*Journal of Global Positioning Systems (2025)*
*Vol. 21, Issue 1: 65-78*
*DOI:10.5081/jgps.21.1.65*



# Optimizing window and component selection in SSA for GNSS coordinate time series offset detection

Zhiwei Yang[1], Guangyu Xu[1,2,✉], Aiping Zhao[3], Xiaowei Xie[1]

1 School of Surveying and Geoinformation Engineering, East China University of Technology, Nanchang 330013, China

2 Key Laboratory of Mine Environmental Monitoring and Improving around Poyang Lake of Ministry of Natural Resources, East China University of Technology, Nanchang 330013, China

3 Jiangxi Earthquake Agency, Nanchang 330026, China

✉ The corresponding author: gyxu@ecut.edu.cn

**Abstract**: Addressing the challenge of extracting coseismic offset signals from GNSS coordinate time series using earthquake catalog information, this study introduces a method based on optimized window and component selection in Singular Spectrum Analysis (SSA). The proposed approach automatically selects relevant components for time series reconstruction according to the magnitude of eigenvalues and the contribution rate of each component, without relying on prior information or assumptions. This effectively overcomes the limitations associated with arbitrary decomposition and reconstruction of time series in conventional SSA. By subtracting the reconstructed series from the original data, a residual time series is obtained, from which reliable offset signals can be extracted as comprehensively as possible. Through simulation tests and an application to the March 9, 2011, Mw7.3 earthquake event in Japan, comparative experiments were conducted to evaluate different window lengths and varying numbers of reconstructed components. The results indicate that a window length of 365 days, combined with the selection of principal components whose cumulative contribution rate exceeds 95%, constitutes the most suitable strategy for detecting offset signals in GNSS residual time series.

**Keywords**: GNSS coordinate time series; offset signal; singular spectrum analysis; signal detection

## 1.Introduction

The long-term accumulated coordinate time series from Global Navigation Satellite System (GNSS) reference stations serve as a fundamental dataset for geodetic and geodynamic research (Tehranchi et al., 2021; Jiang et al., 2018). GNSS coordinate time series record linear site displacements resulting from plate motions and interseismic strain accumulation on active faults, in addition to offset events caused by volcanic, tectonic, or hydrologic process (King et al., 2007; He et al., 2017; Yang et al., 2023). These phenomena typically span several orders of magnitude in both spatial and temporal scales. The objective and reliable detection of offset signals is critical, as they contain valuable information on the rheological properties and stress state of near-surface faults, as well as of the Earth's crust and mantle. For long-term GNSS coordinate time series, the offsets may seriously affect the estimation of GNSS site velocity (Gazeaux et al., 2013). Therefore, detecting potential offset signals constitutes a key preprocessing step, while automated offset detection is particularly important for managing dense station arrays or large-scale GNSS networks. However, the detection of offset signals is



**Editor-In-Charge: Dr. Xiaolin Meng**

challenging for two reasons. First, the vast volume of data generated by modern geodetic networks renders visual inspection of time series for each site highly time-consuming. Second, the amplitude of these transients can be close to or even lower than the background noise inherent to geodetic time series (Walwer et al., 2016). For the detection of offsets, many researchers have conducted studies and proposed different solutions, though several limitations persist. For instance, Chen et al. (1990) proposed a random level-shift autoregressive moving average model to detect unknown offsets, but only large offsets could be detected. Williams (2003) proposed an offset detection algorithm using change detection, which can be used to detect small-amplitude offsets. Gazeaux et al. (2015) designed a joint segmentation program to simultaneously estimate the trend, seasonal signal, and offset of adjacent GNSS sites, and used spatial redundancy to detect possible offsets; however, this method is prone to over-segmentation. More recently, Khazraei et al. (2021) proposed a method to detect offsets using multivariate analysis, which enhances detection performance by utilizing an improved spline function algorithm. Yang et al. (2023) proposed a new method for automatically detecting coseismic offset signals in GPS coordinate time series without an additional earthquake catalog for reference. However, the focus of this method lies in the use and processing of GPS coordinate time series data. Yang et al. (2023) also developed a statistical method using Bayesian inference to jointly estimate break points, velocity change values, and their associated uncertainties in GNSS time series. But it struggles with small velocity changes, where time-correlated noise can lead to erroneous break point estimations.

Offset signals can arise from various sources, including equipment malfunction, human intervention, and geological events such as earthquakes and volcanic activity. This study primarily focuses on offset signals caused by earthquakes in GNSS coordinate time series. Singular Spectrum Analysis (SSA) is an advanced time series analysis technique that leverages both spatial and temporal correlations in geophysical data to extract empirical basis functions representing the dominant modes of spatiotemporal variability. This makes SSA particularly suitable for extracting geophysically relevant information from GNSS coordinate time series, including offset signals. In this work, we propose an offset detection method based on an optimized Singular Spectrum Analysis framework. The method employs the Interquartile Range (IQR) to eliminate outliers in the original time series. Before applying SSA, the data undergoes mean-standardization, which can reduce the complexity of SSA processing and improve its computational efficiency. Based on a comparative analysis of experimental results, the window length for the SSA procedure is set to 365 days. The number of components selected for reconstructing the time series is determined by their contribution rate. In this study, a 95% cumulative contribution rates threshold is adopted to mitigate subjectivity in the selection of principal components.

## 2.Methodology

### 2.1 GNSS coordinate time series model

The original GNSS coordinate time series comprises multiple components, such as site velocities, seismic deformations, seasonal variations (including annual and semiannual cycles), as well as unmodeled transient deformations and observational noise (Langbein, 2008; Fu & Freymueller, 2012; Tian & Shen, 2016). To facilitate the accurate detection of coseismic offsets in subsequent analyses, it is essential to establish a parametric model for the GNSS coordinate time series. Owing to the low temporal correlation between components across different epochs (Zhang, 1996), the GNSS coordinate components (ΔE, ΔN, ΔU) at epoch $t_i$ can be expressed by the following model (Nikolaidis, 2002):

$$y(t_i) = a + bt_i + \sum_{f=1}^{2}[c_f \sin(2\pi f t_i) + d_f \cos(2\pi f t_i)] + \sum_{j=1}^{n_g} g_i H(t_i - T_{g_i}) + \varepsilon \tag{1}$$

where $t_i$ represents the epoch starting at $t_0$ in years; $a$ represents the initial displacement value; $b$ represents the interseismic velocity; $c_f$ and $d_f$ represent the coefficients for the annual and semiannual cycle terms; and $g$ represents the coseismic offsets at the $Tg$ epoch, $\varepsilon$ is the observation error; and H represents the Heaviside step function (Nikolaidis, 2002):

$$H = \begin{cases} 0, & t_1 < T < 0 \\ 1, & t_1 - T \geq 0 \end{cases} \quad (2)$$

### 2.2 The formulation of Singular Spectrum Analysis

Singular Spectrum Analysis (SSA) is a principal component analysis-based technique whose core lies in the decomposition and reconstruction of signals. Window length L denotes the size of the sliding window configured when converting a one-dimensional time series into a high-dimensional lagged Hankel matrix, i.e., the number of original sequence elements included in each row of the matrix. It transforms the local correlation of the sequence into the structural information of the matrix, laying the foundation for subsequent Singular Value Decomposition (SVD), and its value directly impacts the ability to capture features of different scales in the sequence. The number of reconstructed components k refers to the first k components selected from the eigenvectors corresponding to the singular values derived from SVD for signal reconstruction. The selection of k determines the proportion of information retained in the reconstructed signal—the first k singular values usually correspond to the main components of the sequence, while the remaining components are mostly noise or minor fluctuations.

By assuming that the length of a window is L(L<N/2), a lagged matrix $\boldsymbol{X}$ of L×(N-L+1) dimension is constructed. Let $\boldsymbol{C}$ be the L×L autocovariance matrix of the lagged matrix X—which exhibits a structure similar to a Toeplitz matrix, characterized by constant diagonal elements. By performing eigenvalue decomposition on C, each eigenvalue corresponds to a component used for reconstructing the GNSS time series, where the number of components for reconstruction is denoted by k. Sorting the eigenvalues in descending order ensures that the components with a larger proportion of the signal in the time series occupy the front positions, and simultaneously solve for their corresponding eigenvectors. The sum of all reconstructed components constitutes the complete GNSS time series, with each individual component representing a distinct signal constituent. The objective of this study is to remove the components that account for a larger proportion of the signal from the time series, and to detect offset signals within the residual series formed by the retained components.

### 2.3 Detection of offsets

The selection of the window length during decomposition and the number of reconstruction components significantly influences the detection of offset signals. Currently, there is no established standard in the existing literature for determining these two parameters when applying singular spectrum analysis to GNSS coordinate time series, and they are often chosen subjectively. In this study, we experimentally evaluate four commonly used window lengths—365 days, 730 days, N/3, and N/2—along with reconstruction component numbers of 2 and 6, using data from multiple GNSS stations. It is found that a window length of 365 days and the minimum number of reconstruction components with a cumulative contribution rate of 95% for detecting offset signals in GNSS coordinate time series have the best effect. The overall process of the method is shown in Figure 1.

The complete GNSS coordinate time series, as expressed in formula (1), should incorporate velocity and periodic signals as comprehensively as possible in the reconstructed series derived from SSA, thereby improving the reliability of offset signal detection. Since the reconstructed time series contains main component signals such as velocity and period terms, the offset signal is retained in the residual time series. The number of retained signal components determines the completeness of the residual time series, which indirectly impacts the detection of offset signals. This study investigates the window length and the number of reconstruction components when SSA processes GNSS time series. The underlying rationale is that when SSA is applied to the coordinate time series, signals with stronger trends exhibit higher contribution rates, whereas random offset signals contribute minimally. Therefore, the main components extracted by SSA are signals with strong trends. In the residual time series obtained after subtracting the reconstruction of the main components, offset signals can be highlighted and made easier to detect and identify. The specific steps are as follows:

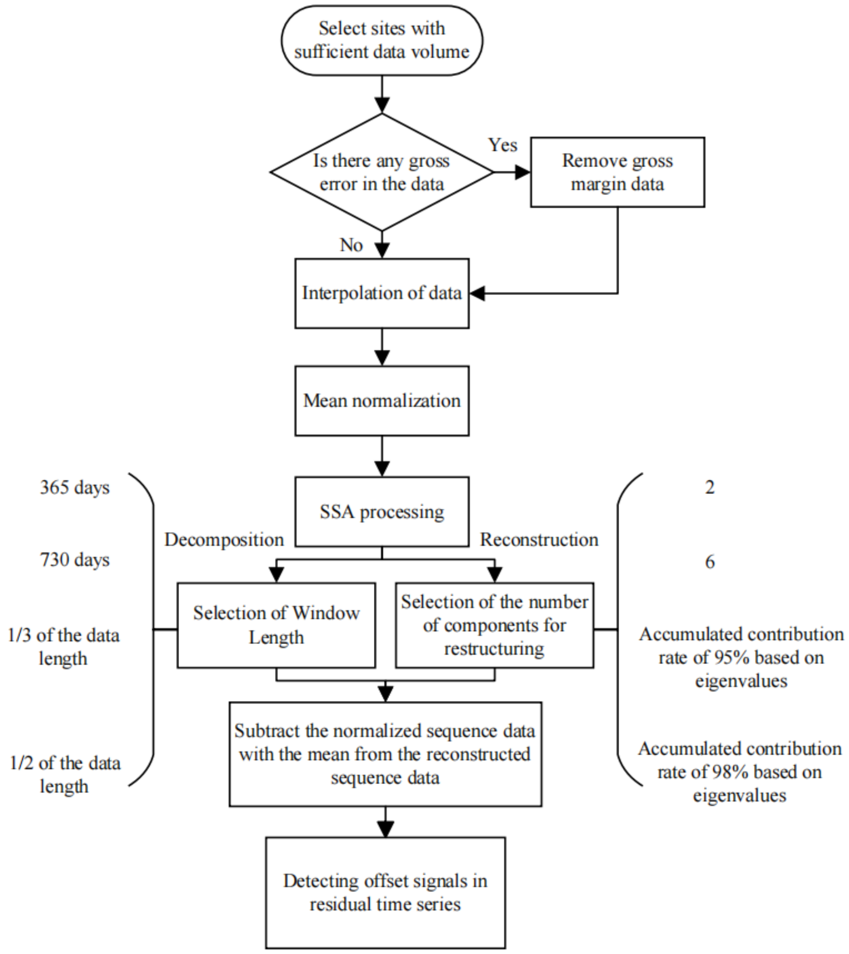


Fig.1 Algorithm flowchart

(1) Applying IQR on the site data in three directions to remove outliers, and then the data is de-meaning and normalized. The purpose of mean-standardization is to map the data to the range of 0~1, which not only retains the essential characteristics of the GNSS coordinate time series but also enhances computational efficiency and convenience.

(2) SSA is applied to the coordinate time series data processed in step 1. The procedure begins by constructing the lag matrix, followed by performing singular value decomposition on the autocovariance matrix derived from this lag matrix to extract each principal component series. Several components are automatically selected for reconstructing the coordinate time series based on the contribution ratio of the eigenvalues. After experimenting with different window lengths, the residual time series is obtained by subtracting the reconstructed time series from the time series standardized by the mean. Based on the principle of minimizing the root mean square error (RMSE), a window length of 365 days is selected for constructing the lag matrix in SSA. Following a comparison of different numbers of reconstructed components, the minimum number of components whose cumulative eigenvalue contribution ratio exceeds 95% is chosen as the number of principal components for reconstruction.

(3) The residual time series is obtained by subtracting

the SSA-reconstructed time series from the mean-standardized original data. Offset testing is then performed sequentially on each epoch of the residual series to determine the presence of offset signals. Simultaneously, the reconstructed GNSS coordinate time series from all sites are stacked to enhance the detection of potential offset signals. The detection criterion for an offset is met when the difference between the three-day averages at the start and end of the residual series exceeds twice the overall weighted average of the series.

(4) All identified offsets are recorded, and Steps 1 to 3 are repeated to determine whether any offset signals remain undetected. If no additional offsets are found, the detection process is terminated; otherwise, the procedure continues iteratively until no new offsets are identified.

## 3. Synthetic data experiment

To evaluate the feasibility of the proposed method, simulated GNSS coordinate time series were generated using data from 63 sites within a specific region of the Nevada Geodetic Laboratory GNSS network. The original coordinate time series from these sites were processed to extract long-term linear trends and seasonal components. Subsequently, the coseismic offset caused by earthquakes at these sites were simulated, and the simulated coseismic offset signals are combined with the linear trends and seasonal terms in the time series of the original GNSS coordinate data to construct a simulated GNSS coordinate time series. Then Gaussian noise was then introduced as observation error in the simulated data. Finally, the method proposed in this article is applied to analyze the simulated GNSS coordinate time series and identify the coseismic offset within it. Prior to implementing SSA, necessary preprocessing steps were performed on the data. The first step involved removing gross errors using the IQR method, which provides a robust approach for outlier detection. To enhance computational efficiency, mean-standardization was subsequently applied. This balances the features in all three directions of the site without changing the inherent distribution characteristics of the original data, providing an ideal data foundation for subsequent SSA.

When applying SSA to mean-standardized GNSS coordinate time series data, the selection of the window length L is a critical consideration. Studies have shown that the window length should not exceed half of the length of the time series, it is considered that the optimal decomposition can often be achieved when L is chosen as the median of N (Golyandina, 2010; Hassani et al., 2011). Some researchers also believe that in order to prevent the statistical error in the autocovariance estimation for the maximum lag window from exceeding the estimate itself, the window length should not exceed one-third of the length of the time series (Zheng and Liang, 2022). Some scholars chose the least common multiple of the known period 365 days as the window length when extracting the common mode error of the time series (Zhou et al., 2018). Considering these perspectives, this study mainly tested window lengths of 365, 730, N/3, N/2 as L values and selects the most appropriate L value through experiments. As shown in Figure 2, when conducting SSA on all sites in this experiment, the reconstruction results of L with the same but different values of k are compared. The results showed that when the window length was set to 365 days, the root mean square error of subtracting the reconstructed sequence from the original sequence reached its minimum. From Figure 2, it can be seen that at L=365 days, the residual time series RMSE in all directions are all smaller than other L values. Even at a few sites where the RMSE for L = 365 was not strictly the lowest, it remained comparable in magnitude to the minimum observed values When L=730, N/3, N/2, the window length was too large, resulting in a relatively coarse reconstructed time series, thus retaining a more obvious trend signal in the residual time series. For the detection of offset signals, it is advisable to minimize interference from other signals. Therefore, choosing L=365 is more suitable for detecting offset signals from residual time series.

In addition to L, the selection of the number k of SSA reconstructed time series also varies. Some studies use the first six principal components, while others use the first two. The method proposed in this paper selects key components to reconstruct the time series based on the relative size of eigenvalues and the cumulative contribution rate of each component. As shown in Figure 3, when comparing the impact of different reconstruction numbers k on the residual time series of MONT sites, it is found that selecting k with a cumulative contribution rate of reconstruction components exceeding 95% is more appropriate. When the first two principal components are selected, certain periodic signal components are clearly ignored during reconstruction, resulting in the offset signal in the residual time series of the site being masked by the periodic signal. When the first six components are chosen, a significant portion of the offset signals in the east and north directions residual time series of the site data are removed. With the selection threshold raised to a 98% cumulative contribution rate, the residual time series in the east and up directions retain excessively limited information. In fact, this selection method also led to information loss at other sites. Taking all factors into consideration, selecting components with a cumulative contribution rate exceeding 95% can make it easier to detect offset signals from residual time series.

In this experiment, the window length for SSA of the simulated data was set to 365. The number of reconstructed components in the singular spectrum analysis is determined based on the criterion that the cumulative contribution rate of signal components reached 95%. First, the coordinate time series in the three directions were mean-standardized, and then reconstructed using SSA. The difference between the two is used to obtain the residual time series, and then offset detection is performed in the residual time series; Figure 4 shows the residual time series of all sites in three directions after processing. The green solid line, light blue solid line and red solid line represent the residual time series for all sites in three directions, the detected offset signals are indicated by the two pink rectangular boxes. The coordinate time series from all sites were processed to obtain the residual time series, and then stack the residual time series obtained by processing the coordinate time series of all sites in different directions to detect their offset signals. As shown in Figure 5, the blue solid line represents the offset values obtained after processing in three directions. The results show that the coseismic offset signals of the simulated GNSS coordinate time series occurred at the epochs of 2019.71 and 2021.12.

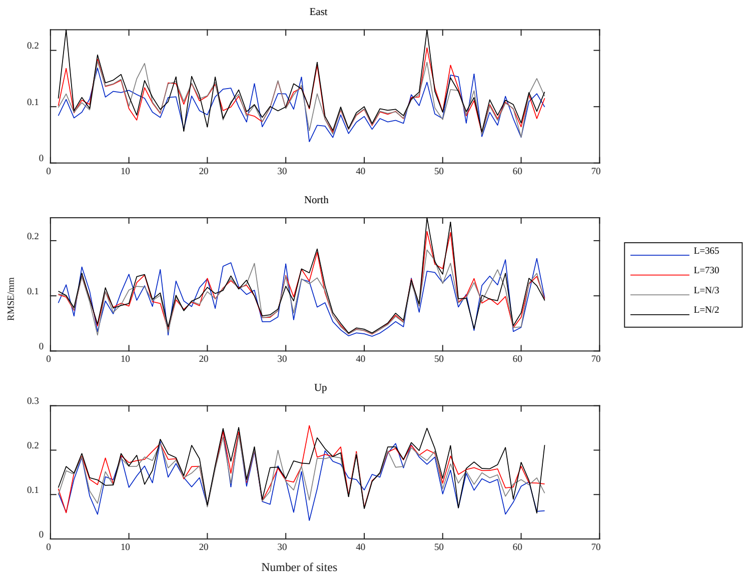


Fig.2 Comparison of RMSE of GPS time series after SSA with different window lengths across all sites in synthetic tests

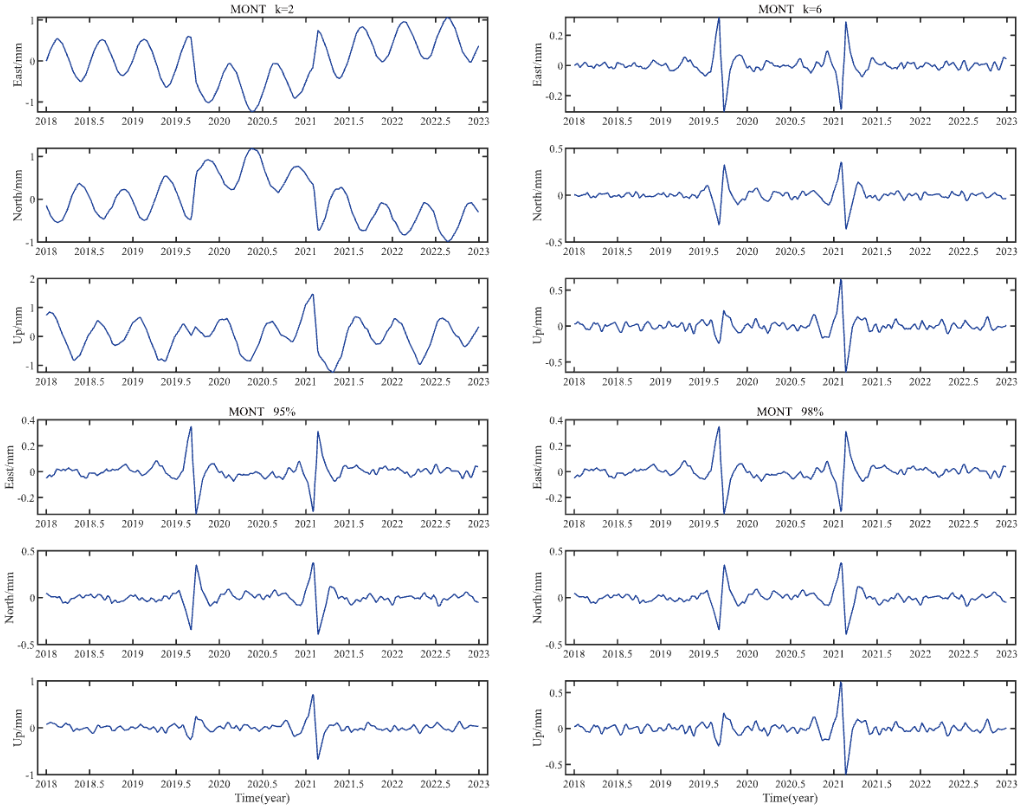


Fig.3 Result of SSA for MONT site with different numbers of reconstituted components

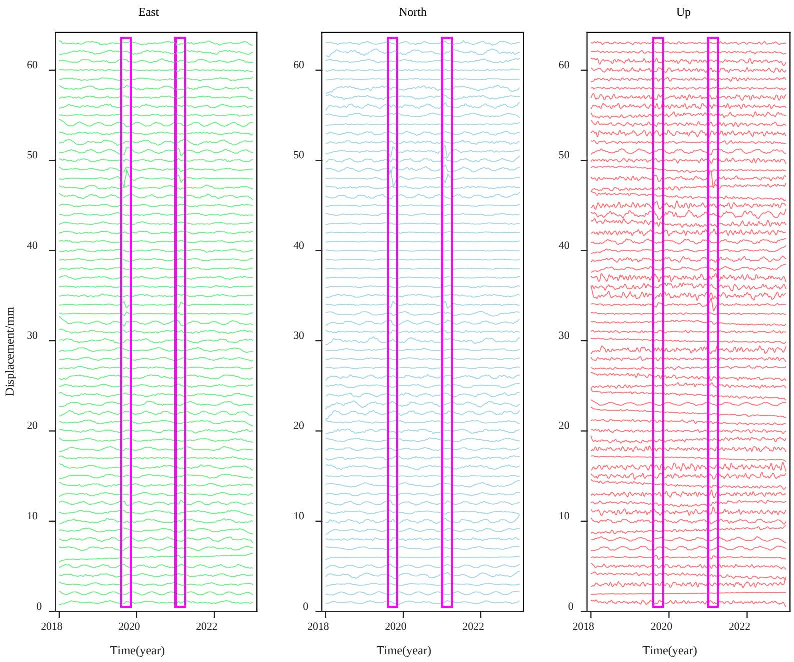


Fig.4 Residual time series after processing for all sites

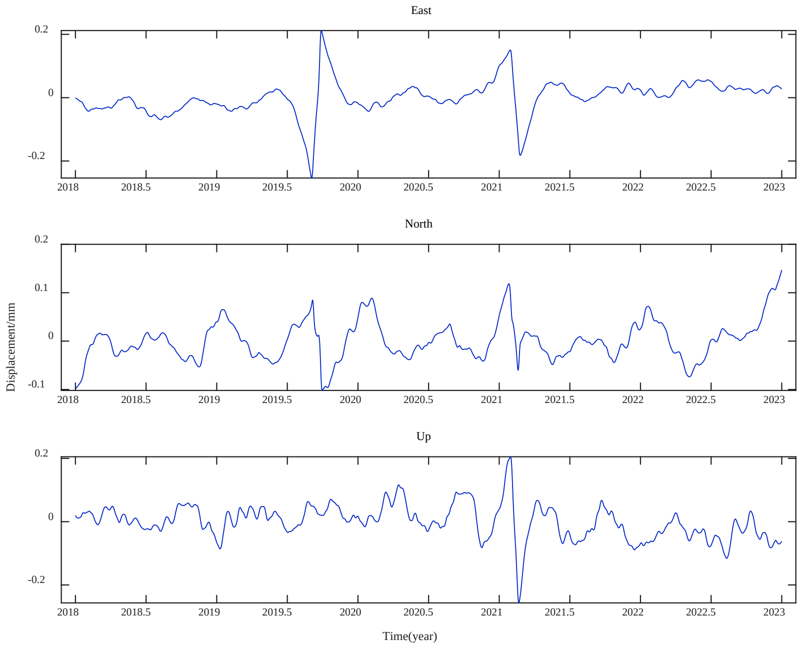


Fig.5 The overlay of residual time series after processing for all sites

## 4. Real data experiment

The premise of this experiment is that the time and location of the earthquake event are unknown, and offset signals are then detected in GNSS site data. This earthquake serves as a test case for the proposed method. A complete set of Japanese GNSS site coordinate time series data from Nevada Geodetic Laboratory was obtained, which consists of real-time records from 56 sites. Given the unknown nature of the seismic event, offset signals of varying magnitudes may be observed at individual sites; furthermore, due to the uncertain distance between each site and the epicenter, some sites may exhibit no detectable offset signals.

The spatial distribution of all sites used in this experiment is shown in Figure 6. The red triangles represent each site, with inter-site distances ranging from a minimum of 10.21 km to a maximum of 1,494.96 km. As can be seen from Figure 7, when only the window length is a variable, the unreconstructed time series clearly has a smaller RMSE at L = 365 compared with the reconstructed time series, which is better than the other three cases, Therefore, L=365 is most suitable for detecting offset signals in the residual time series. As shown in Figure 8, compares the impact of different numbers of reconstruction components k on the residual time series of J442 site. The experimental results show that selecting k values corresponding to a cumulative contribution rate of 95% or higher is more effective for offset signals detection.

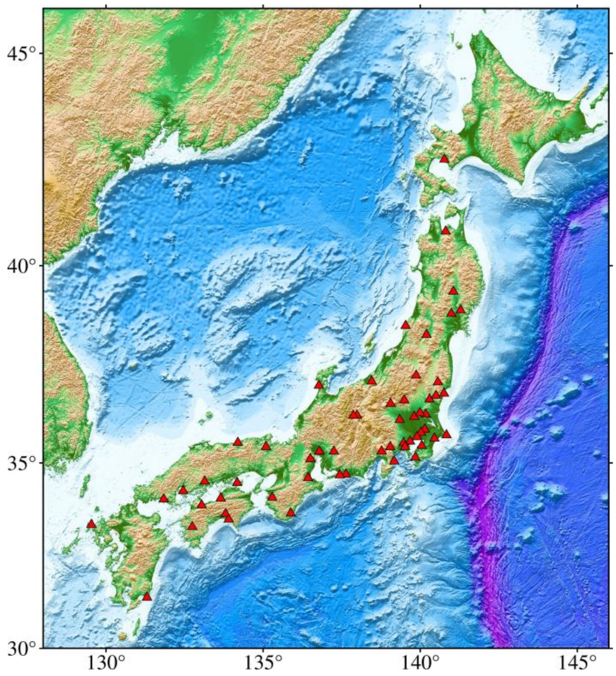


Fig.6 Locations of GNSS sites (red triangle) used in real data experiments

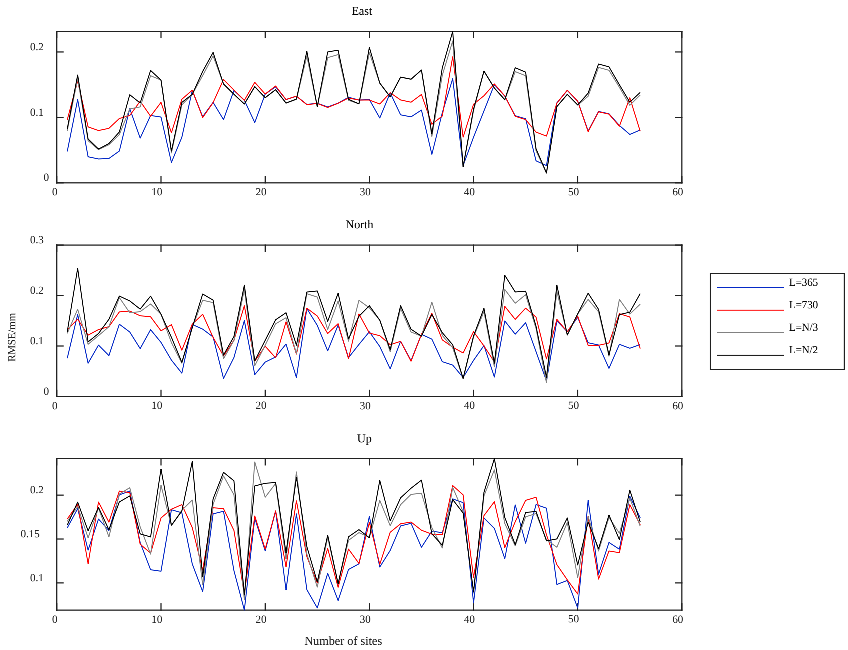


Fig.7 Comparison of RMSE of GPS time series after SSA with different window lengths across all sites in the earthquake case

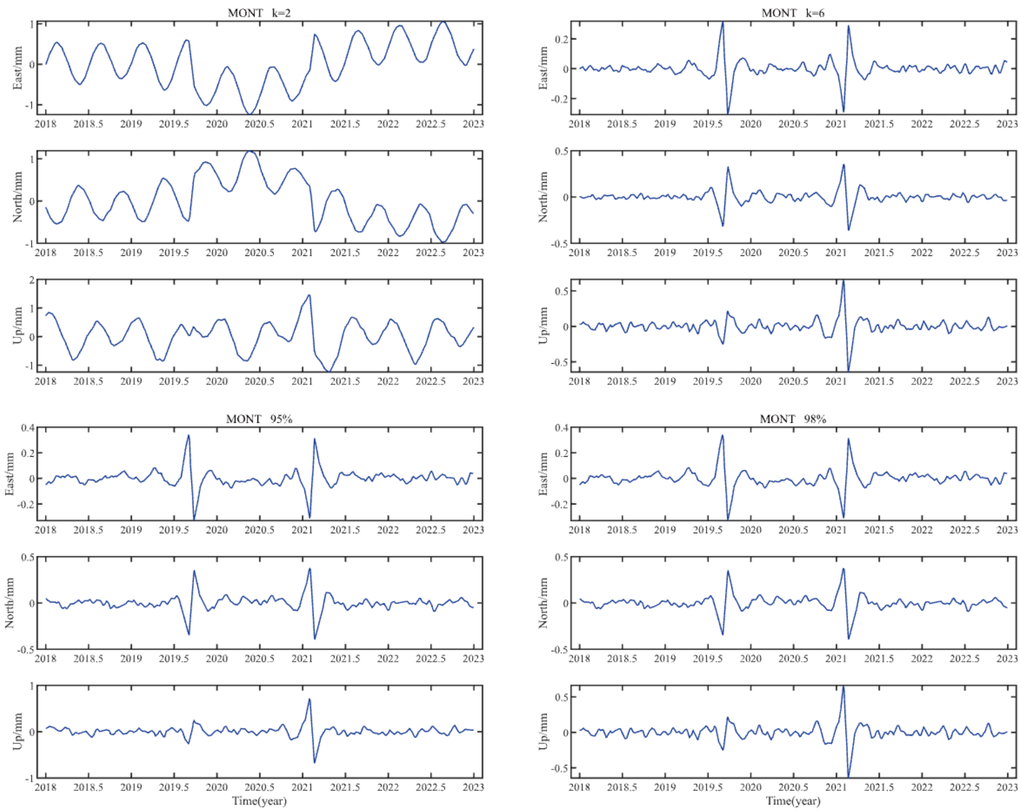


Fig.8 Result of SSA for J442 site with different numbers of reconstituted components

The window selected for SSA in this experiment is 365 days, and the number of reconstructed components k is chosen based on the principle of achieving a cumulative contribution rate of 95%. Firstly, mean-standardization was applied on the time series of site coordinates in three directions, and then use SSA to decompose and reconstruct the standardized sequence. By comparing the reconstructed results with the standardized data, the residual time series was derived. By using this method to process the coordinate data of all sites in various directions, the resulting residual time series are shown in Figure 9, which displays the characteristics of the processed results. As shown in Figure 10, the residual time series obtained by processing the coordinate time series of all sites in various directions are overlaid together to observe their offset variations. Through the proposed detection method, the occurrence of a coseismic offset signal in the GNSS coordinate time series is identified at epoch 2011.19.

Given that this study utilizes data from multiple sites, it is feasible to calculate both the offset magnitude at individual sites and the average offset across all sites. However, due to the varying distances between different sites and the epicenter, simply summing the offset values and dividing by the number of sites is clearly inappropriate. To address this, the present study designates the site with the largest offset magnitude among all sites as the "epicenter-like center" and assigns a weight to each site based on its distance from this center. The weighted offsets of all sites are then summed and averaged, so that the average offset quantity of all sites can be calculated. After detecting the occurrence of coseismic offset signals in 2011.19, the offset quantities of all sites are calculated as shown in Figure 11. From the graph, it can be seen that the 10th site has the largest offset size, reaching 3,055.7 mm in the east direction and 1413mm in the north direction, and it can be inferred that this site is G145 site. Using the G145 site as the "epicenter like center" and following Bransdon's geographically weighted regression approach (Brunsdon et al., 1998), sites closer to the epicenter like center have greater weights. According to the formula, the spatial weight function used to assign weights to each site in this article is the Gauss function. Assuming that site *n* is the epicenter like center and site *m* corresponds to the spatial weight, as shown in formula (3).

$$p_n(m) = \exp(-d_{n\_m} / a) \tag{3}$$

for $m = 1, 2, ..., M, n \leq M$.

In the formula, $d_{n\_m}$ represents the distance (in kilometers) between the epicenter-center and each site. The parameter $a$ is a non-negative attenuation factor, known as the bandwidth, which governs the functional relationship between weight and distance. A larger bandwidth results in a slower decay of weight with increasing distance, whereas a smaller bandwidth leads to a more rapid decay. In this study, the value of $a$ is set as the average distance between all sites and the epicenter-like center. The calculated average distance from all sites to site G145 is 498.44 km; thus, a is assigned a value of 498.44. The weights of all sites obtained in this experiment are shown in Table 1. Based on the weights and offset values of each site, the average offset magnitude in the east direction across all sites in 2011.19 is 304.19mm, and the average offset size in the north direction is 87.76mm.

## 5. Results

The method proposed in this article considers both window length and the number of reconstruction components for detecting GNSS coordinate time series offset signals, and has achieved good detection performance in both simulation experiments and actual seismic cases. Based on the above two experiments, it can be found that when using SSA to detect coseismic offset signals in GNSS coordinate time series, the detection performance is most significant when the window length is selected as 365 days, and the optimal number of reconstructed components is selected based on the principle of cumulative eigenvalue contribution threshold of 95%. This method succesfully detected offset signals in simulated GNSS coordinate time series data in 2019.71 and 2021.12, with detected offset magnitudes ranging from millimeter to centimeter. In real experiments, the coseismic offset signal is detected in 2011.19, with a maximum offset magnitude of 3,055.7 mm in the east direction and 1413mm in the north direction; The average offset size in the east direction is 304.19mm, and the average offset size in the north direction is 87.76mm.

According to relevant information, on March 9, 2011, a 7.3-magnitude earthquake occurred near the east coast of Honshu, Japan, with its epicenter located near the plate boundary of the subduction zone between the Pacific Plate and the North American Plate (38.435°N, 142.842°E), with a depth of approximately 32 kilometers. The experimental results are consistent with the information obtained from the references.

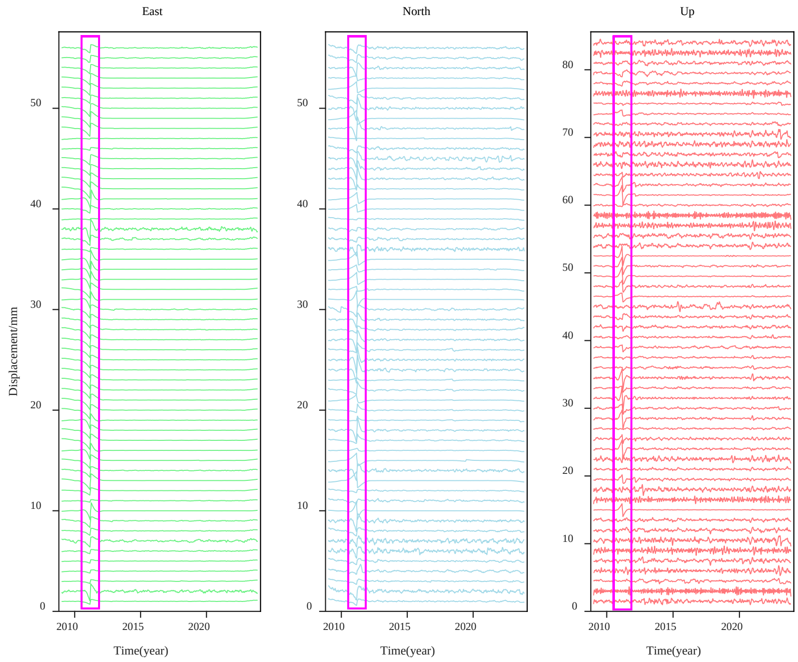


Fig.9 Residual time series after processing for all sites

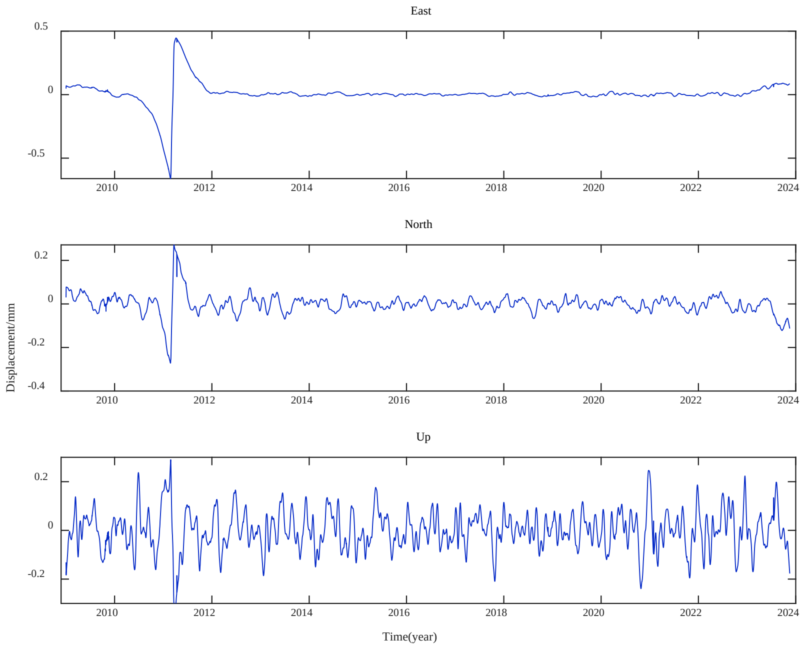


Fig.10 The overlay of residual time series after processing for all sites

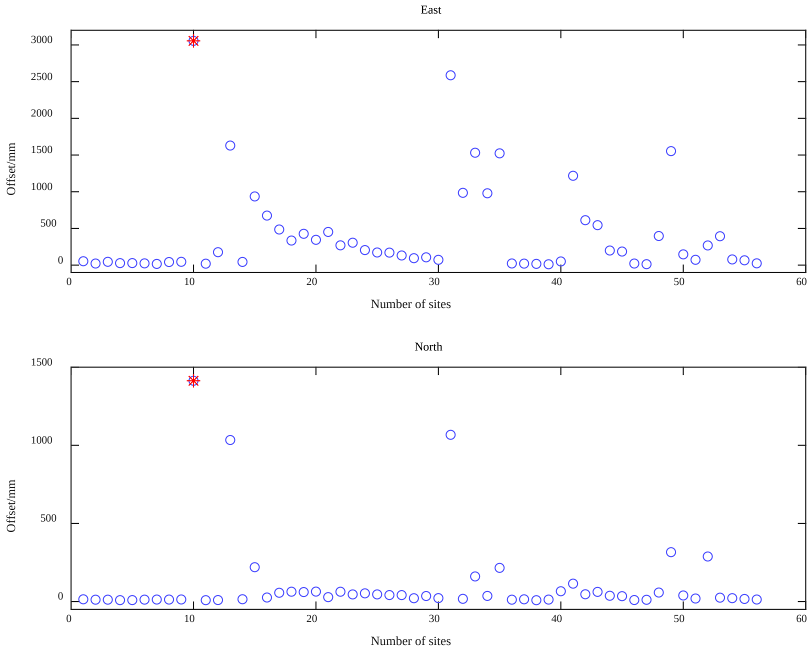


Fig.11 Offset values for all sites

Table 1. List of weights for all site in the real experiment

| Site | Weight | Site | Weight | Site | Weight | Site | Weight |
|---|---|---|---|---|---|---|---|
| G001 | 0.2235 | G162 | 0.6730 | I072 | 0.4335 | J589 | 0.5715 |
| G012 | 0.2257 | I002 | 0.5954 | I105 | 0.4438 | J608 | 0.4215 |
| G014 | 0.1871 | I003 | 0.5660 | J173 | 0.9352 | J609 | 0.4123 |
| G033 | 0.1419 | I005 | 0.5252 | J209 | 0.6549 | J666 | 0.1214 |
| G044 | 0.1747 | I014 | 0.5592 | J211 | 0.7027 | J716 | 0.0796 |
| G047 | 0.1338 | I018 | 0.5454 | J213 | 0.6393 | J752 | 0.5269 |
| G049 | 0.1211 | I022 | 0.5713 | J214 | 0.6818 | J803 | 0.7681 |
| G129 | 0.2724 | I023 | 0.5296 | J428 | 0.1528 | J804 | 0.4887 |
| G136 | 0.3393 | I024 | 0.5522 | J439 | 0.1530 | J822 | 0.3099 |
| G145 | 1 | I026 | 0.5079 | J442 | 0.1542 | J844 | 0.7037 |
| G147 | 0.1055 | I028 | 0.4926 | J459 | 0.0631 | J964 | 0.4962 |
| G158 | 0.3479 | I030 | 0.5188 | J525 | 0.5256 | J994 | 0.3377 |
| G159 | 0.9095 | I031 | 0.4592 | J581 | 0.6618 | Z101 | 0.2887 |
| G161 | 0.3278 | I039 | 0.4854 | J582 | 0.5865 | Z109 | 0.2106 |

## 6. Discussion and conclusions

When selecting the optimal window length for SSA processing GNSS coordinate time series, this study considered only four commonly used values: 365 days, 730 days, and 1/3 and 1/2 of the total series length. Among these four window lengths, 365 days is chosen as the window length for simulation experiments and real experiments. For other GNSS coordinate time series, however, the optimal window length may not necessarily be 365 days, and it should be determined adaptively as the sequence data is recorded over time. The 95% threshold adopted in this article is based solely on the experimental data used here, and the contribution percentage selected may vary for time series data with different characteristics. Through the experiments in this article, it can be concluded that the number of reconstructed components should not be directly determined, but should be selected based on the contribution rate of eigenvalues. Furthermore, the window length and the number of reconstructed components in SSA are not independent, but are interrelated. The contribution rates of all eigenvalues will vary with the window length, and the number of selected reconstructions will also change accordingly. Appropriate selection of both the window length and the number of components enables more reliable detection of coseismic offset signals in GNSS coordinate time series. The data adaptation characteristics of this method make it have a simple and concise representation, which is achieved without any prior assumptions regarding noise randomness or underlying physical processes. Nevertheless, it remains necessary to perform visual inspections of the data as an additional verification step.

The effectiveness of this method in detecting offset signals is directly related to the strength of seismic signals received by GNSS sites. Generally, larger-magnitude earthquakes yield more accurate and reliable offset detection results. Furthermore, the current study applies SSA to individual sites independently, without considering spatial relationships among stations. In reality, seismic deformation and offsets caused by fault rupture exhibit inherent spatial correlation. Incorporating such spatial dependencies could potentially mitigate interference from other external factors and yield more physically consistent offset detection. Exploiting this spatial correlation represents an important direction for future research. The optimizing window and component selection in SSA has been experimentally demonstrated to be both feasible and accurate for GNSS coordinate time series coseismic offset detection.

## References:


[1] Brunsdon C, Fotheringham S, Charlton M. Geographically weighted regression[J]. Journal of the Royal Statistical Society: Series D (The Statistician), 1998, 47(3): 431-443.

[2] Chen C, Tiao G C. (1990): Random level-shift time series models, ARIMA approximations, and level-shift detection. Journal of Business & Economic Statistics, 8(1), 83-97.

[3] Fu, Y., & Freymueller, J. T. (2012): Seasonal and long-term vertical deformation in the Nepal Himalaya constrained by GPS and GRACE measurements. Journal of Geophysical Research: Solid Earth, 117(B3).

[4] Gazeaux J, Lebarbier E, et al. (2015): Joint segmentation of multiple GPS coordinate series. Journal de la Société Française de Statistique, 156(4), 163-179.

[5] Gazeaux J, Williams S, et al. (2013): Detecting offsets in GPS time series: First results from the detection of offsets in GPS experiment. Journal of Geophysical Research: Solid Earth, 118(5), 2397-2407.

[6] Golyandina N. (2010): On the choice of parameters in singular spectrum analysis and related subspace-based methods. Statistics and Its Interface, 3(3), 259-279.

[7] Hassani H ,Mahmoudvand R ,Zokaei M. (2011): Separability and window length in singular spectrum analysis.Comptes rendus - Mathématique, 349(17-18), 987-990.

[8] He, X., Montillet, J. P., et al. (2017): Review of current GPS methodologies for producing

accurate time series and their error sources. Journal of Geodynamics, 106, 12–29.

[9] Jiang Weiping, Wang Kaihua, et al (2018): Prospect and theory of GNSS coordinate time series analysis. Geomatics and Information Science of Wuhan University, 2018, 43(12): 2112-2123 [In Chinese].

[10] Khazraei S M, Amiri-Simkooei A R. (2021): Improving offset detection algorithm of GNSS position time-series using spline function theory. Geophysical Journal International, 224(1), 257-270.

[11] King N E, Argus D, et al. (2007): Space geodetic observation of expansion of the San Gabriel Valley, California, aquifer system, during heavy rainfall in winter 2004–2005. Journal of Geophysical Research: Solid Earth, 112(B3).

[12] Langbein, J. (2008). Noise in GPS displacement measurements from Southern California and Southern Nevada. Journal of Geophysical Research: Solid Earth, 113(B5)

[13] Nikolaidis, R. (2002). Observation of geodetic and seismic deformation with the Global Positioning System. University of California, San Diego.

[14] Tehranchi, R., Moghtased-Azar, K., & Safari, A. (2021): Fast approximation algorithm to noise components estimation in long-term GPS coordinate time series. Journal of Geodesy, 95(2).

[15] Tian, Y. F., & Shen, Z. K. (2016): Extracting the regional common-mode component of GPS station position time series from dense continuous network. Journal of Geophysical Research: Solid Earth, 121(2), 1080-1096.

[16] Walwer D, Calais E, Ghil M. (2016): Data-adaptive detection of transient deformation in geodetic networks. Journal of Geophysical Research: Solid Earth, 121(3), 2129-2152.

[17] Williams S D P. (2003): The effect of coloured noise on the uncertainties of rates estimated from geodetic time series. Journal of Geodesy, 76, 483-494.

[18] Yang, Y., Sigmundsson, F., & Geirsson, H. (2023): Joint Bayesian Modeling of Velocity Break Points, Noise Characteristics, and Their Uncertainties in GNSS Time Series: Far-Field Velocity Anomalies Concurrent With Magmatic Activity in Iceland. Geophysical Research Letters, 50(14).

[19] Yang Z, Xu G, Zhang T, et al (2023): A new method for coseismic offset detection from GPS coordinate time series[J]. Geodesy and Geodynamics, 2023, 14(6): 551-558.

[20] Zhang, J. (1996): Continuous GPS measurements of crustal deformation in southern California. University of California, San Diego.

[21] Zheng WY, Liang JL. (2022): Singular spectrum analysis of Urban CORS station time series. Geomatics & Spatial Information Technology, 45(08), 126-129 [In Chinese].

[22] Zhou M S, Guo J Y, et al. (2018). Extraction of common mode errors of GNSS coordinate at time series based on multichannel singular spectrum analysis. Chinese J.Geophys, 61(11), 4383-4395 [In Chinese].

## Authors

**Zhiwei Yang** is a graduate student at East China University of Technology. He mainly engages in GPS coordinate time series analysis and transient deformation detection. Currently studying Geophysics at China University of Geosciences (Wuhan). 2168429792@qq.com

**Guangyu Xu** is a teacher at East China University of Technology, he main research fields include GNSS and InSAR data processing and error analysis, joint inversion of multi-source geodetic data, and seismic cycle deformation modeling.

**Aiping Zhao** is a senior engineer, currently works at the Jiangxi Earthquake Agency, he mainly engaged in seismic precursor analysis. E-mail: zhaoaiping8000@sina.com

**Xiaowei Xie** is a teacher at East China University of Technology, he main research fields include UAV sensor integration, GIS system development, and GRACE data processing. E-mail: xwxie@ecut.edu.cn