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Paper:

Selection of Tsunami Observation Points Suitable for Database-Driven Prediction

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During the Great East Japan Earthquake in 2011, real-time estimate of the earthquake's magnitude was quite low, and consequently, the first report about the tsunami also understated its severity. To solve this issue, some proposed a massive overhaul of Japan's offshore tsunami observation networks and methods to predict tsunamis in real time. In this study, we built a database containing 3,967 scenarios of tsunamis caused by earthquakes with hypocenters along the Nankai Trough, and tested a tsunami prediction method that uses this database along with offshore tsunami observation networks. Thus, we found that an uneven distribution of observation points had a negative effect on predictive accuracy. We then used simulated annealing to select the observation points to be used at each observation site and found that the predictive accuracy improved while using a few selected observation points compared to using every point.

Keywords: tsunami prediction, tsunami database, simulated annealing

1. Introduction

The 2011 Great East Japan Earthquake (GEJE) and tsunami caused enormous damage across the Tohoku region. This can be attributed in part to the real-time forecast underestimating the height of the tsunami [1]. The Japanese Meteorological Agency (JMA) releases tsunami forecasts using a tsunami database. It calculates tsunami propagation in advance under many scenarios and makes its prediction by referring to the calculation that is most likely when the tsunami occurs. At the time, the JMA chose the most likely earthquake scenario based on a preliminary value, Mj (JMA magnitude) [2, 3]. It is difficult to adequately assess the magnitude of a massive earthquake with this Mj value, which was the main factor in the forecast's underestimation of the tsunami. Currently, in order to avoid underestimation in its initial forecasts, the JMA uses methods such as choosing scenarios with high magnitude in relevant ocean regions if the magnitude is expected to exceed 8 [4].

After the earthquake off the Pacific coast of the Tohoku region, the need for more reliable tsunami prediction systems was identified. For example, Koshimura et al. (2014) [5] built a system that performs a high-speed calculation of the tsunami run-up based on an estimated seismic fault model computed right after the occurrence of an earthquake. Further, the system can comprehensively predict tsunami inundation with a high degree of accuracy in about 10 minutes, though the calculations must still be forwarded to municipal and other disaster management agencies in real time. As interruptions or failure in the communications network could crop up in the moments immediately after the occurrence of an earthquake, it would be prudent to devise a handy method to make predictions using normal computers available to municipal agencies, in addition to a high-speed supercomputer prediction system.

Although the method of using the JMA database requires preparation of the database in advance, which takes some work, there is no real-time calculation cost, and it is easy to review the results. Furthermore, there already exist two dense ocean floor manometer networks-S-net [6], laid along the Japan Trench, and DONET [7], laid along the Nankai Trough-along the coast and NOWPHAS [8] GPS wave meters roughly 20 km offshore (**Fig. 1**). Using these, it is possible to see ocean movement that is directly related to the tsunami even without estimating the magnitude of the earthquake, and this system can thus yield more reliable predictions. Takahashi et al. (2017) [9] built a prediction system in which underestimation almost never occurs, by choosing the scenario with the highest tsunami height among scenarios where the average value of the maximum absolute values of the tsunami waveform

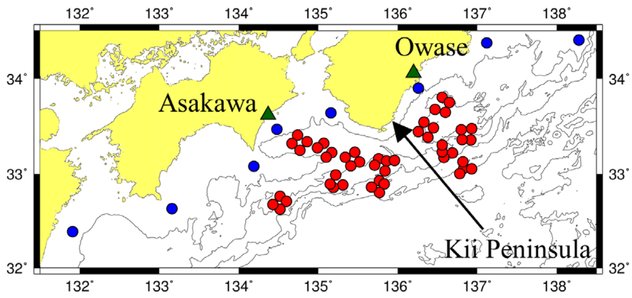

Fig. 1. Tsunami observation points along the Nankai Trough. Triangles indicate prediction target sites, blue circles indicate GPS wave meters, and red circles indicate DONET ocean floor manometers.

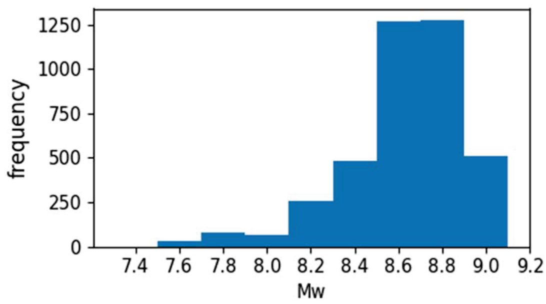

Fig. 2. MW histogram of scenarios in the database.

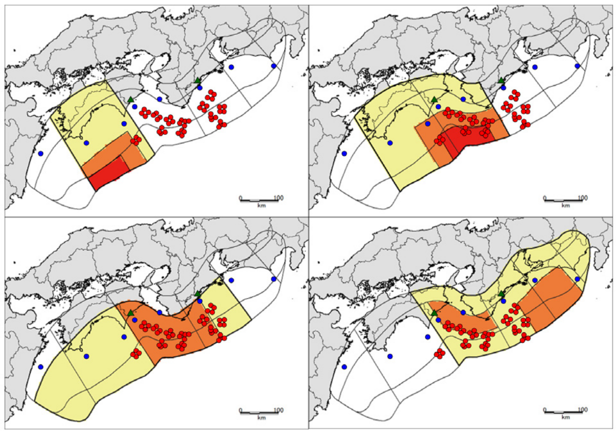

Fig. 3. Example scenario. Yellow indicates slip patches, orange indicates large-slip patches (2x slippage), and red indicates very-large-slip patches (4x slippage).

among all DONET observation points is close to that of the actual tsunami. While this method specifies the scope of the tsunami by averaging data from all the observation points, it does not provide information related to its spatial distribution. To solve this, Yamamoto et al. (2016) [10] proposed a method to search for scenarios using data from offshore observation points. Because it chooses scenarios where the survey records from all observation points are similar, it can choose scenarios where not only the scale of the tsunami is similar, but also its spatial distribution. In addition, Baba et al. (2014) [11] and Igarashi et al. (2016) [12] have tried methods to predict tsunamis using a database-driven machine learning approach, which directly predicts the wave height using information that can be obtained from tsunami observation networks. Another advantage of this method is that the machine learning (calculation) model needs to be built only once, and then it can be used to perform the calculations easily on normal computers.

For this study, we built a database of tsunamis caused by earthquakes with hypocenters along the Nankai Trough. We then tested the precision of the prediction method reported by Yamamoto et al. (2016), which can choose a tsunami scenario from this database with a similar scale and spatial distribution. In doing so, we discovered that uneven distribution of observation points had a negative effect. We also investigated ways to choose observation points that would be more suitable to making predictions using this method.

2. Creating Tunami Database

2.1. Constructing Set of Hypocenter Scenarios

The long-term potential of the occurrence of earthquakes along the Nankai Trough has been summarized, as well as the shape and other properties of its hypocentral region [13]. In this context, the Nankai Trough is divided into 18 sub-areas, which combine to form 15 hypocentral regions. Based on this, Hirata et al. (2017) [14] have created 3,967 Nankai Trough earthquake scenarios, which consist of a base model group, expanded model group, and reenactment model group. The models in the base group place patches based on the aforementioned 15 hypocentral regions in various arrangements in accordance with their “Tsunami Recipe” [15]. These are (1) large-slip patches, where twice as much slippage occurs over 30% of the fault, and (2) very-large-slip patches, where four times as much slippage occurs over 10% of the fault. The models in the expanded group consider 70 other hypocentral regions consisting of combinations of sub-areas besides those in the base 15 and similarly place large-slip and very-large-slip patches. Finally, the models in the reenactment group reenact past earthquakes along the Nankai Trough [16]. This is the dataset we have used for our study. **Fig. 2** shows an MW histogram of the scenarios in the database and **Fig. 3** shows an example scenario.

2.2. Tsunami Propagation Simulation

We performed calculations for tsunamis that might be caused by these earthquake scenarios for Asakawa District (Tokushima Prefecture) and Owase City (Mie Prefecture). These two locations were chosen because there are offshore tsunami-observation networks near them, and they are also on the west and east sides of the Kii Peninsula, which should result in different tsunami phenomena. To estimate the initial distribution of water, which is necessary for the propagation simulation, we used the semi-infinite homogeneous elastic body model described

Table 1. Conditions of calculation.

Calculation time	6 hours
Calculation interval	0.12 seconds
Rise time	60 seconds
Manning's roughness coefficient	0.025

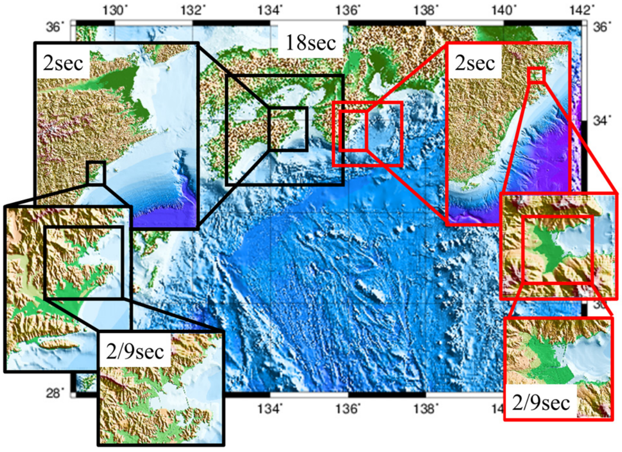

Fig. 4. Topographic data used for wave calculations.

in Okada (1985) [17] to calculate the crust displacement in the ocean floor from the fault parameters. We added the amount of contribution from the horizontal displacement of the ocean floor slope to the vertical ocean floor displacement based on Tanioka and Satake (1996) [18] and applied Kajiura's (1963) filter [19] to it in order to determine the tsunami's initial height. For the sake of simplicity, we did not consider fracture propagation, and we set the rise time to 60 seconds.

We used the open-source software JAGURS [20] to calculate the tsunami propagation and run-up. Non-linear long wave equations were dispersed across a staggered grid so that the leap-frog method could be used to find the temporal development of the height and the flow rate. **Table 1** shows the conditions of the calculation.

We obtained the terrestrial topographical data necessary for tsunami height calculations from 5mDEM, which has been made publicly available by the Geospatial Information Authority of Japan. We interpolated with 10mDEM data where 5mDEM data did not exist. We constructed the marine topographical data primarily from Japan Hydrographic Association's M7000 series of digital ocean floor topographic data. For deep-sea areas with no M7000 data, we interpolated with GEBCO (General Bathymetric Chart of the Oceans)'s global topographic data. We created a nested topographic grid with five layers, using time steps of 18 s, 6 s, 2 s, 2/3 s, and 2/9 s (**Fig. 4**).

We output the time-series change in height at target sites for prediction for Owase and Asakawa and at offshore tsunami observation points (**Fig. 1**) and created a database from these values. Here, the time-series change in height measured by the manometer takes into account the crust displacement caused by the earthquake. We converted water height into pressure at an assumed rate of 1 cm to 1 hPa.

3. Prediction of Coastal Tsunami Height by Tsunami Database Search

3.1. Method of Scenario Search Based on Multi-Index Method

Yamamoto et al. (2016) [4] have proposed a method whereby maximum value of the absolute of tsunami waveform observed at each observation point is used to choose the scenario in the database that most closely matches the tsunami. This method uses the following three indices. If we write the absolute maximum height of the tsunami observed at the i-th observation point r_i as $\boldsymbol{O}(r_i)$ and the absolute maximum height of the tsunami in the scenario taken from the database as $\boldsymbol{C}(r_i)$, it gives us the following:

$$R = \frac{\sum_{i=1}^{n} \boldsymbol{O}(r_i)\boldsymbol{C}(r_i)}{\sqrt{\sum_{i=1}^{n} \boldsymbol{O}^2(r_i)}\sqrt{\sum_{i=1}^{n} \boldsymbol{C}^2(r_i)}} \quad \text{. . . . . (1)}$$

where n is the number of observation points. This equation is the cosine similarity between the vectors $\boldsymbol{O}$ (the observed event) and $\boldsymbol{C}$ (the scenario taken from the tsunami database). For example, when $R = 1$, the distribution of the absolute maximum tsunami height values of one vector is a constant factor of height values of the other. Thus, using the R index makes it possible to choose the scenario with the most closely matching slip patch regardless of the scale.

Next, we will consider the following two variance reductions to help us find the tsunami that is most similar in scale:

$$VRO = 1 - \frac{\sum_{i=1}^{n} (O(r_i) - C(r_i))^2}{\sum_{i=1}^{n} O^2(r_i)} \quad \text{. . . . . . . (2)}$$

$$VRC = 1 - \frac{\sum_{i=1}^{n} (O(r_i) - C(r_i))^2}{\sum_{i=1}^{n} C^2(r_i)} \quad \text{. . . . . . . (3)}$$

Both these indices are 1 when the two vectors O (the observed event) and C (the scenario taken from the tsunami database) are equal and decrease as the vectors diverge. Yamamoto et al. (2016) [10] claim that by choosing a scenario where both VRO (Variance Reduction normalized with Observed data) and VRC (Variance Reduction normalized with Calculated data) exceed a given threshold, the largest and smallest estimates can be as inputs, the maximum and minimum values of the water height and the water pressure waveform that would be obtained at the observation points over the 5-second period

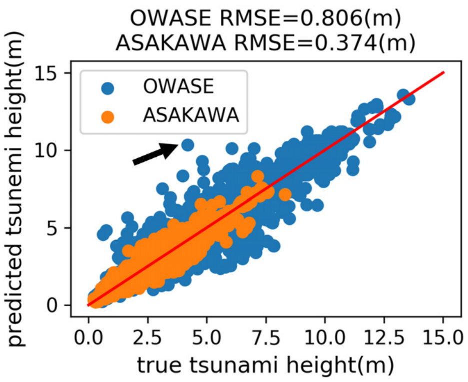

Fig. 5. Result of the LOOCV test using the database-driven search method. The arrow shows the case with the most inaccurate prediction.

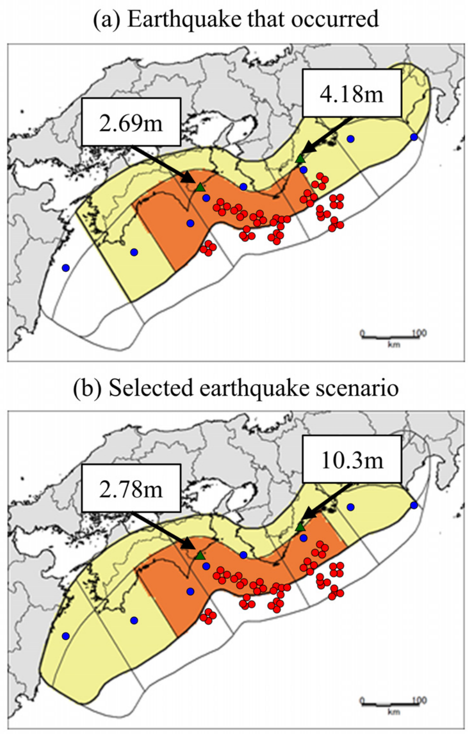

Fig. 6. Most inaccurate prediction. When the earthquake in (a) occurred, the scenario in (b) was chosen. Values shown in figures are maximum tsunami wave height in each prediction target site.

after the occurrence of an earthquake and set an initial threshold of 0.9 for VRO and VRC, to be lowered in increments of 0.8, 0.7 and 0.1 if no scenarios exceeded the threshold. This process narrows the scenarios down to several that are close in scale to the tsunami. For this paper, we have chosen one scenario among these where the value of R is the greatest, under the assumption that the scenario whose tsunami distribution most closely resembles the tsunami will best express the coastal damage.

3.2. Testing Scenario Search Method Based on the Multi-Index Method

We performed leave-one-out cross-validation (LOOCV) to test the predictive accuracy of this method based on the multi-index method. Specifically, the test was aimed to remove a given scenario from the database and see how accurately that scenario could be predicted with the remaining scenarios when it occurred. Predictive accuracy was evaluated using the root-mean-square error (RMSE) between the predicted and actual values for the maximum tsunami height for Asakawa and Owase. **Fig. 5** shows the results of the test. The RMSE values for both Owase and Asakawa were within 1m, with a few appearing to be greatly inaccurate. **Fig. 6** shows the result of the most inaccurate prediction (indicated in **Fig. 5** with an arrow). **Fig. 6a** shows the actual fault scenario and **Fig. 6b** shows the scenario chosen based on the multi-index method. While these two scenarios share similar fault shapes, they differ in the way that the slip patch juts out into the waters off the coast of Owase. In this case, there is no problem with the tsunami height prediction for Asakawa; however, the correct height at Owase has been greatly overestimated. We suppose that the selection of a scenario such as this, which is inappropriate for Owase, is due to an uneven distribution of observation points. As shown in **Fig. 1**, there are fewer observation points near Owase than there are to the west of the Kii Peninsula, which makes it more likely that the algorithm used in this study will choose a scenario with a similar tsunami distribution to the west of the Kii Peninsula. From this, one can surmise that when the observation points are distributed unevenly, insufficiently observed areas may not necessarily receive the most accurate predictions. In other words, it is necessary to change the arrangement of observation points for each prediction target site. Moreover, the method of choosing the one scenario that is most similar to a given earthquake means choosing a scenario whose overall tendencies resemble that earthquake. However, as differences in the location of the local large-slip patch cause the predicted height to vary greatly, as shown in **Fig. 6**, it may be possible to make more accurate predictions by not only changing the arrangement of observation points, but also choosing different scenarios for each prediction site.

3.3. Choosing Observation Points Using Simulated Annealing

Because it seems better not to use all observation points, we used simulated annealing, a method used in optimization problems, to select the observation points that are best suited for database-driven prediction. The following is a simple description of the process:

1. Generate an initial solution x and define the initial temperature t.

2. Run the following operations in a loop until the terminating condition is satisfied:

   A. Choose a solution x' at random among the neighboring solutions $N(x)$ of the initial solution

B. Set $\Delta = f(x') - f(x)$, where $f(x)$ is the evaluated value for the solution x (smaller is better)

C. Move from x to x' with a probability of 1 if $\Delta \leq 0$ (better solution) or a probability of e^t if $\Delta > 0$ (worse solution)

3. If the algorithm's terminating condition is satisfied, apply a cooling rate to t to lower the temperature and return to step 2.

For our purposes, solutions were expressed using the values 1 and 0 to represent usage and non-usage, respectively, of each of the 57 observation points. The initial solution was generated randomly, and neighboring solutions were defined as those where the value for one of the observation points was the opposite of that in the current solution. We used LOOCV RMSEs for the evaluated values and a cooling rate of 0.95. After evaluating the initial solution and all of its neighboring solutions, we set the initial temperature such that the acceptance probability of a worse solution was 0.4, in accordance with Johnson et al. (1989) [14], to reduce the calculation time. We set the terminating condition of the loop as acceptance of the nth solution, where n was the number of neighboring solutions. Neighboring solutions were not generated at random each time but rather taken from a list of neighboring solutions that we created and shuffled. The list of neighboring solutions was regenerated upon the acceptance of a solution in order to see all neighboring solutions. If no solution was accepted even after iterating through the entire list, a solution was chosen with a Roulette wheel whose size corresponded to the number of all transition probabilities in the list of neighbors. This was done in order to continue the search to some extent even at low temperatures. The algorithm's terminating condition was maintained until cooling was applied 140 times.

The number of iterations (that is, the number of times step 2 in the preceding algorithm was repeated) and the evaluated value of the best solution obtained up to each iteration is shown in **Fig. 7**. Calculations were performed with four different seed values for both Asakawa and Owase. The process concluded for Owase after 80 iterations and for Asakawa after 100 iterations.

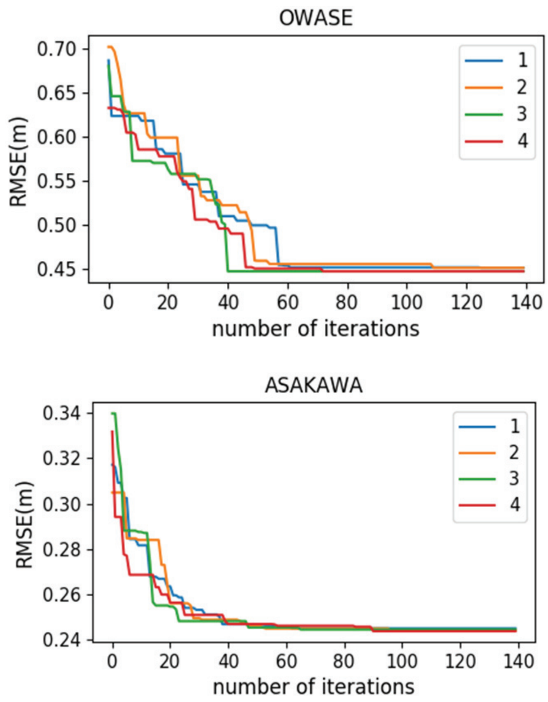

Fig. 7. Finding the optimal solution using simulated annealing. Four searches were performed for both Owase and Asakawa with random seed values.

Figure 8 shows the optimal solutions obtained through simulated annealing, which mostly resulted in the selection of observation points near the prediction site, though some more distant points were selected as well. We interpret this to mean that basically, this method works well if there is good information in the vicinity of the prediction site, but it is also necessary to know whether the fault is far from the site and, if so, its arrangement. Calculations were performed with four different seed values, all of which resulted in the selection of observation points mostly near the prediction site, though with all values, we observed that some more distant points were selected as well.

Figure 9 shows the result of the LOOCV predictions of the maximum tsunami height based on database searches using the observation points chosen through simulated annealing. Compared to the original predictions that used all of the observation points, the RMSE for Owase was 44% lower and the RMSE for Asakawa was 35% lower, indicating vastly improved predictive accuracy. In the case of an earthquake whose original prediction was most inaccurate when all observation points were used (**Fig. 6(a)**), using only observation points for Owase resulted in the selection of the scenario shown in **Fig. 10**. The chosen scenario had a large-slip patch near Owase that was similar to the actual earthquake, which indicates that differences in large-slip patches near prediction sites have a significant effect on predicted tsunami heights. Moreover, for the same earthquake, the algorithm chose the scenario in **Fig. 6(b)** when only observation points chosen for Asakawa were used. Thus, we have determined that when searching a database of scenarios that use offshore observation points to predict tsunamis, changing the observation points used for each site and allowing different scenarios to be chosen for each site results in improved predictive accuracy.

4. Summary

We built a database comprising 3,967 earthquake scenarios with hypocenters along the Nankai Trough and tested the accuracy of database-driven tsunami prediction using offshore observation networks. The use of all observation points to make predictions returned poor results for areas with a sparse collection of observation points; therefore, we performed another analysis wherein the observation points to be used for each prediction target area were chosen by simulated annealing, and it was also pos-

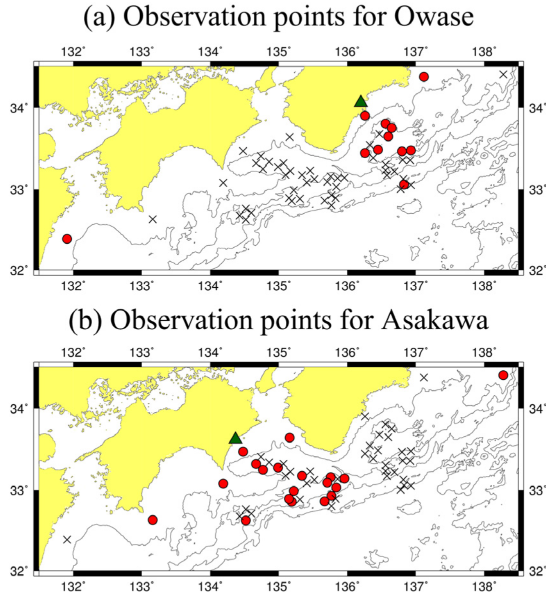

Fig. 8. Observation points suitable for database-driven tsunami height prediction using offshore observation networks. Triangles indicate prediction target sites, circles indicate selected observation points, and x's indicate unselected observation points. The upper figure shows observation points for Owase, and the lower figure shows observation points for Asakawa.

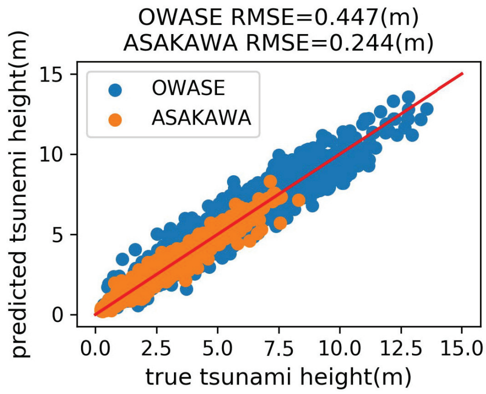

Fig. 9. Result of LOOCV test for the database-driven search method where only observation points chosen through simulated annealing were used.

sible to choose different earthquake scenarios for each area. Consequently, we found that using only a small number of selected observation points rather than using all of them vastly improved predictive accuracy in some cases. In this paper, we analyzed a method to predict a tsunami five minutes after the occurrence of an earthquake. Sequentially updating the prediction every subsequent minute after the earthquake may improve precision , as the method would search for scenarios as the tsunami phenomenon becomes clearer and clearer. However, since we believe that choosing scenarios with a close distribution of tsunami heights near the prediction target site results in high precision, we do not think that the combination of observation points adapted to the prediction would change dramatically even if the prediction timing were changed.

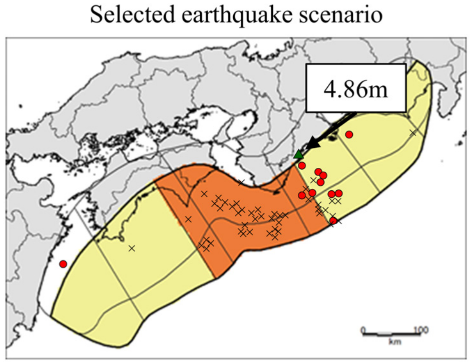

Fig. 10. Scenario chosen for the earthquake in **Fig. 6a** when only observation points chosen for Owase were used. Value in figure denotes maximum tsunami height in Owase.

Furthermore, while the method proposed in this paper was applied to an existing observation network, it can also be used to review the distribution of observation points when a new marine observation network is built.

If a new observation network needs to be built around a certain area, several potential observation points should be arranged around that area and a tsunami database based on various fault scenarios must be created for potential observation points and tsunami height prediction points. If you perform the analysis from section 3.3 on the data derived from those scenarios, with the RMSE of all observation points as the evaluation function, you can exclude potential observation points that do not contribute to the improved predictive accuracy. Finally, it is possible to determine an efficient arrangement of observation points by reviewing the results along with other constraints and requirements, such as the expenses required to build the network.

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• Japan Society of Civil Engineers (JSCE)

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Selected Publications:
- Y. Igarashi, T. Hori, S. Murata, K. Sato, T. Baba, and M. Okada, "Maximum tsunami height prediction using pressure gauge data by a Gaussian process at Owase in the Kii Peninsula, Japan," Marine Geophysical Research, Vol.37, No.4, pp. 361-370, 2016.

Academic Societies & Scientific Organizations:
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2015 Dr. of Science Tsukuba University
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Selected Publications:
- "Earthquake Activity in West Asia; Seismicity in the Mediterranean Sea and Evaluation of the Strong Motion for the AD 365 Crete Earthquake Using the Stochastric Green's Function," Ancient West Asian Civilization, Springer, pp. 65-83, 2016.

Academic Societies & Scientific Organizations:
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- Japan Association for Earthquake Engineering (JAEE)

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Selected Publications:
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Academic Societies & Scientific Organizations:
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Academic Societies & Scientific Organizations:
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Academic Societies & Scientific Organizations:
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