Crustal Deformation Detection Capability Associated With a Fault Slip on the Interplate Boundary in the Gnss-a Seafloor Geodetic Observation Array (SGO-A), Provided By Japan Coast Guard

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Crustal deformation detection capability associated with a fault slip on the interplate boundary in the GNSS-A seafloor geodetic observation array (SGO-A), provided by Japan Coast Guard

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Abstract (327/350)

The GNSS-A technique is an observation method that can detect seafloor crustal deformations with centimeter level accuracy. The GNSS-A seafloor geodetic observation array operated by the Japan Coast Guard, called SGO-A, has been constructed near the Japan Islands along the Nankai Trough and the Japan Trench. This observation array has detected several earthquakes' displacements and episodic slow crustal deformation. To compare the detection results of SGO-

A with other observation networks and expand the SGO-A distribution, it is necessary to correctly understand its detection capability. In this paper, the capabilities of current GNSS-A (frequency: $f = 4\text{--}6$ times/year, position accuracy: σ (standard deviation) = 1.5 cm) to detect a crustal deformation rate only, an event only, and crustal deformation rate and event together were arranged by numerical simulations. Results suggested the following features: when it is known that there is no event, the 95% confidence level (CL) for the estimation of crustal deformation rate with 4-year observation is about 0.5–0.8 cm/year; when the deformation rate is known, a signal of about 3.0 cm can be detected by observations of about 4 times before and after the event. When the deformation rate and the event are detected together, to keep the false positive low (about 0.05), the false negative becomes high (about 0.2–0.7 for detecting a signal of 4.5–6.0 cm). The determined rate and event variations are approximately 1.8 cm/year (95%CL) and 1.5 cm (standard deviation), respectively. We also examined the detection capability for higher frequency and accuracy, to examine how the detection capability improves by technological advancements in the future. Additionally, we calculated the spatial range of event detectability using the determined values of detection sensitivity. Each seafloor site can detect a slip event larger than 0.1 m scale within about 50 km radius. A subseafloor slip event smaller than about 1 m at the distance of 100 km or more from the land can often be detected only on the seafloor observation array.

Keywords

GNSS-A, Seafloor geodetic observation, Earthquake detection limit, SSE detection limit

1 Introduction

A subduction zone where a tectonic plate subducts beneath another plate frequently causes megathrust earthquakes. To prevent associated disasters, it is important to elucidate the physical mechanism involved in such earthquakes. Accurate monitoring of crustal activities related to the earthquake cycle, i.e., inter-, co-, and post-seismic processes, plays an essential role for this purpose. Because the cycle contains many types of geophysical phenomena with different time scales, many types of geodetic and seismological observations are conducted to monitor them (Table 1). These observations contribute to grasping the surface oscillations and crustal movements caused by subsurface geophysical phenomena.

Space geodetic observation technique such as the Global Navigation Satellite System (GNSS)

mainly contributes to the monitoring of long-term phenomena such as inter- and post-seismic processes and permanent displacement associated with co-seismic process. However, because most of the subducting plate boundaries, which are the focal regions of megathrust earthquakes, are located underneath the seafloor far away from the coast, it is difficult to monitor these phenomena accurately by terrestrial GNSS (e.g., Yoshioka and Matsuoka, 2013; Schmalzle et al., 2014).

GNSS-A (Global Navigation Satellite System–Acoustic ranging combination technique) is a new geodetic observation technique that grasps such subseafloor boundary processes on the seafloor by combining GNSS and underwater acoustic ranging (Asada and Yabuki, 2001; Fujita et al., 2006). Along the Japan Trench and the Nankai Trough, the GNSS-A seafloor geodetic observation array (SGO-A) has been deployed by the Japan Coast Guard. The SGO-A succeeded in detecting various geodetic phenomena at the seafloor, e.g., interplate coupling condition estimated from long-term crustal velocity (Yokota et al., 2016), transient motions due to slow slip events (Yokota and Ishikawa, 2020), co-seismic slips (Sato et al., 2011), and time-dependent post-seismic deformation (Watanabe et al., 2014; Watanabe et al., 2021).

Meanwhile, the present GNSS-A has a limited ability to detect signals of geodetic phenomena in terms of spatio-temporal resolution and positioning accuracy compared with the GNSS. The GNSS-A requires a sea surface platform to combine the GNSS positioning and acoustic ranging. While the GNSS has achieved continuous observation networks, the GNSS-A is limited to discontinuous campaign observation, because the present platform is mainly a manned vessel. The annual observation frequency of the GNSS-A operated by Japan Coast Guard is at least about 4 times per site (Ishikawa et al., 2020).

Generally, observation results include both systematic and random errors. The systematic errors are considered to be caused by environmental sources, such as an oceanographic disturbance. Although it is difficult to individually identify each error source, the error can be reduced by the sophistication of the underwater sound speed structure model (e.g., Yokota et al., 2019). Empirically, the observation uncertainty can be considered as Gaussian noise (Yokota et al., 2018). In the best cases, the standard deviation of the GNSS-A data is about 1.5 cm and 2.5 cm for the horizontal and vertical components, respectively, using the current analysis method (Watanabe et al., 2020). This is much worse than the daily coordinate data ($\sigma \leq 0.5$ cm) of terrestrial GNSS observation networks such as the GEONET (Nakagawa et al., 2009). Moreover, the low density of observation sites, i.e., the distance between the SGO-A sites is

about 100 km, while that of the GEONET is about 30 km, causes lower spatial resolution than the onshore area.

Due to these limitations, it is necessary to collect enough data through long-term observations to detect geodetic phenomena accurately by the GNSS-A. In addition, the magnitude of the phenomena must be large enough to be detected. In this paper, we examined the detection capability of the geodetic phenomena shown in Table 1 from sparse geodetic time series data using statistical test and numerical experiments. Additionally, we examined the ability to detect interplate boundary slip in the current SGO-A along the Nankai Trough and the Japan Trench.

2 Detection capability tests

Detection of the geophysical phenomena of seismic cycle as crustal deformation events from the geodetic time series can be broadly divided into four types, as shown in Table 1. Steady crustal deformation due to plate coupling or rigid block motions in the absence of events is simply detected as linear steady trends (gray line in Table 1). The trend is estimated by regression analysis (Fig. 1a). The effect of the amount and duration of the data on the estimation of the trend was discussed in subsection 2.1. Regular earthquake or cumulative change of SSE were detected as non-continuous step signal (yellow line in Table 1). The step is estimated by taking the difference between the average positions before and after the event (Fig. 1b). The effect of the amount of the data on the statistical test of the significance of the step was discussed in subsection 2.2. In the actual cases, the trend and the step are often estimated simultaneously (blue line in Table 1). Thus, in subsection 2.3, we discussed the methods for estimating these two values simultaneously and their uncertainties (Fig. 1c). Post-seismic deformations are detected as non-linear change that decreases with time (orange line in Table 1). To estimate the change, various models have been considered such as logarithmic or exponential. In this paper, although we do not consider non-linear change of time series due to the complexity of models, we discussed it supplementarily in subsection 2.1.

In this section, we examined the ability of sparse geodetic data to detect these phenomena using numerical pseudo datasets. In the following tests, we assumed that the time series data has a Gaussian noise with standard deviation of σ and no systematic errors.

2.1 Trend estimation

First, we assessed the uncertainty of trend estimation (Fig. 1a). The steady trend corresponds to

the crustal movement velocity caused by plate coupling or rigid block motion. To detect the heterogeneity of plate coupling in the focal region of the megathrust earthquake, it is necessary to estimate the velocity with an accuracy of less than 1 cm/year. Here, we assessed how much data are needed for this purpose.

The trend was estimated by linear regression with a linear function, $a + bt$. The unbiased variance of the trend b is represented as

$$\text{Var}(b) = \frac{\sigma^2}{\sum_i (t_i - \bar{t})^2},$$

where t_i is the time of i -th data, and $\bar{t}$ is the average of t_i .

Fig. 2a shows the 95 % confidence level (CL) of the trend normalized by σ with respect to the annual observation frequency (f). 95 %CL is calculated using Student's t-distribution function. Each color of the series represents the cases of observation period (T) of 1–5 years. In the case of $f \sim 4$ -6 times/year, which is equivalent to our current GNSS-A observation, at least 4 years of observation is required to achieve the accuracy of about 0.5σ /year. For example, with the present GNSS-A data of $\sigma = 1.5$ cm, the accuracy of approximately 0.75 cm/year is achieved by observing for 4 years. If daily observation ($f = 365$ times/year) is realized, an accuracy of less than 1 cm/year will be achieved by less than 1 year of observation.

To detect the heterogeneity of the crustal velocity field, the significance test of the differences of the trend among adjacent sites is necessary. This test is also effective to detect the temporal variation between two periods in the case of a non-linear trend such as post-seismic deformation. We conducted a statistical hypothesis test to examine if the null hypothesis that the trends of two time series are the same can be rejected at a significance level of 0.05. We tested 1,000 numerical experiments on two time series data with the same period, observation frequency, and noise level. Fig. 2b shows the smallest difference for which the null hypothesis is rejected at the 0.05 level.

2.2 Step detection without trend

When a seismic event occurs, a step-like signal appears in the time series. The step is detected from the difference between the average position before and after the event. In this subsection, we examined the effect of the amount of the data on the statistical test of the significance of the step. For simplicity, we assumed that there is no trend in the time series of our statistical tests. This means that either the trend has been removed by trend estimation, or the period of the data

is short enough to neglect the trend. Simultaneous estimation of both trend and step is discussed in the next subsection.

We considered the case of detecting a signal in a time series as shown in Fig. 1b and conducted a statistical test for the difference between the means value before and after the event. The significance of the event is judged based on whether the null hypothesis that the mean value before and after the event is equal is rejected or not. There are two types of errors in the statistical test. A type I error (false positive) α is the rejection of a true null hypothesis and a type II error (false negative) β is the non-rejection of a false null hypothesis. To detect an event accurately, these two types of errors need to be small. In the statistical test, we first fixed α , and then considered the condition to reduce β . The condition is determined by the amount of the data (sample size) and the magnitude of the event (effect size).

The statistical power γ is defined as

$$\gamma \equiv 1 - \beta = P(Z_1 \leq Z(\alpha/2) + \Delta\sqrt{n}) + P(Z_1 \geq Z(\alpha/2) - \Delta\sqrt{n}). \quad (1)$$

Parameters in the equations are defined as follows:

P : One-sided probability of Gaussian distribution

Z_1 : Test statistic

Z : Value in Gaussian distribution

n : Sample size

Δ : Effect size (Difference between the mean values of the two samples normalized by the standard deviation.)

α : Two-sided confidence level (false positive rate).

Fig. 3a shows the statistical power γ with respect to the effect size Δ for $\alpha = 0.05$. The statistical power increase with increasing sample size and effect size. If the threshold of γ is set to 0.8, sample size of 12 and 4 are required to detect events with size of 1σ and 2σ , respectively.

In the actual case, it is necessary to evaluate the detection as soon as possible. Fig. 3b shows γ when the sample size after event (S_2 in Fig. 1b) is set to 2. If the threshold of γ is set to 0.8, required sample size before the event are 12 and 4 to detect events with size of 2σ and 2.7σ , respectively. Fig. 3c shows the uncertainty of the detected step size with respect to the sample size obtained by the law of propagation of errors. The uncertainty decreases according to $1/\sqrt{n}$.

2.3 Step detection with trend

In the actual case, it is necessary to detect the event from a short time series, in which the trend

and the timing of the event are unknown. If the trend is assumed to be unchanged before and after the event, the time series is represented as a piece-wise line (Fig. 1c) as follows,

$$f(t) = (a_1 + bt)\theta(t_1 - t) + (a_2 + bt)\theta(t - t_2),$$

$$\theta(t) = \begin{cases} 1 & (t > 0) \\ 0 & (t < 0) \end{cases},$$

where t_1 and t_2 are the beginning and the ending time of the event, respectively. Because the estimation of t_1 and t_2 is a non-linear regression problem, we used the numerical estimation using grid search which is similar to the method proposed in Yokota and Ishikawa (2020). Once t_1 and t_2 are fixed, fitting a piece-wise line is a linear regression problem. We searched the best result which minimizes the c-AIC (Akaike, 1974; Sugiura, 1978), by varying t_1 every 0.1 year. The duration of the event ($t_2 - t_1$) is fixed to 1 year; the uncertainty of the estimation of duration is discussed later. The c-AIC is defined as follows:

$$\text{c-AIC} = m \ln(2\pi) + m \ln\left(\frac{RSS}{m}\right) + \frac{2mk}{m-k-1}, \quad (3)$$

where m , k , and RSS are the number of total data, number of model parameters, and the residual sum of squares, respectively. In addition, we calculated the c-AIC when fitting a straight line, which assume no events in the time series. If the c-AIC when fitting a piece-wise line is smaller than that of a straight line, the event has been detected statistically.

To examine the detection capability of this method, we examined the difference between the model estimated from pseudo data and the original model which is used to generate the pseudo data.

Based on the result of subsection 2.1, we used 6-year time series data for stable estimation of the trend, and the 1-year event was set in the center of the time series. We used pseudo data with various event size and sample size and examined in each case with 1,000 trials. Here, we changed the event size (D) from 0 to 8σ and the annual frequency (f) from 1–365 times/year.

First, we examined the detection probability of the event. Fig. 4a shows the rate of false positive of our method, when applying thresholds of 0, 5, and 10 for the $-\Delta\text{c-AIC}$. It shows the probability that the piece-wise line is incorrectly determined to be more significant than the straight line despite the absence of the event, i.e., $D = 0$. If the threshold is set to 0, the false detection rate becomes larger than 0.6–0.7, suggesting that this threshold cannot be used practically for detection of a step in a trend. The false detection rate can be improved by increasing the threshold; in the case where the threshold is set to 10, the false detection rate is

about less than 0.05, which can be used practically.

Figs. 4b-d shows the probability of false negative of our method. These figures show the probability that the piece-wise line is incorrectly determined to be less significant than the straight line, despite the existence of an event. It is improved by increasing annual frequency and event size. Contrary to the case of the false positive, the false negative rate deteriorates by increasing the threshold of $-\Delta c\text{-AIC}$. In the actual case, it is necessary to set appropriate thresholds according to the purpose, due to the trade-off relation between false positive and false negative. For example, accepting a high false negative rate will decrease the false positive rate due to the trade-off relation. However, a high false negative rate indicates that we are failing to detect many of the events that are actually occurring. Thus, an exceedingly high false negative rate has an adverse effect on earthquake disaster prevention, so it will be necessary to accept false positive to some degree. On the other hand, an exceedingly high false positive rate indicates that we are detecting events that are not actually occurring, which might lead to false findings for research of the physical earthquake process; thus, it is also necessary to reduce the false positive rate.

Next, we discuss the accuracy of trend and event determinations. Since the determination accuracy cannot be discussed for thresholds with high false positive rates, we evaluated the case of $-\Delta c\text{-AIC} > 10$ and $f = 2\text{--}365$ times/year. Fig. 5 shows the difference between the parameters of the estimated model (O) and the original model (C). Comparing to the former subsections where the trend and step are estimated independently (Figs. 2 and 3), the accuracy of trend and step estimation becomes worse when these parameters are estimated simultaneously (Figs. 5a-b). Fig. 5c shows the 90th percentile width, median, and average of O-C of occurrence times. These results suggest that the occurrence time can be determined approximately ± 0.5 years with a 90% probability in cases where the annual observation frequency is larger than 4 times/year and the event size is larger than 3σ .

The duration of the event was fixed to 1 year in this verification. The event duration is estimated from two unknown parameters, the occurrence time and the end time of the event. Therefore, the detection accuracy of the duration is always worse than that of the occurrence time.

2.4 Summary of detection capability

As concrete cases, we compared the cases of campaign GNSS-A and daily-GNSS (Table 2). The annual observation frequency (f) is set to 4–6 times/year. The standard deviation of

horizontal positioning (σ) is set to 1.5 cm. In the case of daily-GNSS, the standard deviation of positioning is better than 0.5 cm in the horizontal component (e.g., Nakagawa et al., 2009; Suito, 2016). From Table 2, we can conclude that daily-GNSS can detect all types of phenomena considered in this study accurately with less than one year of data.

On the other hand, GNSS-A needs longer observation period to detect the phenomena accurately. Because the crustal deformation due to the actual interplate coupling is in the order of centimeters, it is desirable to determine the crustal deformation rate with an accuracy of less than 1 cm/year (95%CL). According to Fig. 2a, GNSS-A can achieve this accuracy with 4-year observation. Differences between the deformation rate of observation sites or different time periods can be detected with an accuracy of 1.0–1.5 cm/year with 4-year observation according to Fig. 2b. For detection of a step-like event, a step with size of 3.0 cm can be detected by 1-year observation (4–6 times) before and after the event according to Fig. 3c. For simultaneous estimation of both the trend and the step, the threshold of $-\Delta c\text{-AIC}$ should be set to about 10 to avoid false detections. In this case, the false negative rate for a signal size of 4.5–6.0 cm is 0.2–0.7 by 6-year observation, according to Fig. 4d. The trend and event size are determined with accuracy of 1.8 cm/year (95%CL) and of 1.5 cm (standard deviation), respectively, according to Figs. 5a and 5b. For a signal of 4.5–6.0 cm, the occurrence time of the event is determined within about ± 0.5 years with 90% probability, according to Fig. 5c.

3 Slip detectability around the Japan trench and the Nankai trough

SGO-A has been deployed to monitor geophysical phenomena beneath the seafloor along the Japan Islands. Therefore, it is important to examine the scale of the phenomena that can be captured by SGO-A. Our results indicate that the detectability at the sea region, which was examined to be low when using only the terrestrial GNSS network (Suito, 2016), is improved by adding SGO-A.

3.1 Method

Here, we divided the plate boundary into 20 km square grids and gave a slip of 1 cm to 100 m for each grid. The dip and the strike angle of each grid follow the plate boundary model. The slip angle was fixed at 90 degree. The plate boundary model is based on Japan Integrated Velocity Structure Model (Koketsu et al., 2009; Koketsu et al., 2012). The amounts of

deformations on the surface are calculated using the Green's function (GF) of Okada (1992) which is calculated under the homogeneous elastic half-space condition. The GF was calculated considering the seafloor depth of each site. For seismological applications, it is convenient to express the scale of the event in terms of the moment magnitude M_w . However, M_w depends on many parameters, i.e., rigidity, amount of slip, and fault size. Although some scaling laws for slip and fault size have been proposed for regular earthquakes, it is not clear for SSEs. Therefore, we evaluated the slip amount instead of the moment magnitude. Note that a slip of 1 m is roughly equivalent to M_w 6.5.

3.2 Results

Based on the result of section 2, detection thresholds for a crustal deformation were set to 5 mm and 5 cm for the GEONET sites and the SGO-A sites, respectively. Fig. 6 shows the minimum slip in each plate boundary grid that can be detected by the current observation sites. Fig. 6a shows that a slip under 2 m cannot be detected in a broad subseafloor area in the case using only the terrestrial network. The result including the seafloor sites indicate improvement of the sensitivity; slips of about 0.1–1.0 m can be detected within a range of about 50 km around the seafloor sites (Fig. 6b). From these results, crustal deformations due to subseafloor slips of about 1 m or less (corresponds to M_w 6.5 or less) in a range of about 100 km or more away from the land area can be detected only on the seafloor observation array. When planning the future expansion of the observation array, it is effective to consider these results and to install sites in locations where the detection capability to detect smaller slip events can be improved. An array with higher spatial density will allow us to analyze the location and physical process of slip events more accurately.

4 Summary

We examined the signal and event detection capability of the current GNSS-A time series data using statistical method. We arranged the detection capability of crustal velocity, size and timing of seismic event in Table 2. In addition to the detection capability of the current low-frequency and low-accuracy time series data, we also examined the detection capability for higher frequency and accuracy, which may be realized in the future. By constructing a seafloor observation array with an interval of 50–100 km like in the Nankai Trough area, it is possible to detect slips larger than 0.1 m with the signal detection threshold of 5 cm. The result of this

study quantitatively demonstrates the effectiveness of the seafloor GNSS-A observation array for improving the detection capability of various geophysical phenomena due to the seismic cycle of megathrust earthquake.

Abbreviations

AIC, Akaike's Information Criterion; CL, confidence level; GEONET, GNSS Earth Observation NETwork system; GNSS, Global Navigation Satellite System; GNSS-A, GNSS-Acoustic combination system; GF, Green's function; SGO-A, seafloor geodetic observation array; SSE, slow slip event

Declarations

Availability of data and material

The dataset supporting the conclusions of this article is included within the article.

Competing interests

The authors declare that they have no competing interest.

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Authors' contributions

TI and YY proposed the topic and constructed the accuracy verification test method. TI, YN, and YY performed the accuracy verification test. SW, YN, and YY performed the spatial detection test. YY wrote a manuscript. All authors read and approved the final manuscript.

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Figure legends

Figure 1 (a) An example of time series used in the numerical test for subsection 2.1 in the case
of frequency (f) = 2 times/year. Blue, orange, and gray lines indicate a fitting line, $\pm 1\sigma$ ranges,
and the 95% confidence levels (CL) for the linear fitting, respectively. (b) An example of time
series used in the numerical test for subsection 2.2 in a regular earthquake case (upper) and an
SSE case (bottom). (c) An example of time series used in the numerical test for subsection 2.3.

Figure 2 (a) The 95%CL of detected trend with respect to the observation frequency. Each color

of the series indicates the cases where the observation periods are 1–5 year. (b) The smallest difference in the trends that can reject the null hypothesis that the trends are same, at a significance level of 0.05.

Figure 3 (a) Sample size (S) with respect to effect size (Δ) and statistical power (γ) when $\alpha = 0.05$. (b) One-side sample size S_1 (in Fig. 1b) with respect to Δ and γ when S_2 (in Fig. 1b) is 2 and $\alpha = 0.05$. (c) The standard deviation of O-C of normalized event size.

Figure 4 Statistical summaries for the signal detection probability. (a) False positive at each observation frequency, i.e., probability of the cases where an event is false detected in the no-event synthetic data. (b–d) False negative, i.e., probability of the cases where no or negative event is detected in the finite-event synthetic data; for the cases where the thresholds of $-\Delta c$ -AIC are 0, 5, and 10, respectively.

Figure 5 Statistical summaries for the determination accuracy. (a) The 95%CL of O-C of normalized rate determined when the threshold of $-\Delta c$ -AIC is 10. (b) The standard deviation of O-C of normalized event size determined when the threshold of $-\Delta c$ -AIC is 10. (c) Occurrence time determination accuracy: the 90th percentile, median, and average of O-C of occurrence time determined when the threshold of $-\Delta c$ -AIC is 10.

Figure 6 Detection limit map along the Nankai Trough and the Japan Trench; (a) a case using no seafloor site and (b) a case using seafloor sites with detection limit: 5 cm. White circles indicate seafloor and terrestrial geodetic observation sites used in each case.

Tables

Table 1 Signals related to the earthquake cycle.

Table 2 Summary of the signal detection and determination capabilities of GNSS-A and daily-GNSS in 2021.

Figures

Figure 1

(a) An example of time series used in the numerical test for subsection 2.1 in the case of frequency (f) = 2 times/year. Blue, orange, and gray lines indicate a fitting line, $\pm 1\sigma$ ranges, and the 95% confidence levels (CL) for the linear fitting, respectively. (b) An example of time series used in the numerical test for subsection 2.2 in a regular earthquake case (upper) and an SSE case (bottom). (c) An example of time series used in the numerical test for subsection 2.3.

Figure 2

(a) The 95%CL of detected trend with respect to the observation frequency. Each color of the series indicates the cases where the observation periods are 1–5 year. (b) The smallest difference in the trends that can reject the null hypothesis that the trends are same, at a significance level of 0.05.

Figure 3

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Statistical summaries for the signal detection probability. (a) False positive at each observation frequency, i.e., probability of the cases where an event is false detected in the no-event synthetic data. (b–d) False negative, i.e., probability of the cases where no or negative event is detected in the finite-event synthetic data; for the cases where the thresholds of $-\Delta c-AIC$ are 0, 5, and 10, respectively.

Figure 5

Statistical summaries for the determination accuracy. (a) The 95%CL of O-C of normalized rate determined when the threshold of $-\Delta c-AIC$ is 10. (b) The standard deviation of O-C of normalized event size determined when the threshold of $-\Delta c-AIC$ is 10. (c) Occurrence time determination accuracy: the 90th percentile, median, and average of O-C of occurrence time determined when the threshold of $-\Delta c-AIC$ is 10.

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Detection limit map along the Nankai Trough and the Japan Trench; (a) a case using no seafloor site and (b) a case using seafloor sites with detection limit: 5 cm. White circles indicate seafloor and terrestrial geodetic observation sites used in each case.

Supplementary Files

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- [table1v2.pdf](#)
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