

Kriging-Based Atmospheric Phase Screen Compensation Incorporating Time-Series Similarity in Ground-Based Radar Interferometry

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Abstract—Accuracy of radar interferometry is often hindered by the atmospheric phase screen (APS). To address this limitation, the geostatistical approach known as Kriging has been employed to predict APS from sparse observations for compensation purposes. In this article, we propose an enhanced Kriging approach to achieve more accurate APS predictions in ground-based (GB) radar interferometry applications. Specifically, the Kriging system is augmented with a time-series measure through correlation analysis, effectively leveraging spatiotemporal information for APS prediction. The validity of the introduced Kriging method in the APS compensation framework was tested with Ku-band GB radar datasets collected over two different mountainous sites. A comparison of this method with simple Kriging reveals a noticeable improvement in APS prediction accuracy and temporal phase stability.

Index Terms—Atmospheric phase screen (APS), differential radar interferometry, ground-based (GB) radar, ground-based synthetic aperture radar (GB-SAR), interferometric synthetic aperture radar (InSAR), Kriging.

I. INTRODUCTION

TIME-SERIES interferometric synthetic aperture radar (InSAR) enables precise displacement measurement, finding numerous applications [1]. InSAR technique has historically been applied to spaceborne and airborne synthetic aperture

radar (SAR). Meanwhile, since the late 1990s, ground-based (GB) radar, also known as terrestrial radar interferometer, has emerged as a potential tool for displacement monitoring, offering greater flexibility in observation geometry and acquisition intervals. The zero-baseline configuration of GB radar observations eliminates various sources of decorrelation, further enhancing its capability. Due to these advantages, GB radar has found widespread applications, including landslide monitoring [2], [3], minefield monitoring [4], glacier dynamics monitoring [5], [6], [7], infrastructure vibration measurement [8], [9], and volcano displacement monitoring [10], [11].

Nevertheless, the accuracy of time-series InSAR is constrained by atmospheric conditions. The time-varying distribution of air moisture content, pressure, and temperature induces changes in the refraction index, leading to a differential interferometric phase, known as the atmospheric phase screen (APS) [12], [13]. This disturbance becomes more pronounced at higher radar operational frequencies and longer observation ranges.

Various APS compensation approaches have been proposed for GB radar applications [5], [7], [14], [15], [16], [17], [18], [19], [20], [21]. A common correction approach involves modeling the spatial distribution of atmospheric refractivity. Such model-based deterministic solutions aim to estimate the APS component behaving as low-spatial frequency. The vertical stratified refractivity profile often found in steep topographic fields results in the stratified APS [17], which has been corrected using height-dependent APS models [7], [17], [20]. On the other hand, APS caused by atmospheric turbulence, known as the turbulent APS, cannot be described by the deterministic approaches mentioned above, as it generally exhibits local heterogeneity. Instead, the geostatistical Kriging approach has been employed to spatially estimate the turbulent APS.

Previous articles in [7], [13], [20], [22], and [23] have demonstrated the effectiveness of the Kriging approach in time-series interferometric measurements. Kriging interpolation predicts the turbulent APS using a weighted average of neighbor observation values, with weights determined based on spatial covariance. In the conventional Kriging method, the covariance function depends solely on the geographic location of data points.

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This article attempts to enhance the conventional Kriging approach in spatial APS prediction by incorporating the time-series similarity of sample points. Despite the availability of multitemporal datasets in the context of time-series InSAR, temporal information has rarely been leveraged for spatial prediction through the Kriging approach until now. However, temporal information is of crucial for understanding the local distribution of the attributes. For instance, pixels exhibiting similar APS temporal behavior may share similar atmospheric variations along the propagation path. This insight suggests that the similarity measure of temporal phase evolution can serve as an index for spatial similarity measurement.

The presented Kriging-based solution is motivated by recent advancements in the Kriging method [24], [25], known as semantic Kriging (SemK), which maps traditional covariance to a higher dimension to blend the semantic of the local features for more informative estimation. The SemK utilizes semantic similarity between geometries in conjunction with the ordinary Kriging method. In our approach, we integrate a similarity measure of time-series APS, estimated through correlation analysis, into the conventional covariance to achieve a more precise prediction of turbulent APS. As a result, spatiotemporal information is effectively exploited for the spatial prediction of turbulent APS in the proposed Kriging method.

The introduced Kriging approach, namely, Kriging incorporating time-series similarity (KTS), was validated using two types of datasets observed in different mountainous fields: a postlandslide mountainous slope in Japan and an Alpine glacier in Switzerland. Both datasets were acquired by Ku-band GB radar.

The rest of this article is organized as follows. Section II explains the time-series InSAR velocity inversion procedure for GB radar adopted in this article. Section III elaborates on the concept and methodology of the introduced KTS approach. Section IV presents the validation experiments and compares the results with the conventional Kriging method, followed by a discussion of applicability in practical scenarios in Section V. Finally, Section VI concludes this article.

II. OVERVIEW OF DISPLACEMENT ESTIMATION IN GROUND-BASED RADAR DATA

A. Signal Model and Displacement Estimation Procedure

The j th unwrapped differential interferometric phase for the GB radar case can be expressed as the sum of several components

$$\begin{aligned}\phi^j(\Delta t) &= \phi_{\text{disp}}^j + \phi_{\text{APS}}^j + \phi_{\text{decorr}}^j \\ &= \frac{4\pi}{\lambda} \Delta t v + \phi_{\text{APS}}^j + \phi_{\text{decorr}}^j.\end{aligned}\quad (1)$$

Here, ϕ_{disp} is the phase contribution related to ground displacement, ϕ_{APS} is the atmospheric phase delay, ϕ_{decorr} is the decorrelation component, Δt accounts for temporal baseline, and λ accounts for the wavelength of the operational frequency. In (1), the nonlinear displacement component is omitted by assuming a short temporal baseline, such that the displacement velocity v is considered constant.

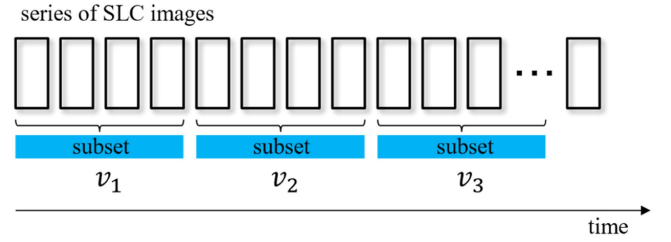


Fig. 1. Schematic illustration of the processing chain in this article. The v_1 , v_2 , and v_3 account for inverted velocity of corresponding image subset.

It is noteworthy that certain phase contributions present in spaceborne SAR data, such as flat Earth phase, topographic phase contribution, phase error induced by orbit information errors, and ionosphere phase contributions, can be omitted in the GB scenario when adopting the zero-baseline configuration. This simplifies interferometric pair selection significantly compared to spaceborne SAR. This article utilizes the daisy chain interferogram network [26], which connects consecutive chronological N single look complex (SLC) images with the shortest temporal baseline. This network minimizes temporal phase wrapping issues and temporal decorrelation.

Typically, time-series InSAR algorithm aims to separate ϕ_{disp} from other disturbances. To mitigate the decorrelation phase component ϕ_{decorr} , only stable pixels, referred to as persistent scatterer candidates [27] or coherent scatterers (CSs) [28], [29], are processed. A temporal phase quality estimator, such as the mean interferometric coherence, is employed to select these stable pixels. For the daisy chain, it is computed from image subsets as

$$\bar{\gamma}_{\text{coh}} = \frac{1}{M} \sum_{j=1}^M \left| \frac{\langle s_j \cdot s_{j+1}^* \rangle}{\sqrt{\langle s_j \cdot s_j^* \rangle} \sqrt{\langle s_{j+1} \cdot s_{j+1}^* \rangle}} \right| \quad (2)$$

where M is the number of interferograms, s_j (reference image) and s_{j+1} (secondary image) are complex values corresponding to the same pixel forming an interferogram, and $\langle \cdot \rangle$ indicates the ensemble averaging. Pixels with higher $\bar{\gamma}_{\text{coh}}$ are selected as the CSs.

After completing the APS correction using the approaches demonstrated in the following sections, the displacement velocity v can be ultimately estimated. In this study, pixel-wise inversion of v in (1) is carried out at selected CSs using the ordinary least squares (OLS) [7]. Given continuous radar observation, velocity inversion is repeatedly applied to subsets of radar images, as schematically depicted in Fig. 1. In this processing chain, a processing window is defined, covering N SLC images. Sliding the processing window provides a series of image subsets. Therefore, the processing chain adopted in this study yields a time-series of arbitrary displacement patterns by linking all the constant velocity values. This continuous monitoring approach allows for the derivation of displacement patterns over time, providing valuable insights into ground movements.

B. APS Compensation: Classical Kriging Approach

In the context of areas with high topography, the unwrapped ϕ_{APS} is further expressed as the superposition of stratified APS ϕ_{str} and other residual APS components ϕ_{res}

$$\phi_{\text{APS}} = \phi_{\text{str}} + \phi_{\text{res}} = \mathbf{X}\boldsymbol{\beta} + \phi_{\text{res}}. \quad (3)$$

Here, $\mathbf{X}$ is a matrix of regressors, representing functions of coordinates at corresponding locations or functions thereof [7], [17], [20], and the $\boldsymbol{\beta}$ is the vector of regression coefficients. The $\mathbf{X}$ and $\boldsymbol{\beta}$ are varied depending on the defined APS model. This article applies the model-based approach presented in [20] to correct ϕ_{str} , which assumes the APS to consist of a low-spatial frequency component in the interferometric phase. To complete APS compensation, the residual component ϕ_{res} needs to be further estimated and compensated.

We predict and compensate ϕ_{res} by a geostatistical interpolator known as Kriging, considering the spatial correlation of observations. The process generally involves three steps. First, pixels of interest, usually corresponding to displaced locations, are masked. Second, ϕ_{res} is predicted over the masked area by extrapolating from nondisplaced CSs using the Kriging approach. Finally, compensation is completed by subtracting the predicted ϕ_{res} from the two-dimensional (2-D) interferograms. This procedure is repeated for each interferogram before velocity inversion.

According to (3), ϕ_{res} is assumed to be zero-mean, spatially correlated, and second-order stationarity. In this case, simple Kriging (SK) method is appropriate to be applied among various Kriging methods [30], [31]. In Kriging method, the residual APS at the prediction pixel $\mathbf{x}_0$ can be estimated as a weighted average of the residual APS at neighboring CSs

$$\hat{\phi}_{\text{res}}(\mathbf{x}_0) = \sum_{i=1}^n w_i \phi_{\text{res}}(\mathbf{x}_i) \quad (4)$$

where i indicates the index of neighboring CSs (interpolating CSs) and w_i are weights assigned to these neighboring CSs. The weights are determined such that minimizing the estimation variance, and consequently, we get the SK system as [30]

$$\mathbf{C}_1 \mathbf{w}_{\text{SK}} = \mathbf{C}_0 \quad (5)$$

where

$$\mathbf{C}_1 = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{n1} & \cdots & C_{nn} \end{bmatrix} \quad (6)$$

$$\mathbf{w}_{\text{SK}}^T = [w_1, w_2, \dots, w_n] \quad (7)$$

$$\mathbf{C}_0^T = [C_{01}, C_{02}, \dots, C_{0n}] \quad (8)$$

Here, $C_{\alpha\beta}$ accounts for spatial covariance, and its indices correspond to pixel numbers (with $\alpha, \beta = 0, \dots, n$). The weight vector $\mathbf{w}_{\text{SK}}$ is determined based on the spatial auto-correlation structure. In second-order stationarity assumption, where both the expectation and covariance are independent of location, the covariance function is given by the bounded variogram function γ as

$$C(\mathbf{h}) = \gamma(\infty) - \gamma(\mathbf{h}). \quad (9)$$

The empirical variogram is computed using the formula

$$\gamma(\mathbf{h}) = \frac{1}{2} E[(\phi_{\text{res}}(\mathbf{x}) - \phi_{\text{res}}(\mathbf{x} + \mathbf{h}))^2] \quad (10)$$

where $E[\cdot]$ indicates an expectation and $\mathbf{h}$ is a spatial separation vector from a position vector $\mathbf{x}$. A parametric model, such as an exponential model (used in this article), is then fitted to the empirical variogram to obtain a variogram function.

Finally, the estimation of residual APS at prediction pixel $\mathbf{x}_0$ is given as an unbiased, minimum variance estimator through the SK

$$\hat{\phi}_{\text{res}}(\mathbf{x}_0) = (\mathbf{C}_1^{-1} \mathbf{C}_0)^T \mathbf{z}_{\text{res}} \quad (11)$$

where $\mathbf{z}_{\text{res}}^T = [\phi_{\text{res}}(\mathbf{x}_1), \phi_{\text{res}}(\mathbf{x}_2), \dots, \phi_{\text{res}}(\mathbf{x}_n)]$.

Prediction error variance for SK σ_{SK}^2 is given by Kriging system in (11)

$$\sigma_{\text{SK}}^2 = \sigma^2 - \mathbf{C}_0^T \mathbf{C}_1^{-1} \mathbf{C}_0 \quad (12)$$

where σ^2 is the variance of the process [30]. Therefore, the prediction accuracy gets worth as the spatial covariance C_0 decreases with the increasing distance between interpolating pixels and prediction pixel.

III. KTS-BASED APS ESTIMATION

A. Concept

The classical Kriging approach determines the spatial importance of observations in interpolation/extrapolation to new locations, represented by Kriging weights, based on the location of the data points by evaluating spatial covariance. The Kriging concept in this article considers the similarity of temporal phase evolution as a measure of spatial importance. This assumption is grounded in the relationship between phase and atmospheric parameters.

The two-way propagation atmospheric phase term, backscattered from the slant range distance r_s , can be expressed as the integration of atmospheric refractive index n_r along the propagation path length

$$\varphi_{\text{atm}}(t) = \frac{4\pi}{\lambda} \int_l n_r(r_s, t) dr_s. \quad (13)$$

As the signal propagates through the atmosphere, $n_r(r_s, t)$ varies only slightly greater than the refractive index of vacuum ($n_r = 1$) [32]. Therefore, n_r is generally expressed as

$$n_r = 1 + 10^{-6} N_r \quad (14)$$

where N_r is the refractivity index, considered a scale-up index. For radio frequency, N_r is empirically approximated as [33]

$$N_r = \frac{77.6 \cdot P}{T} + \frac{3.37 \cdot 10^5 \cdot e}{T^2} \quad (15)$$

where T , P , and e represent pressure, temperature, and partial pressure of water vapor, respectively.

The APS is defined as the phase difference between $\varphi_{\text{atm}}(t_1)$ and $\varphi_{\text{atm}}(t_2)$

$$\phi_{\text{APS}}(\Delta t) = \varphi_{\text{atm}}(t_1) - \varphi_{\text{atm}}(t_2)$$

$$= 10^{-6} \frac{4\pi}{\lambda} \left(\int_l N_r(r_s, t_1) dr_s - \int_l N_r(r_s, t_2) dr_s \right). \quad (16)$$

Hence, the temporal variation of N_r determines the temporal behavior of ϕ_{APS} . The similarity of ϕ_{APS} temporal behavior directly reflects the similarity of the temporal variation of atmospheric parameters (i.e., pressure, temperature, and water vapor) along the propagation path. The prediction of ϕ_{APS} at unobserved points is thus better performed by assigning higher Kriging weights (spatial importance) to pixels representing similar atmospheric conditions as the prediction point. This prediction concept is realized by the method presented in the following.

B. Methodology

The KTS approach modifies the spatial covariance matrices by incorporating the similarity of temporal APS evolution. To achieve this, a similarity measure based on the cross-correlation between a pair of temporal residual APS profiles is initially computed at each prediction point.

Assuming the vector of N phase values of the SLC images φ in chronological order

$$\mathbf{y}^T = [\varphi(t_1), \varphi(t_2), \dots, \varphi(t_N)] . \quad (17)$$

The vector of M interferogram phases ϕ is denoted as

$$\mathbf{z}^T = [\phi^1, \phi^2, \dots, \phi^M] . \quad (18)$$

Due to the adoption of the daisy chain for interferogram generation, the reference and secondary SLC images vary in each interferogram. Therefore, the interferometric phase in (18) is given as

$$\begin{aligned} \phi^j &= \varphi(t_m) - \varphi(t_{m+1}) \\ m &= 1, 2, \dots, N-1 \\ j &= 1, 2, \dots, M. \end{aligned} \quad (19)$$

Before the correlation analysis, a low-order detrending along the temporal axis is performed to eliminate the possible displacement signal, simplifying the cross-correlation analysis to focus solely on the APS signal. In this article, linear detrending along the cumulative sum of the phase time-series is performed. Additionally, the model-based APS compensation is applied to the 2-D interferograms at this stage.

As a result, the temporal variation of the residual APS is given by cumulative sum along the temporal axis, denoted as

$$\boldsymbol{\omega}^T = [\omega_1, \omega_2, \dots, \omega_M] . \quad (20)$$

The spatial cross-correlation between $\boldsymbol{\omega}_\alpha$ and $\boldsymbol{\omega}_\beta$ ($\alpha, \beta = 1, \dots, n$) is computed by

$$C C_{\alpha\beta} = \frac{\sum_{j=1}^M (\omega_\alpha(j) - \bar{\omega}_\alpha) (\omega_\beta(j) - \bar{\omega}_\beta)}{\sqrt{\sum_{j=1}^M (\omega_\alpha(j) - \bar{\omega}_\alpha)^2 \sum_{j=1}^M (\omega_\beta(j) - \bar{\omega}_\beta)^2}} \quad (21)$$

where $\bar{\omega}$ denotes the mean value. The similarity measure based on $C C_{\alpha\beta}$ is then defined as

$$S_{\alpha\beta} = C C_{\alpha\beta} + 1 \quad (22)$$

ranging from 0 to 2, where a higher value indicates similarity and vice versa.

Next, the similarity measure in (22) is introduced to the spatial covariance in the SK system represented by (6) and (8). For this purpose, the $[n \times n]$ symmetric matrix S_1 for n interpolating points as well as the vector S_0 representing the similarity between the prediction pixel $\mathbf{x}_0$ and each interpolating points $\mathbf{x}_i$, are defined as

$$S_1 = \begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{n1} & \cdots & S_{nn} \end{bmatrix} \quad (23)$$

$$S_0^T = [S_{01}, S_{02}, \dots, S_{0n}] . \quad (24)$$

The modified covariance matrices in the SK system are denoted by introducing similarity matrices in (23) and (24) to spatial covariance matrices, given as

$$\mathbf{M}_1 = \mathbf{C}_1 \circ \mathbf{S}_1 \quad (25)$$

$$\mathbf{M}_0 = \mathbf{C}_0 \circ \mathbf{S}_0 \quad (26)$$

where “ $\circ$ ” indicates Hadamard (or elementwise) product. As the covariance has been modified, the weights associated with each interpolating pixels are also adjusted

$$\mathbf{w} = \mathbf{M}_1^{-1} \mathbf{M}_0. \quad (27)$$

Accordingly, prediction error variance is given as

$$\sigma_{\text{KTS}}^2 = \sigma^2 - \mathbf{M}_0^T \mathbf{M}_1^{-1} \mathbf{M}_0. \quad (28)$$

Consequently, the newly derived weights are a function of both spatial distance and temporal profile similarity. The prediction of ϕ_{res} is finally realized by incorporating the derived weights in (27) into (4). The incorporation of the similarity measure in (22) effectively maps the conventional covariance to a higher dimension of covariance, resulting in a more informative system. Through this modification, weights are adaptively determined based on the temporal APS behavior in the multitemporal interferograms.

IV. VALIDATION TEST ON APS PREDICTION AND COMPENSATION

This section presents evaluation of the applicability of KTS using acquired GB radar data. To demonstrate performance across different applications, two types of datasets observed in mountainous fields are utilized. Both observations were conducted by GB radar systems in continuous operational mode. To quantitatively assess the performance of APS correction, validation is specifically conducted in nondisplaced regions in this section.

The first dataset pertains to images acquired for monitoring a postlandslide mountainous slope using GB-SAR. The second dataset consists of images for monitoring an alpine glacier in Switzerland using GB real aperture radar. Fig. 2(a) and (b)

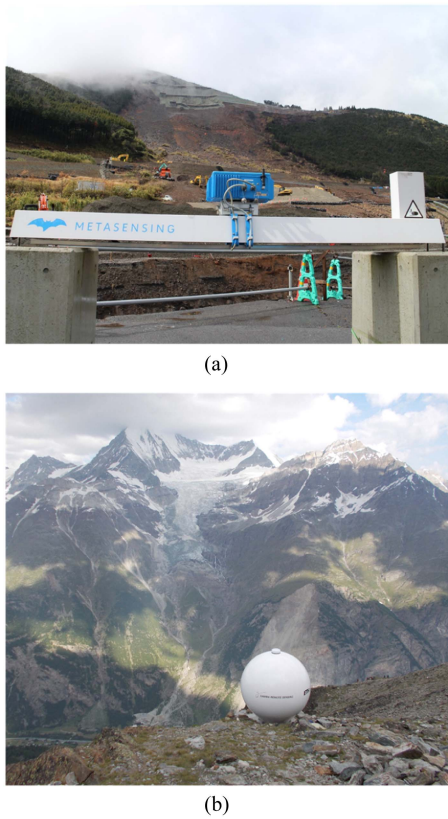


Fig. 2. (a) GB-SAR deployed for monitoring the postlandslide slope, at Minami-Aso, Kumamoto, Japan. (b) Ground-based radar covered by a radome, deployed for surface velocity measurement of the Alpine glacier, Switzerland.

depicts the GB radar systems deployed in these two campaigns, respectively. Detail analyses and comparison results for each dataset are provided in the followings sections.

A. Validation Test With the Postlandslide Slope Data

The employed GB-SAR system in the first dataset is a frequency-modulated continuous-wave (FMCW) radar (metasensing fast GB-SAR), operating at Ku-band (17.2 GHz) center frequency with a 300-MHz frequency bandwidth. The GB-SAR campaign was initiated to monitor the stability of a postlandslide slope located in the caldera of Mt. Aso in Kumamoto, Japan. Throughout the campaign, GB-SAR image acquisition was made each 5 min.

In the observation field, the atmospheric conditions exhibited a heterogeneous spatial distribution of the refractivity index, as confirmed by on-site meteorological sensors [20]. Therefore, the model-based APS compensation alone is not sufficient to eliminate all APS from the interferograms. Due to the basin structure in the observation field, high temporal variability of local winds is expected, leading to significant errors even after stratified APS correction.

Three image subsets are selected from the observed data, each comprising 25 SLC images measured over the course of 2 h. The criterion of $\bar{\gamma}_{\text{coh}} > 0.8$ is employed for selecting CS in the analysis. As a postprocessing step, the minimum cost flow phase

unwrapping algorithm [34] and model-based APS compensation in [20] are applied to all interferograms.

During this campaign, no major associated deformation has been observed. In other words, the observed dataset includes only an APS signal, along with potential temporal and noise decorrelation. In Fig. 3, three displacement velocity images (projected on the digital elevation model) estimated from the three image subsets are given. These selected subsets are labeled as subset-I, II, and III, respectively, with the acquisition time in Japan standard time (YYYY.MM.DD) at the top of each map in Fig. 3. It is noteworthy remarking that all three displacement maps reveal significant residual APS, indicating the insufficiency of the model-based APS correction. This fact demands further APS compensation to achieve reliable velocity observation.

The evaluation of compensation performance is conducted at motionless CSs. In the evaluation, the pixels are divided into two groups: one used for interpolating pixels to infer the spatial covariance and the other used for prediction (interpolation) pixels to assess the correction performance.

Fig. 4 exhibits two examples of interferograms chosen from subset-I and III, respectively. Those interferograms now represent the residual APS as no deformation was observed. In Fig. 4, the prediction area is arbitrarily defined and identified by a white circle. Both the KTS and the SK methods are applied to predict the residual APS over the prediction area using measured APS variables from randomly selected 300 interpolating CPs located outside the circle. Fig. 4(a) and (d) shows the original interferograms after stratified APS compensation. The KTS prediction results are presented in Fig. 4(b) and (e), while Fig. 4(c) and (f) shows the SK prediction results. Upon visual comparison of the results from both Kriging methods, the prediction by the KTS approach appears more similar to the original than SK. The spatial pattern of residual APS in SK is not well accordant with original interferograms. In contrast, the predicted residual APS patterns by KTS agree with the original interferograms. This observation is quantitatively evaluated by the root-mean-square error (RMSE) between the original interferometric phase and predicted APS at the prediction pixels, labeled in each Kriging result. The results reveal that a KTS yields smaller RMSE than SK for both interferograms.

Further validation of the proposed approach is conducted on the final velocity inversion results. Fig. 5 summarizes the histograms of inverted velocity for three subsets with different approaches. Three types of correction approaches are tested: 1) a model-based approach without Kriging-based correction, 2) a model-based approach plus KTS-based correction, and 3) a model-based approach plus SK-based correction. The mean and standard deviation (SD) values of each histogram are compared and labeled in the corresponding figures. According to the results, both Kriging-based approaches demonstrate lower absolute mean and SD than the method without Kriging for all subsets, indicating that the Kriging-based correction can further reduce the APS signals. Comparing between KTS and SK results, KTS yields a lower absolute mean and SD than SK, especially for subset-I. Consequently, KTS shows the best APS correction performance among the three approaches.

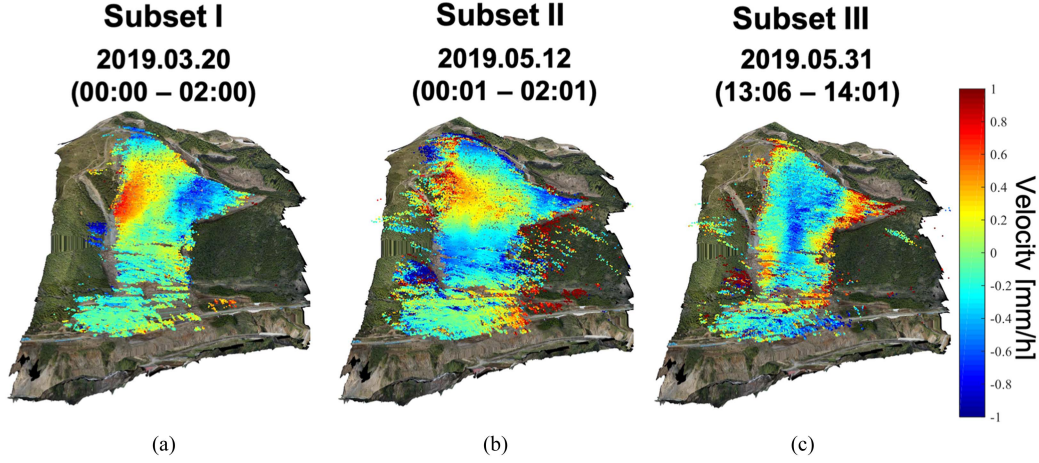


Fig. 3. Displacement velocity images estimated from three image subsets acquired over the postlandslide mountainous field without residual APS compensation. Each figure is generated from SLC images observed in 2-h with 5 min time interval: (a) 2019.03.20 00:00–02:00, (b) 2019.05.12 00:01–02:01, and (c) 2019.05.31 13:06–14:01 (YYYY.MM.DD JST). The positive sign of the velocity corresponds to the direction from the target to the GB-SAR position.

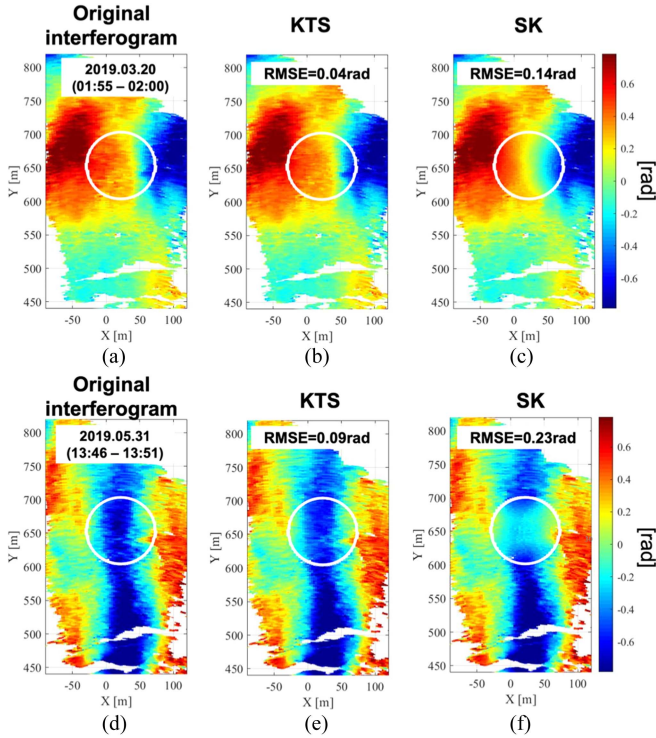


Fig. 4. Prediction results of the residual APS over the white circle area for two interferograms. (a), (d) original interferograms after the stratified APS correction, (b), (e) KTS prediction results, and (c), (f) SK prediction results. RMSE values are labeled at the top of each Kriging results.

B. Validation Test With the Glacier Monitoring Data

The radar images used in this subsection are data of the Bissetschers, a steep and fast-flowing glacier located on the eastern side of the Weisshorn and Bishorn mountains in the Valais Alps, Switzerland, showing ~ 55 mm/h surface displacement velocity [35] during the summer season. Those were observed by a

polarimetric terrestrial radar interferometer (KAPRI) under the campaign led by ETH Zürich [7]. The employed radar system operated at the Ku-band (17.2 GHz) center frequency with a 200 MHz frequency bandwidth. The radar reflectivity image is shown in Fig. 6(a) with the indication of glacier tongue zone.

During the campaign, SLC images were acquired each 2.5 min to minimize temporal decorrelation and phase wrapping on the glacier tongue. The surrounding areas, such as rock and soil surfaces, are relatively stable, assuming no displacement at the timescale of the repeat rate.

The observed interferograms revealed the local heterogeneity in the APS whose magnitude is similar to the surface displacement of the glacier [7]. Fig. 6(b) shows the interferogram after the stratified APS compensation formed by two SLCs with the indication of glacier boundary. The presented residual APS strongly influences and makes it difficult to distinguish the actual displacement signal from the results. Hence, the model-based APS correction alone is not sufficient, and further compensation is required for a precise displacement estimation.

To quantitatively illustrate the methods' performance, we performed the validation using only motionless CSs in this section. Specifically, the stable rock and soil surfaces surrounding the moving glacier, assuming an absence of displacement at the observation time, were used to evaluate. Among motionless CSs, we define the test area (circled area in Fig. 6) as prediction (interpolation) pixels and surrounding motionless CSs as interpolating pixels, also used for covariance matrix inference. For the efficient computation of the Kriging method, only 300 interpolating CSs are selected. To be specific, the KTS method selects 300 CSs showing higher CC to prediction pixels. On the other hand, the SK chooses 300 spatially closest CSs to the prediction pixels.

The three-day dataset from 08:00 July 13 to 00:00 July 16 (CEST) is employed. This experiment compared the performances of three types of correction approaches (as demonstrated in Section IV-A) on final displacement velocity results. For this

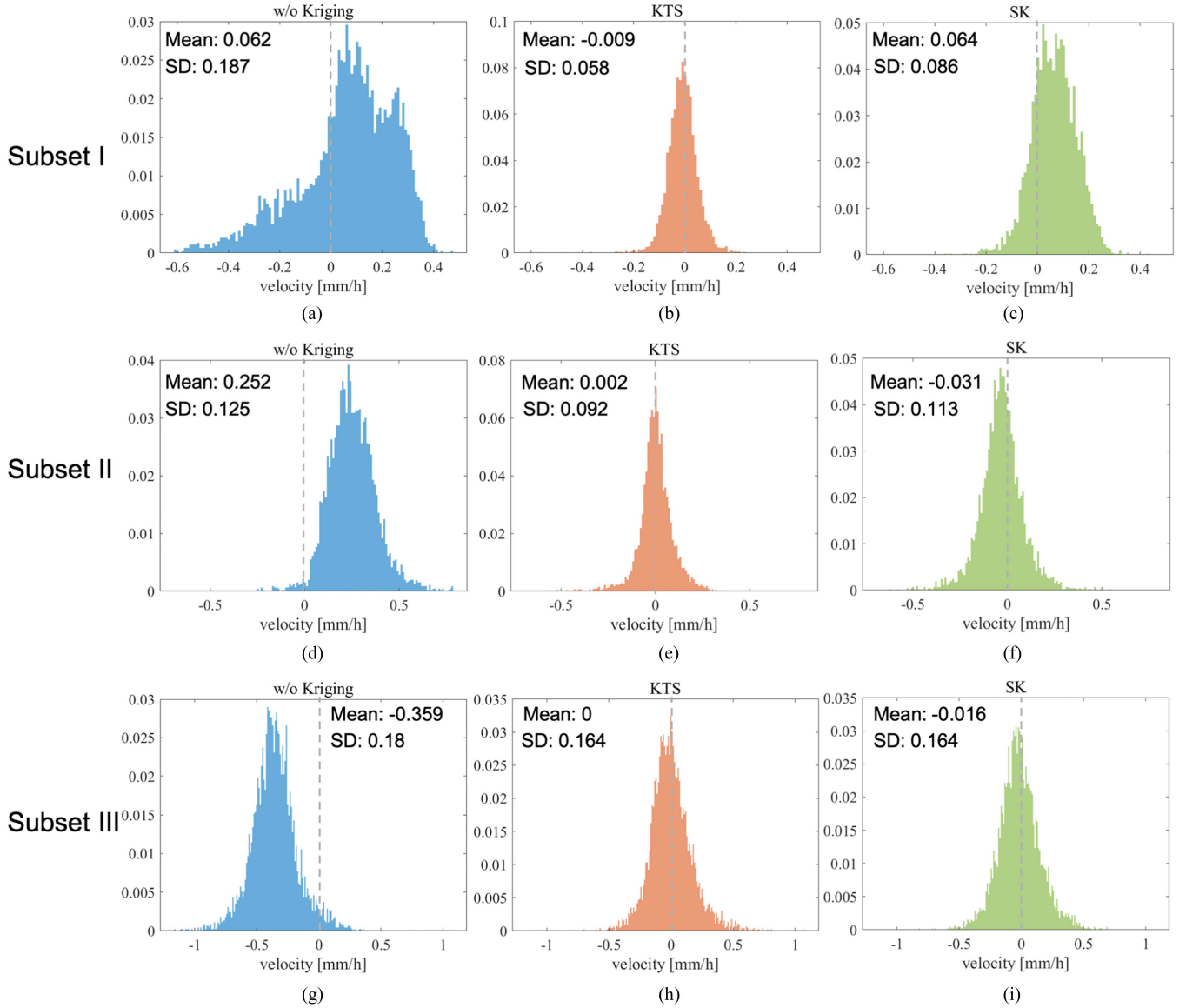


Fig. 5. Histograms of inverted velocity for three subsets with different compensation approaches. (a), (b), (c) subset-I, (d), (e), (f) subset-II, (g), (h), (i) subset III, (a), (d), (g) model-based approach without Kriging-based correction, (b), (e), (h) model-based approach plus KTS-based correction, and (c), (f), (i) model-based approach plus SK-based correction.

purpose, the OLS displacement velocity inversion was applied to subsets of SLC images divided by an hour (i.e., each subset includes SLC images observed within 1 h), generating the velocity time-series. In total, 64 image subsets were obtained; thus, 64 corresponding velocity maps were produced. All displacement velocity values that appeared over the test area are assumed to be caused by APS. Fig. 7 reports the root mean squares (rmss) of the derived displacement velocity results averaged by 64 velocity maps for three approaches. The time-series of line-of-sight velocity at the center part of the test region are plotted in Fig. 8.

According to Fig. 7, a significant reduction in rms values over the test region is observed after applying the Kriging correction. When comparing the KTS and SK methods, the rms values for KTS are notably lower than those for SK, with the improvement being particularly enhanced at the center part shown in Fig. 7.

Accordingly, Fig. 8 illustrates that the KTS method results in less fluctuation in velocity time-series compared to the other two approaches.

V. DISCUSSION

The Kriging-based method incorporating time-series similarity demonstrated more accurate APS spatial prediction than conventional Kriging interpolation in Section IV, as validated in stable regions. However, to avoid bias estimation of spatial correlation and the inclusion of displacement signal in the weighted averaging process, this approach typically requires exact knowledge of the displacement region, which is unpredictable in some scenarios. Nevertheless, this issue is not a concern in certain applications, such as glacier monitoring, where the displaced region is clearly visible.

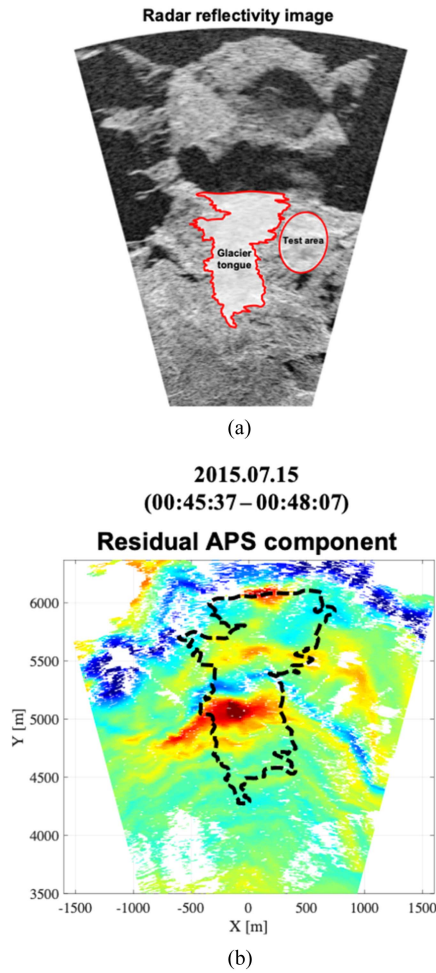


Fig. 6. Locations of investigated area for glacier dataset overlaid on an obtained radar reflectivity image.

From Fig. 7, the rms values at the center of test region appear to be relatively high in kriging results. This could be explained by the fact that the farther the interpolating CSs are located from a prediction pixel, the smaller the prediction accuracy will be, as indicated by the prediction error variance in (12) and (28). Hence, when the displacement area is relatively large compared to radar image, inaccurate predictions are expected. Nonetheless, this issue might be improved by the KTS, as the KTS reduces rms values, particularly in the center part of the test region, as shown in Fig. 7.

Considering a more practical scenario, we discuss the applicability of APS correction by the Kriging-based approach on a moving glacier. For this purpose, the glacier monitoring dataset presented in Section IV-B is employed. It is important to note that the quantitative error comparison is not feasible for the employed dataset due to the absence of ground-truth information for glacier moving velocity. Therefore, this section illustrates the performance of the approaches by investigating temporal phase evolution variability, assuming that the fluctuated phase component is generally contributed from APS.

A total of 47 SLC images acquired from 0:00 a.m. to 2:00 a.m. were utilized to study the phase evolution. For the correction of

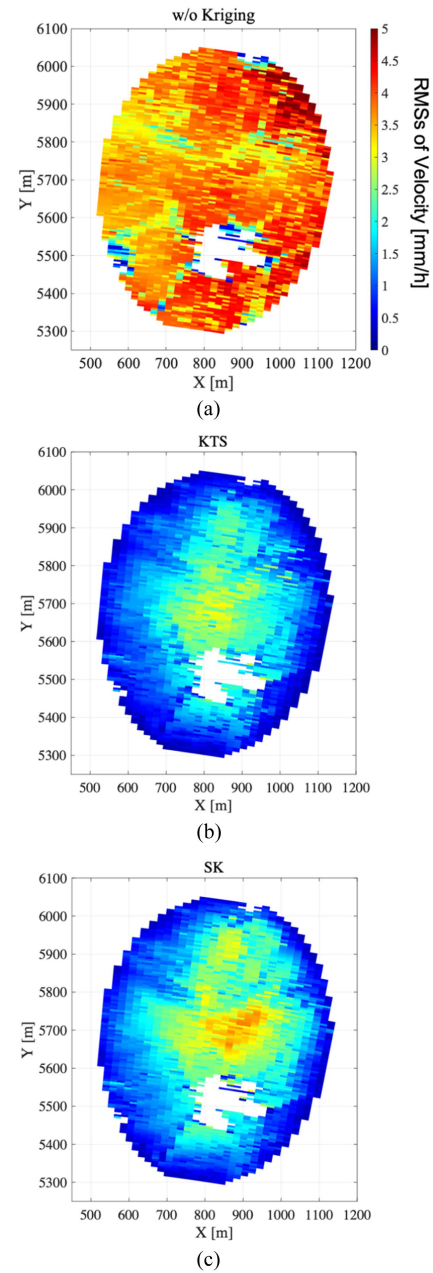


Fig. 7. Mean rmss of velocity maps derived by 64 displacement velocity results (from July 13 to July 15) over stable test area (rock and soil surfaces assuming no displacement at the timescale of the repeat rate) indicated in Fig. 6. (a) Model-based approach without Kriging-based correction. (b) Model-based approach plus KTS-based correction. (c) Model-based approach plus SK-based correction.

residual APS over glacier, we initially masked the glacier tongue zone and then predicted the residual APS by extrapolating from CSs on the rock and soil surface. From the stack of corrected interferograms, we computed the SD of the temporal differential phase variation at pixels corresponding to the glacier tongue, as depicted in Fig. 9.

Comparing both SD maps, the KTS method exhibits a lower SD than the SK method. Fig. 10 illustrates temporal phase evolution plots at the bottom part of the glacier tongue, revealing the overall phase trend caused by actual movement with a certain

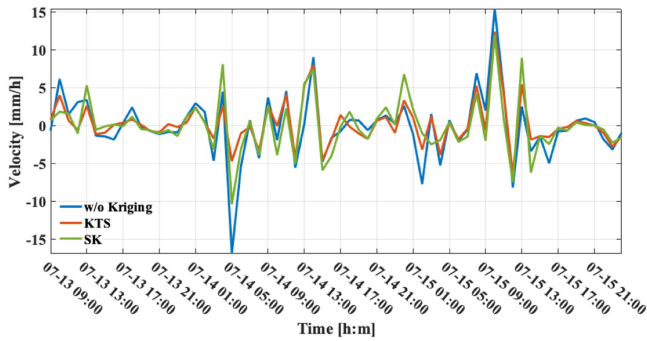


Fig. 8. Time-series of LOS displacement velocity at the center part of the test area.

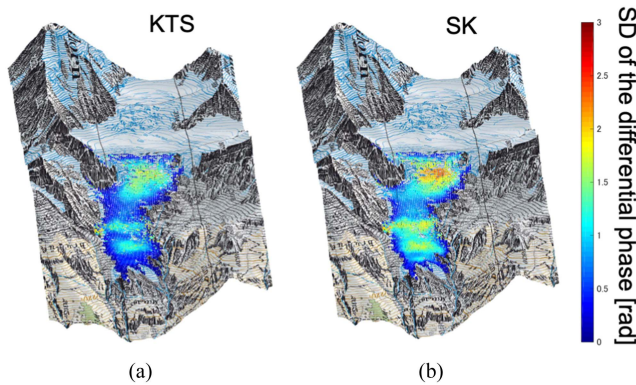


Fig. 9. Geocoded SD map over the glacier tongue computed along the temporal axis. (a) KTS method. (b) SK.

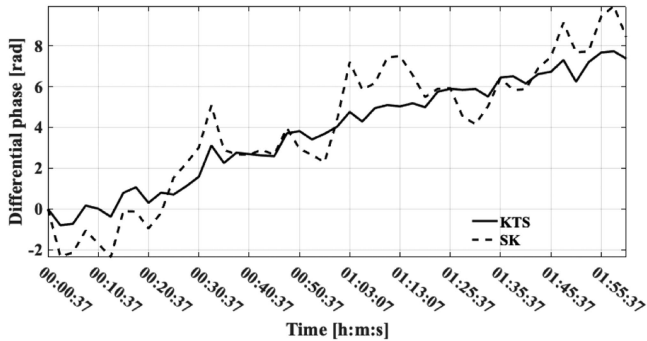


Fig. 10. Phase evolution plots at the bottom part of the glacier tongue after residual APS compensation by (solid line) the KTS method or (dashed line) the SK.

fluctuation. Additionally, Fig. 10 indicates the smoother phase evolution of the KTS compared to the SK, demonstrating better mitigation of possible APS signals for the KTS.

The intense phase variability can lead to the misinterpretation of the target dynamics, potentially decreasing the reliability of the results, especially when the radar is used as a real-time early warning system. The KTS approach, with its enhanced APS mitigation performance, is thus considered an effective solution when a priori knowledge of the deformation region is known.

VI. CONCLUSION

In this article, an adapted APS compensation method designed explicitly for the time-series InSAR framework is presented. A similarity measure based on cross-correlation of temporal APS profiles is incorporated into the conventional covariance, enriching the covariance model with a higher dimension in the KTS method. The spatial prediction in the KTS method simultaneously leverages temporal similarity and spatial correlation.

The validity of the KTS method was assessed using Ku-band FMCW GB radar datasets. Two types of datasets from mountainous regions were employed: the first dataset was observed over a postlandslide mountainous slope in Japan, and the second dataset was observed in the Swiss alps. The validation was conducted over the stable, motionless pixels to quantify the residual phase error. The comparative study revealed a noticeable improvement in the APS correction with the Kriging-based correction in addition to the model-based solution. When comparing the proposed KTS with the SK, the KTS demonstrated superior APS correction performance, highlighting that the incorporation of temporal phase evolution similarity enables more informative covariance estimation and better Kriging prediction.

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