

Article

The Sequential Joint-Scatterer InSAR for Sentinel-1 Long-Term Deformation Estimation

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Highlights

What are the main findings?

- The sequential-based JS-InSAR framework is proposed to solve the problem of large computation burden and temporal decorrelation in the long time series InSAR analysis with DS processing.
- The long-term deformation results in Tangshan with high precision and more details have revealed the decreasing trend in subsidence rate, and have shown strong relationship between subsidence pattern and groundwater level.

What are the implications of the main findings?

- The sequential estimator with appropriate grouping method has greatly improved the processing efficiency of DS without significant accuracy loss.
- The spatial-temporal deformation trend in Tangshan has proven the effectiveness of the groundwater protection measures of the local government in recent years.

Abstract

Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR) techniques have received rapid advance in recent years, and the Multi-temporal InSAR (MT-InSAR) has been widely applied in various earth observations. Distributed scatterer (DS) InSAR is one of the most advanced MT-InSAR methods, and has overcome the limitation of the lack of enough measurement points in the low coherent regions for traditional methods. While the Joint-Scatterer InSAR (JS-InSAR) is the extension of DS InSAR method, which exploited the overall information of Joint Scatterers to carry out DS identification and phase optimization. And it can avoid the inaccuracy caused by the offset errors between scatterers in complex terrain areas. However, the intensive computation and low efficiency have severely restricted the application of JS-InSAR, especially when dealing with massive and long historical SAR images. As the sequential estimator has proven to successfully improve the efficiency of MT-InSAR and obtain near-time deformation time series, in this work, we proposed the sequential-based JS-InSAR (S-JSInSAR) method with flexible batches. This method has adaptively divided large single look complex (SLC) stack into different batches with flexible number and certain overlaps. Then, the JS-InSAR processing



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is performed on each batch, respectively, and these estimated results are integrated into the final deformation time series based on the connection mode. Thus, S-JSInSAR can efficiently process large InSAR dataset, and mitigate the decorrelation effect caused by long temporal baselines. To demonstrate the effectiveness of the S-JSInSAR, a multi-year of 145 Sentinel-1 ascending SAR images in Tangshan, China, were collected to estimate the long deformation time series. And the results compared with other methods have shown the processing time has substantially decreased without the loss of deformation accuracy, and obtain deformation spatial distribution with more details in local regions, which have well validated the efficiency and reliability of the proposed method.

Keywords: InSAR; joint-scatterer InSAR; distributed scatterer; sequential estimation; sentinel-1

1. Introduction

The rapid advancement of Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR) techniques [1] have greatly facilitated the launch of various satellite SAR systems, and a large amount of SAR images with unprecedented spatial coverage and temporal revisit time have promoted the various earth observation applications, such as Sentinel-1 [2], Lutan-1 [3], NISAR [4], etc. Among them, Multi-temporal InSAR (MT-InSAR) methods [5,6], like Permanent Scatterers Interferometry (PSI) [7,8] and Small Baseline Subsets (SBAS) [9,10], conduct the time series analysis for the interferometric phase of stable scatterers in the SAR images, and have well overcome the shortcomings of the geometrical and temporal decorrelation in Differential Interferometry (DInSAR). Thus, MT-InSAR methods have been widely used in the deformation monitoring and geodetic applications in the past few decades, including city subsidence [11–13] and landslide disaster [14–17], thanks to its non-contact, large-scale, and high-precision characteristics.

As traditional MT-InSAR methods mainly focus on the permanent scatterer (PS) or high coherent scatterer, they have been severely restricted in the complicated natural terrain, such as bare land, vegetation, and mountainous areas, where there are only sparse and low reliable measurement points. In 2011, Ferreti [18] introduced the distributed scatterer (DS) and SqueeSAR method, which focus on the temporary coherent ground targets, such as bare land and sparse vegetation regions. It utilized the spatiotemporal adaptive filtering to improve the coherence of statistically homogeneous pixels (SHP), which can be detected by statistical analysis of the amplitude information. And then DS can be integrated with PS into traditional PSI processing flow. This method can provide better deformation results with higher density, more reliability and details in the low scattering regions. Thus, the DS-based methods have received wide attention and continuous improvement in recent years [19]. Goel [20] leveraged the Anderson–Darling (AD) test to improve the performance of SHP identification, which is more suitable for hypothetical test with few SAR images, compared to the Kolmogorov–Smirnov (KS) test in SqueeSAR. Jiang [21] proposed the FaSHPS to utilize the parametric test and confidence interval estimation method for SHP detection with high efficiency. Wang [22] combined deep learning and DS methods, and proposed the Distributed Scatterers Prediction Net (DSPN), which can automatically extract SHPs from SAR image stack with small computational load and processing time. In addition, Ansari [23] presented the maximum likelihood estimator of Interferometric phase (EMI) for DS processing, and it used the eigenvalue decomposition (EVD) to retrieve the optimal phase for covariance matrix. Liu [24] used nonlocal minimum mean square error (NL-MMSE) method for multi-master InSAR phase optimization. Vu [25] proposed the covariance fitting-based Phase Linking framework, and the majorization–minimization

(MM) and Riemannian optimization were used for efficient phase optimization. Bai [26] presented the LaMIE method for large-dimensional DS coherence matrix retrieval with Phase Linking. Joint-Scatterer InSAR (JS-InSAR) [27] is an extension of SqueeSAR method, and it constructed a Joint-Scatterer vector to replace the single scatterer with new patch similarity test and spatially adaptive filter, which can acquire more reliable and richer deformation information.

As Sentinel-1 and NISAR with global coverage and small revisit time have provided massive and abundant historical SAR dataset, the demand for long time series deformation monitoring application with the increasing number of SAR image has posed a great challenge to DS InSAR methods. To efficiently process InSAR big data, the sequential estimator has been introduced into MT-InSAR to achieve dynamic deformation monitoring. Wang [28] proposed a sequential SBAS InSAR framework based on the Kalman Filter and least-squares algorithm to stepwise update deformation results with every new image, without the need of reprocessing the whole dataset. But this method cannot directly apply in the DS InSAR due to the phase estimation in the DS preprocessing. Hajjar [29] extended the sequential estimator to Phase Linking method for dynamic phase optimization result update with maximum likelihood estimation, and a Block Coordinate Descent (BCD) algorithm was used to connect new arrival image and previous stack to avoid process all interferograms with whole time series. And, Hajjar [30] involved the sequential integration with covariance fitting Phase Linking method to efficiently carry out DS phase optimization. Ansari [31] introduced a novel sequential DS InSAR method through eigenvalue decomposition for covariance matrix, which can reduce redundancy and improve processing efficiency by dividing the dataset into small batches with equal size. Gu [32] exploited the similar sequential DS InSAR with image compression method to conduct long-term landslide monitoring over Jinsha River Basin, and has proven it outperforms SBAS and traditional DSI methods. Nevertheless, the EVD-based image compression for each DS has greatly increased computation burden. Ao et al. [33] proposed the Recursive Sequential Estimator with Flexible Batches (RSEFB) method, which segmented SAR dataset into flexible batches based on periodic characteristics of the coherence matrix without image compression. Then it performed Phase Linking on the independent batch, and the estimation results of subsets are integrated in the recursive sequential adjustment. However, the head-to-tail connection mode of RSEFB linked with single common SAR image are easily affected by estimation errors, which may lead to the inconsistency of final deformation results. In addition, RSEFB does not provide the details of the data segmentation method.

In this work, we propose the sequential JS-InSAR method (S-JSInSAR) to overcome the problems of intensive computation burden and long temporal baselines with large SAR stack in conventional JS-InSAR processing. Firstly, the statistically homogenous pixels (SHP) have been extracted with JS signal model for the overall dataset, which can guarantee the consistency of the DSs in different subsets. Next, the SLC stack is adaptively segmented into different batches with certain overlaps between adjacent batches. Then, in each batch, the JS-InSAR spatial adaptive filtering and phase optimization are carried out on the temporal subset, respectively, and followed by the PSI processing with the combination of PS and DS. Finally, the deformation results of all the subsets are integrated together to retrieve long deformation time series based on the connection mode. In the experiment, we utilized 145 Sentinel-1 ascending SAR images to validate the proposed method with time spanning from 22 January 2018 to 16 November 2023, in Tangshan, China. The results have been compared with PSI, JS-InSAR, and leveling measurements, which have well certified the reliability and accuracy of the S-JSInSAR method. In addition, the long-term displacement time series results with high density by S-JSInSAR have better revealed the deformation patterns of city subsidence in Tangshan.

2. Methods

The work flowchart of the proposed S-JSInSAR is shown in Figure 1. We assume a stack of SLC images are generated by $N + 1$ SAR images, which have been preprocessed by data conversion and Sentinel-1 image coregistration [34]. And the S-JSInSAR mainly consists of three processing steps. To begin with, the JS vector is first denoted with given parameter, and then the AD test with JS vector is utilized to identify SHP for the whole dataset. After the SHP candidates are obtained, the average coherence matrix of several randomly selected SHPs is calculated, and the large SLC stack is adaptively separated into multiple groups in different temporal subsets with overlaps based on the coherence distribution. Subsequently, the JS-InSAR preprocessing is performed on each subset, respectively, follow by the joint MT-InSAR processing with both DS and PS. Thus, the limited length of SLC stack can significantly improve the overall processing efficiency and reduce the temporal decorrelation. In the final step, the deformation parameters of different subsets are integrated into the final results based on the connection mode, and the certain overlaps between adjacent subsets ensure the consistency of the final deformation time series.

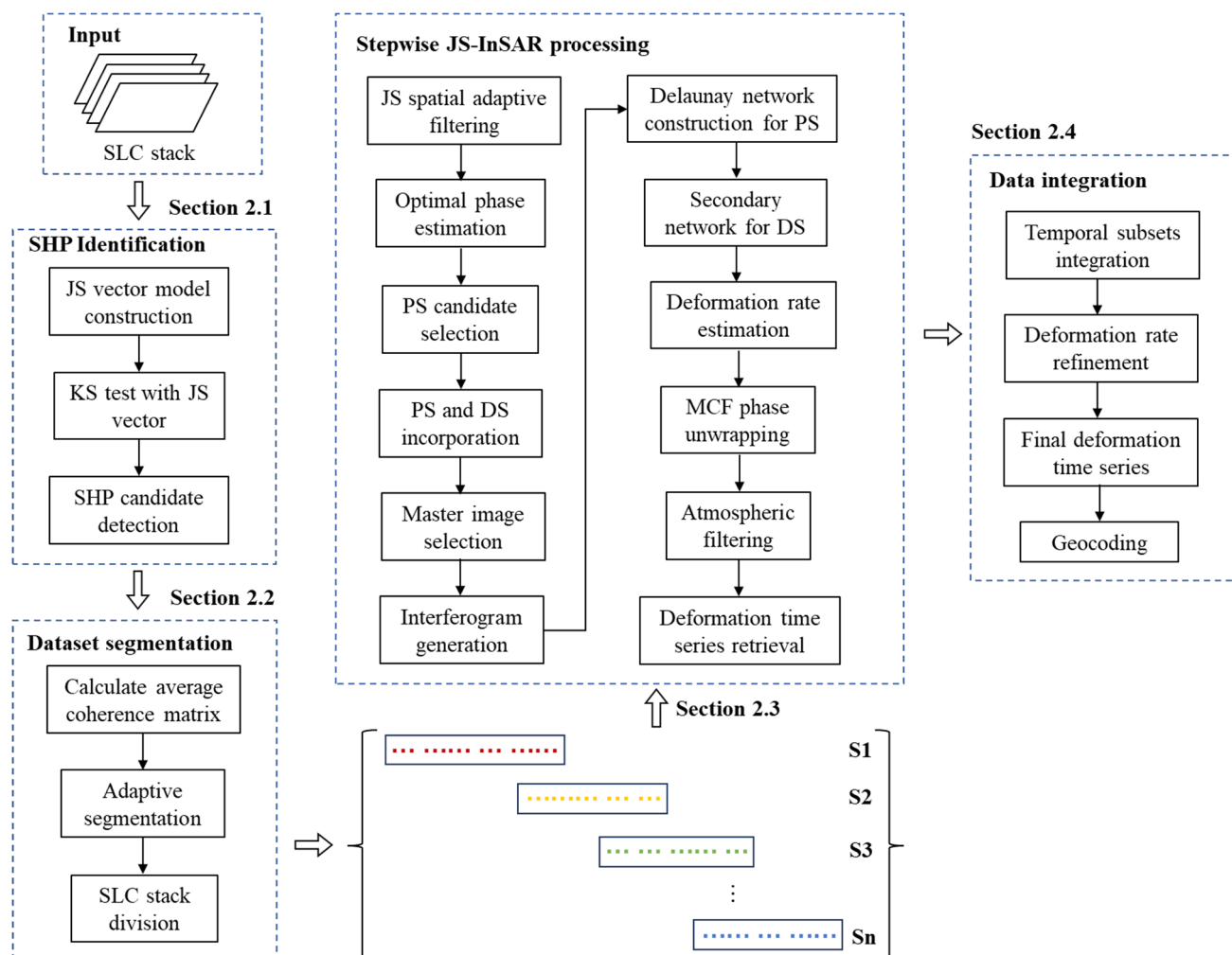


Figure 1. The workflow of the proposed S-JSInSAR method.

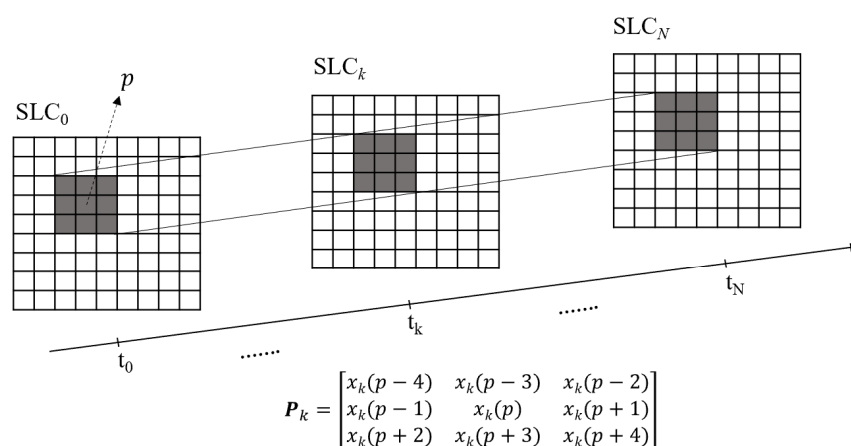
2.1. SHP Identification with JS Vector

The conventional DS InSAR can only deal with the single pixel in SHP identification and phase optimization, and they will be influenced by the local coregistration errors. While the JS-InSAR method mainly evaluates the pixel patch with similar scattering characteristics,

it can overcome the above shortcomings and improve the DS density. Considering $N + 1$ SLC images, the complex interferometric phase denotes $\mathbf{X} = [x_0, \dots, x_k, \dots, x_N]$. Given the sub-window size l_1 and l_2 in range and azimuth, respectively, and the pixel number of the sub-window $L = l_1 \times l_2$ (odd number). For certain pixel p in the SLC, the JS vector $\mathbf{UX}(p)$ can be given as follows:

$$\mathbf{UX}(p) = \{ \mathbf{X}_0(p)^T, \dots, \mathbf{X}_k(p)^T, \dots, \mathbf{X}_N(p)^T \} \quad (1)$$

where $\mathbf{X}_k(p)$ is the vector of pixel collection in the sub-window, $\mathbf{X}_k(p) = [x_k(p - (L - 1)/2), \dots, x_k(p), \dots, x_k(p + (L - 1)/2)]$. T denotes transpose operation, and the $\mathbf{UX}(p)$ can be seen as the spatial composite single pixel vector of DS InSAR. We denote the amplitude of the complex phase value $\mathbf{A} = [a_0, \dots, a_k, \dots, a_N]$, and the complex exponential of phase vector $\boldsymbol{\eta} = [e^{j\theta_0}, \dots, e^{j\theta_k}, \dots, e^{j\theta_N}]$. $\mathbf{a}_k$ and θ_k are also the vectors of pixel collection in the sub-window. Then, the JS vector can be expressed by the Hadamard multiplication of the two vectors $\mathbf{UX} = \mathbf{A} \odot \boldsymbol{\eta}$. To further illustrate the structure of JS vector, we displayed it in the temporal domain in Figure 2, where $\mathbf{P}$ is the pixel matrix and $\text{vec}()$ means vectorization of the matrix.



JS vector: $\{\text{vec}(\mathbf{P}_0)^T, \dots, \text{vec}(\mathbf{P}_k)^T, \dots, \text{vec}(\mathbf{P}_N)^T\}$

Figure 2. The JS vector with 3×3 sub-window for $N + 1$ SLC stack in S-JSInSAR.

The SHP identification is to search the scattering similarity of neighboring pixels around the center pixel, which can be conducted by the statistical behavior evaluation based on the probability distribution function (pdf). As JS vector has a multi-dimensional (temporal and spatial) structure, the traditional hypothesis test algorithms of DS InSAR cannot be directly applied in the S-JSInSAR. To accelerate the SHP identification with JS vector, the average amplitude of pixels in the sub-window is calculated in the spatial domain. Then, the average amplitude vector in the temporal domain is the same as the single pixel vector in DS InSAR, and the two-sample KS test is used to detect SHP.

For $N + 1$ SLC stack, the spatial average amplitude $\tilde{a}_k = \sum_{i=0}^{L-1} a_k(p + (L - 1)/2 - i)$, $k \in (0, N)$, and the average amplitude vector is $\tilde{\mathbf{A}} = [\tilde{a}_0, \dots, \tilde{a}_k, \dots, \tilde{a}_N]$. Assuming $\mathbf{B}$ is the sorted amplitude vector of $\tilde{\mathbf{A}}$ with the ascending order, and for certain center pixel p , its sorted vector can be given as $\mathbf{B}(p) = [b_0(p), \dots, b_k(p), \dots, b_N(p)]$. And the unbiased estimate $F_M(b)$ of pdf can be calculated by the cumulative distribution, which can be expressed by the following equations:

$$F_M(b) = \begin{cases} 0, & b < b_0 \\ \frac{k-1}{M}, & b_{k-1} \leq b < b_k \\ 1, & b > b_N \end{cases} \quad (2)$$

where b_{k-1} denotes the k th sorted amplitude value of $\mathbf{B}$, and M is the length of vector, and $M = N + 1$. For two pixel patch p_1 and p_2 , their cumulative distribution function can be denoted as $F_M^{p_1}(b)$ and $F_M^{p_2}(b)$. The maximum dissimilarity D_M in KS test of two pdf can be given as follows:

$$D_M = \sqrt{M/2} \times \sup_{b \in \mathbb{R}} |F_M^{p_1}(b) - F_M^{p_2}(b)| \quad (3)$$

Use the KS distribution function [35] fitting the maximum dissimilarity D_M . When the estimated value is located in the given confidence interval, the two pixel patches can be regarded as statistically homogenous distribution based on the KS hypothesis test. Where the confidence level of KS test is usually set to 0.05 based on the significance test. These calculations are performed on all the pixels of SLC image, and the SHP candidates of the SLC can be obtained, where the subsets are sharing the same SHP candidates.

2.2. Dataset Segmentation

As the computation of DS InSAR is closely related to the length of SLC stack, the growing number of time series SAR images has brought about heavy burden on the storage and computing resource. Moreover, with the temporal baseline lengthened, the scattering characteristics of DS cannot remain stable during the whole acquisition time, caused by the seasonal terrain variation. And the sequential estimator and dataset segmentation have proven to be the effective way for processing long time series Sentinel-1 SAR images. In the S-JSInSAR processing, the adaptive data grouping method based on the average covariance matrix has been used to efficiently segment the SLC stack into several subsets. For certain pixel patch with center pixel p , the covariance matrix with JS vector can be calculated by the following equations:

$$\mathbf{\Sigma}(p) = \mathbf{UX}(p) \cdot \mathbf{UX}(p)^H = \mathbf{\gamma}(p) \odot (\boldsymbol{\eta}(p) \cdot \boldsymbol{\eta}(p)^H) \quad (4)$$

where $\mathbf{\Sigma}(p)$ is the covariance matrix of pixel patch p . H denotes the Hermitian transpose operation. $\mathbf{\gamma}(p)$ is the coherence of the covariance matrix. The spatial average coherence of sub-window has replaced the coherence of single pixel in DS InSAR, which can improve the phase stability of DSs. Assuming Ω is the detected SHP candidates of pixel patch p , the estimated JS covariance matrix $\tilde{\mathbf{\Sigma}}(p)$ can be given as follows:

$$\tilde{\mathbf{\Sigma}}(p) = 1/|\Omega| \cdot \sum_{p \in \Omega} \mathbf{UX}(p) \cdot \mathbf{UX}(p)^H \quad (5)$$

$|\Omega|$ denotes the number of SHP for pixel patch p . To reduce the effect of noise, we random select several pixel patches from SLC image with intensity threshold above average intensity, and calculate the average JS covariance matrix of these patches. Afterwards, the average coherence matrix $\tilde{\boldsymbol{\psi}}$ is obtained by extracting the amplitude of this JS covariance matrix. The grouping strategy should strike the balance between processing efficiency and accuracy. The length of subset should be enough for JS phase optimization and PSI processing without large temporal baselines, and the overlap between subsets should be located in the relatively high coherent SLC images. To ensure enough numbers of SLC images for PSI processing and JS-InSAR preprocessing, we set the minimum number of subset is 20. And then search the high coherent SLC images in the coherence matrix $\tilde{\boldsymbol{\psi}}$. The overlaps are set in the range of 4 to 6 with the consideration of computation and calculation consistency, and the $N + 1$ SLC images $\mathbf{S}$ are divided into the temporal subsets $[\mathbf{S}_1, \mathbf{S}_2, \dots, \mathbf{S}_n]$, as shown in Figure 3.

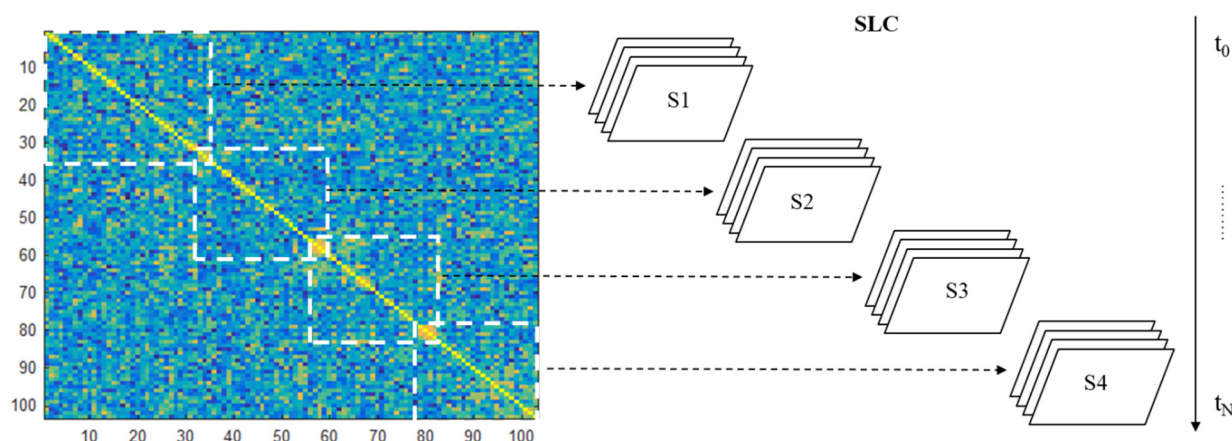


Figure 3. The dataset segmentation based on the coherence matrix.

2.3. Stepwise JS-InSAR Processing for Subsets

In each subset, the JS-InSAR adaptive filtering and phase optimization are conducted to retrieve the optimal phase time series. Then, the estimated phase of DSs is incorporated with PS, and the deformation parameters of the subset are obtained in the PSI processing. Through large dataset segmentation, the dimension of coherence matrix for each subset has been greatly decreased, which can significantly improve the JS-InSAR processing efficiency for the overall dataset.

Firstly, the interferogram filtering of DS is performed by JS spatial adaptive filtering, which can reduce the speckle noise of DSs. As the different DSs in the SHP Ω have slightly different similarity with center pixel patch p , their contributions in the filtering procedure should not be treated equally. The KS test is used as the weight function in the JS covariance matrix estimation. For certain JS vector p , the weight function and corresponding covariance matrix can be given as follows:

$$\tilde{\mathbf{Z}}(p) = 1 / \left(\sum_{p \in \Omega} w(p) \right) \cdot \sum_{p \in \Omega} w(p) \cdot \mathbf{UX}(p) \cdot \mathbf{UX}(p)^H \quad (6)$$

$$w(p) = e^{-\frac{D_M(p)}{C_\alpha}},$$

where $D_M(p)$ is the KS test value between the JS vector of center pixel and its SHP candidate, and C_α is the confidence level of KS test. The weight is calculated by the exponential value of the ratio between KS test and confidence level. The more similarity between two JS vectors, the calculated weight will be larger. After the JS spatial adaptive filtering, the DS phase estimation is processed to reduce the decorrelation of DSs. And, the optimal phase of DS can be obtained by maximum likelihood estimator (MLE) based on the following formula:

$$\hat{\theta}_{MLE} = \operatorname{argmin}(\eta^H (|\mathbf{Y}|^{-1} \odot \mathbf{Y}) \eta) \quad (7)$$

where $\hat{\theta}$ is the estimate phase time series, $\mathbf{Y}$ is the coherence matrix, and η is the complex exponential of phase vector. The optimal phase will replace the original phase of the DS, and then DSs and PSs are combined into the PSI workflow. For N SLC images, the computation complexity of the original JS-InSAR is $O(N^3)$. While the S-JSInSAR method has divided SLC stack into multiple subsets, the computation time of the whole stack is proportional to the single subset with given length. Thus, the computation complexity of S-JSInSAR is $O(N)$, which has certified the efficiency of the proposed method in large InSAR dataset.

The PSI processing begins with the PS candidate selection, which has carried out the stability analysis for the time series of SLC images by amplitude dispersion index (ADI)

algorithm. Based on the selected Master image, the interferometric phase stack of PS has been obtained, and followed by the differential interferometric phase with external DEM. The differential interferometric phase φ can be defined as follows:

$$\varphi = \varphi_{topo} + \varphi_{def} + \varphi_{orb} + \varphi_{atm} + \varphi_{noise} \quad (8)$$

where φ_{topo} is the topography phase caused by DEM errors, φ_{def} is the deformation phase reflected ground movement, φ_{orb} is the orbital errors, φ_{atm} is the atmospheric phase errors, and φ_{noise} is the noise. Through the double phase differential between two adjacent scatterers, most of the above errors can be reduced due to their spatial coherent distribution. Through constructing scatterers network, the differential deformation parameter in the network can be calculated, and the final deformation parameters are acquired by the network adjustment. And, the differential deformation parameter is estimated based on the following formula:

$$\Delta\varphi = \frac{4\pi}{\lambda} \frac{B_{\perp}}{r \cdot \sin\theta} \cdot \Delta h + \frac{4\pi}{\lambda} T \cdot \Delta v \quad (9)$$

$\Delta\varphi$ is the differential phase in the network, r is the slant range, λ is the radar wavelength, θ is the incidence angle, $B_{\perp}$ and T are the spatial perpendicular and temporal baseline, respectively, Δh is the differential residual height, and Δv is the differential deformation rate parameter.

While DSs have shown significantly local characteristics, and some of them may be of low coherence in some regions. In addition, the vast number of DS will bring about a large-scale Delaunay network. Thus, a two-layer network is established by the PS network and the secondary PS-DS local network, as shown in Figure 4. Firstly, the PSs alone are constructed with the Delaunay network, and the deformation parameters of PS are estimated in this network. Then, in each triangle network, the internal DSs with reference PS are constructed with the local Delaunay network, and the deformation parameters of DS are calculated based on the reference parameters of PS. This two-layer network can mitigate estimation error propagation and decrease the computation of network adjustment.

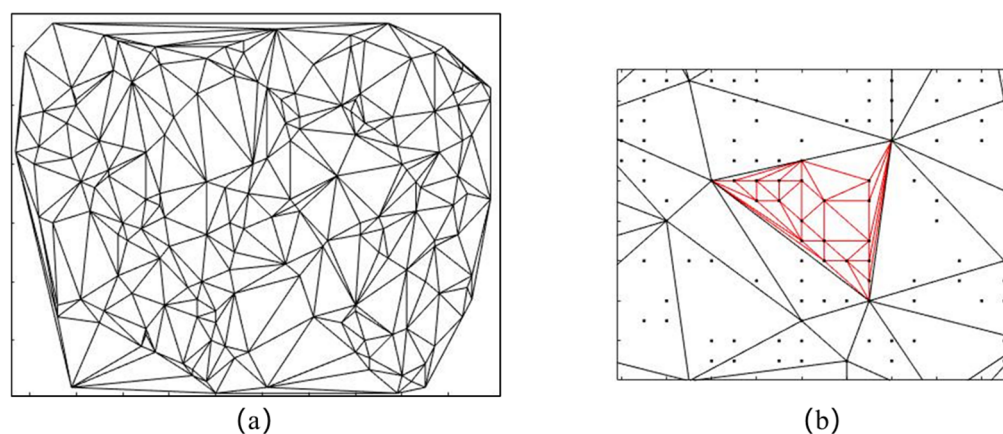


Figure 4. (a) The PS Delaunay network and (b) DS secondary local Delaunay network with red line.

After deformation estimation, the residual wrapped phase is conducted by the minimum cost flow (MCF) phase unwrapping algorithm through the global Delaunay network. Then, the generated unwrapped residual phase is atmospheric filtering with spatial low-pass filter and temporal high-pass filter, and the atmosphere errors are removed from unwrapped phase. Finally, the displacement time series are obtained for the subset.

2.4. Data Integration

After all the temporal subsets have finished the deformation estimation, the results are combined into the common Master image. Firstly, the selected scatterers above the temporal coherence threshold of both PS and DS in the different subsets have been confirmed, and those scatterers that fade in some subsets are discarded. Then the common scatterers with high quality are identified, and their displacement time series results are extracted. Assuming the temporal subsets $S_1, S_2, \dots, S_n$ have the design matrix $A_1, A_2, \dots, A_n$ and the subset deformation vector $D_1, D_2, \dots, D_n$, while the deformation results are reference to the respective Master image of each temporal subset, the observation equation can be expressed as follows:

$$D_i = A_i \cdot X_i, i = 1, 2, \dots, n \quad (10)$$

where X is the deformation time series vector. Then, the subsets are integrated into the large dataset, with the joint design matrix $\tilde{A}$ and the joint subset deformation vector $\tilde{D}$. The final deformation vector $\tilde{X}$ can be given as the following linear equation.

$$\begin{pmatrix} A_1 & 0 & 0 \\ 0 & A_2 & 0 \\ \vdots & \vdots & \vdots \\ 0 & \dots & A_n \end{pmatrix} X^T = \begin{pmatrix} D_1 \\ D_2 \\ \vdots \\ D_n \end{pmatrix} \quad (11)$$

where there are overlaps in column between adjacent matrix A_i in the joint design matrix $\tilde{A}$. And the deformation vector $\tilde{X}$ can be estimated by the least-squares solution as the following formula.

$$\tilde{X} = \left(\tilde{A}^T \tilde{A} \right)^{-1} \tilde{A}^T \tilde{D} \quad (12)$$

where T is denoted as the matrix transpose operation. The above estimation is performed on all the scatterers independently, and they are sharing the same joint design matrix in the calculation, which can be accelerated with the parallel computing. After obtaining the final deformation time series results, the deformation rate for the whole SLC stack is re-estimated. Finally, the refined deformation rate and deformation time series are geocoded and output with given formats.

3. Experiment

3.1. Study Region and Dataset

Tangshan is one of the most important industrial cities in the North China Plain, which is located in the northeastern coastal area of Hebei province, adjacent to the Bohai sea, as shown in Figure 5a,b. This region is characterized by flat terrain with primary aquifer system of unconsolidated quaternary sedimentary deposits. Meanwhile, situated in the Yanshan–Bohai seismic zone, Tangshan has been strongly affected by several active faults, which can be seen in Figure 5c. The purple line is the fault zone. And during the SAR image acquisition time, this area has experienced six earthquakes with Mw above 3.0, as shown with black star marker in Figure 5c. The fast development of economy in past decades, especially the heavy industry transfers to this region, has resulted in the over-exploitation of underground water, and the acceleration of urbanization and population has further aggravated the city subsidence [36]. The serious subsidence in Tangshan has brought about sea flowing backward and city waterlogging, and it also has posed great threat to the city infrastructures, with huge social and economy loss, including railway, bridges, and buildings. Despite many measures being taken to tackle the city subsidence, the long-term

groundwater extraction has caused irreversible damage to the ground aquifer, and has become one of the most important factors restricting sustainable development in Tangshan.

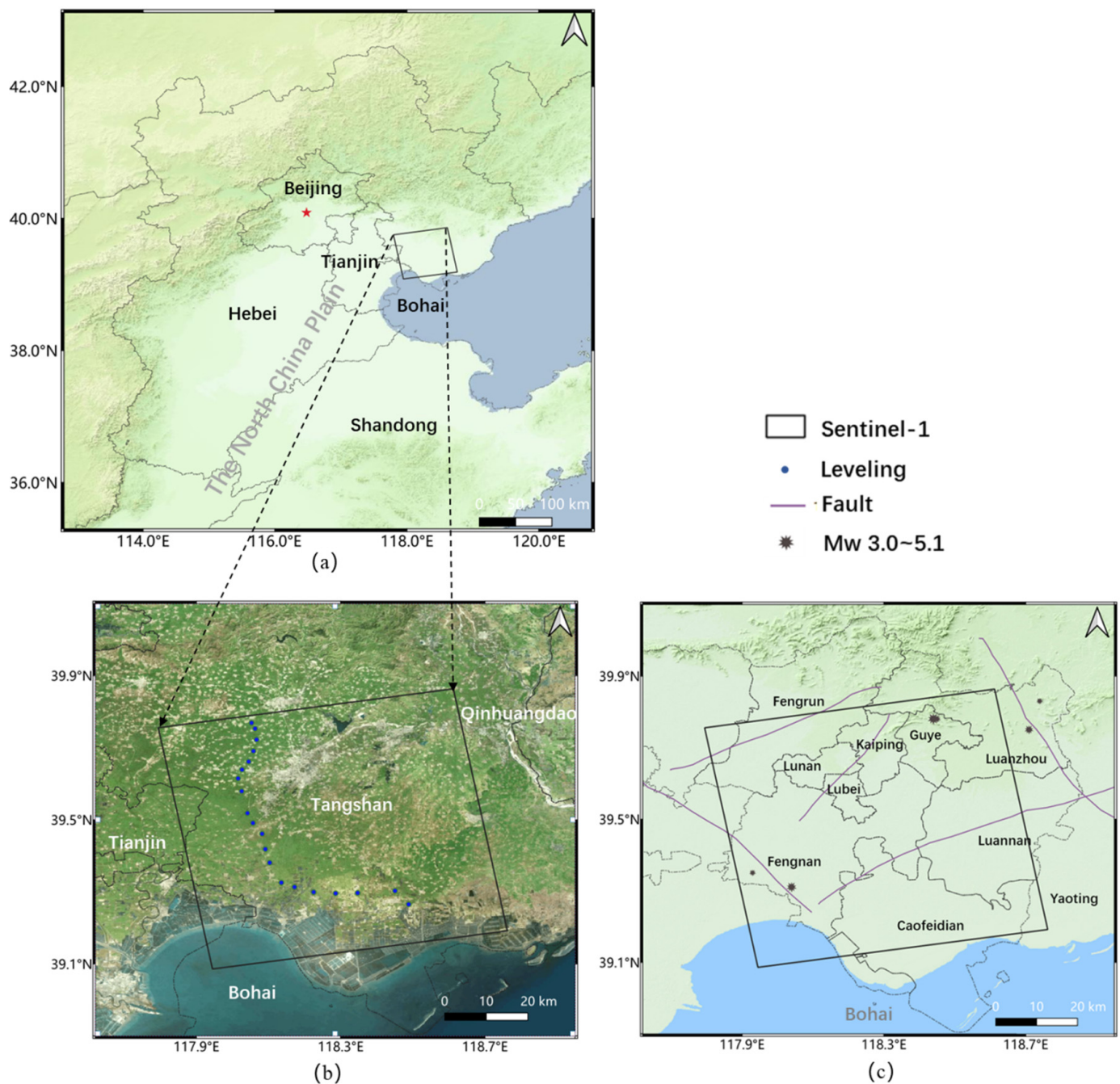


Figure 5. (a) The location map of Tangshan in the North China Plain. (b) The Google satellite map of Tangshan. (c) The geological map of Tangshan district. And the black box is the footprint of Sentinel-1 SAR image dataset; the blue dot in (b) is the leveling points; the purple lines are the fault zones of Tangshan; the star marker is the earthquake with Mw above 3.0 during the study time.

The time series of 145 C-band Sentinel-1 SAR images over Tangshan was used to validate the proposed method in the experiment, taken between January 2018 and November 2023. The SAR images are acquired with IW/VV mode, using ascending orbit with relative path 69. The black box in Figure 5a–c has shown the footprint of SAR image, and the specific Sentinel-1 dataset information can be seen in Table 1. In addition, the digital elevation model (DEM) TanDEM by DLR with 90 m ground resolution was utilized in the InSAR processing. The precise orbit files by ESA are used in the SAR image coregistration.

Table 1. The Sentinel-1 SAR image parameters in the study region.

SAR Parameter	Value
Sensor	Sentinel-1 A
Path	69
Orbit direction	Ascending
Polarization/mode	VV/IW
Wavelength (m)	0.055
Incidence angle	33.27°
Resolution (m)	14.0 (Azimuth), 2.3 (Range)
SAR image number	145
Revisit time (Day)	12
Date	22 January 2018~16 November 2023

3.2. Results

The PSI, JS-InSAR, and S-JSInSAR methods were used in the experiment to derive the long-term surface deformation of Tangshan district from January 2018 to November 2023. To begin with, the 145 ascending Sentinel-1 images are extracted and coregistered to the common reference image by correlation and ESD coregistration algorithms. Afterwards, the generated 145 SLC images are processed with the above methods. The Master image in PSI and JS-InSAR is used in the SLC image 17 February 2020, and all the reference points are the same in the three methods. The sub-window size of JS vector is 3×3 , and the SHP search window size is 7×7 . In the S-JSInSAR processing, after SHP identification and average coherence matrix calculation, the SLC stack dataset is divided into four subsets: 22 January 2018~18 March 2019 (35 scenes), 10 February 2019~24 March 2020 (34 scenes), 29 February 2020~20 December 2021 (49 scenes), and 21 October 2021~16 November 2023 (38 scenes). The reference Master image of the subset is set to 26 August 2018, 20 October 2019, 18 January 2021, and 15 December 2022. Then, the JS-InSAR preprocessing and PSI processing are performed on each subset, and the temporal coherence threshold is set 0.7. To better illustrate the phase optimization of S-JSInSAR method, samples of the multi-looked interferograms are shown in Figure 6.

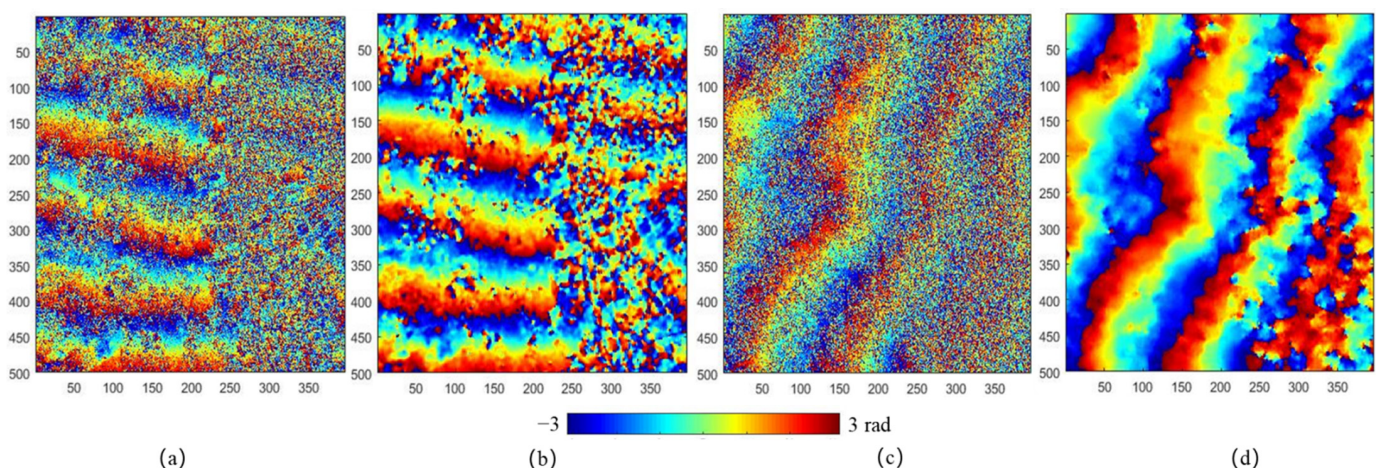


Figure 6. The optimized phase estimated by S-JSInSAR. (a,b) are the original and optimized phase of interferogram 26 August 2018–19 September 2018. (c,d) are the original and optimized phase of interferogram 20 October 2019–7 December 2019.

From Figure 6, we can see that the optimized interferograms by S-JSInSAR are clearer with less noise, and it greatly enhances the overall coherence, which will obtain more accurate deformation results. The spatial–temporal baseline maps and deformation results

in line of sight (LOS) direction of different subsets are shown in Figure 7a–h. We can see from Figure 7 that the subsidence rate in Tangshan has shown the evident trend of slowing down from 2018 to 2023, and the obtained measurement points in the subsets are densely distributed even in the natural terrains.

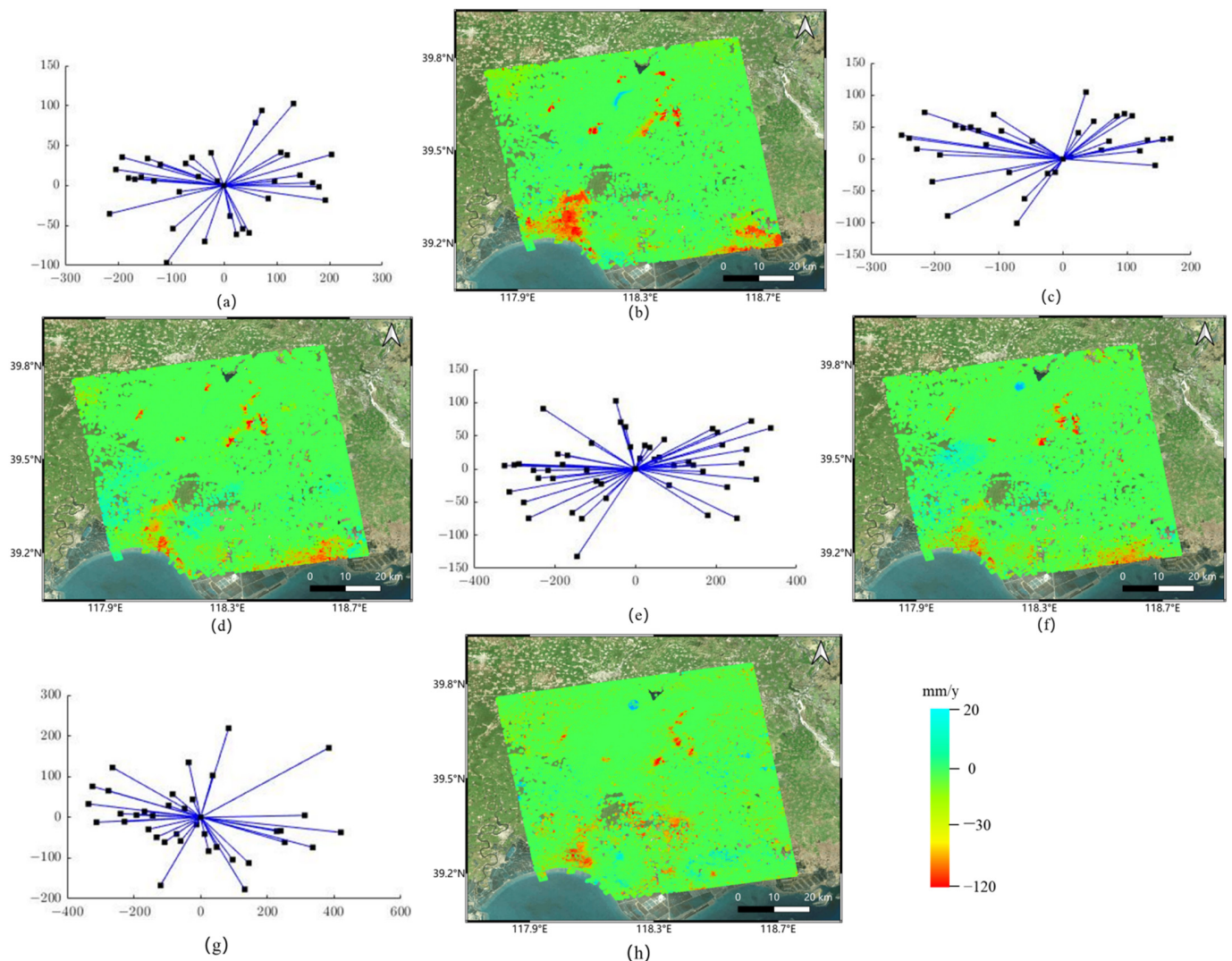


Figure 7. The baseline and deformation rate map for 4 subsets, 22 January 2018~18 March 2019, 10 February 2019~24 March 2020, 29 February 2020~20 December 2021, and 21 October 2021~16 November 2023. (a,c,e,g) are the baseline maps, and (b,d,f,h) are the LOS deformation rate maps, respectively.

After integrating the four subsets, the deformation results for the whole dataset are derived, and the final validated scatterers are selected based on the temporal coherence threshold 0.7. The overall InSAR processing time for PSI, JS-InSAR, and S-JSInSAR is 1.9 h, 28.4 h, and 12.5 h respectively, using the Intel I7-114700K CPU and 128 GB RAM, while the Sequential-Estimator has cost 16.7 h with more processing step of image compression compared to S-JSInSAR. Thus, the sequential segmentation and the parallel processing for different subsets in S-JSInSAR have greatly improved the processing efficiency of JS-InSAR in the large InSAR dataset with less storage burden and computation time. The final LOS deformation rates from 2018 to 2023 for the three methods are shown in Figure 8a–d. And, we can see that all of the three methods have obtained the deformation results with similar subsidence distributions, which include the northern mining regions and the southern coastal urbanization regions. The maximum deformation rate is 129 mm/y, which is caused

by the mining activities, while the average subsidence rate in the coastal economy zones is 81 mm/y. In addition, PSI has detected very sparse measurement points in the natural terrain and farmland areas, with the total PS number of 1,846,443. JS-InSAR has increased the density of measurement points by 2,580,556 through DS optimization, but the long temporal baselines have affected its performance in the low coherent regions. Sequential-Estimator has obtained 2,939,011 measurement points, but its deformation results are easily influenced by the atmospheric errors. In addition, the uniform batches of subset in Sequential-Estimator have missed some unstable scatterers in the larger temporal baselines. S-JSInSAR has overcome these limitations with the total measurement points number 3,172,065, and it has obtained the deformation results with more details in the non-urban and large deformation regions, which has proven the effectiveness of the proposed method in the long time series InSAR analysis.

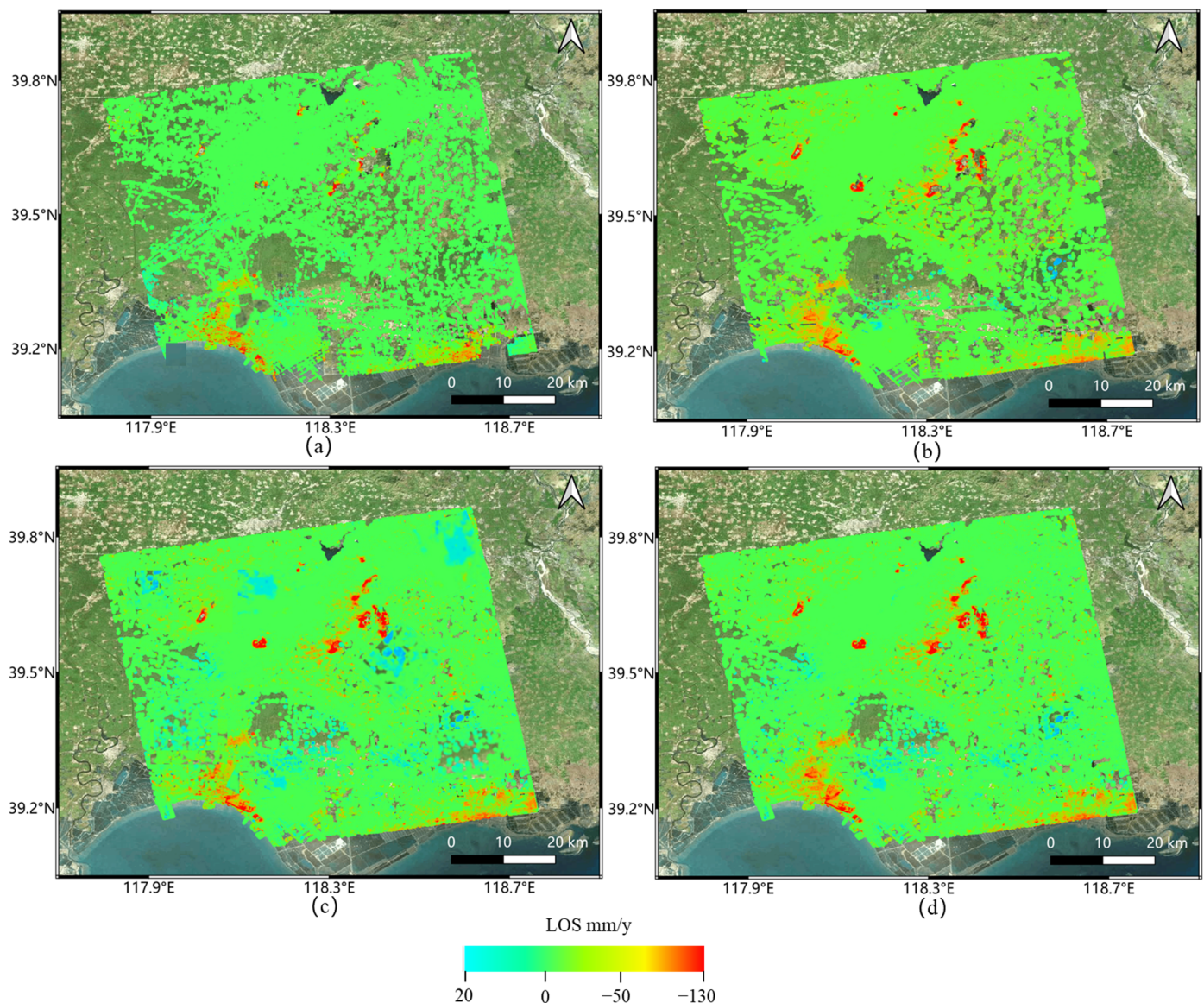


Figure 8. The LOS deformation rate maps for Tangshan by (a) PSI, (b) JS-InSAR, (c) Sequential-Estimator, and (d) S-JSInSAR.

To further evaluate the reliability of the proposed method, the correlation analysis among PSI, JS-InSAR, and S-JSInSAR is performed. The more similar of the two measurements, the correlation value is closer to 1. And the correlation results between each two

methods are displayed in Figure 9a–c. Figure 9a has shown the correlation between the deformation rate of PSI and JS-InSAR, and the correlation coefficient is 0.78 with the root mean square error (RMSE) is 6.29 mm/y. In Figure 9b, we can see that the JS-InSAR and S-JSInSAR have the highest correlation between each other with the correlation coefficient 0.89 and RMSE 3.25 mm/y, while S-JSInSAR has obtained larger deformation results compared to the former. Figure 9c has exhibited the lowest correlation coefficient between PSI and S-JSInSAR is 0.71 with RMSE 8.33 mm/y. The high correlation and consistency of the deformation rate among the three methods have demonstrated the reliability of the deformation estimation results by S-JSInSAR.

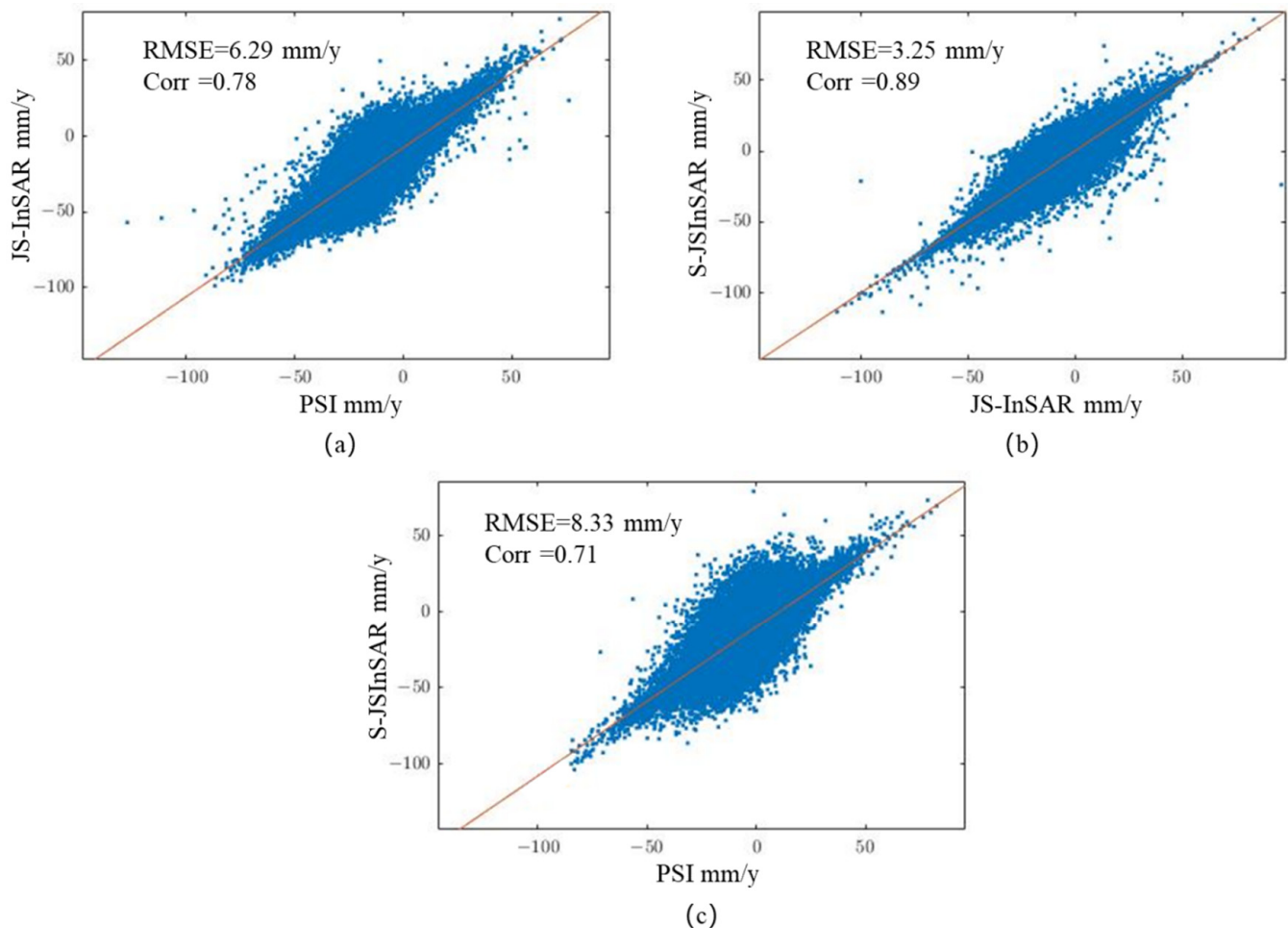


Figure 9. The correlation results between different methods, (a) PSI and JS-InSAR, (b) JS-InSAR and S-JSInSAR, and (c) PSI and S-JSInSAR.

The leveling measurements are used to evaluate the deformation estimation accuracy of S-JSInSAR, and the location of the leveling is shown in Figure 5b, which was taken between 2018 and 2023. Firstly, the leveling measurements are transformed into the average deformation rate and then projected into the InSAR LOS direction based on the incidence angle. And the corresponding nearest InSAR points have been obtained. Due to the low resolution of Sentinel-1 SAR image, several outliers have been discarded, and the deformation rate of InSAR and 20 leveling measurements are shown in Figure 10. From Figure 10a, we can learn that the spatial distribution of InSAR deformation rate has been in good agreement with leveling measurements, with the similar decreasing trend of subsidence rate from the south to the north. The RMSE between two methods is 2.88 mm/y, and the maximum error is 9.71 mm/y. The regression analysis of InSAR and leveling is

shown in Figure 10b, and the correlation coefficient value is 0.93, which has certified the deformation accuracy of the S-JSInSAR method.

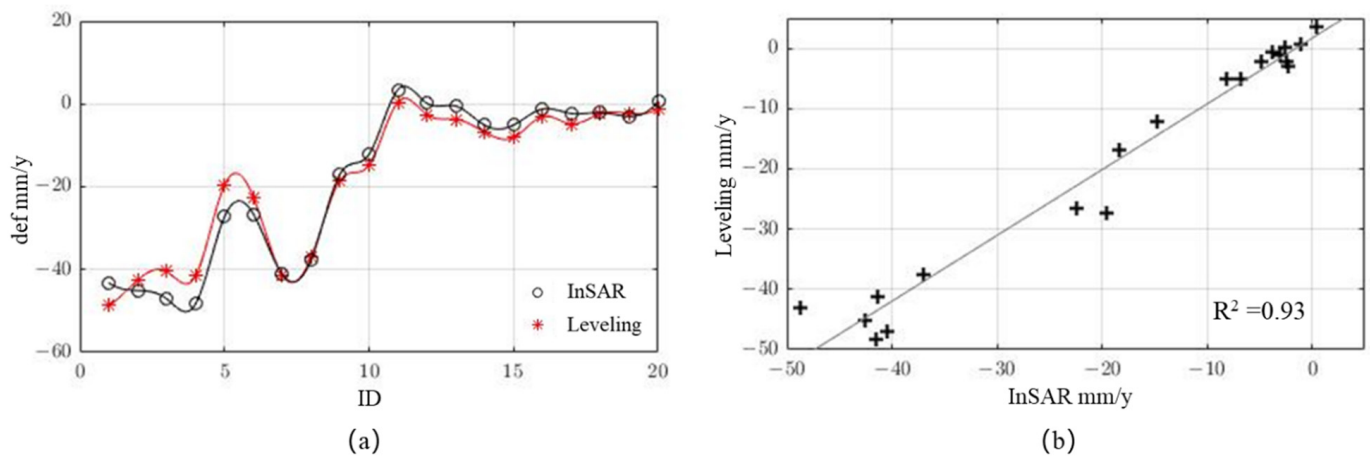


Figure 10. The comparison results between InSAR and leveling. (a) The spatial distribution of the subsidence rate of InSAR and leveling (from the south to the north), and (b) the regression analysis between InSAR and leveling measurements.

4. Discussion

4.1. Subsidence Analysis

Figures 10b and 11a show the subsidence results and the typical displacement time series in Tangshan by S-JSInSAR, and it can be seen that there are mainly three different subsidence regions, with the corresponding optical satellite images shown in Figure 11c–e. Region 1 is located in northern Tangshan (including Fengnan, Guye, Kaiping, and Lubei), where many mining activities and historical coal tailings are widely distributed. The displacement time series of P1 in Figure 11b indicated that these regions have exhibited continuing large subsidence with linear deformation rate 116.8 mm/y. The cumulative subsidence of P1 is more than 0.6 m during the acquisition time, which has caused great risks to the nearby buildings and citizens. Region 2 lies in the southern Fengnan coastal areas, and there are several significant subsidence centers with total subsidence area more than 124.15 km². Owing to the expansion of city and population in this region, the long-term underground water over-exploitation in the past decades has brought about several deep groundwater funnels. The displacement time series of P2 has shown its cumulative subsidence has reached near 0.4 m during the study time with deformation rate 76.7 mm/y, and we can also learn that the subsidence in this region has displayed the decreasing trend from 2018 to 2023, which benefited from the strict management of groundwater protection policy by the local government in recent years [37]. Region 3 is located in the Caofeidian coastal areas, where there is the major industrial zone in Tangshan. With the large-scale urbanization and infrastructure construction, coupled with the soft ground, the subsidence area in this region reached 73.49 km² during the study time. The P3 displacement time series have shown the sinking rate in Region 3 has slowed down and gradually become stable, which is mainly caused by the decrease in the construction project. The wide area subsidence in Region 2 and 3 has extremely threatened the industry and transport infrastructure, and it should receive continuous monitoring in the future.

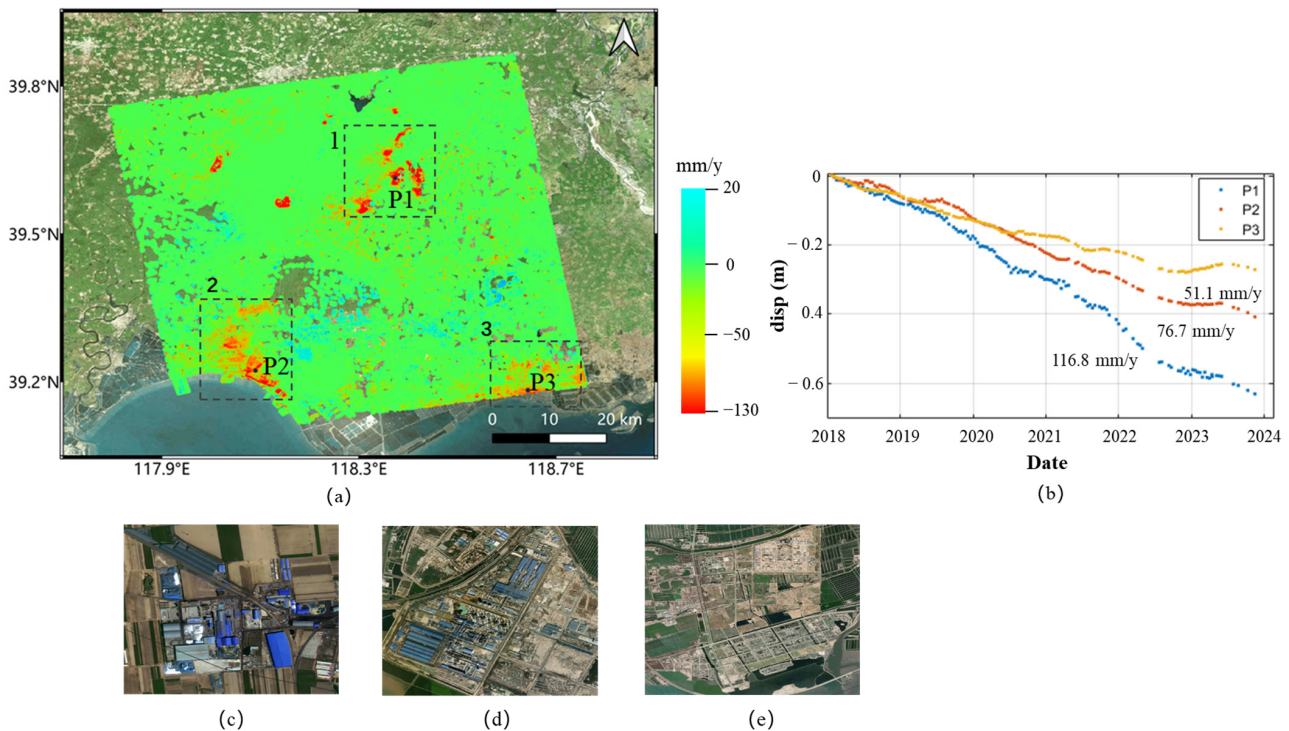


Figure 11. (a) The subsidence distribution of Tangshan by S-JSInSAR, (b) is the displacement time series for P1, P2 and P3, (c–e) are the Google optical satellite map for subsidence Region 1–3.

To evaluate the relation between InSAR displacement time series and groundwater level, we have collected the groundwater data between 2018 and 2021 in Tangshan from the public dataset [38], which is provided by the China Geological Environment Monitoring Institute with more than 11,000 national sites. This dataset is acquired by the inverse distance weighting interpolation of deep ground well measurements with 1 km spatial resolution and 1 month temporal resolution in China. The groundwater levels in two subsidence regions are obtained as shown in Figure 12a, and their nearby average InSAR results with evident seasonal variation are extracted, which is shown in Figure 12b,c. We can see that the ground subsidence by InSAR results was continuously sinking with the decline of the groundwater level from 2018 to 2020, and then in 2020~2021; as the result of groundwater restriction measures in Tangshan, the subsidence of two regions slowed down. And, in S2, the ground deformation even uplifted from 2021 to 2024 with the groundwater level rise. In addition, the groundwater in both S1 and S2 has exhibited significant seasonal fluctuations, which are caused by the rainfall and agricultural irrigation. And the InSAR deformation results have shown a similar variation trend with groundwater level, proving the reliability of the InSAR results by S-JSInSAR method.

4.2. Advantages and Limitations of the Proposed Method

The surging of satellite SAR data has encouraged the long-term deformation monitoring on a large scale, which has brought about huge computation burden for conventional DS InSAR processing. The proposed S-JSInSAR method can effectively process long time series InSAR dataset without reprocessing whole SLC stack through adaptive subset grouping and stepwise JS-InSAR processing. Although the experiment in this work mainly used Sentinel-1 SAR data, the proposed method is also suitable for other datasets, like TerraSAR and ALOS-2. As L band SAR data of ALOS-2 can maintain coherence in larger temporal baseline than Sentinel-1, the SLC images in the subset of S-JSInSAR can have a longer time interval. TerraSAR dataset can only have high coherence with small temporal baseline, and the length of subset in S-JSInSAR should be smaller than Sentinel-1. However,

there are still some limitations of S-JSInSAR. Firstly, the selection of the pixel patches in dataset segmentation is flexible in different regions, which can be strongly affected by the natural terrain. In addition, the different scatterers in the subset have common batch length, and it may cause the loss of those scatterers with low quality, which should be processed individually with different temporal baselines. Future work should temporally incorporate the scatterers into the proposed method to further improve measurement points.

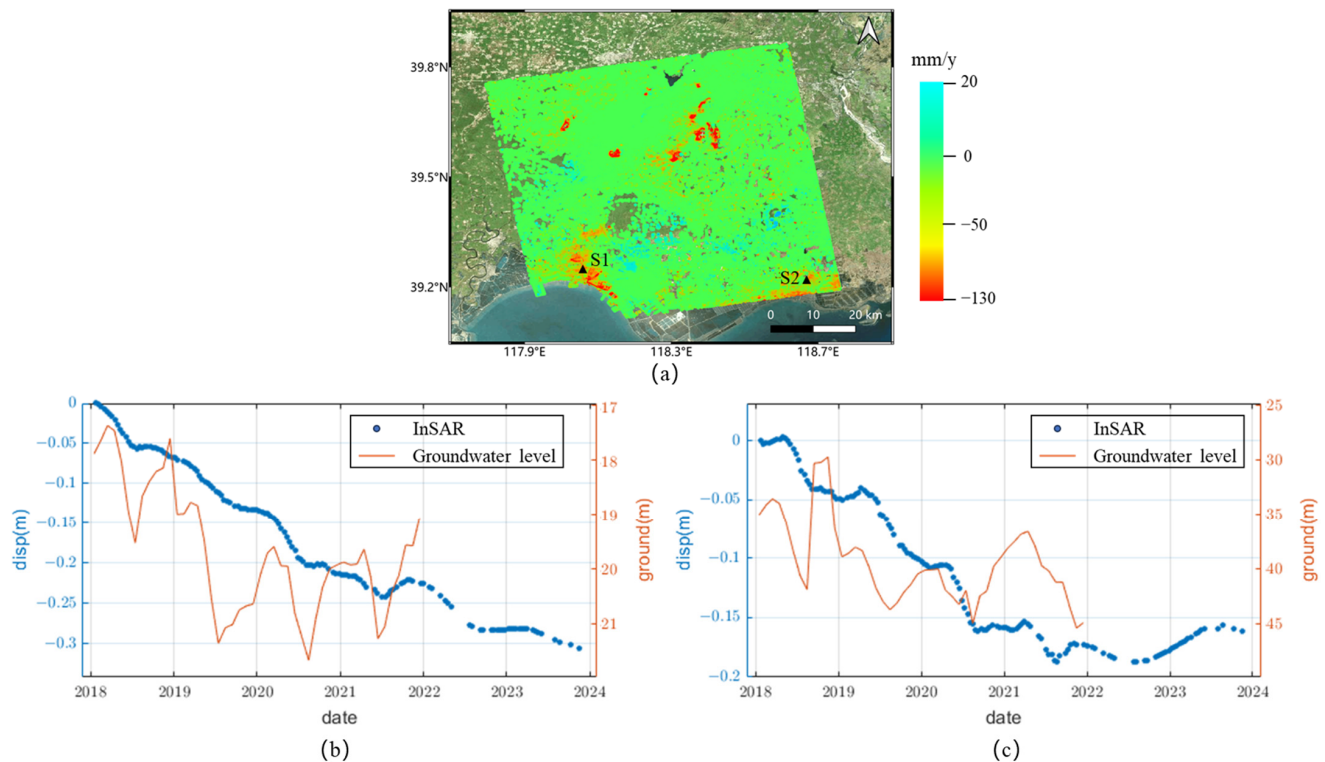


Figure 12. The comparison results between InSAR and groundwater level. (a) is the location of groundwater, (b) is the result in S1, and (c) is the result in S2.

5. Conclusions

In this paper, we present a novel sequential-based JS-InSAR method, which allows efficient long time series InSAR analysis with distributed scatterers. The proposed S-JSInSAR method has first selected the common SHP candidates for the whole processing based on the JS vector and KS test. Next, the large SAR dataset has been adaptively grouped into several subsets by the average JS coherence matrix. Then, the conventional JS-InSAR processing with spatial adaptive filtering and phase optimization are parallel performing on different subsets. And the PSI processing incorporated with PS and DS is conducted on each subset. At the end, the deformation results of different subsets are combined into the final deformation time series. Through the above workflow, S-JSInSAR has solved the problem of intensive computation and storage challenge of DS InSAR in the large InSAR dataset. Moreover, the decorrelation by long temporal baselines and large deformation has been greatly reduced in S-JSInSAR. To validate the effectiveness of the proposed method, the stack of 145 Sentinel-1 SAR images in Tangshan is used to retrieve the long time series deformation results. The comparison with JS-InSAR processing has certified the efficiency of S-JSInSAR with significant decrease in the computation time. In addition, S-JSInSAR has obtained the densest measurement points compared to PSI and JS-InSAR, which has shown more details of the deformation spatial distributions. And the leveling results have also proven the accuracy of estimated results by S-JSInSAR. The deformation results have shown that there are mainly three different subsidence regions in Tangshan, including the

mining regions in the north and the coastal subsidence regions in the south of Fengnan and Caoheidian district. And the deformation time series have exhibited the evident trend of slowing down in the subsidence rate from 2018 to 2023, which has also been verified by the groundwater data. Thus, S-JSInSAR can be well applied in the large InSAR data processing for long-term deformation monitoring.

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