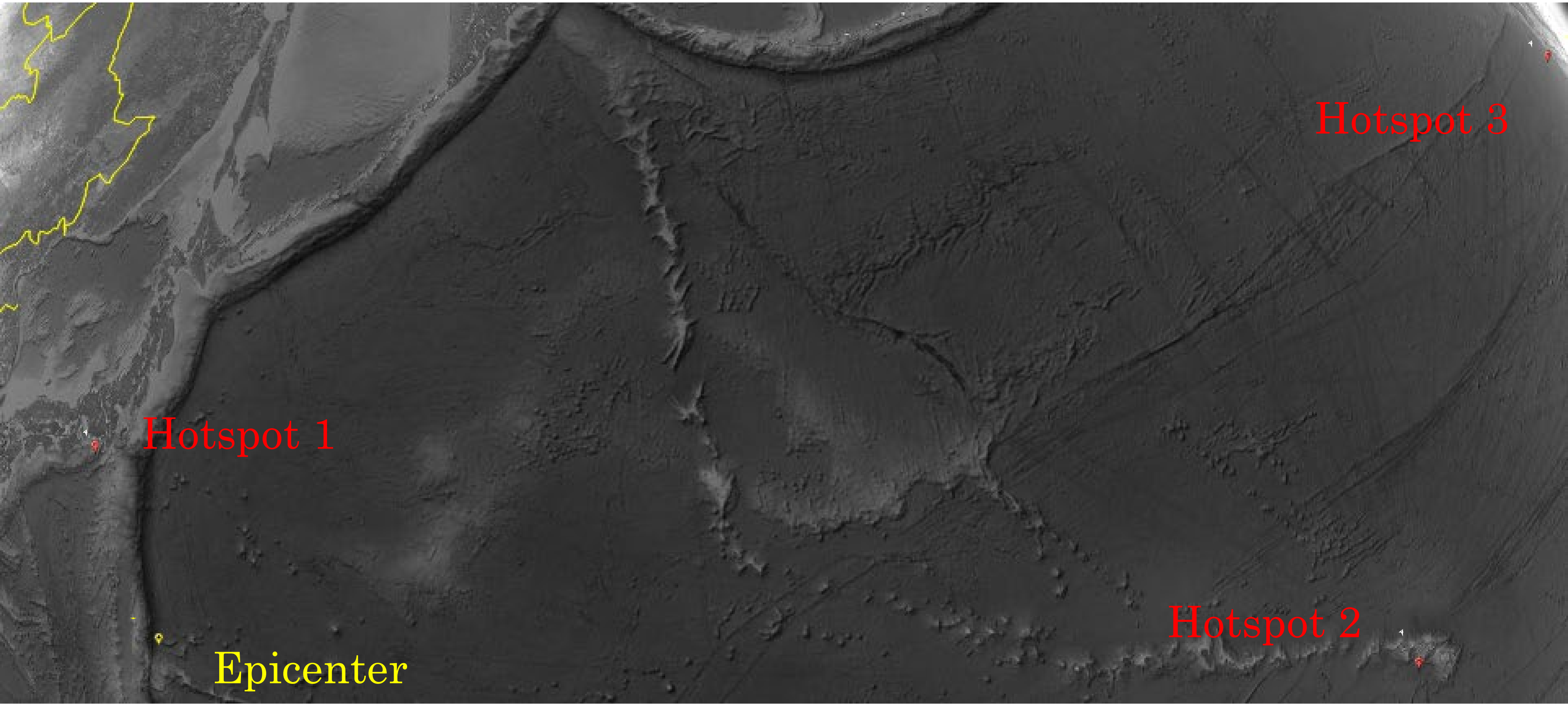
ACOUSTIC-GRAVITY vs TSUNAMI

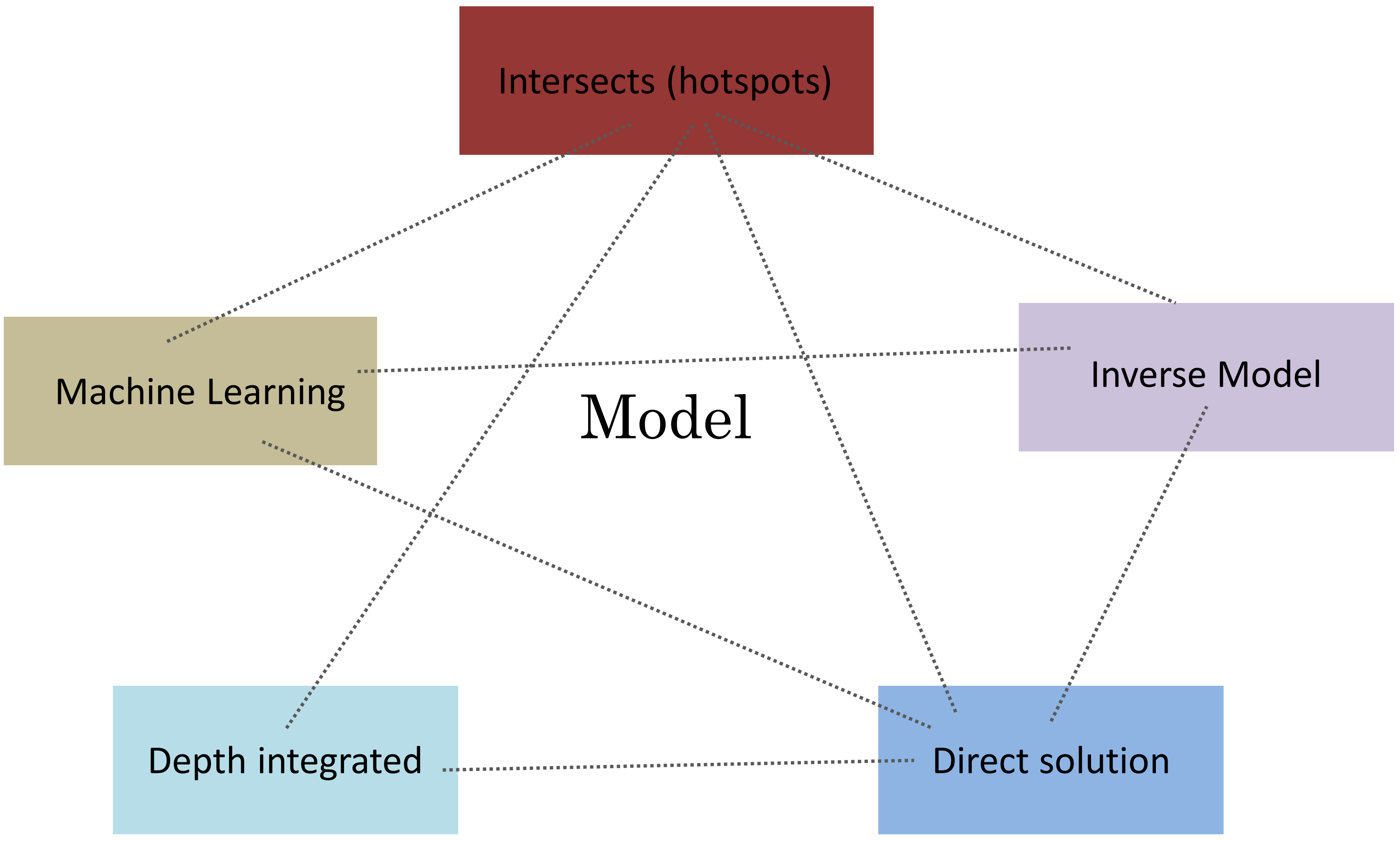


With elasticity/compressibility the tsunami propagation speed is further modified
Reducing discrepancies between tsunami models and in-situ observation

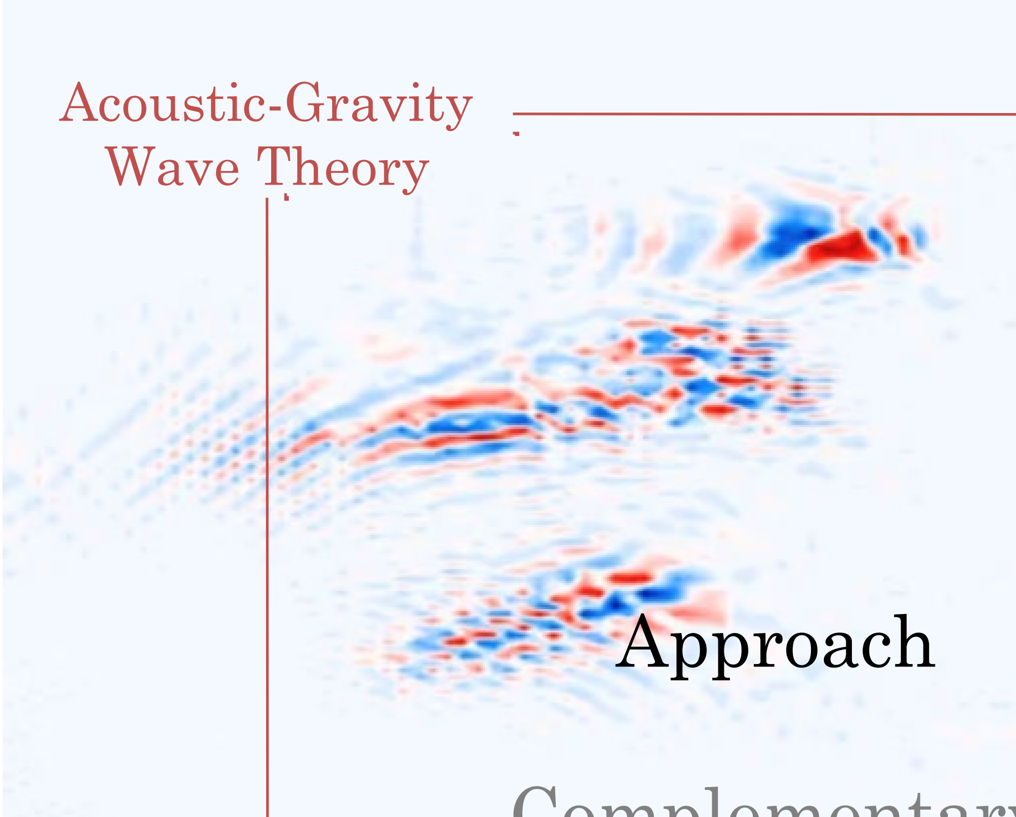
OBJECTIVE

Provide real-time tsunami estimation




Intersects (hotspots)
Machine Learning
Model
Inverse Model
Depth integrated
Direct solution

Acoustic-Gravity Wave Theory



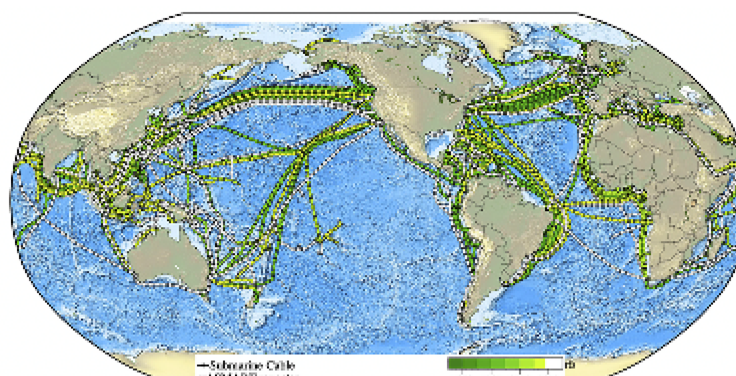
Approach

Complementary

https://www-cdn.eumetsat.int/files/styles/16_9_large/s3/2020-04/img_nws_20190117_jason-3.jpg?h=801334a3&itok=bVdqWBmi

https://www.ocean.washington.edu/files/obs_bb.jpg

http://www.trbimg.com/img-596416d5/turbine/la-1499731666-uzmvd4k3i8-snap-image



Howe et al. 2022. *Frontiers in Earth Science* | Volume 9 | Article 775544

Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)

Model

Acoustic-Gravity Wave theory

Direct solution

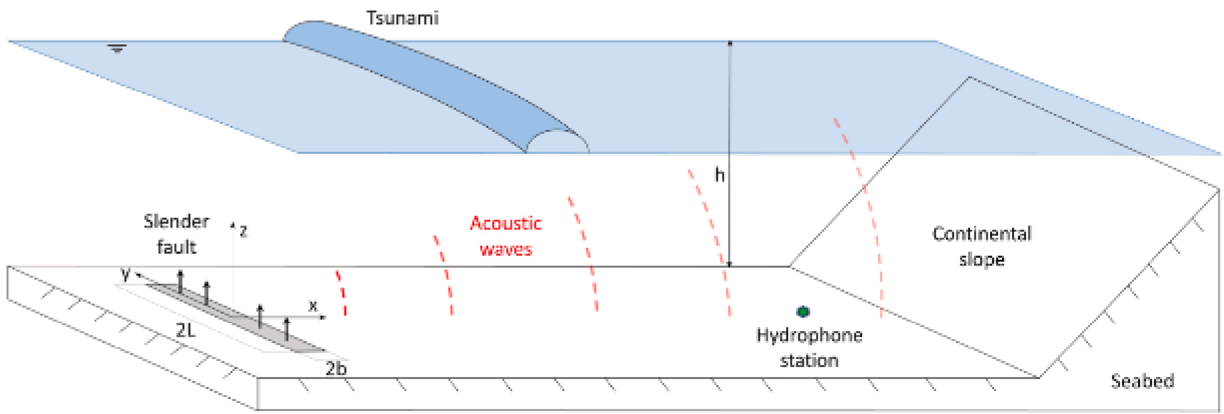
Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)

Assumption/strength: slender fault



Tsunami origin	Earthquake duration (min)	Fault width (km)	Fault length (km)	Sea depth (km)
Chile (1960)	10	200	800	4
Alaska (1964)	10	100	700	4
Indian Ocean (2004)	10	200	1200	4
Tohoku (2011)	6	150	500	3.8

TABLE 1. Key data of some recent tsunamis. The sea depth is approximately 4 km in all cases above. From the lecture by Philip L.-F. Liu, in *Tsunami and storm surges*, Valparaiso, Chile, 2–13 January 2013.

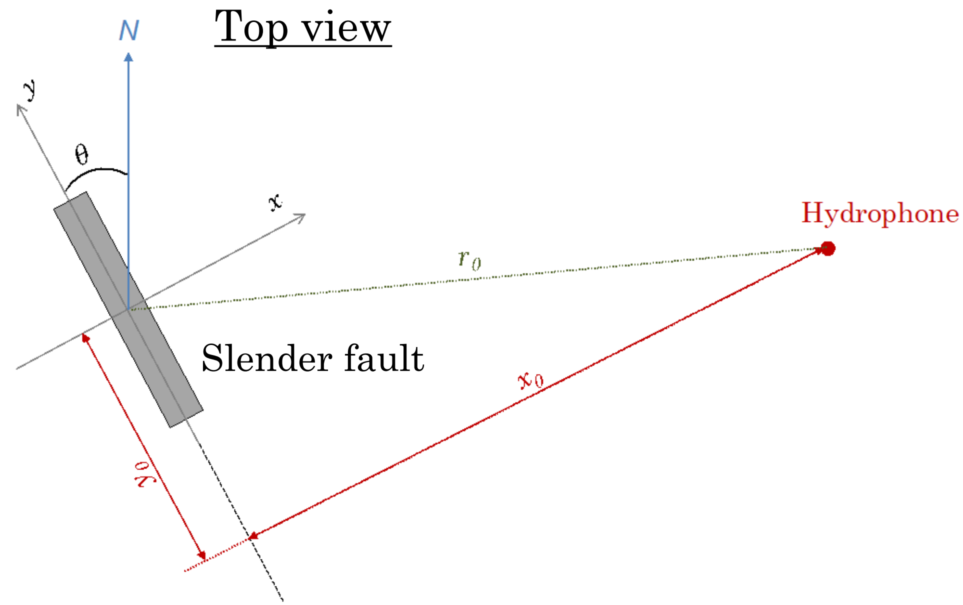
Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)



$$\widehat{P}_1(\hat{t}_j) = \rho W_0 |A_1(K_1, X, Y)| \frac{2^{7/2} C}{\sqrt{\pi^3 x_0 k(\widehat{\Omega}_{i_j})}} \sin[k(\widehat{\Omega}_{i_j}) b] \sin(\widehat{\Omega}_{i_j} T).$$

J. Fluid Mech. (2018), vol. 836, pp. 352–373. © Cambridge University Press 2017 35
doi:10.1017/jfm.2017.811

Sound signals of tsunamis from a slender fault

Chiang C. Mei[1],† and Usama Kadri[2,3]

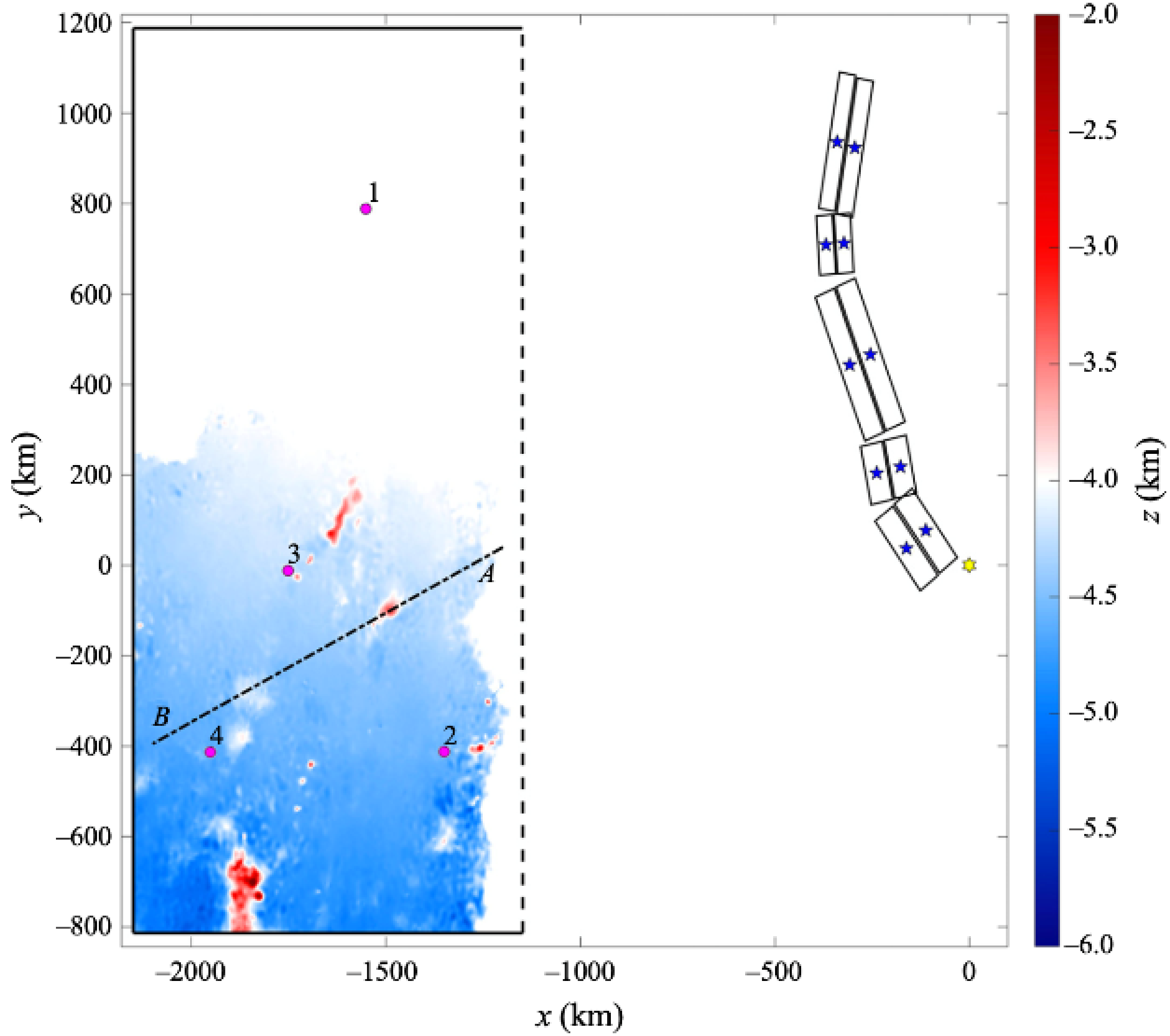
Direct solution

Inverse Model

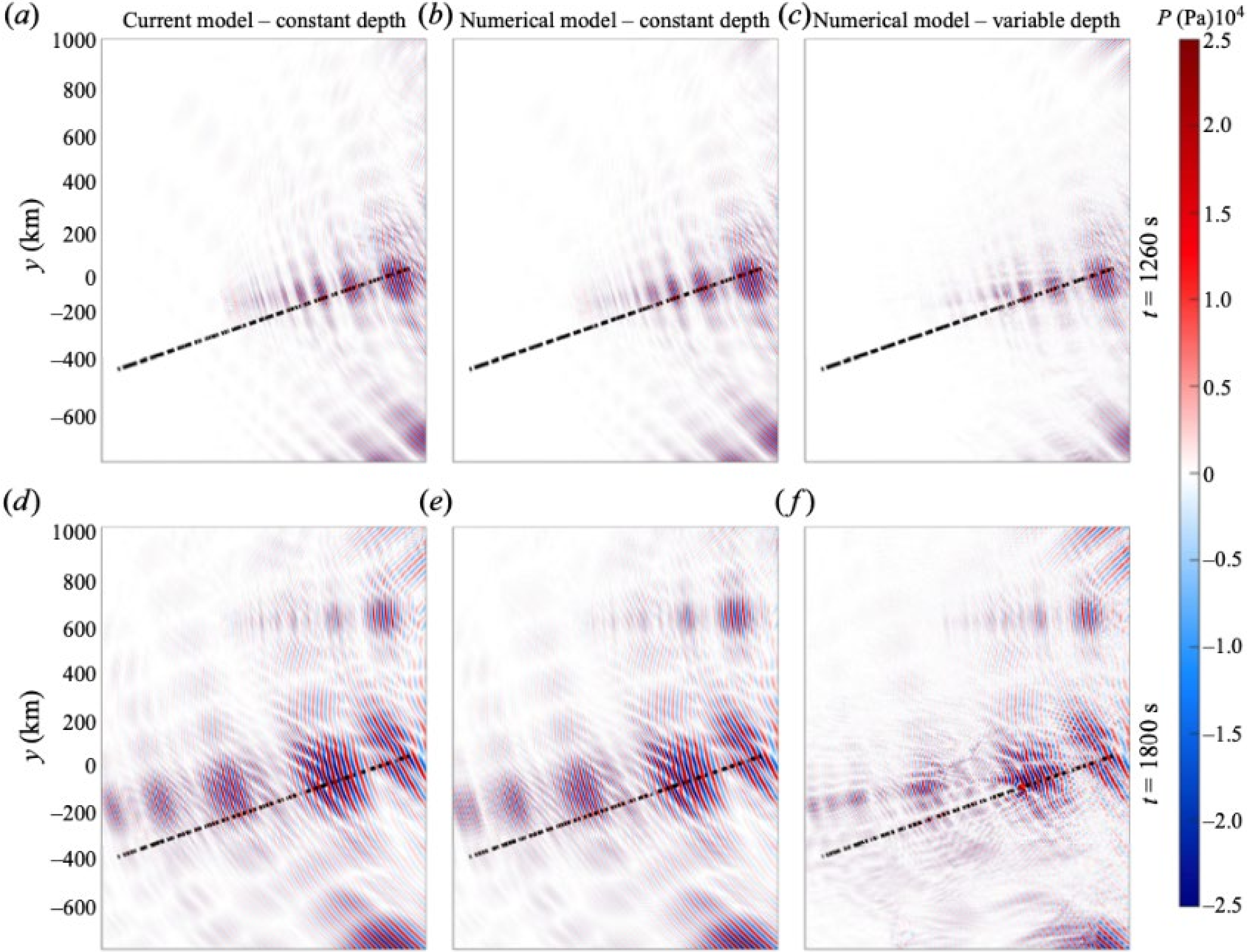
Machine Learning

Depth integrated

Intersects (hotspots)



J. Fluid Mech. (2021), *vol.* 915, A108, doi:10.1017/jfm.2021.101


(a)
Current model – constant depth
(b)
Numerical model – constant depth
(c)
Numerical model – variable depth
P (Pa)10^4
2.5
2.0
1.5
1.0
0.5
0
−0.5
−1.0
−1.5
−2.0
−2.5
1000
800
600
400
200
0
−200
−400
−600
y (km)
t = 1260 s
(d)
(e)
(f)
t = 1800 s

Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)

Direct solution

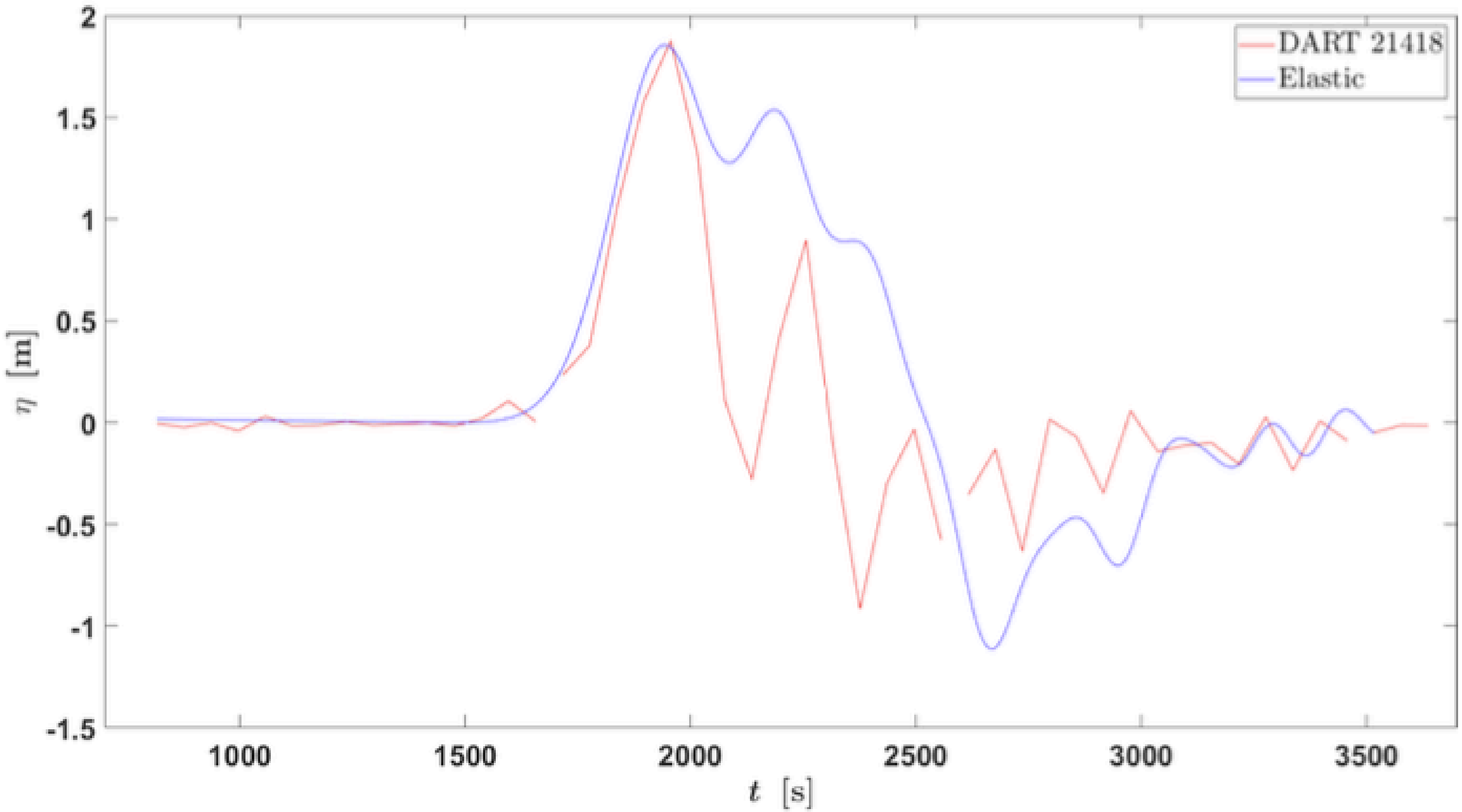
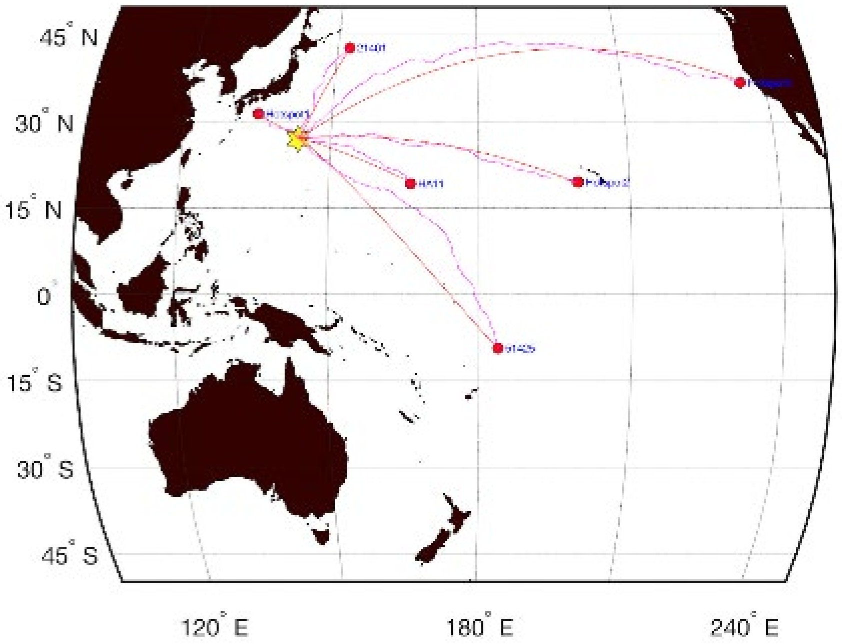
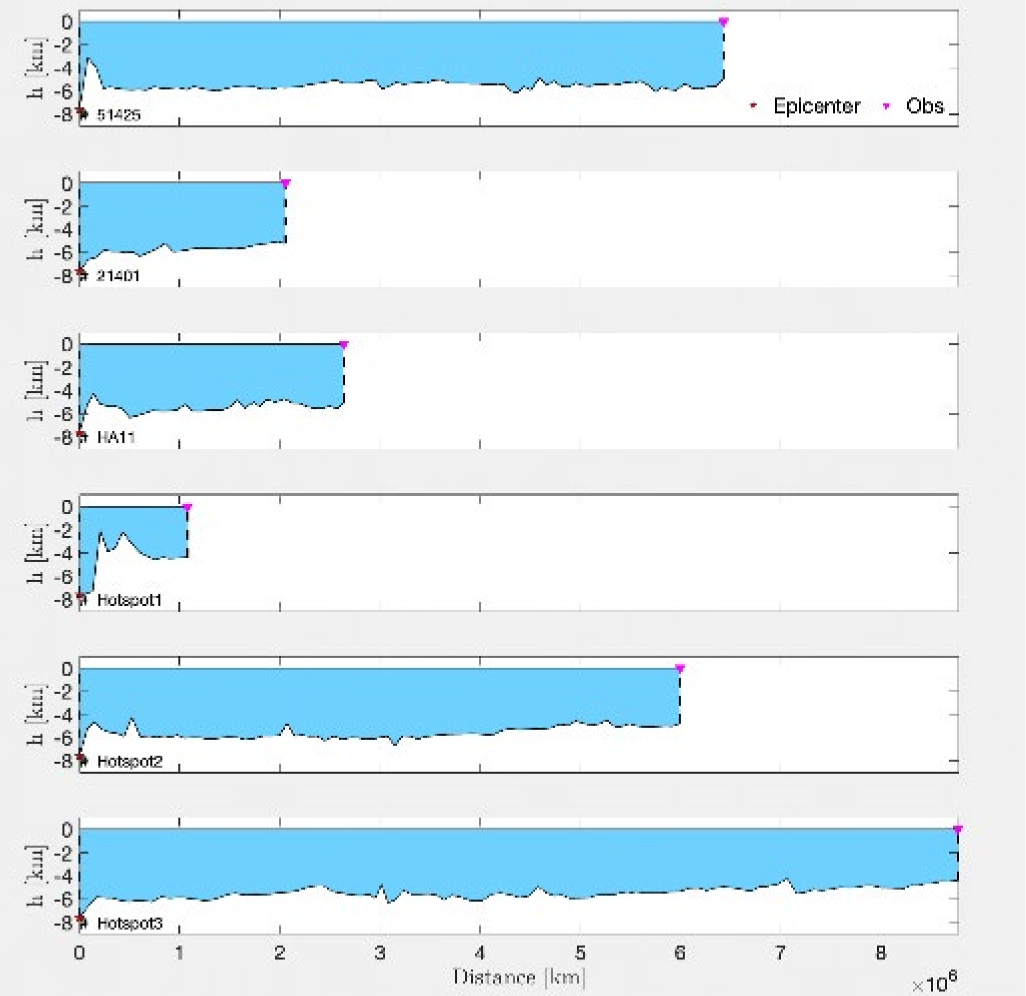


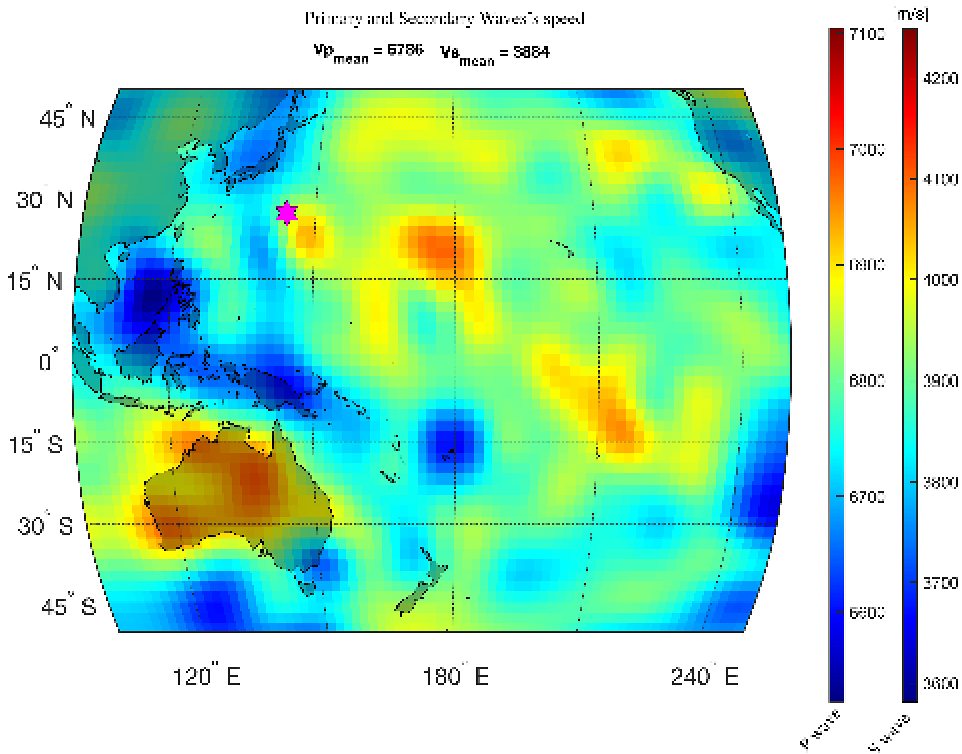
Figure 20: Surface elevations compared for Tohoku 2011 event at DART buoy 21418

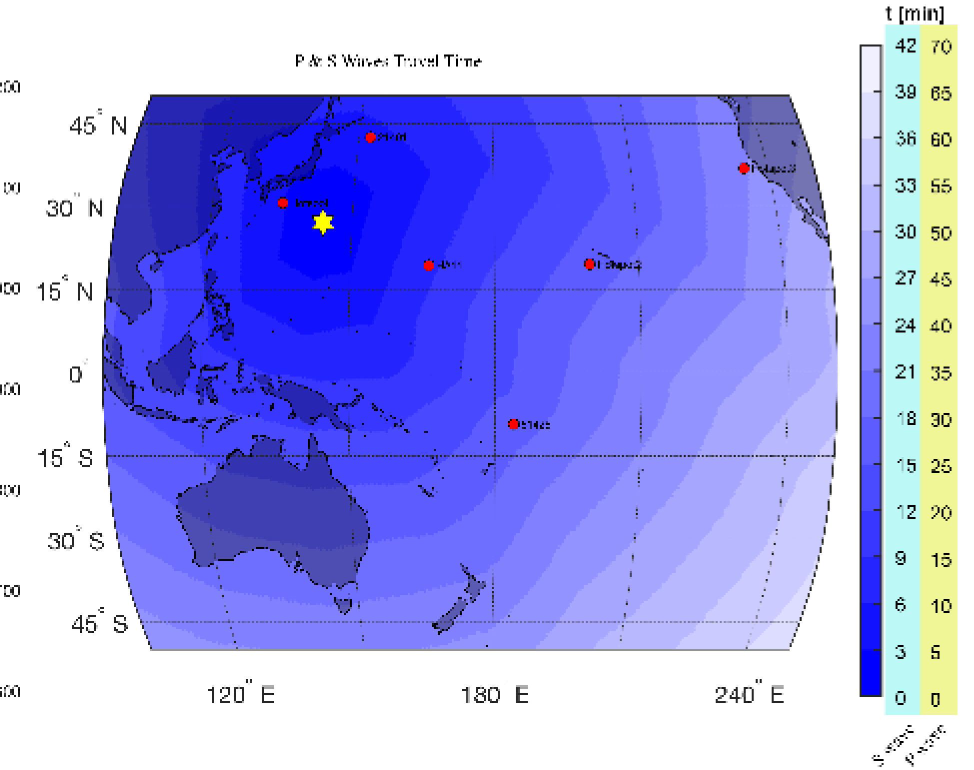




Depth integrated

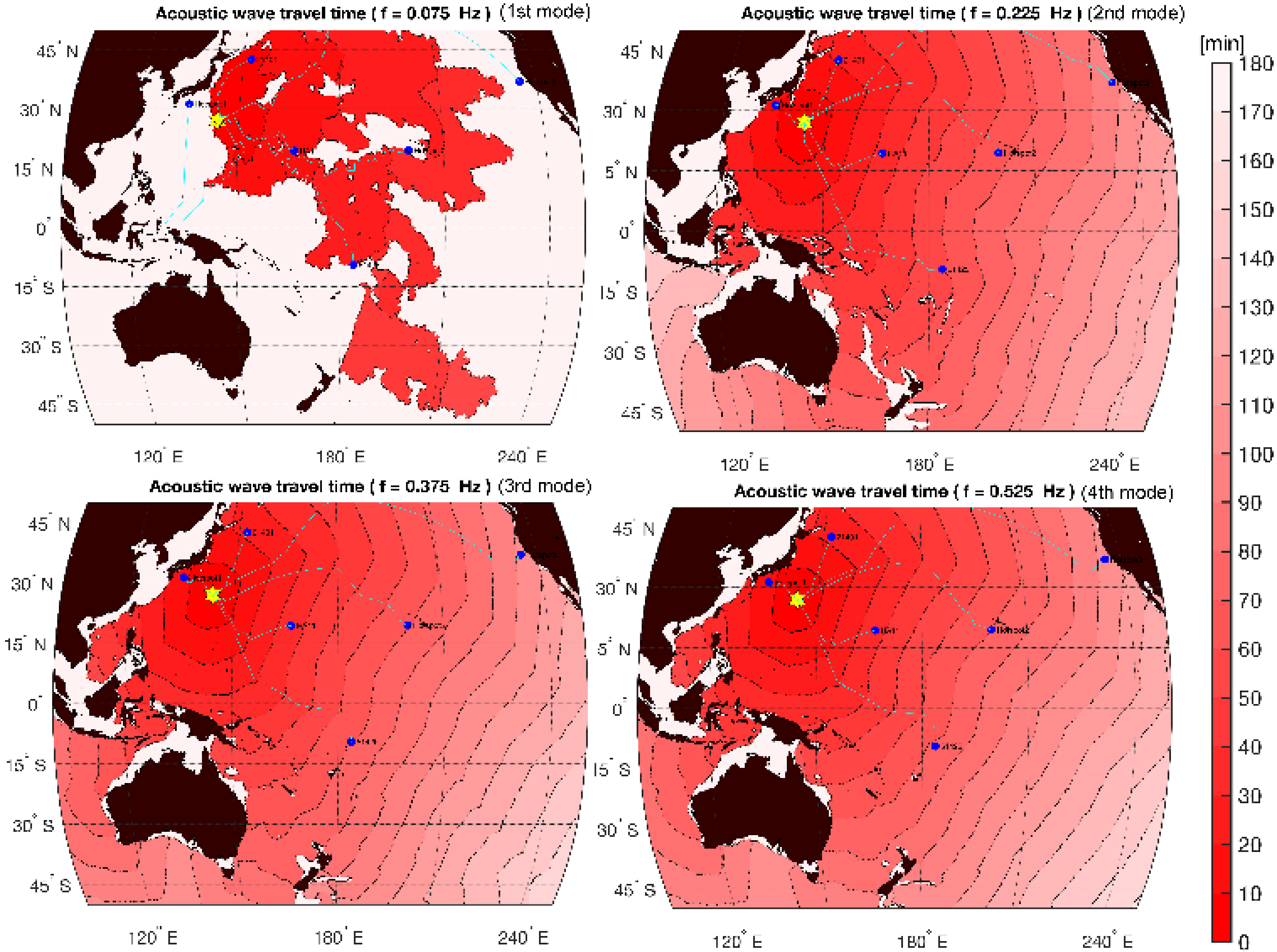
Intersects (hotspots)





Depth integrated

Intersects (hotspots)



Intersects (hotspots)

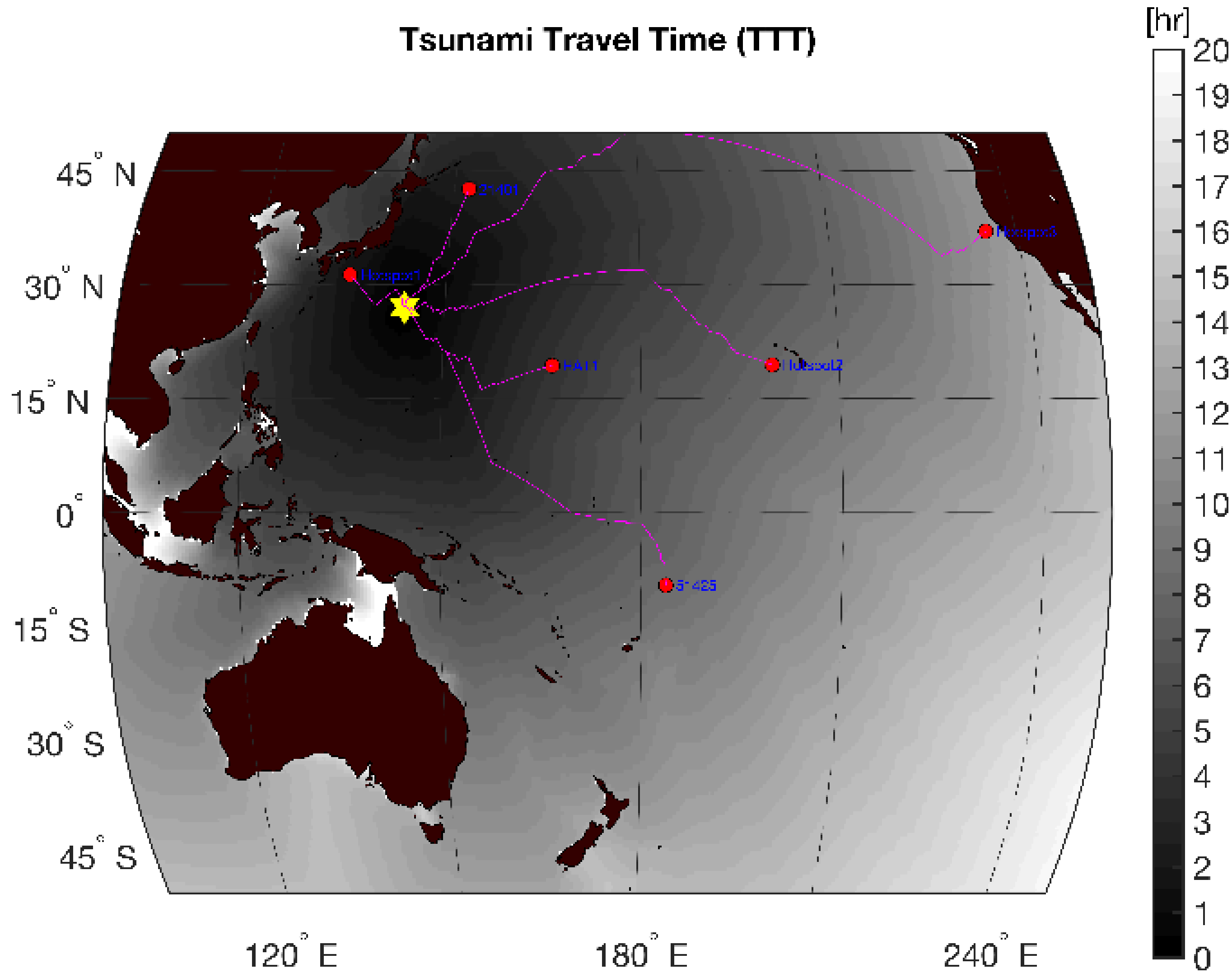
Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)



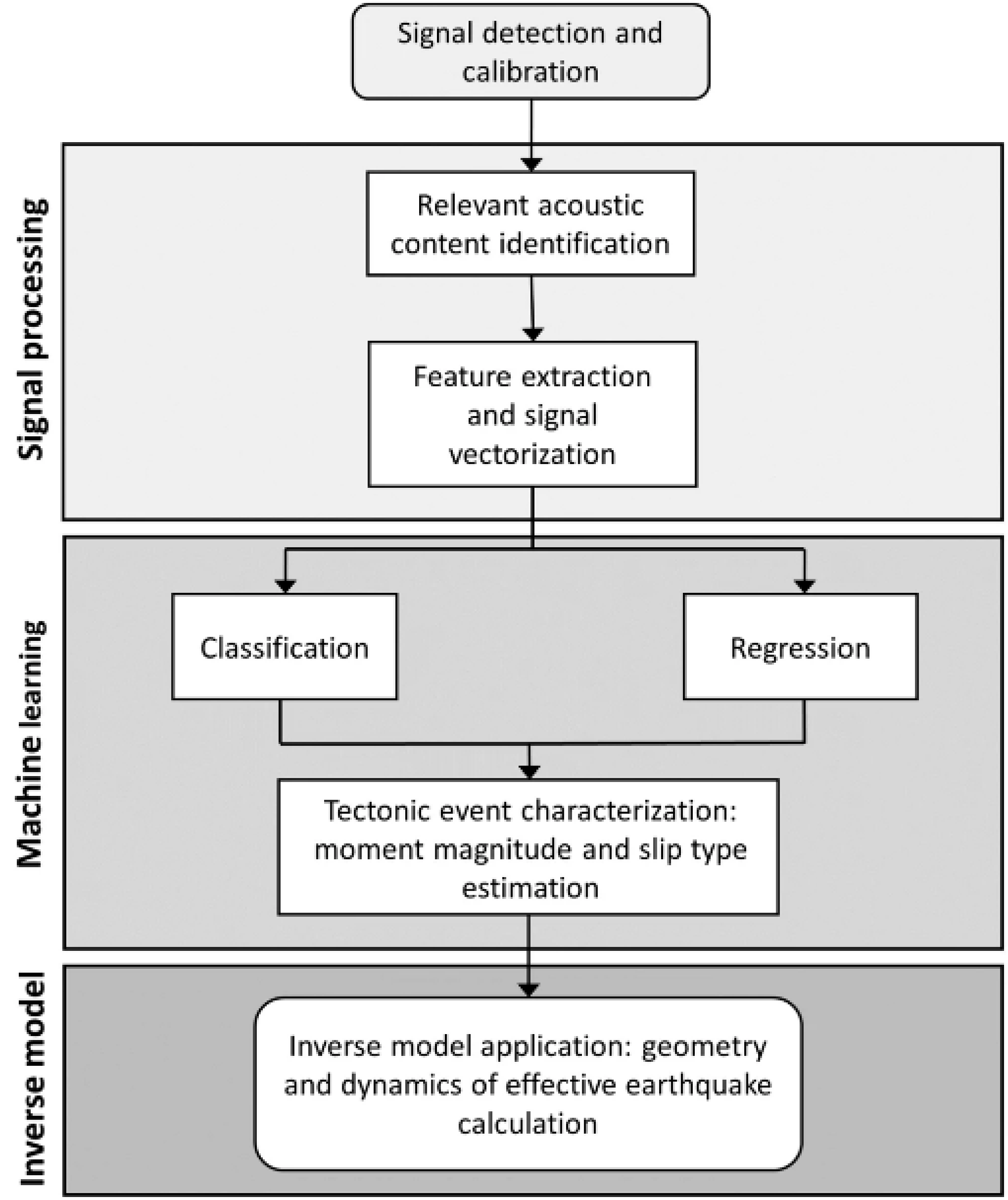
Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)



Direct solution

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Intersects (hotspots)

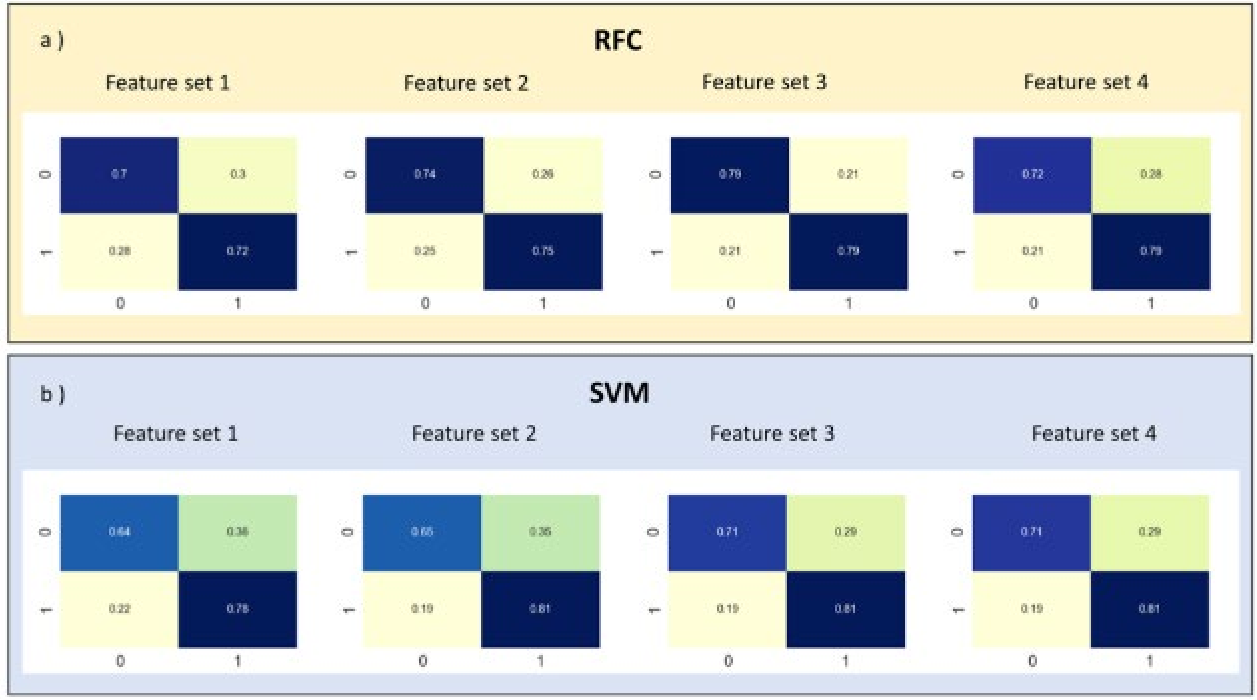


Figure 2. Binary classification confusion matrices for the considered feature sets and classification algorithms. '0' stands for events classified as mainly horizontal slip motion and '1' for events with relevant vertical motion component. (**a**) Normalised absolute errors for the RFC application along with 10-fold validation scheme. (**b**) Normalised absolute errors for the SVM application along with 10-fold validation scheme.

Supervised learning algorithms:
RFC – Random Forest Classifier
SVM – Support-Vector Machine

Direct solution

Inverse Model

Machine Learning

Depth integrated

Intersects (hotspots)

$$\widehat{P}_1(\hat{t}_j) = \rho W_0 |A_1(K_1, X, Y)| \frac{2^{7/2} C}{\sqrt{\pi^3 x_0 k(\widehat{\Omega}_{\hat{t}_j})}} \sin[k(\widehat{\Omega}_{\hat{t}_j}) b] \sin(\widehat{\Omega}_{\hat{t}_j} T).$$

Speed

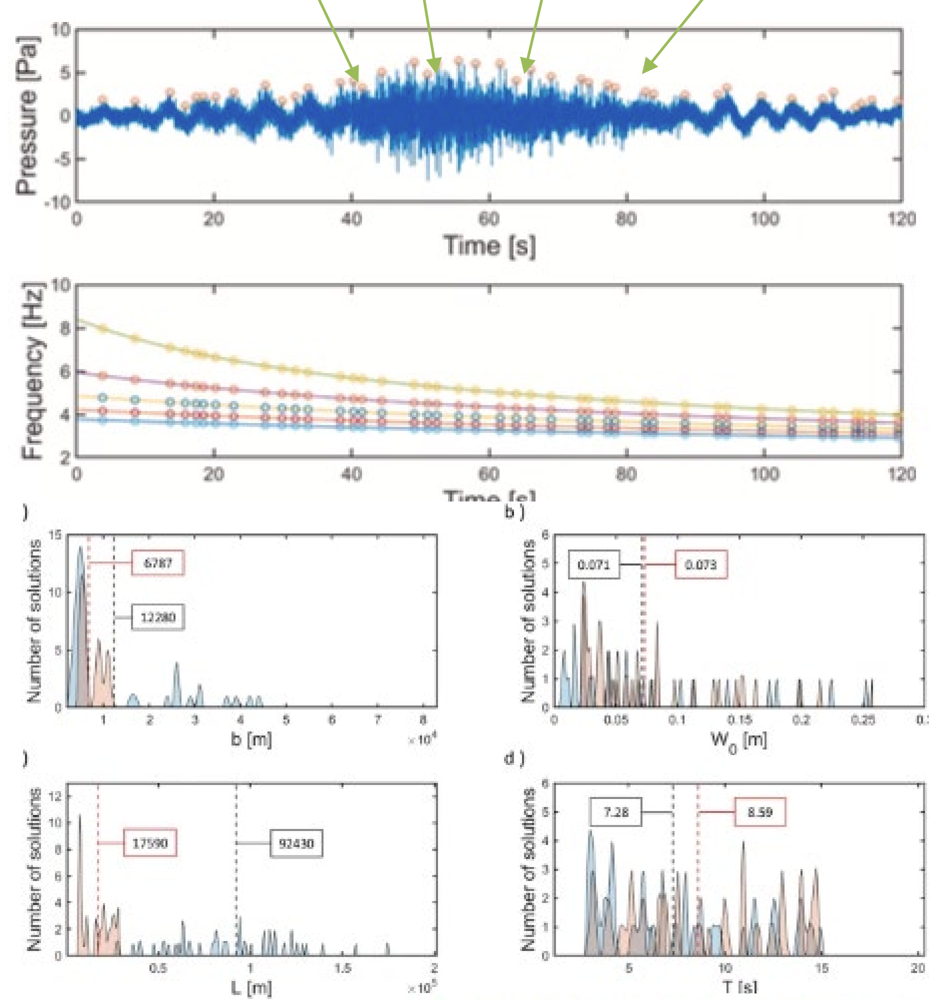
Length & location

Horizontal location

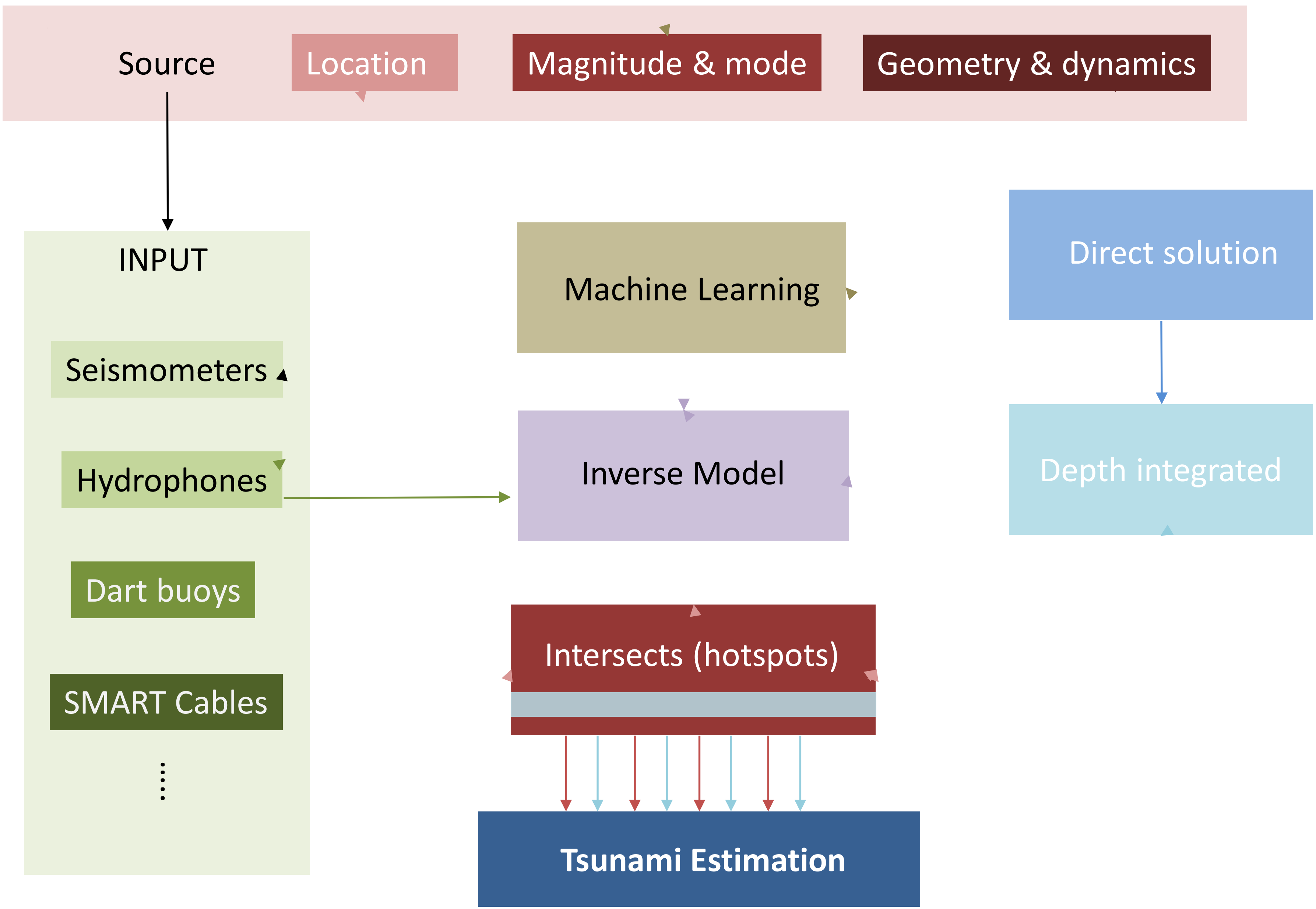
Width

Duration

UNKNOWNS



Applied Ocean Research 109 (2021) 102557


Source
Location
Magnitude & mode
Geometry & dynamics
INPUT
Seismometers
Hydrophones
Dart buoys
SMART Cables
Machine Learning
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Tsunami Estimation

Example

21st December 2010 Earthquake & Tsunami
(27.10N, 143.76E)

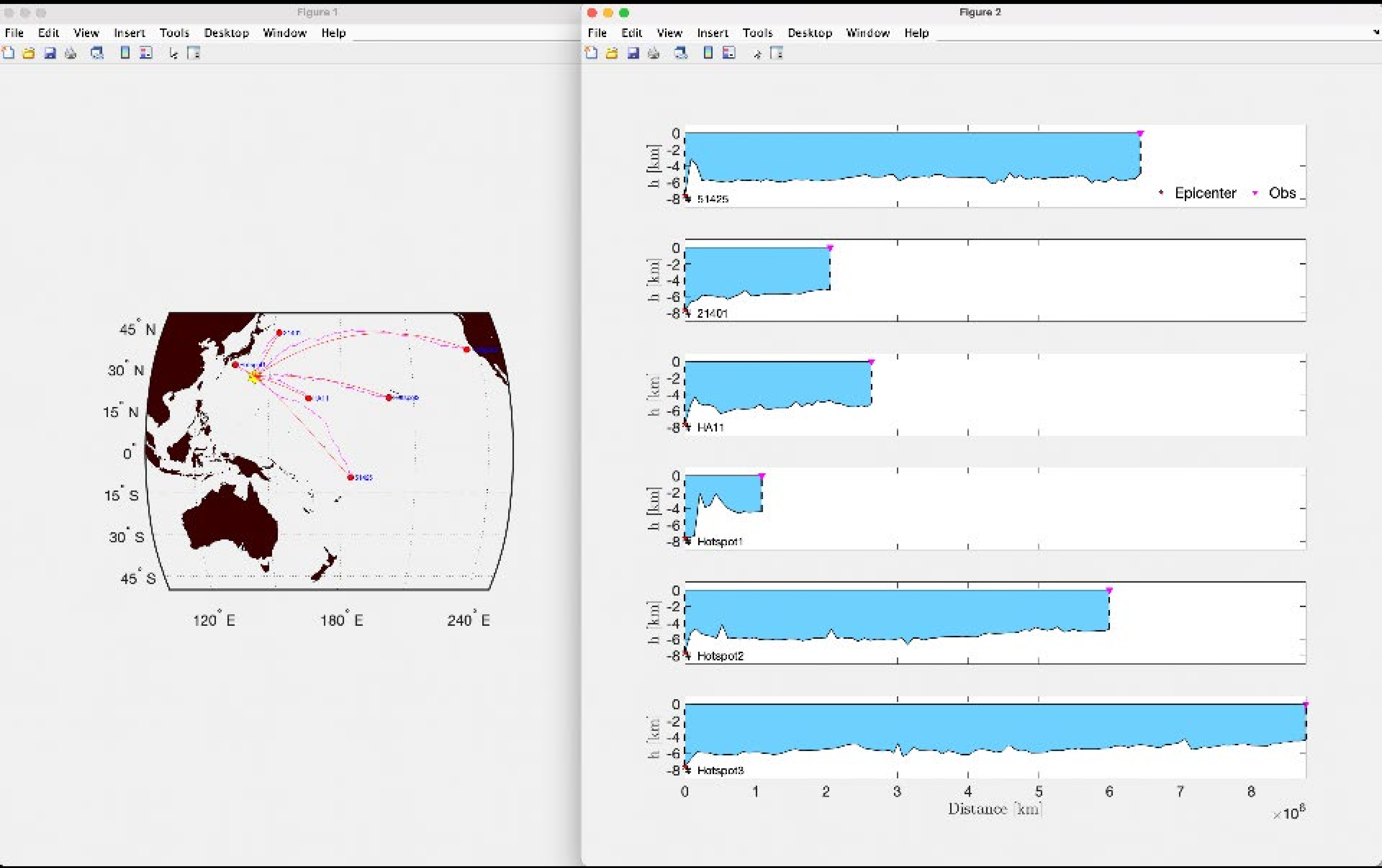

Figure 1
File Edit View Insert Tools Desktop Window Help
45° N
30° N
15° N
0°
15° S
30° S
45° S
120° E
180° E
240° E
Figure 2
File Edit View Insert Tools Desktop Window Help
h [km]
0
-2
-4
-6
-8
51425
Epicenter
Obs
21401
HA11
Hotspot1
Hotspot2
Hotspot3
0 1 2 3 4 5 6 7 8
Distance [km]
×10^6

Inverse model:
pressure signal analyzed

Direct model: tsunami @ hotspot

HA11

Inverse model:
Fault properties calculated

Direct model:
pressure@ hotspots

Summary

- Acoustic-gravity wave theory is a strong tool
- A complementary real-time tsunami methodology

Future plans

- Develop an operational package: recruit software engineer(s) (by Nov. 2022 subject to funding)
- Real-time data (CTBTO): through tsunami centres
- Integrate other models (e.g. elastic, cylindrical, nonlinear)
- Team up with more groups (synergy)