Millimeter slope ratcheting from multitemporal SAR interferometry with a correction of coastal tropospheric delay: A case study in Hong Kong

Guoqiang Shi\textsuperscript{a,e}, Bo Huang\textsuperscript{a,b,e,*}, Anthony Kwan Leung\textsuperscript{c}, Charles W.W. Ng\textsuperscript{c}, Zhilu Wu\textsuperscript{f}, Hui Lin\textsuperscript{g}

\textsuperscript{a} Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong SAR, China
\textsuperscript{b} Department of Geography and Resource Management, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong SAR, China
\textsuperscript{c} Department of Civil and Environmental Engineering, The Hong Kong University of Science and Technology, Kowloon, Hong Kong SAR, China
\textsuperscript{d} Key Lab of Poyang Lake Wetland and Watershed Research of Ministry of Education, School of Geography and Environment, Jiangxi Normal University, Nanchang 330022, China
\textsuperscript{e} Shenzhen Research Institute, The Chinese University of Hong Kong, Shenzhen 518063, China
\textsuperscript{f} School of Geodesy and Geomatics, Wuhan University, Wuhan 430079, China

ABSTRACT

Tropospheric delays (TDs) limit the accurate detection of slow slope motion using interferometric synthetic aperture radar (InSAR), especially in subtropical coastal regions prone to frequent changes in humidity. Although TDs can be estimated through external weather data, their spatiotemporal resolution and data availability are greatly limited, which is not applicable for individual slopes. This paper presents new TD correction methods for slopes with both small dimensions and small elevation changes. We simultaneously estimated and eliminated the TD signal from a line-of-sight (LOS) time series through a blind source separation (i.e., independent component analysis). The stratified TD sources were isolated according to a spatially elevation-linked and temporally periodic independent-component (IC), which was determined via a correlation test and power spectrum analysis. Hence, the TD was corrected without the use of any external weather products/meteorological data and had unprecedented spatiotemporal details equivalent to the synthetic aperture radar (SAR) images. The proposed method was verified using CosmoSkyMed (CSK) and Sentinel-1 (SNT-1) images covering a slope in Tai O, Lantau Island, Hong Kong, and validated using a series of geodetic, meteorological, and hydrological data. Up to 3–4 cm relative TDs were measured in the LOS directions of CSK and SNT-1. The relative TD exhibited a slower increment rate than the slope elevation and was largely affected by specific air conditions (e.g., temperature and humidity) on the SAR image-acquisition days. The analysis of InSAR data yielded reasonably good estimates of millimeter-scale downslope slips (due to increases in pore-water pressure in the wet season) and upslope rebound (due to soil shrinkage in the dry season). It was found that soil swelling and shrinkage of the slope (also known as seasonal ratcheting) and the reclamation were likely regulated by rainfall and sea levels, respectively. Although the slope motion in Tai O was determined to be small (i.e., seasonal variations of 10 mm), the TD correction reduced the root-mean-square error by 42.3%, such that InSAR time-series measurements with millimeter-level accuracy (potentially 1–3 mm) were obtained.

1. Introduction

The use of Interferometric Synthetic Aperture Radar (InSAR) for slope surveillance has received growing attention in the scientific literature, especially in recent years (Solari et al., 2020; Cigna and Tapete, 2021). Inversion of slope deformation from interferometric phases is affected by radar refractivity in a heterogeneous atmosphere. Thus, atmospheric delays, particularly the stratified tropospheric delays (TDs), must be corrected (Ding et al., 2008; Darvishi et al., 2020). Slope motion is typically regulated by rainfall and other hydrological factors (Handwerger et al., 2013; Cohen-Waeber et al., 2018), which induce seasonal waveforms that can interfere with the seasonal atmosphere. This interference can lead to misinterpretation of measurements, especially when the surface deformation is insignificant compared with (thus

\* Corresponding author at: Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong SAR, China. E-mail address: bohuang@cuhk.edu.hk (B. Huang).

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more easily contaminated by) the atmospheric noise. The subtraction of phases measured at adjacent locations (i.e., spatial differencing) can mitigate such disturbances in the horizontal plane (Shi et al., 2018). However, the vertical heterogeneity of TD, which is influenced by elevation-related humidity, air pressure, and air temperature, cannot be effectively corrected in this manner. Instead, previous studies have used auxiliary weather data to reduce vertical TDs (Li et al., 2005, 2009, 2019; Doin et al., 2009; Jolivet et al., 2014) and have addressed large-scale and significant elevation changes, such as volcanic activities (Wicks et al., 2002; Remy et al., 2003) and interseismic slips (Schmidt et al., 2005; Grandin et al., 2012). Unfortunately, weather products have much lower spatial resolution than that of SAR images and the temporal sampling and layering are not fine either. This lack of spatiotemporal detail meant that the TD corrections for a single landslide were partly based on interpolated weather models and meteorological data (Dong et al., 2019; Darvishi et al., 2020). In addition, sufficient auxiliary weather data are not always available, and the correction procedure integrated into the phase modeling and compensation is complicated. These limitations lead to the difficulty to determine TD corrections for small-dimension and low-altitude slopes. For example, in Hong Kong, slope stability is assessed for relatively small catchments or subcatchments that are typically only a few to 50 ha in area (Parry and Hart, 2012). The continual improvements in the resolution of SAR imagery have increased the needs to seek for more effective methods that can accurately determine TD corrections, particularly in coastal regions where humidity, that directly affects TD, varies substantially and frequently (Jin et al., 2007; Zhang et al., 2020).

Blind signal separation methods such as principal component analysis (PCA; Abdi and Williams, 2010) and independent component analysis (ICA; Comon, 1994; Hyvärinen and Oja, 2000) have been developed to directly isolate individual contributions from an observed time series without a priori knowledge of the underlying sources. In the field of geodeics, PCA or ICA have been adopted to separate and interpret multisource deformation signals in data from the global navigation satellite system (GNSS) (Dong et al., 2006), InSAR (Cohen-Waebber et al., 2018), borehole tiltmeters (De Lauro et al., 2018), and tension-wire alignment systems (Dai et al., 2014). Compared with PCA, ICA allows for more effective separation of mixed sources according to the statistical properties of independence and non-Gaussianity (Yan et al., 2019), which has been proved efficient for isolating atmospheric disturbances in coastal regions from the GNSS time series (Zhang et al., 2020).

The aim of this paper was to develop an ICA-based method for automatically separating and removing stratified TDs from massive InSAR time-series data. In contrast to existing methods that require compensation of phase contributions from the atmosphere, the proposed method involves post-processing of InSAR-derived line-of-sight (LOS) measurements. The TD signals are isolated according to the spatially elevation-linked and temporally periodic independent-component (IC) source, which is determined through a correlation test and power spectrum analysis of separated ICs. This method is easy to implement and is not limited to the resolution of weather products or meteorological data. Thus, it enables TD corrections to be determined for sub-km² areas and small elevations (e.g., 100 m). The method was verified through a case study in a hilly and vegetated slope in Tai O, Hong Kong, using CosmoSkyMed (CSK) and Sentinel-1 (S1T-1) SAR images. Persistent scatterers (PS) interferometry and distributed scatterers (DS) interferometry were both used to improve the InSAR measurements of low-coherence vegetated slopes. The extracted TD and InSAR deformation measurements were validated and interpreted using a series of geodetic, meteorological, and hydrological datasets from the study areas.

2. Study area and data

2.1. Tai O, west coast of Lantau Island

In coastal subtropical monsoon regions such as Hong Kong, humidity varies substantially and frequently with elevation, which leads to considerable stratification of the troposphere. The study area in Tai O (Fig. 1) has an elevation range of 0 to ~400 m a.s.l. (above sea level), with a slope facing approximately southwest and a slope gradient of approximately 30°. The vegetation consisted mainly of trees, shrubs, and herbs, and the biomass reduced from the slope toe (trees and shrubs) to slope body (grass) and slope crest (bare soil).

In June 2008, an exceptionally intense rainstorm (top hourly precipitation >100 mm) hit Lantau, resulting in over 2400 small-volume (mostly <1000 m²) landslides on its natural hillside (Lam et al., 2012; Sewell et al., 2015). This was a widespread disaster that had enormous impacts on local society (e.g., it blocked the North Lantau expressway, the only land access to Hong Kong’s international airport) and caused unprecedented damage to the small clusters of residential dwellings distributed across the island (Leung and Ng, 2013), particularly in Tai O (Ko and Sun, 2016). Measuring surface deformation on the remote and vegetated hillslopes of Hong Kong is challenging. Although the Hong Kong government has implemented intermittent monitoring in Lantau, the spatial detail of ground measurements is unsatisfactory for the purposes of quantitative risk assessment. In recent years, slope deformation due to seasonal variations at North Lantau was observed to be only a few to tens millimeters (Leung and Ng, 2016). In 2015 and 2017, the Geotechnical Engineering Office (GEO) of the Civil Engineering and Development Department (CEDD) of the Hong Kong government continuously monitored the slope surfaces at Tai O using distributed prisms. These prism measurements revealed that although this slope is not prone to immediate failure, it is creeping slowly (at a millimeter level) and therefore, long-term high-resolution monitoring is needed to prevent disasters similar to the intense rainstorm of 2008. Indeed, given the small amount of slope deformation, adequate correction of TD in this application is deemed important to obtain accurate measurements in Tai O and on other hillslopes that share similar characteristics.

2.2. Data

We used 63 descending CosmoSkyMed (CSK, from 20131004 to 20190728) and 143 ascending Sentinel-1 (SNT-1, from 20150615 to 20200811) images to measure the ground motion in the study area. Local monthly water-vapor pressure from the Hong Kong Observatory (HKO) was used for TD signal seasonality analysis. We validated and interpreted the estimated TD using meteorological records of temperature, humidity, and weather reanalysis products (ERA5). Measurements of slope surface movement between December 2015 and December 2017 were collected from four prisms to validate the InSAR deformation estimates after TD correction using the developed method and the Generic Atmospheric Correction Online Service (GACOS, Yu et al., 2018). As shown in Fig. 2, each prism was structurally fixed to a standing pole made of aluminum (with a diameter of ~25 mm, a height of 500–800 mm above ground, and an embedded depth with grouting of up to 500 mm). The reference point of these prisms, which also served as the InSAR zero reference, was set on a stable building (red triangle in Fig. 1). The measurements obtained from each prism represent the near-surface displacement at the exact site location (i.e., pointwise), whereas InSAR measures the slope surface deformation of a ground patch in most cases (e.g., distributed scatterers in vegetated area). Due to the extreme weather conditions at Lantau Island, some prisms were disturbed and even destroyed by strong wind or lightning. Accordingly, for some periods, the prism measurements might not represent a highly credible information for the slope deformation at the measurement sites. We validated our method using measurements from four prism sites that had relatively complete and continuous records, which were distributed
from the slope foot to the crest (Fig. 1). We interpreted the observed seasonal movement of the slope and reclaimed land using monthly rainfall records (January 2013–August 2020) obtained from a rain gauge installed at Ngong Ping (~3 km from the study area) and monthly average tidal (sea-level) records (January 2013–October 2019) obtained from the Tai O tide station. Monthly average tide level was calculated using minute-wise raw data obtained from the Drainage Services Department of the Hong Kong government. The geographic locations of the instruments are marked in Fig. 1.
3. Methodologies

3.1. Combined processing of PS and DS

Vegetation on slope surfaces could reduce the radar coherence and challenges the deformation inversion from interferograms (Ferretti et al., 2011). To reveal more details of slope movement, we used a two-tier network strategy for the detection of PS and DS (Shi et al., 2018). The 20170201 and 20180424 acquisitions were used as master single-look complex (SLC) images for full-pixel-resolution interferometry processing of the CSK and SNT-1 datasets, respectively. We adopted a triangular network to establish the first-tier PS measuring layer, which connected the pixels with an amplitude dispersion index (ADI) of <0.4 (Ferretti et al., 2001). To extend the DS measurements over moderate coherence surfaces, we first applied spatiotemporal homogeneous filtering to denoise the interferograms. The filtering involves a topographically homogeneous pixel selection (Shi et al., 2022) and a phase history reconstruction based on iterative phase-linking algorithm (Guarnieri and Tebaldini, 2008). Then, DS candidates were connected to their nearest PS points via a local star network to form the second measuring layer (Shi et al., 2018). The inversion of geophysical parameters (e.g., topography elevation and LOS deformation rate) was achieved using a beamforming estimator for both the PS and DS arcs (Reigber and Moreira, 2000). We retained arc solutions with the normalized temporal coherence >0.7 (Shi et al., 2018). Finally, we obtained the values of LOS deformation rates and elevation for the PS and DS locations from network adjustment by using one reference point in the monitoring area (red triangle in Fig. 1). Fig. 3 depicts the image baseline configurations and the annual LOS deformation rates at Tai O (positive values indicate movement toward satellites). The extension of DS provided incredible measurement density, revealing detailed deformation for the main vegetated slope area. The first acquisition date was taken as the zero temporal reference for the two datasets (i.e., 20131004 for CSK and 20150615 for SNT-1). The red colour in Figs. 3c-d indicates considerable movement away from satellite owing to the subsidence of the reclaimed sea wall (flat area), whose construction was completed in 2005. The LOS rates show that the slope terrain was generally stable during the InSAR monitoring period. Spatial heterogeneity of the atmospheric component was mitigated in the horizontal plane via spatial differencing (i.e., PS and DS networking). However, the vertical tropospheric heterogeneities remained in the InSAR LOS estimates, whereas they are not visually recognizable in the rate maps.

3.2. ICA for InSAR LOS measurements

The LOS measurements can be regarded as comprising multisource contributions from the remained atmospheric disturbances, seasonal deformation (e.g., hydrogeology-regulated soil deformation), long-wave deformation (e.g., slow slip or subsidence), and systematic and random noise. The optimal separations of mixed blind sources are those that have maximum non-Gaussianity, which is determined by quantifying their negentropy (Hyvärinen and Oja, 2000). One can assume the stratified TD disturbance and the deformation are statistically independent in space and/or in time. ICA is a statistical and computational technique that can transform mixed sources into non-Gaussian mutually ICs that have maximum negentropy (Comon, 1994; Bell and Sejnowski, 1995). In this paper, we use a temporal ICA (tICA) to determine the spatiotemporal patterns of the TD. The matrix of spatiotemporal InSAR
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LOS measurements is organized as $LOS_{z:m}$ that is populated by the LOS “deformation” (at this stage, the deformation is mixed with TD) of $n$ ground locations (the detected PS/DS pixels) considered at each of $m$ time steps (image acquisitions). For example, the SNT-1 has $n = 14,419$ pixels detected (and $m = 143$ images), so that $LOS$ is a $14,419$ by $143$ matrix. The tICA decomposition can be defined as:

$$LOS_{z:m} = S_{z:k} \bullet T_{z:m} \quad (1)$$

where $S_{z:k} = [S_1, S_2, \ldots, S_k]$ is an unknown mixing matrix representing the spatial distribution of the $k$ source signals that are retained for analysis from the ICA decomposition; $S_{z:k}$ contains elements of $S_j(1 \leq i \leq n, 1 \leq j \leq k)$, which is also called the spatial response that indicates the contributions of the $j^{th}$ source signal to the $i^{th}$ observation (pixel); and $T_{z:m}$ is the unknown matrix representing temporal behavior of the underlying sources, for the $T_{z:m}(1 \leq j \leq k)$ source its time series is recorded as $[T_{z1}, \ldots, T_{zm}]$. Because of the difficulty to simultaneously solve the two unknown mixing variables, ICA first identifies the identification of a linear decomposition matrix $W_{k:m}$ which transforms the original observation $LOS_{z:m}$ to a set of mutually independent variable series, i.e.,

$$Y_{z:m} = W_{k:m} \bullet LOS_{z:m} \quad (2)$$

where $Y_{z:m}$ contains the independent variable series $y_j = [y_{j1}, \ldots, y_{jm}]$, $1 \leq j \leq k$ and $y$ can well represent the underlying sources $T_{z:m}$. In this paper, we use the fixed-point algorithm called FastICA (Hyvärinen and Oja, 1997) to iteratively solve $W$, see details in Text S1 in the supplement. Once $W$ is determined, $S$ (i.e., the generalized inverse of $W$) can be evaluated. Thus, the spatial ($S$) and temporal ($T$) patterns of the independent sources can be isolated. Before estimating the ICs, the PCA is first performed to reduce data dimensionality. To determine the dimensions that best describe the LOS data, we tested the stability of the principal components (PCs) using a risk function based on bootstrap resampling (Besse, 1992). Fig. S1 (in the supplement) shows the PC scree plot (describes data variances explained by the PCs) and the risk estimates (stability analysis of the PCs). The results suggest that the first six dimensional subspaces are sufficient and stable descriptions of the LOS data, as they explain the majority (> 96%) of the variance in both the CSK and SNT-1 datasets. Therefore, we retain the first six PCs for the ICA analysis in the Tai O case study.

3.3. TD identification

The TD includes the hydrostatic (dry air) and wet components (Hurter and Maier, 2013). The hydrostatic component has a greater magnitude than the wet components, but considerably smaller seasonal fluctuations (Zebiker et al., 1997; Samsonov et al., 2014). The InSAR measurements (interferograms) are affected by the difference between master SLC and slave SLC atmospheric disturbance, so that the temporal variability (seasonal fluctuations) of TD is more important than its absolute value on individual dates (Samsonov et al., 2014). In the space domain, the TDs remained are the relative values to the zero reference after PS/DS networking. Therefore, the stratified effects to be solved in the LOS measurements is a spatiotemporal relative TD. As this stratification is highly related to the topography (Murray et al., 2020), if a separated source is caused by the desired TD, its spatial response (i.e., $S$ in Eq. (1)) should theoretically be correlated with the terrain elevation. To determine the TD source from the isolated ICs, we define the following correlation index:

$$\rho(k) = \frac{\sum_i (S_i - \bar{S})(H_i - \bar{H})}{\sqrt{\sum_i (S_i - \bar{S})^2} \sqrt{\sum_i (H_i - \bar{H})^2}} \quad (3)$$

where $\rho(k)$ is the correlation coefficient of the $k^{th}$ IC ($k = 1, \ldots, 6$ in this case); $S_k$ contains the IC spatial responses at each of the pixels, i.e., $S_{ik}$; $i = 1, \ldots, n$ is the pixel index; $H$ is the slope elevation estimated from InSAR; and $\bar{H}$ and $\bar{S}$ represent mean values. A high $\rho \in [0, 1]$ value reveals that the two variables of the IC spatial response and the topography are highly correlated. In addition, TD is expected to have clearly discernible seasonal cycles controlled by air temperature and humidity level (Fattahi and Amelung, 2015). Thus, we also estimate the seasonality of the IC time series (i.e., $T$ in Eq. (1)) by computing their spectra:

$$P(k) = \frac{F(T_k) \bullet F(T_k)^*}{L} \quad (4)$$

where $P(k)$ is the power spectrum of the $k^{th}$ IC time series; $F$ indicates a Fourier transform; $(*)^*$ denotes a complex conjugate; and $L$ is the length of the time-series vector. $P$ can be solved via a fast Fourier transform (FFT) (Welch, 1967). $T_k$ was interpolated into an even temporal sampling before the FFT operation. The power spectrum indicates the periodicity of temporal patterns of the isolated ICs. Therefore, the TD component (i.e., $IC_{TD}$) can be determined from the IC sources using the highest spatial correlation ($\rho$) and strong seasonality revealed by their spectra. $IC_{TD}$ is then subtracted from the original InSAR LOS measurements to obtain the TD-free slope deformation.

4. Results

4.1. InSAR-derived TD in Tai O slope

The values of correlation $\rho$ and normalized power ($P$) of the six isolated IC signals are given in Figs. 4a–d. The fourth IC from the CSK data and the fifth IC from the SNT-1 data exhibit a distinctively strong correlation with the slope elevation and a seasonality of approximately 1 year. The order of the ICs does not indicate any priority exists in the separated sources. Given the observed features in Figs. 4a–d, we inferred that the fourth IC of the CSK data (i.e., CSK-IC4) and the fifth IC of the SNT-1 data (i.e., SNT-1-IC5) represent their respective TD disturbances. The temporal variation of the TD is regulated by variations in atmospheric temperature and water-vapor pressure (Delacourt et al., 1998; Hofmann-Wellenhof et al., 2012). To validate this, temporal patterns of the CSK-IC4 and the SNT-1-IC5 were compared with that of the local monthly water-vapor pressure. The latter was obtained using averaged values of 30 years of observations between 1981 and 2010 from the HKO. The waveforms of inferred TD source matched well with the variation in the water-vapor pressure (Fig. 4e), validating the extracted TD signals. Small inconsistency between the CSK and SNT-1 IC time series in Fig. 4e is reasonable as the temporal sampling (acquisition time) and looking geometries (LOS directions) of the two sensors are not the same, thus causing different TDs in their respective signal paths (Fig. S2).

Fig. 5 shows the temporal (scaled $T$, Figs. 5a–b) and spatial ($S$ normalized to score values between 0 and 1, Figs. 5c–d) patterns of the TDs determined from the CSK and SNT-1 datasets and the InSAR-estimated topography (i.e., elevation, Figs. 5e–f). The product of scaled $T$ and normalized $S$ equals to the product of their original values from the ICA decomposition. The TDs in this study were temporally referenced to the first SAR acquisition dates and spatially referenced to the deformation zero reference point. The spatiotemporal patterns of other ICs of the two datasets are given in Fig. S3. As the reference point was set in a residential area close to the sea level, the amplitude of the relative TD increases with the topographical elevation (Figs. 5c–d). Interferometry measurements were conducted at full pixel resolution without multi-looking; therefore, the obtained TD has a fine spatial sampling of $\sim 3 \times 3$ m for CSK and $\sim 5 \times 20$ m for SNT-1. The score maps (Figs. 5c–d) can be converted to TD (in mm) by multiplying the corresponding scaled IC values (Figs. 5a–b) at the given time. According to the time series in Figs. 5a–b, the relative TD reaches a maximum seasonal variation of $\sim 4$ and $\sim 3$ cm in the CSK LOS and SNT-1 LOS directions, which is larger than the true slope deformation discussed in
Section 4.2.

Hong Kong has a wet season (April to October) and a dry season (November to March; Gao et al., 2018). Accordingly, we plotted the relative TDs in the wet months (centered around the beginning of July) and dry months (centered around the beginning of February) in 2017 and 2018 for the two datasets (Fig. 6). Because the temporal references are different, the relative TD maps of CSK and SNT-1 data do not agree in the dry and wet months. However, this does not affect the results of a similar yearly TD variation from the CSK and SNT-1, i.e., wet – dry, shown in the right column in Fig. 6. Although they were obtained on similar dates in adjacent years, the yearly TD differ between years. This indicates that the frequent changes in the weather conditions of coastal Tai O result in ever-changing TDs. For example, during a similar period for the CSK data, the TD variation in 2018 (Feb. 4, 2018 to Jul. 11, 2018) is approximately 10–15 mm greater than that in 2017 (Feb. 1, 2017 to Jul. 7, 2017) in the slope top; this is presumably related to the random and specific atmospheric conditions (e.g., humidity and temperature) that regulated the TDs on these 4 days. To prove this, we collected meteorological data from two nearby weather stations to compare their atmospheric conditions. One is located at the Hong Kong International Airport (~6 m a.s.l.), which is ~6 km away from Tai O (referred as WS1), and the other (WS2) is at Sha Lo Wan (~61 m a.s.l.), which is ~4.5 km away from Tai O. Table 1 summarizes the details of meteorological elements obtained from WS1 and WS2 on the four CSK days. The relative changes in both the air temperature and the humidity between Feb. 4, 2018, and Jul. 11, 2018, are more than twice those between Feb. 1, 2017, and Jul. 7, 2017. The differences in the low atmosphere (humidity and temperature) of Tai O between these days could support and explain our findings of yearly TD inconsistency in Fig. 6, which accumulates to centimeters at the top of slope (hundreds-meter elevation change). Therefore, the similar observation periods can be subject to highly different TDs. Products from GACOS also revealed this difference of relative TD between years; however, our estimations have provided much more spatial details compared with the weather products (Fig. S4). From this perspective, the proposed method enables TD estimations that are consistent with the SAR imaging time and pixel details. Readers can refer to the supplementary videos for three-dimensional visual representations of the TD dynamics (in mm) in Tai O (see CSK_TD.gif and SNT_TD.gif, in which the spatiotemporal reference is the same as that in Fig. 6).

4.2. Deformation validation from terrestrial prisms

To validate the TD-free deformation, we used measurements from terrestrial prisms installed in Tai O between 2015 and 2017. The locations of the prism stations (SPs) are given in Fig. 1, with the following elevations: SP01, 78 m a.s.l.; SP02, 216 m a.s.l.; SP03, 217 m a.s.l.; and SP04, 245 m a.s.l. Owing to the looking geometry, the ascending orbit of SNT-1 is not sensitive to the slope motion in Tai O with a southwest slope aspect. If the deformation occurs only in the downslope direction (i.e., the largest topography gradient), the sensitivity of slope displacement to the LOS direction can be estimated as follows:

$$S_{\text{LOS}} = \sin \theta \cdot \sin \varphi \cdot \cos \alpha \cdot \cos \sigma - \sin \theta \cdot \cos \varphi \cdot \cos \alpha - \sin \theta \cdot \sin \alpha$$

where $S_{\text{LOS}}$ denotes sensitivity, which means that a per-unit downslope displacement (corresponding to a positive displacement) results in an $S_{\text{LOS}}$ unit LOS displacement (a positive value indicates LOS movement toward satellite); $\theta$ and $\varphi$ are the satellite incidence angle and the orbit azimuth angle, respectively; and $\alpha$ and $\sigma$ are the slope and aspect angles, respectively. According to the high-resolution LiDAR digital surface model (DSM), the slope gradient and aspect for the Tai O site are...
approximately 30° and 230° (clockwise from the north), respectively, and the $S_{LOS}$ value for the SNT-1 orbit is ~0.1. Consequently, the lower sensitivity weakens the dominance of deformation signals in the SNT-1 LOS observations, which amplifies the effect of noise. In addition, compared with the X-band (wavelength 3.1 cm) CSK data, the C-band (wavelength 5.5 cm) SNT-1 data are less sensitive to small deformations. Thus, for the deformation validation, we used InSAR measurements from the descending CSK data that has an $S_{LOS}$ value of approximately 0.7. In this validation, we also used GACOS to assess its performance on TD correction for the Tai O case. Fig. 7 presents the time-series deformations, where the standard deviations (stds) of the InSAR and prism measurements are presented by error bars and shadows, respectively. Higher std. at SP01 indicates lower InSAR measurement quality in the mountain foot affected by intensive vegetation, than the other sites (SP02-04). Strong winds, rainstorms, and lightning frequently disturbed the prisms. For example, the wind shifted the direction of a prism, thereby causing losses of data in its time series (Fig. 7b), and external disturbance resulted in abnormal prism movement (Fig. 7d). These damages were recorded by the instrument maintainers; however, some other incidents might have been undocumented, and thus will affect the accuracy of the prism measurements on some dates.

The TD-free time series estimated from the proposed method (InSAR-C) agrees better with the prism time series than the original InSAR data (InSAR-O). Given that the prism data were the ground truth, the root-mean-square errors (RMSEs) of the InSAR-C time series for SP01, SP02, SP03, and SP04 were 2.5, 2.9, 3.4, and 4.4 mm, respectively. The RMSE was calculated using the overlap period of the InSAR and prism data: the prism observations were interpolated to the InSAR dates. The
RMSEs of the InSAR-C are lower than InSAR-O by 40.5%, 47.3%, 46.0%, and 35.3% at SP01, SP02, SP03, and SP04, respectively (i.e., an average of 42.3%). However, such improvement was not achieved by the GACOS corrections (InSAR-G). Due to the frequent change of low atmosphere in the subtropical region, the spatiotemporal interpolated GACOS may not precisely represent a true TD at the exact location (pixel) and the imaging time of the SAR data. The correction using GACOS is even more challenging when both the TD and deformation are rather small, e.g., 10-20 mm in Fig. 7. Table 2 lists the values of the deformation from prism and InSAR for the overlap period at SP02. The RMSEs of the InSAR-C time series, except for SP01, are mainly contributed by the biased measurements made around February 2017 (Fig. 7, also see the values in Table 2). Otherwise, the overall RMSE would be accordingly smaller (if excluding Feb. 2017 measurements, i.e., 2.6, 1.4, 2.6, and 2.2...
mm for SP01, SP02, SP03, and SP04, respectively) than the current estimates. As mentioned, the prism measured deformation at point-wise locations (the footing grout in Fig. 2), whereas InSAR reflected the average deformation of a ground patch covered by a pixel (or pixels, if the patch was not. Thus, outliers may occur between the InSAR and prism measurements. As mentioned, the prism measured deformation at point-wise locations (the footing grout in Fig. 2), whereas InSAR reflected the average deformation of a ground patch covered by a pixel (or pixels, if the patch was not. Thus, outliers may occur between the InSAR and prism measurements. As mentioned, the prism measured deformation at point-wise locations (the footing grout in Fig. 2), whereas InSAR reflected the average deformation of a ground patch covered by a pixel (or pixels, if the patch was not. Thus, outliers may occur between the InSAR and prism measurements. 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Fig. 7. Validation of InSAR deformation time series using prisms. Comparison of the original InSAR deformation (InSAR-O), the TD-corrected InSAR deformation from the proposed method (InSAR-C), the GACOS-corrected InSAR deformation (InSAR-G), and the LOS-projected prism deformation (SP-LOS) for sites (a) SP01, (b) SP02, (c) SP03, and (d) SP04. Gray shadows indicate the observation stds of the prism measurements, brown shadows indicate abnormal data records, and blue crosses indicate the zero reference. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
hydrological forcing, which led to variation in the effective stress within the soil water content due to tidal fluctuations and changes in rainfall. Such seasonal oscillations were also observed in the time series of slope deformation (Fig. 7). In coastal areas, variations in soil water content due to tidal fluctuations and changes in rainfall significantly influence short-term (months or quarters) deformation processes (Totani et al., 2007). However, given their different locations and geological environments, the hydrological forcing behind the seasonal deformation could be different for the slope and the marine reclamation.

5.1. Rainfall regulated millimeter slope ratcheting

Before interpreting the slope motion, we projected the LOS measurements to the downslope direction, assuming the slope predominantly moved along the largest gradient (Sun et al., 2016). The integration of different InSAR orbits can afford more robust estimates of downslope deformations; however, the SNT-1 looking geometry is significantly moved along the largest gradient (Sun et al., 2016). The average downslope deformation (calculated from all of the InSAR points on the slope) against the annual rainfall. In several cases, the downslope movement meets the wet (rainfall accumulating) seasons and the upslope rebound meets the dry (rainfall decreasing) seasons. The mean value of the estimated downslope/upslope motion in Tai O was approximately 10 mm, which, if projected to the vertical direction (i.e., $10\text{mm} \times \sin(30^\circ) = 5\text{mm}$), is in accordance with the measurement obtained from prisms.

5.2. Reclamation deformation associated with ocean tides

In marine rejections, the water level in the underlying substrate varies in response to the tidal level outside the site and to rainfall (Plant et al., 1998). The resulting fluctuation in soil water content may lead to seasonal swelling of the soft and loose filling materials. In addition, ocean tidal loading is significant in many coastal regions as the elastic response of the Earth to the redistribution of water mass from the ocean tides (Agnew, 2012). In this case, the seasonal oscillations in the vertical deformation were found to be slightly larger in magnitude than that of the slope movement, with a variation of roughly 10–20 mm (Fig. 11). Tidal influence on reclamation deformation has been observed in the Hong Kong International Airport (Jiang et al., 2010) and in the nearby coastline of Shenzhen City (Liu et al., 2018). However, the relationship between such seasonal displacements and ocean tides is not clear. Fig. 11 shows the waveforms of the detrended vertical deformation (average deformation of all the detected points on the seawall), the monthly rainfall, and the tidal records. The tide gauge was located near the reclamation site (Fig. 1). The wave peaks of the tide and rainfall are not temporally synchronous in Tai O. The deformation peaks were generally in line with the tidal peaks (green-shadowed periods), suggesting that the increase in sea level contributed to the ground uplift of the reclamation. Owing to the more frequent temporal sampling, the SNT-1 has more clearly revealed the seasonal fluctuation of vertical deformation than the CSK. The annual variation in vertical deformation was found to be approximately 1.5 cm, corresponding to a tidal variation of ~0.2–0.4 m. However, it was unexpected to see that the deformation valleys (subsidence) coincided with the rainfall peaks in most situations.

### Table 2

| InSAR-dates | SP-LOS | InSAR-O | $|\Delta_1|$ * | InSAR-C | $|\Delta_2|$ * |
|-------------|--------|---------|-------------|---------|-------------|
| 20160114    | 3.8    | 3.4     | 0.4         | 1.6     | 2.2         |
| 20160318    | -2.1   | 4.8     | 6.9         | -0.9    | 1.2         |
| 20160501    | -6.8   | -0.1    | 6.7         | -6.0    | 0.8         |
| 20161129    | -2.2   | -2.0    | 0.2         | -1.6    | 0.6         |
| 20170201    | 4.7    | -2.7    | 7.4         | -2.2    | 6.9         |
| 20170217    | 6.0    | -1.9    | 7.9         | -1.9    | 7.9         |
| 20170418    | 2.0    | 5.1     | 3.1         | -0.3    | 2.3         |
| 20170524    | -1.1   | 7.2     | 8.3         | 0.0     | 1.1         |
| 20170621    | -0.8   | 7.3     | 8.1         | 0.2     | 1.0         |
| 20170707    | -0.7   | 6.7     | 7.4         | 0.3     | 1.0         |
| 20170828    | -2.0   | 3.0     | 5.0         | -0.5    | 1.5         |
| 20170910    | -2.8   | 2.5     | 5.3         | -0.5    | 2.3         |
| 20171012    | -2.4   | 2.1     | 4.5         | -0.1    | 2.3         |
| 20171113    | 0.5    | 1.4     | 0.9         | 0.1     | 0.4         |
| 20171120    | 0.6    | 1.2     | 0.6         | 0.1     | 0.5         |
| 20171214    | 0.0    | 0.0     | 0.0         | 0.0     | 0.0         |

$\Delta_1 = |\text{SP-LOS} - \text{InSAR-O}|$; $\Delta_2 = |\text{SP-LOS} - \text{InSAR-C}|$.
6. Conclusion

This paper reveals the importance of TD correction for accurate monitoring of small deformations in coastal catchment-wise slopes. An ICA-based method is developed to automatically extract and remove the atmospheric disturbance via a convenient procedure, without the need for auxiliary data or an empirical phase model. Instead of compensating for the atmospheric phase contribution, the method treats the TD as a blind source and directly isolates it through fast post-processing of the LOS estimations. Therefore, it provides a fine spatiotemporally resolved TD that is consistent with the SAR images. The method was tested and validated using a series of geodetic, meteorological, and hydrological datasets from Tai O, Hong Kong. Our results demonstrate that even for small elevation changes, the seasonal stratified TD could not be balanced out through spatial differencing. At an elevation of ~400 m in Tai O, up to 3–4 cm relative TDs remained in the LOS directions of the CSK and SNT-1 datasets.
SNT-1 measurements, which are difficult to be corrected via weather models. The increase rate of relative TD was found to be slightly attenuated with increasing slope elevation. The TD correction improved the accuracy of InSAR deformation time series; the RMSE (with respect to prism measurements) was reduced by 42.3% compared with the uncorrected InSAR deformation.

Different hydrological forcings were found to regulate the seasonal ratcheting in the slope (≈10 mm) and reclamation deformation (≈15 mm) in Tai O. Downslope movement occurred when rainfall accumulated from a dry season to a wet season, whereas upslope rebound occurred when rainfall decreased from a wet season to a dry season. However, the periodic deformation of the seawall substrate seemed to be more related to the sea level, instead of rainfall. The developed method is efficient and can be widely adapted to similar InSAR monitoring tasks, to obtain accurate measurements on small-scale/individual slopes, where meticulous weather products are unavailable.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2022.113148.
Fig. 11. Waveforms of the average vertical seasonal deformation at the reclaimed seawall against the monthly rainfall and the tide level.

CRediT authorship contribution statement

Guoqiang Shi: Methodology, Investigation, Validation, Writing – original draft, Writing – review & editing, Visualization, Data curation.
Bo Huang: Validation, Writing – review & editing, Funding acquisition, Resources.
Anthony Kwan Leung: Writing – review & editing, Resources.
Charles W.W. Ng: Writing – review & editing, Funding acquisition.
Zhilu Wu: Writing – review & editing.
Hui Lin: Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References
