



Three-dimensional bridge displacement reconstruction through Kalman filter fusion of multi-track InSAR observations

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ABSTRACT

This paper presents a novel and scalable framework for the monitoring of civil structures and infrastructures, particularly bridges, using multi-track InSAR data within a recursive Kalman Filter (KF) approach. While InSAR is a well-established technique for detecting millimetric ground displacements, its direct application to Structural Health Monitoring (SHM) is often limited by the one-dimensional nature of Line-of-Sight (LOS) measurements and the need for on-site instrumentation to achieve three-dimensional reconstructions. The proposed framework mitigates these constraints by introducing a data-fusion procedure that combines LOS observations from multiple geometries with environmental and structural information, without requiring additional sensors on site. The framework is demonstrated on the A21 highway viaduct over the Po River, Italy, where ascending and descending EGMS datasets are integrated using the KF together with temperature data. The reconstructed displacements show close agreement with GNSS measurements, confirming the capability of the proposed approach to provide reliable 3D structural information using fully remote data sources.

1. Introduction

Inspection and monitoring are essential activities for ensuring the safety and prolonging the service life of civil structures and infrastructure [1–3]. Bridges, in particular, play a critical role in connectivity, yet they are continuously exposed to environmental loads, material degradation, and time-dependent processes such as creep, shrinkage, and settlement [4–6]. In this context, Structural Health Monitoring (SHM) has become an important complement to traditional inspection practices, providing continuous or periodic measurements of structural response and enabling informed maintenance and management decisions [7–9]. Among monitored parameters, the observation of displacements is of particular relevance. Conventional monitoring relies on on-site instrumentation, such as linear variable displacement transducers, inclinometers, or Global Navigation Satellite System (GNSS) receivers [10]. While these methods are highly precise, they are also costly, require access to the structure, and are typically limited to a sparse set of locations. For large bridge networks, such systems are difficult to scale.

In recent decades, Interferometric Synthetic Aperture Radar (InSAR) has emerged as a powerful alternative for remote displacement monitoring [11–14]. InSAR is based on the processing of radar images acquired by satellites equipped with Synthetic Aperture Radar (SAR)

sensors, which actively transmit microwave pulses and record the backscattered signal [15,16]. Each radar image contains both amplitude and phase information; by comparing the phase of two acquisitions over the same area, surface displacements along the satellite's Line-of-Sight (LOS) can be estimated with millimetric precision. Reliable time series are typically derived from so-called Persistent Scatterers (PSs), i.e. radar targets such as buildings, bridges, or other stable reflectors that maintain coherence over long periods. This makes InSAR particularly suitable for monitoring large areas and infrastructure networks without the need for ground-based sensors. Numerous studies have demonstrated its ability to capture settlements, thermal displacements, and even structural anomalies in bridges and other structures [17–19]. The method offers clear advantages: It is non-intrusive, cost-effective for large networks, and capable of providing historical data thanks to the systematic archives of SAR missions such as ERS, ENVISAT, TerraSAR-X, COSMO-SkyMed, and Sentinel-1. Retrospective analyses are particularly useful for forensic investigations, for example, in understanding the progression of damage or settlement leading up to observed structural collapses [20–23].

With the establishment of the European Ground Motion Service (EGMS), InSAR now offers an unprecedented opportunity for systematic, large-scale, and long-term monitoring of civil infrastructure [24], paving the way for its integration into routine management practices

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[25,26]. The EGMS is a continental-scale Earth observation initiative developed under the Copernicus Land Monitoring Service and coordinated by the European Environment Agency (EEA). It delivers publicly accessible, harmonised ground deformation products derived from Sentinel-1 satellite data, with the primary goal of supporting environmental monitoring, land management, and civil protection across Europe.

Despite the advantages, the interpretation of InSAR data presents several challenges [27]. A first issue concerns the reliability of the underlying interferometric observations. In particular, rapid or large displacement amplitudes may challenge the interferometric processing chain because of temporal sampling limitations and phase-unwrapping ambiguity [28]. Under such conditions, the resulting InSAR time series may become unreliable or incomplete. A second fundamental limitation is its one-dimensional sensitivity as widely recognised in the literature and technical guidelines [29]. Each acquisition provides only a scalar projection of the displacement vector along the LOS; therefore, displacement components that have null projection along the available LOS directions cannot be identified and cannot be reconstructed, unless additional modelling assumptions or auxiliary data are introduced.

The problem of reconstructing the 3D displacement vector has been primarily addressed in the domain of mapping ground movements [30,31]. In this regard, Hu et al. [32] identified three main strategies for deriving three-dimensional displacement fields from InSAR data: (i) combination of multi-pass LOS and azimuth measurements, (ii) integration of InSAR and GPS data, and (iii) prior information-assisted approaches. The first strategy combines LOS displacements from multiple viewing with azimuth information obtained through techniques such as Multi-Aperture InSAR (MAI) or Offset-Tracking [33–35]. This enables the reconstruction of full 3D displacement fields, although the accuracy strongly depends on interferometric coherence and the quality of azimuth estimates. The second strategy integrates InSAR with GPS, exploiting their complementarity: InSAR provides dense spatial coverage but only LOS sensitivity, while GPS delivers accurate 3D point measurements with sparse coverage [36]. Their fusion, typically via statistical or optimisation methods, produces spatially continuous 3D displacement maps that are more robust to noise and atmospheric artefacts. The third strategy introduces prior information to compensate for the lack of multiple independent InSAR observations. Examples include assuming surface-parallel flow in glaciers, applying mass-conservation principles, or constraining the deformation to a plane by fixing the north–south component to zero [37,38].

In the field of bridge monitoring, where PSs are typically employed, the prior information-assisted approach is most often used when InSAR observations are limited to one or two viewing geometries, which represents the majority of practical cases. In general, the problem is formulated as a system of equations linking the LOS measurements to the three displacement components, and linear algebra is used to retrieve the unknowns. The number of available LOS observations defines the number of equations, while the number of unknowns is reduced by introducing assumptions that make the system solvable. When only data from a single satellite orbit are available (one equation for three unknowns), a common strategy is to set two displacement components to zero, thereby reducing the system to a single equation with one unknown. Tonelli et al. [39] investigated the behaviour of the A22 Po River Bridge in Italy using COSMO-SkyMed data acquired in the descending geometry, since the dataset of ascending images was highly incomplete. To overcome the limitation of having only one viewing geometry, they analysed the structural response under two extreme scenarios: (i) assuming that the deck undergoes exclusively vertical displacements, and (ii) assuming that the deck undergoes exclusively horizontal displacements along the bridge axis.

When both ascending and descending geometries are available, one displacement component is typically set to zero, resulting in a system of two equations with two unknowns. Most often, the North–South component is neglected because of the low sensitivity of InSAR in this

direction. This assumption is particularly effective for bridges oriented predominantly along the East–West axis. For example, Giordano et al. [17] analysed the behaviour of the Schottwien Viaduct on the S6 Semmering motorway in Austria using EGMS ascending and descending datasets under the assumption of null North–South displacement, successfully reconstructing its displacement pattern. Similarly, Farneti et al. [12] investigated the pre-collapse behaviour of the Albiano-Magra Bridge in Italy using COSMO-SkyMed data from ascending and descending orbits, assuming null transverse displacements of the bridge. In all these cases, the accuracy of the reconstructed displacements depends strongly on the magnitude of the neglected component.

Some studies go further by incorporating simplified structural knowledge into the inversion process. For example, Huang et al. [40], in a study on a railway bridge, assumed that LOS displacements were entirely due to longitudinal movements along the bridge, and proposed a simplified method to convert LOS data directly into longitudinal displacement. More recently, Vorwagner et al. [41] developed an approach for bridges that integrates structural behaviour by explicitly modelling longitudinal displacements induced by temperature variations while assuming null transverse motion. Tonelli et al. [42] proposed a probabilistic framework to integrate topographic surveys with single-orbit InSAR measurements in order to reduce uncertainty in the estimated displacements. Milillo et al. [20] combined data from COSMO-SkyMed and the Sentinel-1A/B constellation, exploiting multiple tracks from different satellites to reconstruct the three-dimensional deformation field of the Morandi Bridge. Their approach was based on a Markov Chain Monte Carlo (MCMC) framework, which allowed them to integrate heterogeneous datasets and explicitly account for uncertainties.

Nonetheless, the combination of PSs from different orbits requires preliminary operations such as temporal and spatial resampling to make the datasets consistent and comparable [11]. In the temporal domain, acquisitions are asynchronous and often separated by several days, so linear interpolation is typically applied to align the time series [43]. In the spatial domain, PSs identified in different orbits are not co-located, which makes resampling necessary; methods such as grid subsampling are commonly adopted [44,45]. In addition, the identification of PSs actually belonging to the monitored structure is a non-trivial step. For instance, Caspani et al. [46] proposed a clustering-based approach to distinguish structural scatterers from the surrounding environment, improving the reliability of the analysis.

This paper introduces a novel Kalman Filter (KF) framework for automatically reconstructing structural displacements from multiple InSAR geometries. Unlike static fusion methods, the KF operates within a recursive estimation scheme, which allows asynchronous observations to be combined while explicitly accounting for measurement uncertainty [47]. The KF is widely used to reconstruct the behaviour of dynamic and mechanical systems and has become a standard tool in SHM applications [48–50]. In the geoscience domain, KF formulations are also frequently employed for land deformation monitoring, where they are used to fuse InSAR with other data sources and to mitigate noise [51–54]. However, to the best of the authors' knowledge, a formulation specifically tailored for structural monitoring that integrates InSAR data has not yet been proposed. Specifically, in this work the KF is formulated for the fusion of asynchronous multi-track InSAR observations, prior and environmental information, with the specific aim of reconstructing quasi-static bridge displacements. The main contributions of the proposed framework can be summarised as follows.

1. Conventional approaches rely on restrictive assumptions about the displacement field, such as imposing null North–South or transverse displacements when ascending and descending datasets are available. By contrast, the proposed KF framework enables the automatic reconstruction of three-dimensional displacements with reduced reliance on restrictive kinematic assumptions.

2. The formulation is highly flexible and can integrate not only multiple InSAR datasets but also environmental data and basic structural information to enhance reconstruction accuracy. In the case study presented in this paper, thermal deformations are explicitly modelled within the filter to support the estimation of all three displacement components.
3. The method employs grid subsampling for spatial resampling while avoiding the need for temporal interpolation, thereby removing a common source of error in conventional processing.
4. The KF framework explicitly accounts for multiple sources of uncertainty, an aspect that is not straightforward in traditional approaches based solely on algebraic inversion of the system of equations.

The methodology is demonstrated on the A21 highway viaduct over the Po River in northern Italy, a prestressed concrete bridge representative of large-scale transport infrastructure. In this study, InSAR time series from both ascending and descending Sentinel-1 tracks from EGMS are processed and combined using the proposed KF framework. Independent GNSS measurements collected on the bridge are used for validation, allowing a direct assessment of the accuracy of the reconstructed displacement time series.

From a measurement-science perspective, the problem addressed in this paper is the estimation of a three-dimensional structural displacement quantity from indirect, asynchronous, and one-dimensional LOS observations affected by measurement uncertainty and incomplete observability. In this sense, the proposed framework should be interpreted as an estimation framework that combines observations, prior information, and uncertainty models to reconstruct the displacement components together with their associated covariance-based uncertainty.

The paper is organised as follows. [Section 2](#) presents the InSAR data processing workflow, including spatial and temporal resampling, displacement reconstruction, and the formulation of the KF. [Section 3](#) reports the results of numerical analyses based on synthetic simulations, designed to evaluate the method under controlled conditions. [Section 4](#) describes the application of the framework to the A21 viaduct, with comparisons against the conventional approach and GNSS observations. [Section 5](#) discusses the results obtained in the previous sections. Finally, [Section 6](#) summarises the main findings and outlines future perspectives.

2. InSAR data processing

This section begins by addressing the problem of spatial and temporal resampling, which is used to align independently processed datasets onto a common reference grid and shared time axis. Subsequently, the conventional inversion framework used to estimate the components of the displacement vector is introduced. Displacements are represented either in the conventional East-North-Up (ENU) reference frame or in a local bridge-aligned Longitudinal-Transverse-Vertical (LTV) coordinate system, depending on the structural context. The LOS observations from multiple viewing geometries are then combined under the assumption that the motion is constrained to a known plane. This assumption reduces the dimensionality of the problem and enables the estimation of structural displacements by solving an otherwise underdetermined system through the introduction of kinematic or geometric constraints. The final part of this section presents an enhanced estimation strategy based on a KF approach. This method enables the sequential estimation of the displacement components together with their associated uncertainties. By integrating multi-track InSAR observations with prior structural and environmental information, the proposed framework provides estimates of all three components of the displacement vector.

2.1. Spatial and temporal resampling

As discussed in the Introduction, InSAR displacement measurements acquired from different viewing geometries, typically ascending and descending orbits, can be combined to reconstruct the direction of ground or structural motion. However, because these datasets are generated from independent image stacks with different acquisition geometries and acquisition dates, resampling in both space and time is typically carried out to ensure consistency and enable joint analysis, see [Fig. 1](#).

One of the main challenges in combining multi-geometry InSAR data is the non-coincidence of measurement points across different datasets. The spatial locations of PSs are determined independently for each stack, depending on factors such as radar viewing angle, surface reflectivity, and coherence. As a result, PSs from ascending and descending datasets are typically located at different positions and cannot be directly matched one-to-one. The most commonly adopted method is the grid subsampling approach, which involves:

- Defining a regular reference grid over the area of interest, typically composed of square/rectangular cells whose size is chosen based on the expected structural deformation scale and the geometric characteristics of the monitored object (e.g., bridge deck width, span length, or structural segmentation);
- Aggregating the PSs located within each cell of the reference grid, independently for each dataset, to compute a representative displacement value for that cell and viewing geometry.

This process reduces spatial resolution but ensures that both datasets are consistently represented on a shared spatial reference. The selection of the size, shape, and position of the grid is a critical aspect of this method [\[45,55\]](#). The reconstructed displacement should be interpreted as a representative value for the selected cell, since it is obtained from the aggregation of the available PSs within that area. If significant spatial variability exists within a cell, the resulting estimate may smooth local displacement gradients or combine responses associated with different structural behaviours. Therefore, the cell definition should account for the expected deformation pattern, the spatial density and distribution of PSs, the geometric characteristics of the monitored object, and the characteristics of the SAR acquisition system, such as radar band. In general, smaller cells may improve the spatial detail of the reconstruction, but they may also reduce the number of available PSs and increase the sensitivity to localisation uncertainty.

In addition to spatial misalignment, temporal inconsistencies also arise, as acquisitions from different orbital geometries (e.g., ascending and descending passes) typically occur on different dates and with non-uniform temporal sampling intervals. A common solution is temporal resampling via linear interpolation, applied as follows:

- A common reference time grid is defined, either by choosing a uniform set of epochs or by selecting the union or intersection of available acquisition dates;
- Each displacement time series is interpolated linearly onto this common temporal grid.

After completing both spatial and temporal resampling, the LOS measurements from different viewing geometries are consistent in space and time, allowing their combined use in inversion schemes to estimate the displacement vector components, as described in the following section.

2.2. Reconstruction of structural displacements

In InSAR studies, displacements are typically represented in a local, right-handed Cartesian coordinate system whose orthogonal axes point east-west (d_E), north-south (d_N) and up-down (d_U). In this system, the

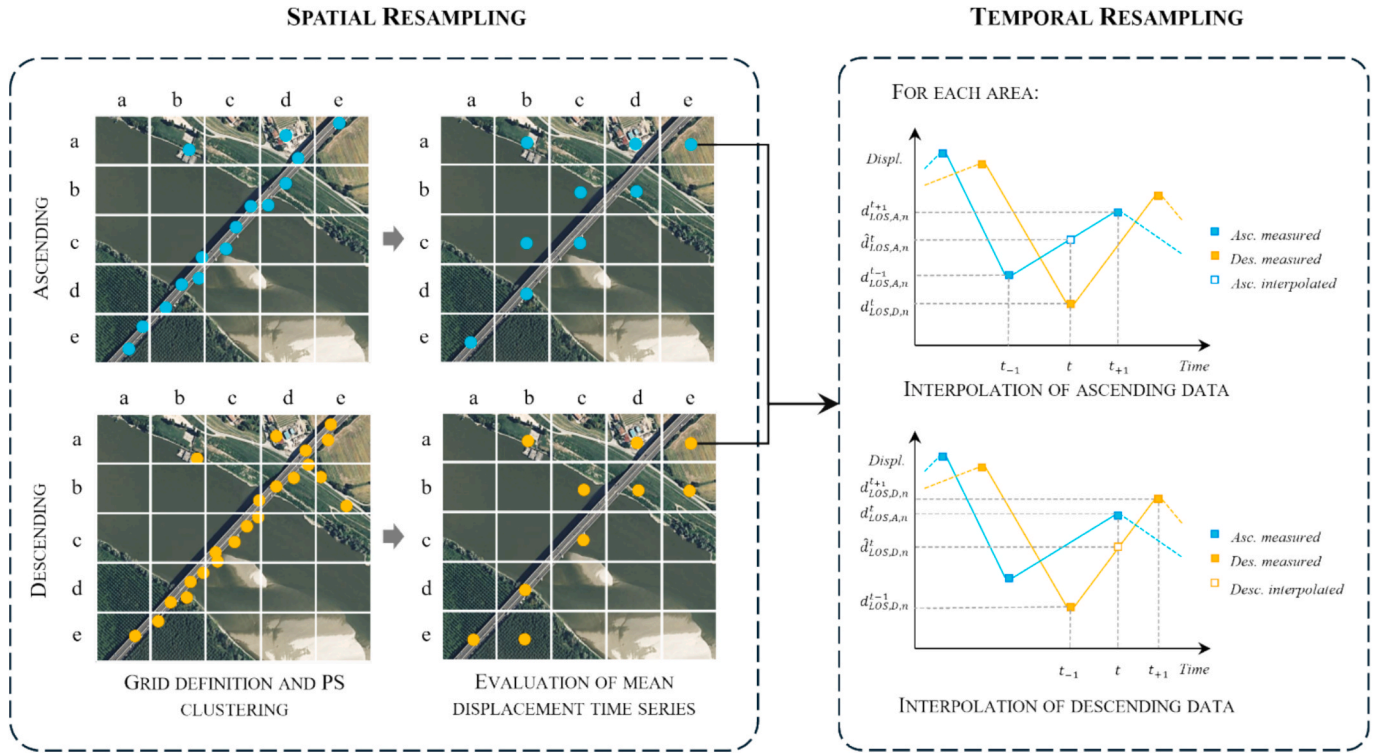


Fig. 1. Resampling procedures typically applied to InSAR data.

LOS displacement $d_{LOS}^{(i)}$ measured by a given acquisition i can be written as the scalar product between the unit look-vector $\mathbf{u}_{LOS}^{(i)} = [\sin\theta^{(i)}\cos\alpha^{(i)}, -\sin\theta^{(i)}\sin\alpha^{(i)}, \cos\theta^{(i)}]^T$ and the true displacement vector $\mathbf{d} = [d_E, d_N, d_U]^T$:

$$d_{LOS}^{(i)} = \sin\theta^{(i)}(\cos\alpha^{(i)}d_E - \sin\alpha^{(i)}d_N) + \cos\theta^{(i)}d_U \quad (1)$$

where $\theta^{(i)}$ is the incidence angle (from vertical), $\alpha^{(i)}$ is the look-azimuth measured clockwise from the east axis, as shown in Fig. 2(a). Dealing with linear structures like bridges, it is frequently more intuitive to decompose displacement into longitudinal (along the bridge span, d_L), transverse (across the span, d_T), and vertical (d_V) components, where the latter corresponds to the up-down component in the ENU reference system. These are obtained by a horizontal rotation of the (E , N) axes about the vertical one by an angle ϕ measured clockwise from the east

axis, as shown in Fig. 2(b), using the orthogonal rotation matrix $\mathbf{R}(\phi)$, as follows:

$$\begin{bmatrix} d_E \\ d_N \\ d_U \end{bmatrix} = \mathbf{R}^T(\phi) \begin{bmatrix} d_L \\ d_T \\ d_V \end{bmatrix} = \begin{bmatrix} \cos\phi & \sin\phi & 0 \\ -\sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} d_L \\ d_T \\ d_V \end{bmatrix} = \begin{bmatrix} \cos\phi d_L + \sin\phi d_T \\ -\sin\phi d_L + \cos\phi d_T \\ d_V \end{bmatrix} \quad (2)$$

Substituting (2) into (1) gives

$$d_{LOS}^{(i)} = \sin\theta^{(i)}[\cos(\alpha^{(i)} - \phi)d_L - \sin(\alpha^{(i)} - \phi)d_T] + \cos\theta^{(i)}d_V \quad (3)$$

A full reconstruction of the displacement field would require LOS measurements from at least three non-parallel viewing directions, or alternatively the integration of InSAR with independent in-situ observations. In practice, however, only two viewing geometries are usually available, namely the ascending and descending orbital tracks. The in-

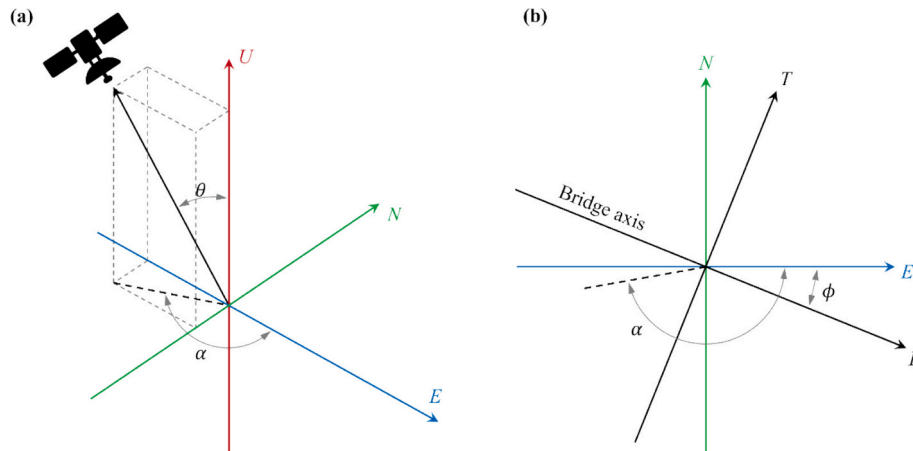


Fig. 2. Representation of (a) the global reference system and (b) its projection within the bridge local reference system defined by the angle ϕ .

dependent processing of the two image stacks therefore provides two LOS displacement time series, $d_{LOS}^{(A)}$ and $d_{LOS}^{(D)}$, referred to the same area and observation period. Under these conditions, the displacement components d_L, d_T, d_V satisfy the following system:

$$\begin{cases} d_{LOS}^{(A)} = \sin\theta^{(A)} [\cos(\alpha^{(A)} - \phi) d_L - \sin(\alpha^{(A)} - \phi) d_T] + \cos\theta^{(A)} d_V \\ d_{LOS}^{(D)} = \sin\theta^{(D)} [\cos(\alpha^{(D)} - \phi) d_L - \sin(\alpha^{(D)} - \phi) d_T] + \cos\theta^{(D)} d_V \end{cases} \quad \# \quad (4)$$

The reconstruction of the bridge behaviour is commonly performed by assuming one of the horizontal displacement components to be negligible. For instance, by setting $d_T = 0$, the motion is assumed to lie in the longitudinal-vertical plane, and the system of Equation (4) reduces to a solvable 2×2 system for the remaining components d_L, d_V :

$$\begin{cases} d_L = \Delta^{-1} (\cos\theta^{(D)} d_{LOS}^{(A)} - \cos\theta^{(A)} d_{LOS}^{(D)}) \\ d_V = \Delta^{-1} [\sin\theta^{(A)} \cos(\alpha^{(A)} - \phi) d_{LOS}^{(D)} - \sin\theta^{(D)} \cos(\alpha^{(D)} - \phi) d_{LOS}^{(A)}] \end{cases} \quad \# \quad (5)$$

where $\Delta = \sin\theta^{(A)} \cos(\alpha^{(A)} - \phi) \cos\theta^{(D)} - \sin\theta^{(D)} \cos(\alpha^{(D)} - \phi) \cos\theta^{(A)}$. A fundamental limitation related to the observability of the displacement components should be highlighted. The LOS measurements can be interpreted as linear projections of the three-dimensional displacement vector through an observation operator, defined by the look vectors and the acquisition geometry, which maps the displacement vector into the measured LOS quantities. When only two independent LOS directions are available, as in the case of ascending and descending tracks, the observation operator has rank at most two and therefore spans only a two-dimensional subspace of the displacement space. Consequently, a non-trivial null space exists, defined as the set of displacement vectors that produce zero projection onto all available LOS directions and are therefore completely invisible to the measurement system. In the present case, when the two LOS directions are independent, this null space is a line in the three-dimensional displacement space. Any displacement component lying along this line does not affect the LOS observations and therefore cannot be inferred from them. These components are unobservable from the measurements and cannot be reconstructed independently of the estimation strategy adopted. The degree of observability of each displacement component depends on its projection onto the LOS directions and is therefore strongly influenced by the structural orientation ϕ with respect to the satellite geometry. In particular, under the common assumption of negligible transverse displacement, the longitudinal component for bridges aligned approximately in the north-south direction may become weakly observable, leading to estimates that are poorly constrained by the measurements.

These limitations are intrinsic to the measurement model and define the information content available for the estimation problem. Consequently, the achievable accuracy of the reconstructed displacement components depends not only on the noise affecting the LOS observations, but also on the geometry of the acquisition system and on the prior information introduced to compensate for incomplete observability.

2.3. Proposed Kalman Filter formulation

The KF is a linear recursive estimator designed to compute the best estimate of an evolving state vector based on a system model and a sequence of noisy observations. It operates in two stages: a prediction step, which advances the state estimate using the system model, and an update step, which corrects this estimate using new measurements. In this study, we define the state vector at time step k as:

$$\mathbf{d}_k = [d_L \quad d_T \quad d_V]^T \quad \# \quad (6)$$

where d_L, d_T , and d_V represent the longitudinal, transverse, and vertical displacements of the monitored structure. The state evolves according to the following discrete-time linear system:

$$\mathbf{d}_k = \mathbf{F} \mathbf{d}_{k-1} + \mathbf{B} \mathbf{u}_k + \mathbf{w}_k \quad \# \quad (7)$$

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{d}_k + \mathbf{v}_k \quad \# \quad (8)$$

where, $\mathbf{F} \in \mathbb{R}^{3 \times 3}$ is the state transition matrix, assumed to be the identity matrix $\mathbf{F} = \mathbf{I}_3$ to reflect a quasi-static or slowly evolving displacement process; $\mathbf{B} \in \mathbb{R}^{3 \times p}$ is the input effect matrix, which maps p known external variables, collected in the input vector $\mathbf{u}_k \in \mathbb{R}^p$, to their contributions to the displacement components. The process noise $\mathbf{w}_k \sim N(0, \mathbf{Q})$ accounts for random variations in the state due to unmodeled influences or minor environmental changes; $\mathbf{Q} = \text{diag}(Q_L, Q_T, Q_V) \in \mathbb{R}^{3 \times 3}$ is the process noise covariance, typically diagonal, where Q_L, Q_T , and Q_V denote the expected variability of the longitudinal, transverse, and vertical displacement components, respectively. The observation vector $\mathbf{z}_k \in \mathbb{R}^{n_k}$ contains the LOS displacements available at time step k , and $\mathbf{v}_k \sim N(0, \mathbf{R}_k)$ is the corresponding measurement noise, with $\mathbf{R}_k \in \mathbb{R}^{n_k \times n_k}$ the measurement noise covariance matrix.

At each time step, the KF assimilates a set of LOS displacement observations derived from either an ascending or a descending track. The generic observation vector is expressed as:

$$\mathbf{z}_k = [d_{LOS,k}^{(1)} \quad d_{LOS,k}^{(2)} \quad \dots \quad d_{LOS,k}^{(n_k)}]^T \in \mathbb{R}^{n_k} \quad \# \quad (9)$$

where n_k is the number of measurements at time step k . Each scalar observation $d_{LOS,k}^{(i)}$ represents a one-dimensional projection of the 3D displacement vector $\mathbf{d}_k$, modulated by the InSAR acquisition geometry. Given an incidence angle $\theta^{(i)}$, azimuth angle $\alpha^{(i)}$, and structural orientation ϕ , the LOS projection is:

$$d_{LOS,k}^{(i)} = \sin\theta^{(i)} \cos(\alpha^{(i)} - \phi) d_L - \sin\theta^{(i)} \sin(\alpha^{(i)} - \phi) d_T + \cos\theta^{(i)} d_V + \mathbf{v}_k^{(i)} \quad \# \quad (10)$$

We measure the angles $\alpha^{(i)}$ and ϕ clockwise from the E-axis, taking positive values in that sense. The i -th observation defines the i -th row of the observation matrix $\mathbf{H}_k \in \mathbb{R}^{n_k \times 3}$:

$$\mathbf{H}_k = \begin{bmatrix} \sin\theta^{(1)} \cos(\alpha^{(1)} - \phi) & -\sin\theta^{(1)} \sin(\alpha^{(1)} - \phi) & \cos\theta^{(1)} \\ \sin\theta^{(2)} \cos(\alpha^{(2)} - \phi) & -\sin\theta^{(2)} \sin(\alpha^{(2)} - \phi) & \cos\theta^{(2)} \\ \vdots & \vdots & \vdots \\ \sin\theta^{(n_k)} \cos(\alpha^{(n_k)} - \phi) & -\sin\theta^{(n_k)} \sin(\alpha^{(n_k)} - \phi) & \cos\theta^{(n_k)} \end{bmatrix} \quad \# \quad (11)$$

This formulation allows the KF to integrate any number of observations per step, adjusting to changes in satellite availability, data quality, or missing acquisitions. In the present formulation, the three-dimensional structural displacement vector represents the measurand of interest, while the LOS quantities provided by the different InSAR acquisitions are the available observations. The role of the KF is therefore to provide an estimate of the measurand by recursively combining the observation model, the prior evolution model, and their associated covariance descriptions. The resulting state estimate should thus be interpreted as an indirect estimate of the structural displacement components, obtained from incomplete observations and accompanied by a covariance-based characterisation of the associated uncertainty.

The KF is initialized with an initial state estimate $\hat{\mathbf{d}}_0$ and an initial error covariance $\mathbf{P}_0$. Then, for each time step k , the filter performs a two-stage update: a prediction based on the physical model of the system, followed by a correction informed by the available InSAR observations. During the prediction step, the current state estimate is propagated forward according to the state transition model. Assuming quasi-static behaviour, the evolution is governed by the identity matrix $\mathbf{F}$, and thus the predicted state is computed as:

$$\hat{\mathbf{d}}_{k|k-1} = \mathbf{F}\hat{\mathbf{d}}_{k-1|k-1} + \mathbf{B}\mathbf{u}_k \quad (12)$$

The term $\mathbf{B}\mathbf{u}_k$ explicitly accounts for physical phenomena that affect displacements, such as thermally induced displacements. The associated error covariance also evolves, with the predicted covariance given by:

$$\mathbf{P}_{k|k-1} = \mathbf{F}\mathbf{P}_{k-1|k-1}\mathbf{F}^T + \mathbf{Q} \quad (13)$$

where the matrix $\mathbf{Q}$ represents the process noise and reflects confidence in the structural model's capacity to predict displacements between time steps.

When one or more LOS observations are available at time step k , the filter executes the update step. In this phase, it first computes the Kalman gain matrix

$$\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k)^{-1} \quad (14)$$

which balances the predicted uncertainty and the expected precision of the measurements, represented by the measurement noise covariance $\mathbf{R}_k$. This gain is used to update the state estimate according to the residual between the observed and predicted measurements, yielding

$$\hat{\mathbf{d}}_{k|k} = \hat{\mathbf{d}}_{k|k-1} + \mathbf{K}_k(\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{d}}_{k|k-1}) \quad (15)$$

Finally, the filter updates the error covariance matrix to reflect the reduction in uncertainty after the new measurements are assimilated:

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\mathbf{P}_{k|k-1} \quad (16)$$

If no valid measurements are available at a given time step, the update step is bypassed, and the state estimate remains as predicted. This flexibility makes the KF particularly well suited to InSAR time series analysis, where acquisitions may be irregular and incomplete. A general representation of the proposed method is displayed in Fig. 3.

Spatial consistency between observations from different orbits is achieved using the grid-subsampling strategy described in Section 2.1. Specifically, the input LOS observations are defined as the mean displacement values of the PSs within a given grid cell for each orbit. Accordingly, the reconstructed displacements are interpreted as the mean displacement of the corresponding grid cell. Temporal resampling is not required in the KF approach in the sense that LOS displacement time series are not interpolated onto a common regular temporal grid. In the present implementation, the discrete time index k is defined on the ordered union of the available acquisition dates from the ascending and descending InSAR datasets. At each epoch, the observation vector $\mathbf{z}_k$ is assembled using the measurements available at that date. If only one orbit is available, the update is performed using the corresponding single LOS observation. If multiple observations are available at the same epoch, they can be stacked in $\mathbf{z}_k$ and assimilated within the same update step through the corresponding rows of the observation matrix $\mathbf{H}_k$. In the Sentinel-1/EGMS application considered in this study, ascending and descending acquisitions are asynchronous, so each update step typically contains only one LOS observation. Missing observations from one orbit are handled by omitting the corresponding row from $\mathbf{z}_k$ and $\mathbf{H}_k$. Since the filter timeline is constructed from the union of the available acquisition dates, epochs with no InSAR observation are not explicitly included in the current implementation. If a regular time grid were adopted instead, such epochs could be treated as prediction-only steps, with the update step skipped until a new observation becomes available.

The adopted linear quasi-static formulation is primarily suited to slow-varying displacement processes, such as seasonal thermal deformations, long-term settlements, and progressive structural changes, which are consistent with the temporal sampling and information content of InSAR observations.

It should be emphasised that the KF does not overcome the intrinsic observability limitations imposed by the InSAR measurement geometry.

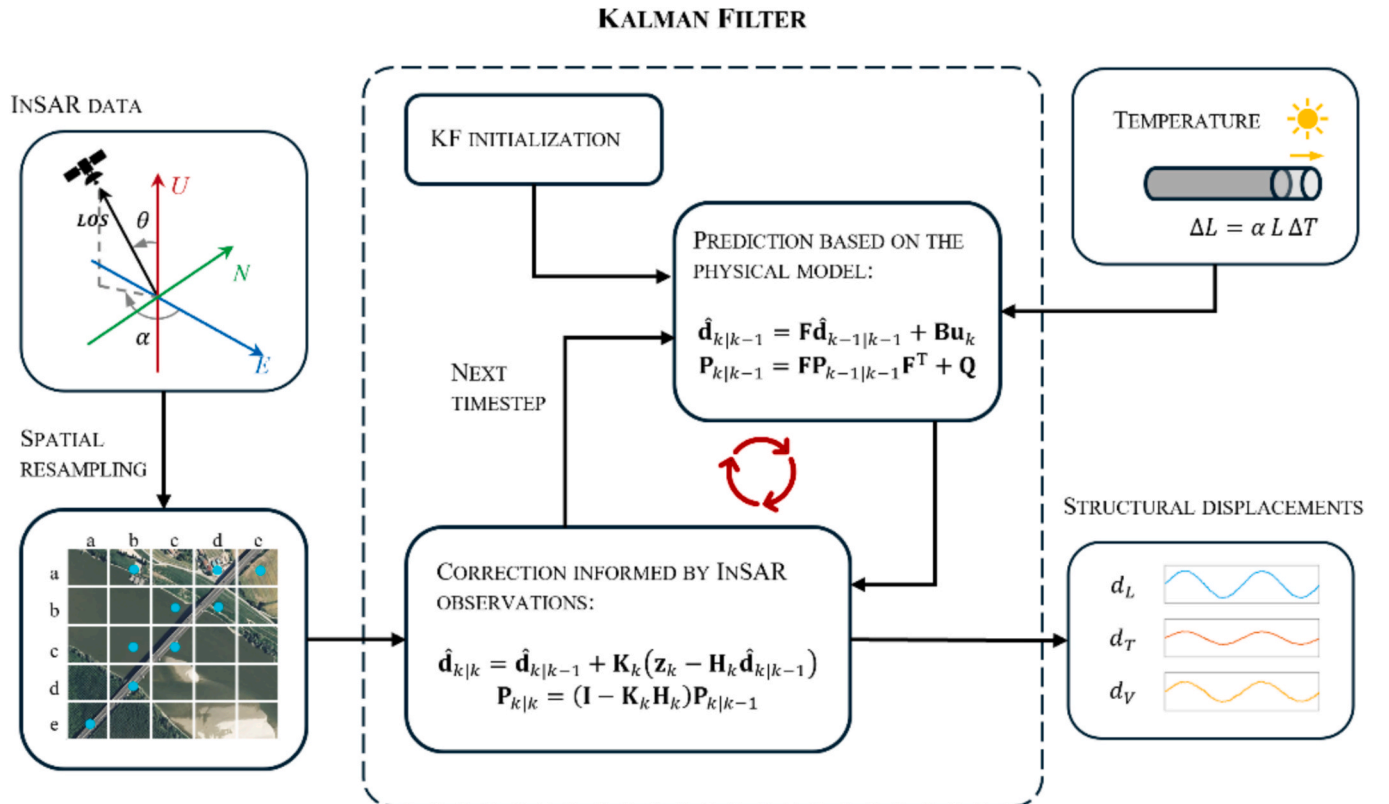


Fig. 3. Proposed KF-based method to reconstruct structural displacements.

Displacement components with negligible or null projection along the available LOS directions remain weakly observable or unobservable from InSAR data alone, and their estimates are therefore increasingly influenced by the adopted state model. In this sense, the KF should be interpreted as a framework for combining measurement information with prior knowledge, rather than as a tool capable of recovering information that is absent from the observations. At the same time, a major advantage of the formulation is its flexibility: when additional sources of information are available, such as in-situ measurements, structural models, or other remote sensing data, they can be naturally integrated into the filtering scheme to improve the conditioning of the estimation problem and reduce uncertainty.

3. Numerical analysis

In this section, the proposed KF framework is validated using a fully synthetic test case, and its performance is compared against that of the conventional reconstruction method. A known three-component structural displacement history is first generated, from which virtual ascending and descending InSAR measurements are produced with controlled noise. The case study is supposed to be a bridge, whose longitudinal axis forms an angle ϕ with the east direction. Both reconstruction methods are then applied to recover the longitudinal, transverse, and vertical displacement time series, and their accuracy is quantified through RMSE analysis.

3.1. Synthetic displacement and InSAR simulation

We define three sinusoidal displacement components in a local LTV frame:

$$d_L(t) = A_L \sin\left(\frac{2\pi}{365}t\right); d_T(t) = A_T \sin\left(\frac{2\pi}{365}t\right); d_V(t) = A_V \sin\left(\frac{2\pi}{365}t\right) \quad (17)$$

with amplitudes $A_L = 3\text{mm}$, $A_T = 1\text{mm}$, $A_V = 2\text{mm}$. Time t runs uniformly over two years with daily sampling ($n_{\text{steps}} = 730$). These displacements correspond to a cell grid covering a reference bridge, where thermal deformations are expected to vary with seasonal temperature changes and are proportional to the bridge dimensions in the corresponding direction.

Two satellite “orbits”, i.e., ascending and descending, are defined by their look-vector parameters (α, θ) . We adopt the look-vector parameters from the Sentinel-1 ascending and descending tracks used in our real-world EGMS case study. Specifically: $\alpha_A = 2.9599\text{ rad}$ (169.6°), $\theta_A = 0.7113\text{ rad}$ (40.8°) for the ascending pass; $\alpha_D = 0.1596\text{ rad}$ (169.6°),

$\theta_D = 0.6966\text{ rad}$ (39.9°) for the descending pass. Each orbit “acquires” simulated displacement measurements at six-day intervals. The descending acquisitions are offset by one day relative to the ascending ones, replicating the temporal acquisition pattern of the Sentinel-1 mission.

At each time step, we rotate the local displacement vector by an angle ϕ about the Vertical axis to ENU displacements according to Equation (2). Then, at each acquisition time, the full ENU displacement vector is projected onto the corresponding LOS direction. Zero-mean Gaussian noise with a standard deviation of $\sigma = 0.10\text{ mm}$ is added to the projected value, yielding a realistic set of synthetic InSAR observations for performance benchmarking. As an example, Fig. 4 illustrates the simulated displacement data in different reference systems and observation geometries for $\phi = 45^\circ$. Specifically, Fig. 4(a) shows the input displacements in the local LTV frame, while Fig. 4(b) presents the corresponding displacements after rotation into the ENU coordinate system. Fig. 4(c) displays the resulting LOS displacements as observed from the simulated ascending and descending orbits, after projection onto their respective viewing geometries. In the following sections, we also loop ϕ over 1° to 360° to evaluate performance across all possible structural orientations.

3.2. Reconstruction of structural displacements using the conventional approach

Initially, we reconstruct the displacements in the longitudinal and vertical directions using the conventional approach described in Section 2.2. This method consists of solving the 2×2 system for d_L and d_V under the assumption of null transverse displacement ($d_T = 0$), according to system of Equation (4). Temporal resampling is carried out using linear interpolation across LOS time series. The results for $\phi = 45^\circ$ are shown in Fig. 5. The longitudinal displacements in Fig. 5(a) are amplified, while the vertical displacements in Fig. 5(b) are slightly reduced. More insight is provided by Fig. 6, which reports the Root Mean Square Error (RMSE) between the reference and reconstructed displacements, for varying ϕ angles. Specifically, Fig. 6(a) and 6(b) show the RMSE for the longitudinal and vertical components, respectively. The vertical axes are plotted on a logarithmic scale. RMSE is minimal when ϕ is close to 0° or 180° , conditions under which the transverse displacement component is nearly perpendicular to the LOS direction and therefore scarcely observable. In such cases, neglecting d_T introduces only a minor error. Conversely, the error reaches its maximum when ϕ is close to 90° or 270° , where the longitudinal component is almost perpendicular to the horizontal projection of the LOS direction, while the transverse component, which is omitted in the inversion, is nearly aligned with it.

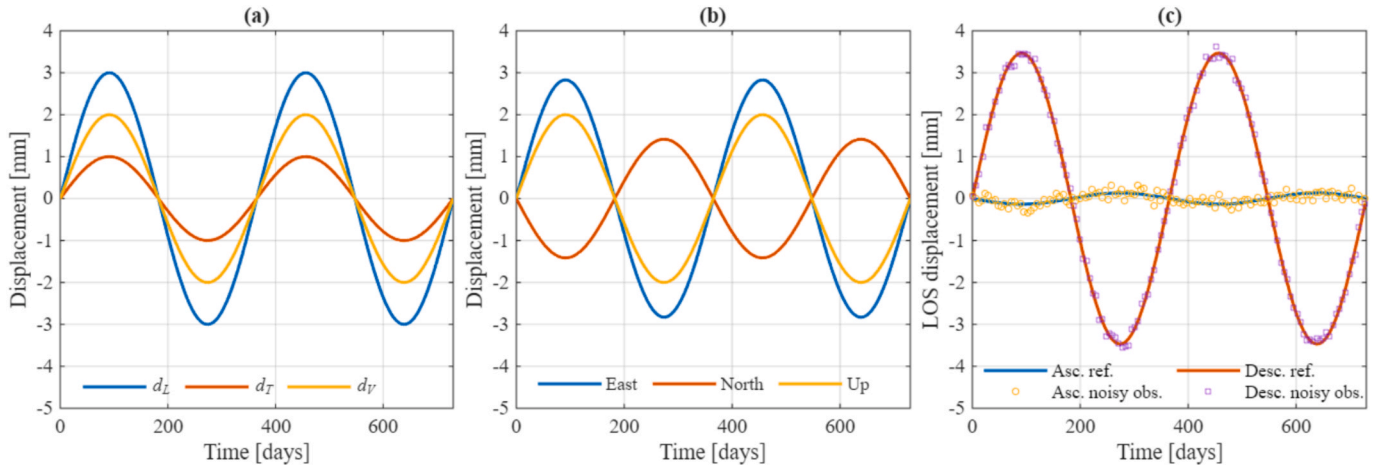


Fig. 4. Simulated data for $\phi = 45^\circ$: a) displacement in the LTV reference system; b) displacement in the ENU reference system; c) LOS displacements from the ascending and descending orbits.

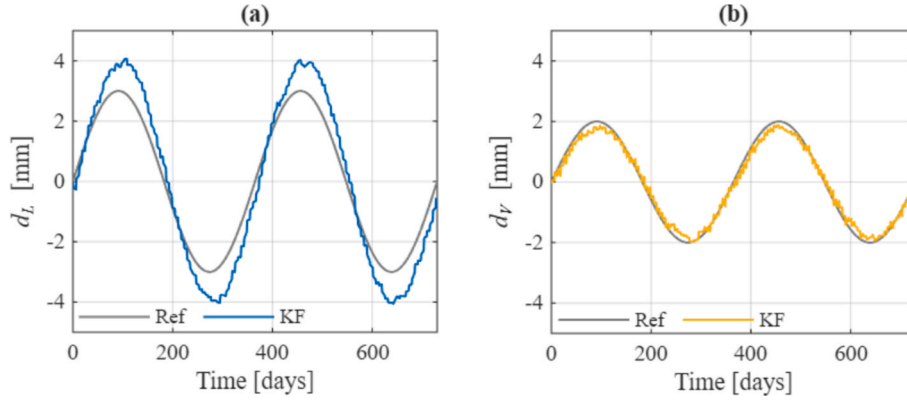


Fig. 5. Results for the conventional approach for $d_T = 0$ and $\phi = 45^\circ$: (a) Longitudinal and (b) Vertical displacements.

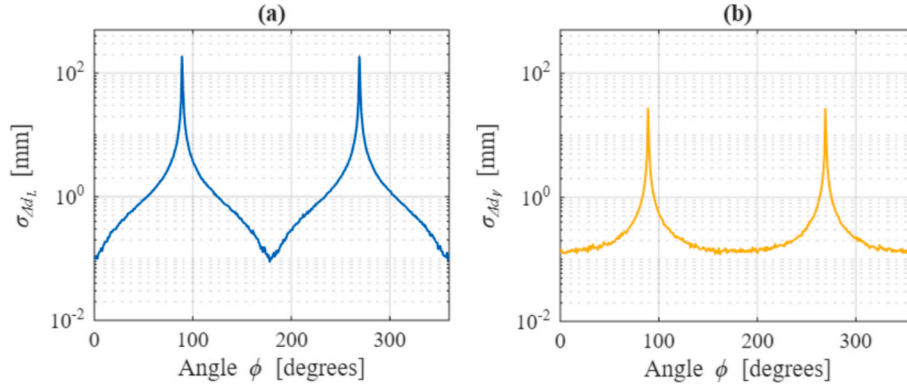


Fig. 6. Results for the conventional approach for $d_T = 0$ and $\phi = 45^\circ$: RMSE for (a) Longitudinal and (b) Vertical displacements for varying ϕ . The y-axes are shown on a logarithmic scale.

Neglecting d_T under these conditions leads to substantial errors, since the disregarded direction is in principle the one best captured by InSAR. As a consequence, the estimation of the longitudinal displacement becomes highly unreliable, which also degrades the accuracy of the vertical component. In these cases, the error in the longitudinal displacement exceeds 200 mm, while the error in the vertical displacement remains smaller but still significant.

3.3. Reconstruction of structural displacements using the proposed KF approach

This section presents the results obtained with the proposed KF framework, without imposing the assumption of zero transverse displacement. It is assumed that the bridge static scheme is known and that the thermally induced displacements in the longitudinal and vertical directions can be estimated from basic structural information. Accordingly, the available structural information comprises the main geometric characteristics of the structure, the material properties, and the static scheme. Temperature data are also assumed to be available, as they can generally be retrieved from publicly accessible online databases. The simulated temperature record consists of a sinusoidal signal,

$T(t) = A_T \sin\left(\frac{2\pi}{365} t\right) + 10$, with an amplitude $A_T = 20^\circ\text{C}$ and one year period, superimposed with white noise having a standard deviation of 1°C . The matrix $\mathbf{B}$ is defined as $\mathbf{B} = [A_L/A_T, 0, A_V/A_T]^T$. Here, $\mathbf{B}$ represents the thermal sensitivity of each displacement component to temperature change. The first and third terms correspond to the longitudinal and vertical displacements per unit temperature change, while the second term is set to zero, assuming negligible thermal effects in the transverse direction. The coefficients were computed as the ratio be-

tween the maximum displacement variation in the longitudinal or vertical direction ($2A_L$ or $2A_V$) and the maximum temperature excursion ($2A_T$). The filter is initialised as follows:

- Initial state estimate: $\mathbf{x}_0 = [0, 0, 0]^T$
- Process noise covariance: $\mathbf{Q} = \text{diag}(0.01, 0.01, 0.01)$
- Measurement noise covariance: $\mathbf{R} = \text{diag}(0.01, 0.01)$
- Initial estimation error covariance: $\mathbf{P}_0 = \mathbf{I}_3$

Furthermore, a soft constraint is introduced by incorporating virtual observations of the transverse displacement [56]. These pseudo-measurements are defined with a mean equal to zero and a variance of 25 mm^2 . In practice, they act as weak priors that stabilise the estimation of the transverse component, limiting the unbounded growth of its variance while still allowing the filter to adjust the results if the estimate of the transverse displacement diverges from this assumption.

Fig. 7 shows the reference and KF reconstructed time histories of the displacement components for $\phi = 45^\circ$. The longitudinal, transverse, and vertical components are shown in Fig. 7(a), 7(b), and 7(c), respectively. For each component, the shaded band represents the posterior uncertainty interval corresponding to ± 1 standard deviation, computed from the diagonal terms of the posterior covariance matrix. Overall, the proposed framework appears capable of reconstructing the longitudinal, transverse, and vertical responses under non-simultaneous LOS acquisitions, although some discrepancies can be observed in the longitudinal and transverse components. The transverse component is affected by greater uncertainty, whereas the vertical component remains associated with only limited uncertainty.

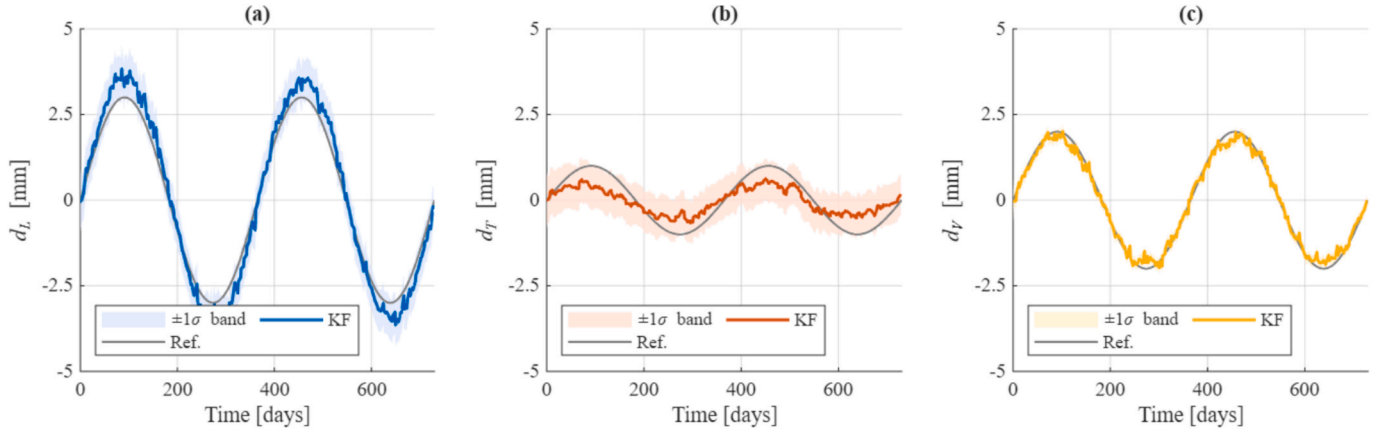


Fig. 7. Reference and KF reconstructed time histories of the (a) longitudinal, (b) transverse, and (c) vertical displacement components and associated confidence bounds.

3.4. Sensitivity analyses

3.4.1. Effect of bridge orientation

Fig. 8 presents the sensitivity analysis for different values of the angle ϕ , considering the RMSE of the (a) longitudinal, (b) transverse, and (c) vertical displacement components. These RMSE values are substantially lower than those obtained with the conventional method and shown in Fig. 6. The largest RMSE values are observed for the transverse displacement, particularly near $\phi = 0^\circ$ and $\phi = 180^\circ$. This behaviour is consistent with geometric considerations, since for bridges oriented approximately along the east–west direction the transverse displacement is aligned nearly with the north–south direction, which is the component to which InSAR measurements are least sensitive. As a result, the transverse motion has only a limited projection onto the available LOS directions and is therefore weakly observable, leading to a less accurate reconstruction. By contrast, the vertical displacement shows the lowest RMSE over the entire range of ϕ , as it always retains a significant projection onto both ascending and descending LOS measurements.

3.4.2. Effect of covariance matrix parameters

To further clarify the role of the parameters adopted in the KF framework, a set of sensitivity analyses is carried out with respect to the covariance parameters. In particular, the influence of the assumed process and measurement covariance matrices on both reconstruction accuracy and posterior uncertainty was investigated. The analyses are performed first by jointly scaling the process and measurement covariance matrices, and then by varying the transverse process covariance

independently from the longitudinal and vertical terms, so as to better isolate its effect on the reconstructed displacement components.

Fig. 9 reports the sensitivity analysis obtained by varying the elements of the process covariance matrix $\mathbf{Q}$ and those of the measurement covariance matrix $\mathbf{R}$ over a broad logarithmic range. The top row shows the RMSE of the longitudinal (a), transverse (b), and vertical (c) displacement components, whereas the bottom row reports the corresponding mean posterior standard deviations (d–f). For clarity, different colour scales are used in the various plots. The star identifies the baseline covariance setting adopted in the reference simulation. The three displacement components do not exhibit the same sensitivity to covariance tuning. In particular, the transverse displacement shows the largest RMSE variations. Its accuracy is influenced by variations in both $\mathbf{Q}$ and $\mathbf{R}$. By contrast, the longitudinal and vertical components are affected mainly by the choice of $\mathbf{Q}$. Among the three, the vertical displacement remains associated with the lowest error levels over most of the investigated parameter range. The maps of the mean posterior standard deviations are consistent with this behaviour, with the vertical component generally exhibiting the lowest uncertainty. Excluding Fig. 9 (b), both the RMSE and the mean posterior standard deviation appear to be more sensitive to the values assigned to the process covariance matrix.

To investigate more specifically the role of this matrix, an additional sensitivity analysis is performed by varying the transverse process covariance independently from the longitudinal and vertical terms. The corresponding results are shown in Fig. 10. As in the previous analysis, the top row shows the RMSE of the longitudinal (a), transverse (b), and vertical (c) displacement components, whereas the bottom row reports

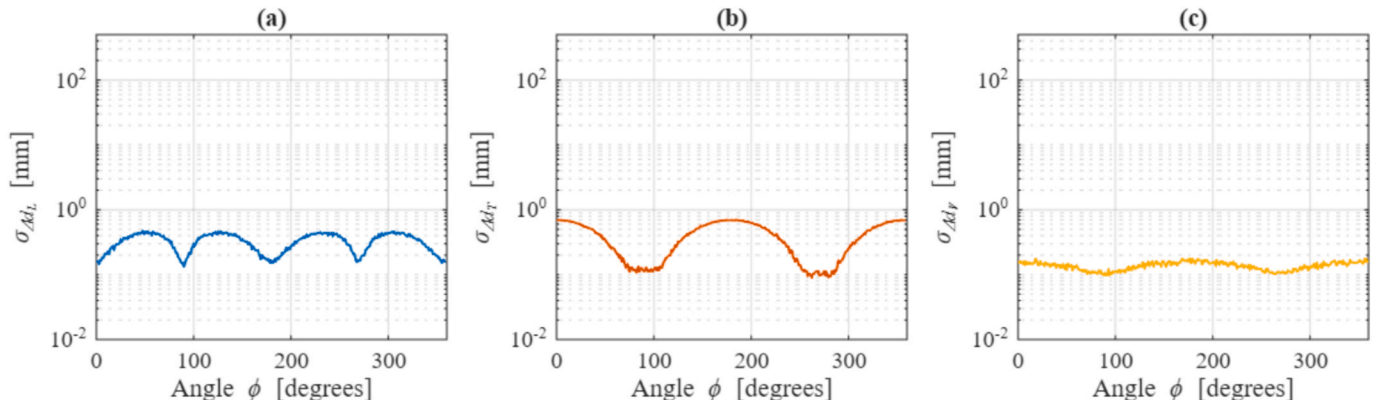


Fig. 8. Results using KF: RMSE for (a) longitudinal, (b) transverse and (c) vertical displacements for varying ϕ angle. The y-axes are shown on a logarithmic scale.

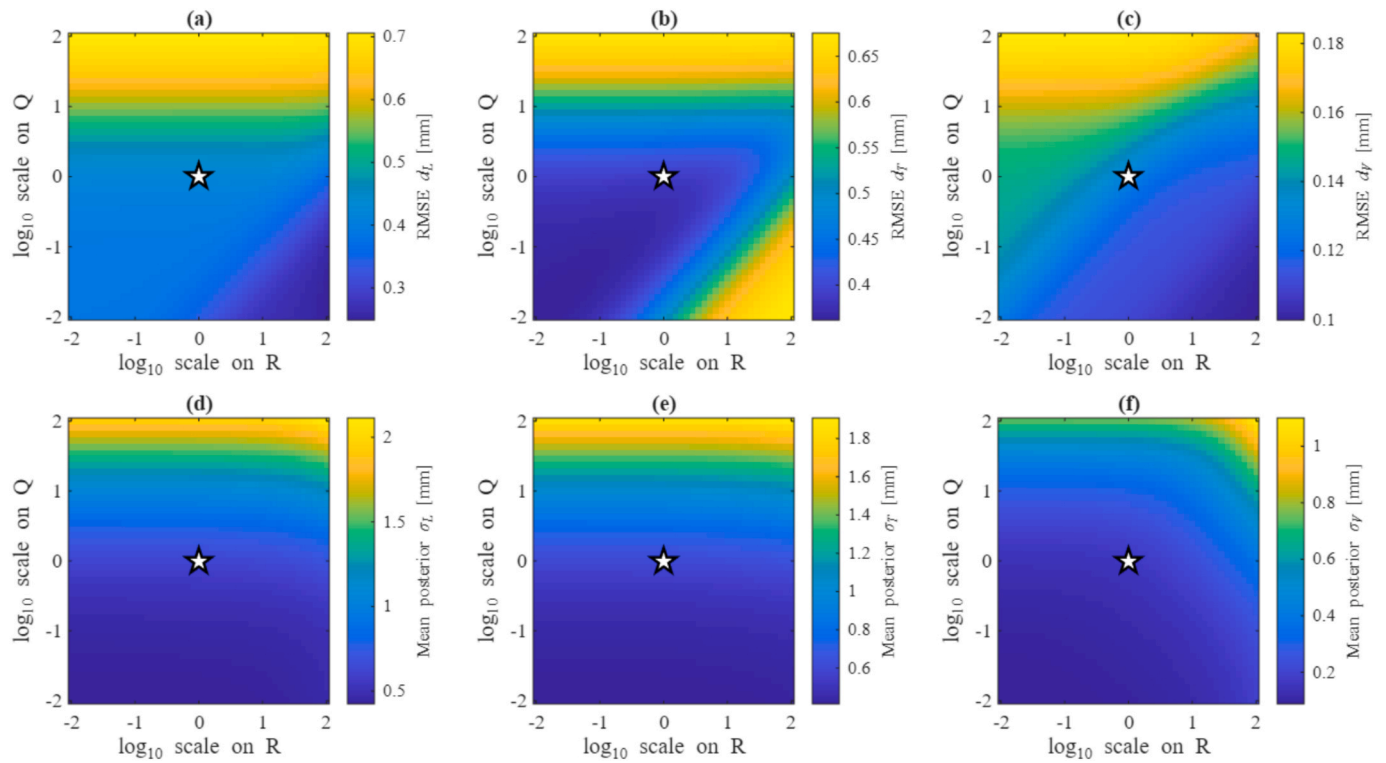


Fig. 9. Component-wise sensitivity of the KF results to the assumed process and measurement covariance matrices. The star marks the baseline covariance setting used in the reference calculation, namely $Q = 0.01\text{mm}^2$ and $R = 0.01\text{mm}^2$.

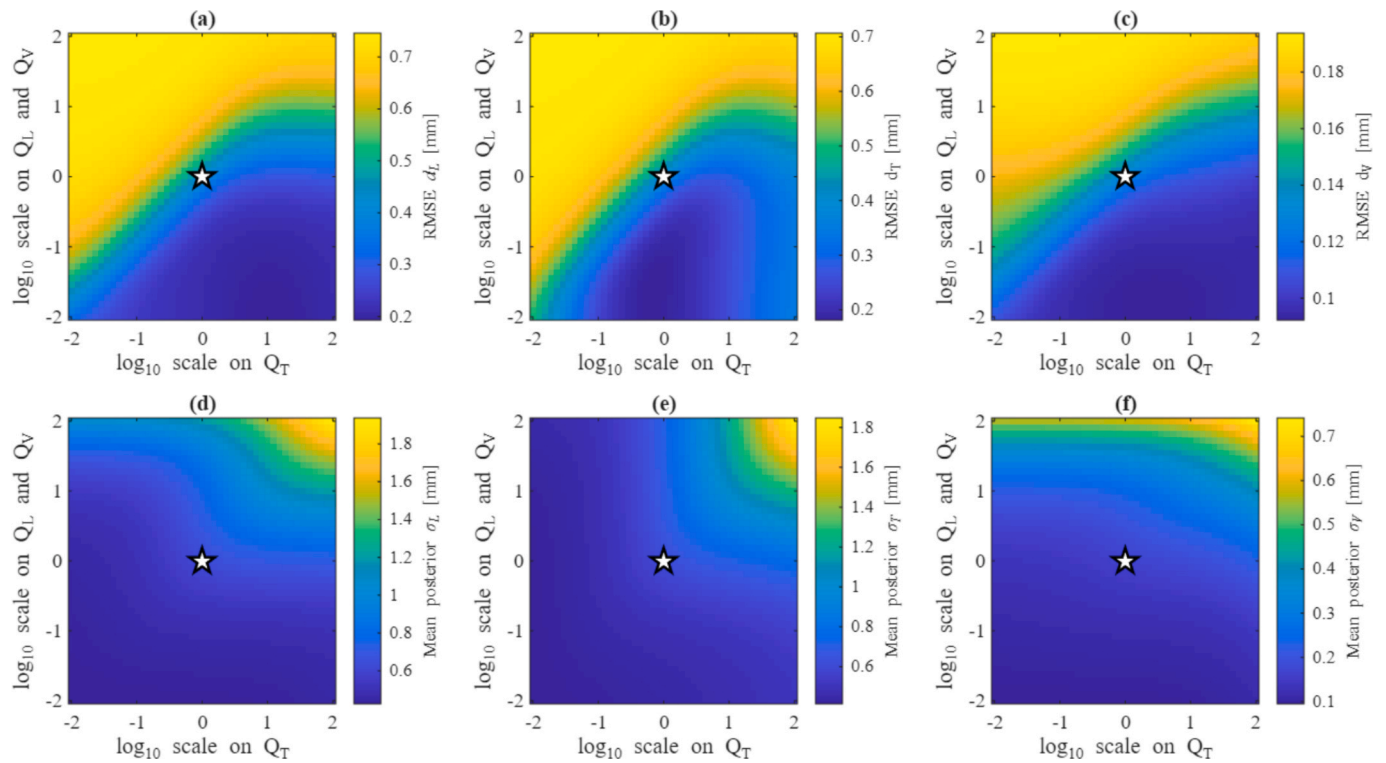


Fig. 10. Component-wise sensitivity of the KF results to variations of the process covariance matrix. The star marks the baseline covariance setting used in the reference calculation, namely $Q_T = Q_{L,V} = 0.01\text{mm}^2$.

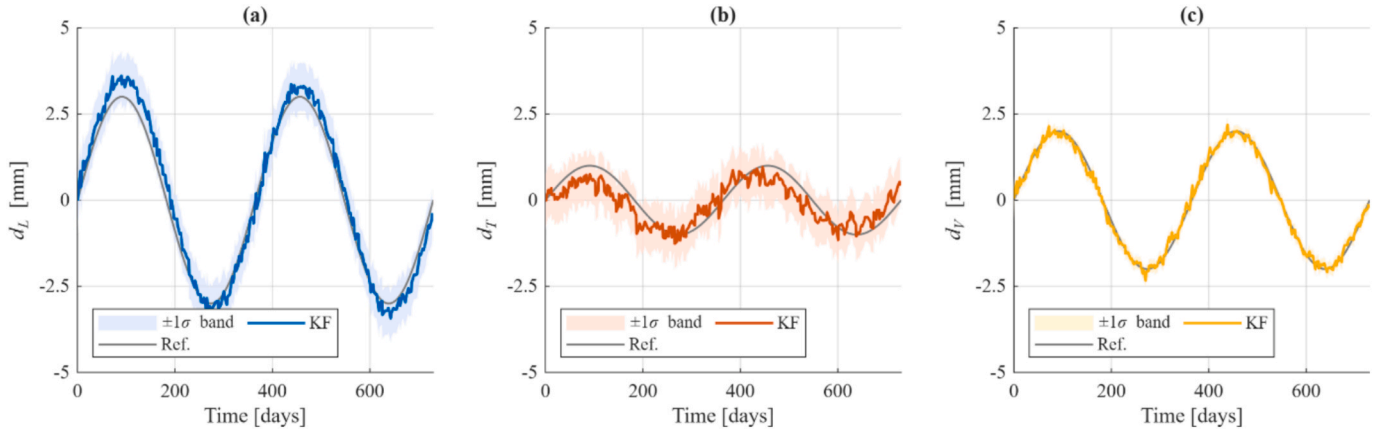


Fig. 11. Reference and KF reconstructed time histories of the (a) longitudinal, (b) transverse, and (c) vertical displacement components and associated confidence boundaries for $\mathbf{Q} = \text{diag}(0.01, 0.1, 0.01)$.

the corresponding mean posterior standard deviations (d-f). Regarding the RMSE, the results increase for relatively large values of Q_T and low values of $Q_{L,V}$. As for the mean posterior standard deviations, they decrease when both covariance terms are reduced. Overall, these results indicate that assigning a relatively large process covariance to the transverse displacement is beneficial for improving the accuracy of the estimates. Fig. 11 shows the reconstructed (a) longitudinal, (b) transverse, and (c) vertical displacement time histories, together with their associated confidence bounds, for the case $\mathbf{Q} = \text{diag}(0.01, 0.1, 0.01)$. The results show a more accurate reconstruction, confirming the benefit of assigning a larger process covariance to the transverse component.

3.4.3. Effect of variance of the virtual observation

To better assess the role of the soft constraint introduced on the transverse displacement, an additional sensitivity analysis was carried out with respect to the variance of the corresponding virtual observation. Fig. 12 reports the sensitivity analysis with respect to the variance of the virtual observation associated with the transverse displacement.

This parameter controls the strength of the pseudo-measurement $d_T \approx 0$: small values correspond to a strong constraint on the transverse component, whereas large values progressively weaken its influence. The top row shows the RMSE of the longitudinal (a), transverse (b), and vertical (c) displacement components, while the bottom row reports the corresponding mean posterior standard deviations (d-f). The results show that the transverse and longitudinal displacements are affected in a similar way by this parameter. In general, when the virtual-observation variance is too small, the filter enforces the transverse constraint too strongly, which may reduce the estimated uncertainty but may also deteriorate the reconstruction accuracy. Conversely, increasing the virtual-observation variance relaxes the constraint, allowing greater flexibility in the transverse estimate, but generally leading to higher posterior uncertainty. These results therefore suggest the existence of a trade-off between accuracy and uncertainty.

3.4.4. Effect of unmodelled vertical settlement

To further investigate the robustness of the proposed framework, an

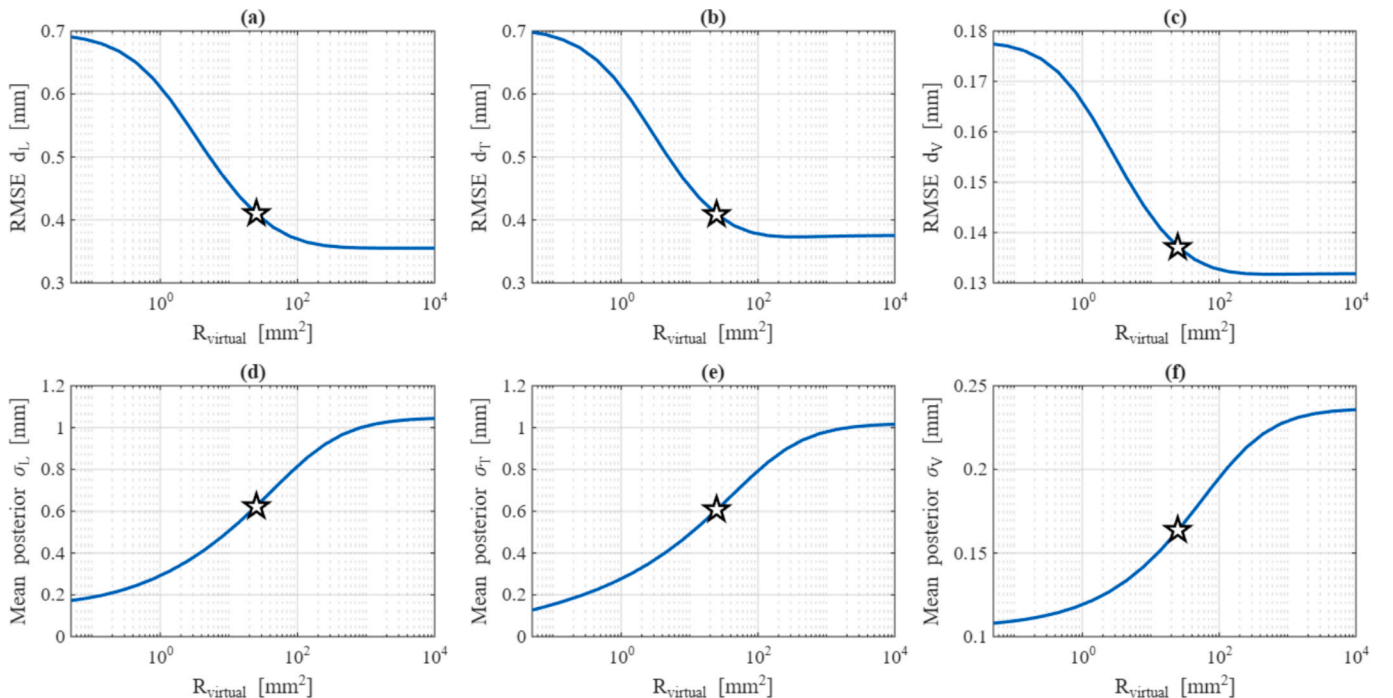


Fig. 12. One-dimensional sensitivity analysis with respect to the value of the variance associated with the virtual observation on the transverse displacement, R_{virtual} . The star identifies the baseline value $R_{\text{virtual}} = 25 \text{ mm}^2$.

additional sensitivity analysis was carried out by introducing an abrupt vertical settlement into the synthetic displacement history. Specifically, a permanent downward step of -1.5 mm was imposed on the vertical displacement component at day 500 of the simulated time series. This settlement was included in the reference structural response and, consistently, in the generated ascending and descending LOS observations, but it was not represented in the temperature-driven prediction model. In other words, the input-effect matrix $\mathbf{B}$, the temperature input, and the state equation were left unchanged, so that the imposed settlement acted as an unmodelled vertical effect present in the InSAR data only. The purpose of this analysis was to assess whether, under these conditions, the KF is still able to correctly reconstruct the vertical event or whether part of the corresponding residual is spuriously redistributed to the other displacement components.

To this end, two representative values of the vertical process covariance were considered, while the longitudinal and transverse terms were kept fixed. In particular, the process covariance matrix was assumed as $\mathbf{Q} = \text{diag}(0.01, 0.10, Q_V)$, with $Q_V = 10^{-2} \text{ mm}^2$ taken as a moderate value and $Q_V = 10^{-4} \text{ mm}^2$ as an unrealistically small one. Fig. 13 compares the reconstructed (a) longitudinal, (b) transverse, and (c) vertical displacement time histories obtained for these two values of Q_V . The results show that the choice of the vertical process covariance has a direct influence on the filter response to the unmodelled settlement. For $Q_V = 10^{-2} \text{ mm}^2$, the abrupt settlement is recovered in the vertical displacement, while the longitudinal and transverse estimates remain only weakly affected. By contrast, when $Q_V = 10^{-4} \text{ mm}^2$, the filter tends to over-trust the vertical prediction model, and the imposed settlement is only partially absorbed by the vertical estimate. Under these conditions, a spurious response appears both in the longitudinal and transverse displacement.

4. Case study

4.1. A21 highway bridge crossing the Po River

The case study, presented in Fig. 14(a-c), is a bridge crossing the Po River along the A21 Piacenza-Brescia highway in northern Italy. Built in 1968, the structure extends for a total length of approximately 1650 m and consists of a Gerber girder system with alternating continuous cantilever and suspended spans, for a total of 41 spans. The deck carries two carriageways, each 11.5 m wide, resulting in an overall width of 24 m including curbs. The superstructure is supported by cast-in-place reinforced concrete piers founded on piles. The longitudinal axis of the bridge forms an angle of approximately -35° with respect to the east direction. This orientation is particularly favourable for InSAR

monitoring, as it allows both the longitudinal and transverse displacement components to retain a meaningful projection onto the available LOS directions. This study focuses on the portion of the bridge crossing the riverbed, which comprises eleven spans between piers 25 and 36, for a total monitored length of 676.50 m. In this segment, the cantilever spans measure 83 m, while the suspended spans measure 23 m, with a regular pier spacing of 61.5 m.

The static scheme follows the classical Gerber configuration represented in Fig. 15. Specifically, each pier supports two cantilever arms, which in turn carry the suspended spans through hinge connections. At the pier level, the cantilever spans rest on roller bearings on the western side, allowing longitudinal translation, and on cylindrical hinge bearings on the eastern side, providing horizontal restraint while permitting rotation. At the saddles, each suspended span is connected to the cantilever arms by a sliding bearing at the western end and an elastomeric bearing at the eastern end, the latter acting as a fixed but rotationally flexible support.

A GNSS monitoring system is installed on the bridge and consists of four antennas: one on pier 34 (PON1), two on pier 35 (POS1 and POS2), and a reference station at the west end of the bridge (POS3), as shown in Fig. 16(a-b). The notation “S” indicates that the antenna is located on the carriageway where traffic travels southbound, while “N” refers to the northbound carriageway.

4.2. InSAR datasets and temperature data

This study employs data provided by the EGMS. Two datasets cover the A21 highway bridge: EGMS_L2a_015_0265_IW2_VV_2019_2023_1 (hereafter referred to as ASC015) for the ascending orbit and EGMS_L2a_168_0806_IW2_VV_2019_2023_1 (hereafter referred to as DSC168) for the descending orbit. Basic products are used spanning the period 2019–2023.

Fig. 17 illustrates the spatial distribution of PSs identified on the bridge deck from the (a) ascending and (b) descending orbits, displayed with a colour scale representing the average velocity of displacements along the LOS during the observation period. Negative velocities (shown in red) indicate movement away from the satellite, while positive velocities (shown in blue) indicate movement toward the satellite. The bridge exhibits extensive PS coverage from both ascending and descending orbits, ensuring robust monitoring capabilities across the structure.

To enable joint processing of the two datasets, a reference grid was defined to spatially cluster PSs located on the bridge deck. The grid cells are not uniform in size but are instead adapted to the bridge geometry and structural configuration. Each suspended span is covered by a single

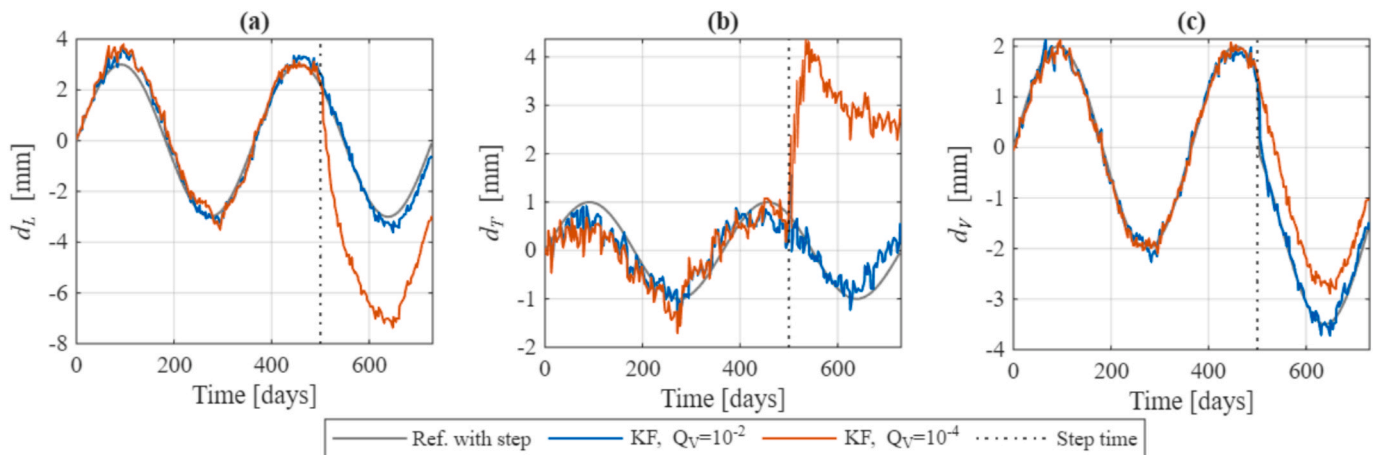


Fig. 13. Reference and KF reconstructed time histories of the (a) longitudinal, (b) transverse, and (c) vertical displacement components in the presence of an unmodelled vertical settlement, for two different values of the vertical process covariance Q_V .

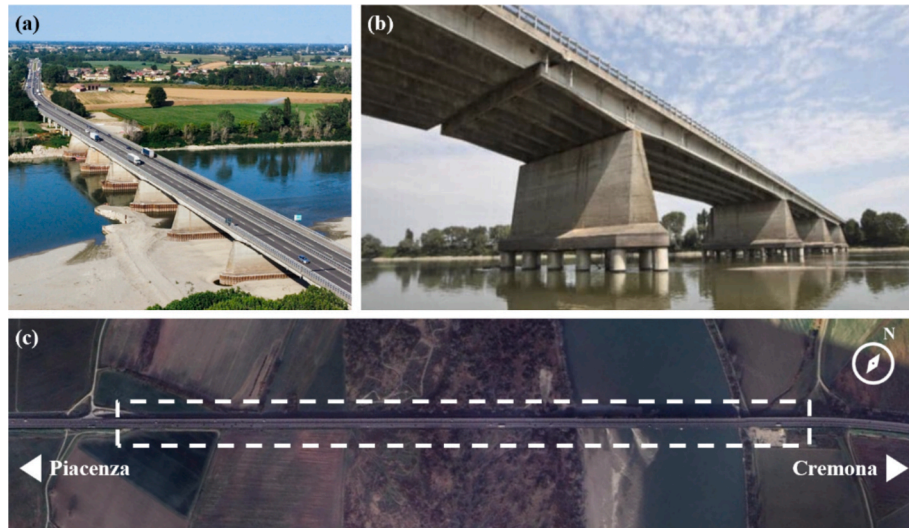


Fig. 14. The A21 highway viaduct: (a) Aerial view from the Piacenza side; (b) Detail of the piers and the Gerber saddles; (c) Plan view.

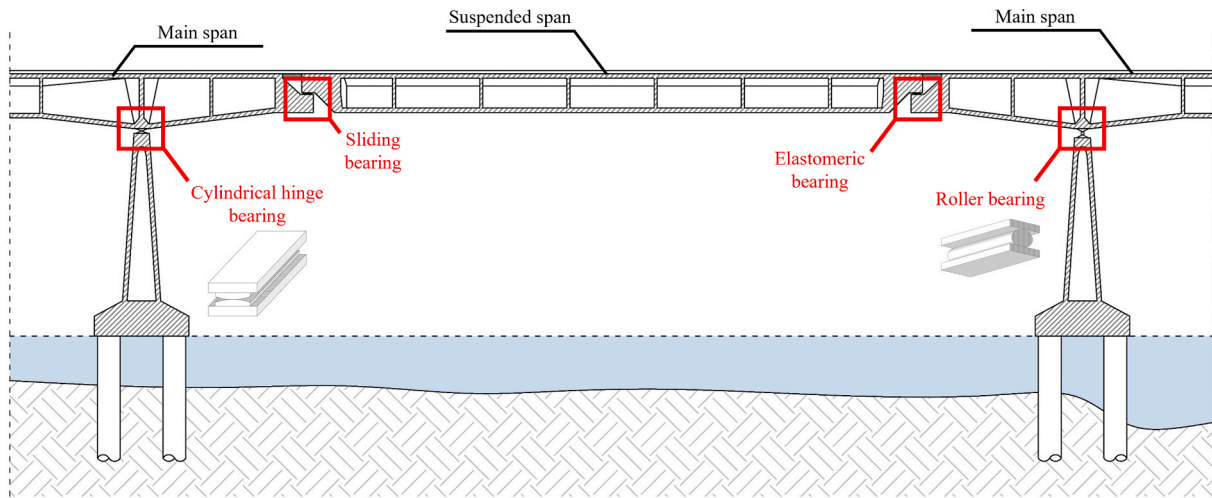


Fig. 15. Detail of the static scheme of the bridge.

cell, while the main spans are subdivided into western (W) and eastern (E) areas to better capture the structural behaviour across different sections of each span. It should be noted that area 34 W does not present PSs from the descending orbit; therefore, displacement reconstruction is not feasible for this specific area. In addition to the InSAR dataset, air temperature records are incorporated as environmental input for the KF formulation. Temperature data are obtained from the ARPA Lombardia portal [57], which provides continuous temperature records throughout the observation period.

4.3. Reconstruction of structural displacements

The structural displacements of the bridge are reconstructed using the proposed KF framework, combining multi-orbit InSAR data from the EGMS with air temperature records. First of all, for each orbit, the displacement time histories of the PSs inside each area are averaged, and the resulting mean displacement time histories are used to feed the KF. Also, the implementation accounts for the static scheme of the viaduct and the thermal deformations expected under seasonal temperature variations.

The vertical response may reasonably be interpreted as being governed mainly by the vertical movement of the supporting elements.

More specifically, the vertical displacements of the two sides of the main spans can be expected to evolve in a similar manner under temperature variations, owing to the comparable dimensions of the supporting piers and to the adopted spatial discretisation, which identifies areas located in correspondence with the supports. A similar behaviour is also assumed for the suspended spans. Furthermore, the support configuration is not expected to induce significant vertical displacement as a consequence of longitudinal thermal elongation. As for the longitudinal displacements, they are expected to vary as a function of the distance between the centre of gravity of each area and the fixed support point. Consequently, different $\mathbf{B}$ matrices are defined for the three areas to model the thermal input effect within the KF framework. The relationship between elongation and temperature variation is expressed as:

$$\Delta d = \alpha L \Delta T \quad (18)$$

where $\alpha = 10 \times 10^{-6} \text{ } ^\circ\text{C}^{-1}$ is the coefficient of thermal expansion of concrete, L is the effective length of the area, and ΔT is the temperature variation. A critical parameter in this modelling framework is the effective expansion length, which is not always straightforward to identify. In hyperstatic schemes, or in the presence of rollers and other support devices, the actual structural behaviour may deviate from the ideal assumptions. Such supports often do not act as perfect connections

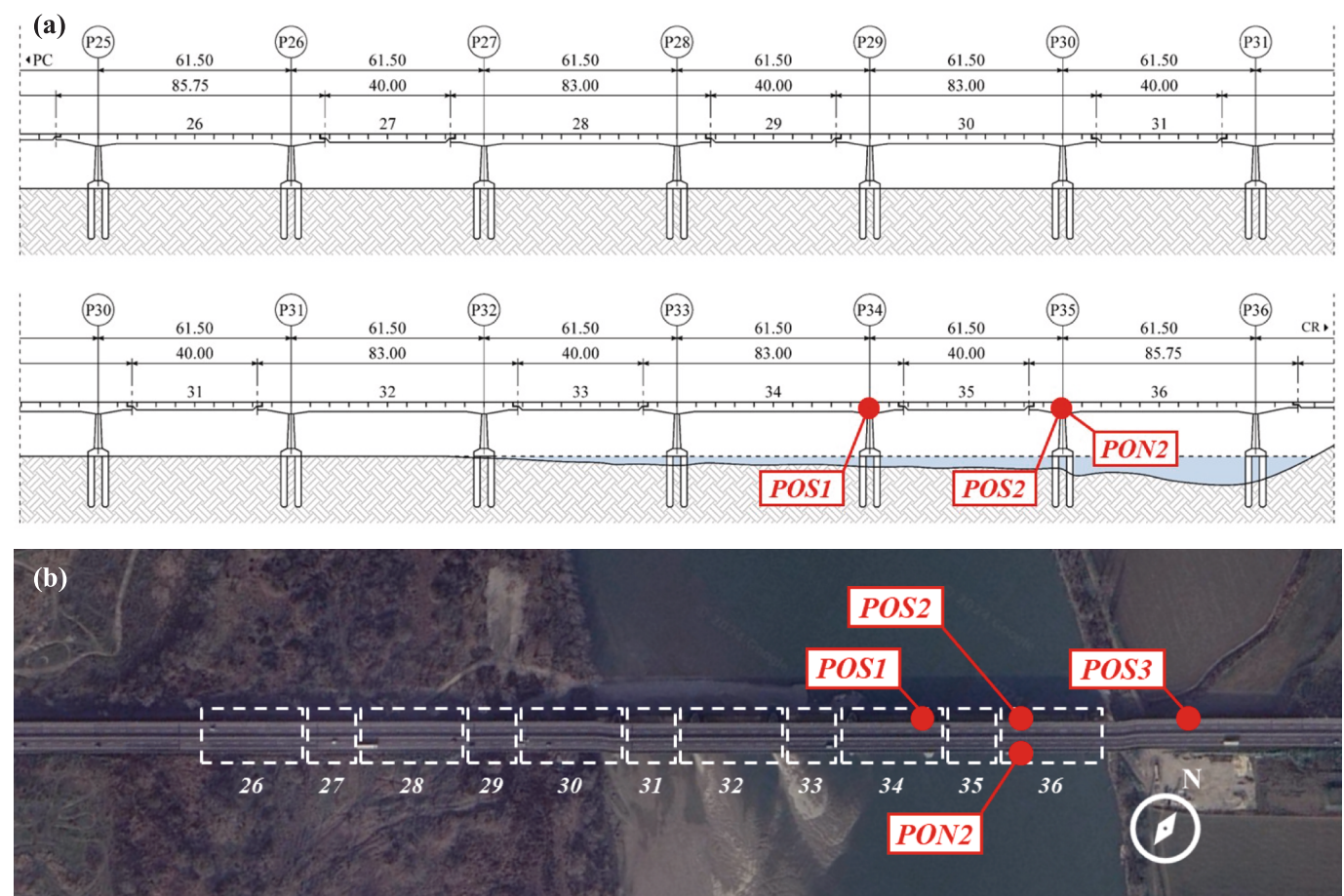


Fig. 16. Monitored spans and GNSS antennas position: a) Longitudinal section; b) Plan view.

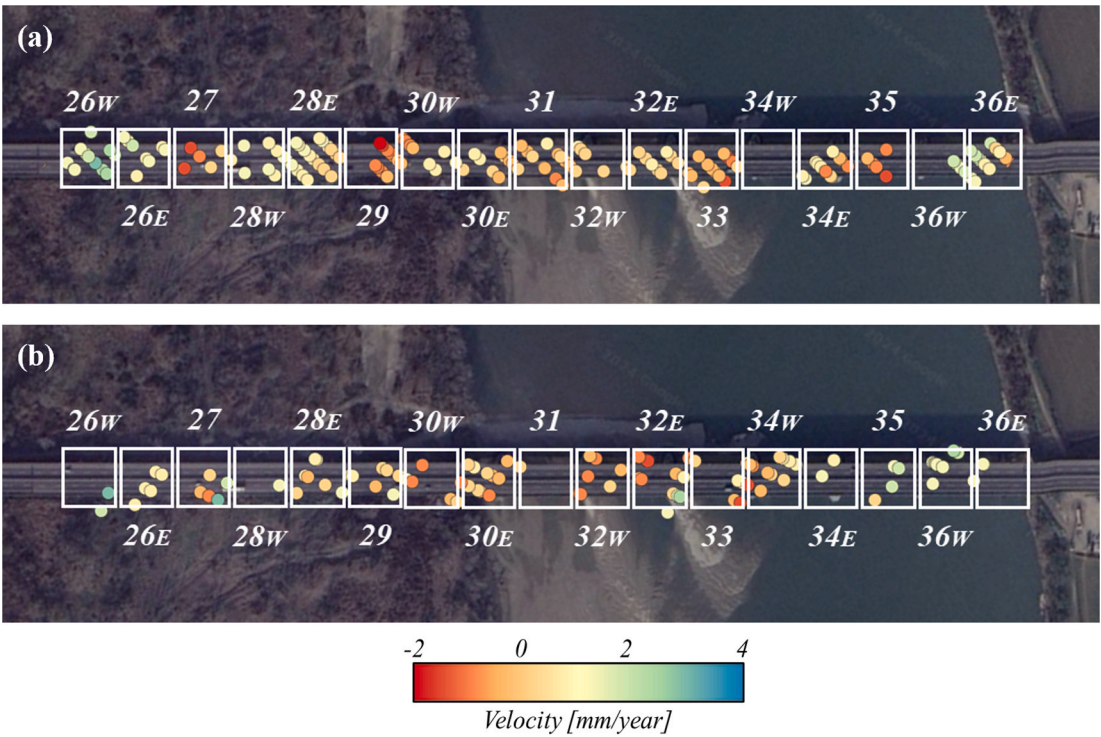


Fig. 17. PSs available on the bridge from the (a) ascending and (b) descending orbits.

for small displacements, thereby inducing internal stresses. Therefore, structural elements may not deform exclusively through longitudinal elongation but may also exhibit more complex deformation patterns. In the case study, the longer spans are assumed to be fixed on the right pier and free to move on the left one. For the supported spans, the situation is more complex: they are connected on the right to the left cantilever beam of the main span, which itself undergoes displacement toward the left during the summer due to thermal expansion, while on the left, they rest on the right cantilever beam through a stainless-steel/PTFE sliding support. As a result, the longitudinal displacement of the suspended span consists of the superposition of its own thermal elongation and the elongation of the main span. Accordingly, an effective expansion length is defined as the distance between the centre of the suspended span and the hinged connection at the right pier of the main span. Fig. 18 illustrates the definition of the static scheme of the bridge and the corresponding input-effect matrices $\mathbf{B}$ for the three area types. The filter is initialised as follows:

- Initial state estimate: $\mathbf{x}_0 = [0, 0, 0]^T$
- Process noise covariance: $\mathbf{Q} = \text{diag}(0.01, 0.01, 0.01)$
- Measurement noise covariance: $\mathbf{R} = \text{diag}(0.01, 0.01, 0.01)$
- Initial estimation error covariance: $\mathbf{P}_0 = \mathbf{I}_3$

The virtual observation associated with the transverse displacement is introduced as a weak prior with zero mean and a standard deviation of 10 mm. The results of the displacement reconstruction are presented separately for the three area types. Fig. 19 reports the results for the three area types. As for the longitudinal displacements, the left and suspended spans show very similar trends. Although the suspended spans are located further from the fixed support (i.e., the right piers of the main spans), their longitudinal movement is constrained by the left

support, resulting in displacements comparable to those of the left spans. In contrast, the right spans show smaller longitudinal displacements, consistent with their shorter distance from the fixed support. Seasonal variations are clearly visible: displacements are negative in summer, as elongation occurs towards the west (left), while in winter they are positive, corresponding to deck shortening. The transverse displacements are smaller in magnitude, as expected, and display modest seasonal variations that follow the same sign pattern as the longitudinal displacements. The vertical displacements of the left and right parts of the main spans are very similar, reflecting the comparable pier heights, and are positive in summer, in agreement with thermal expansion effects.

A further observation concerns the temporal coverage of the InSAR data. From 2022 onward, the number of acquisitions decreases because one of the Sentinel-1 satellites was decommissioned, reducing the effective temporal sampling. Moreover, in 2022, retrofitting works were carried out on the bridge, which are reflected in anomalies observed in the reconstructed displacement time series. Notably, the KF reconstruction can capture not only the seasonal displacements related to thermal effects modelled through the input-effect matrix $\mathbf{B}$, but also additional trends that are not directly linked to temperature, highlighting the flexibility of the proposed approach.

4.4. Comparison with GNSS results

This section compares three types of data: (i) the displacements reconstructed from InSAR data using the proposed KF approach, (ii) the displacements obtained with the conventional method described in Section 2.2, and (iii) the displacements measured by the in-situ GNSS system. The comparison is carried out for the areas equipped with GNSS sensors, namely Areas 34E and 36W. To enable direct comparison, all

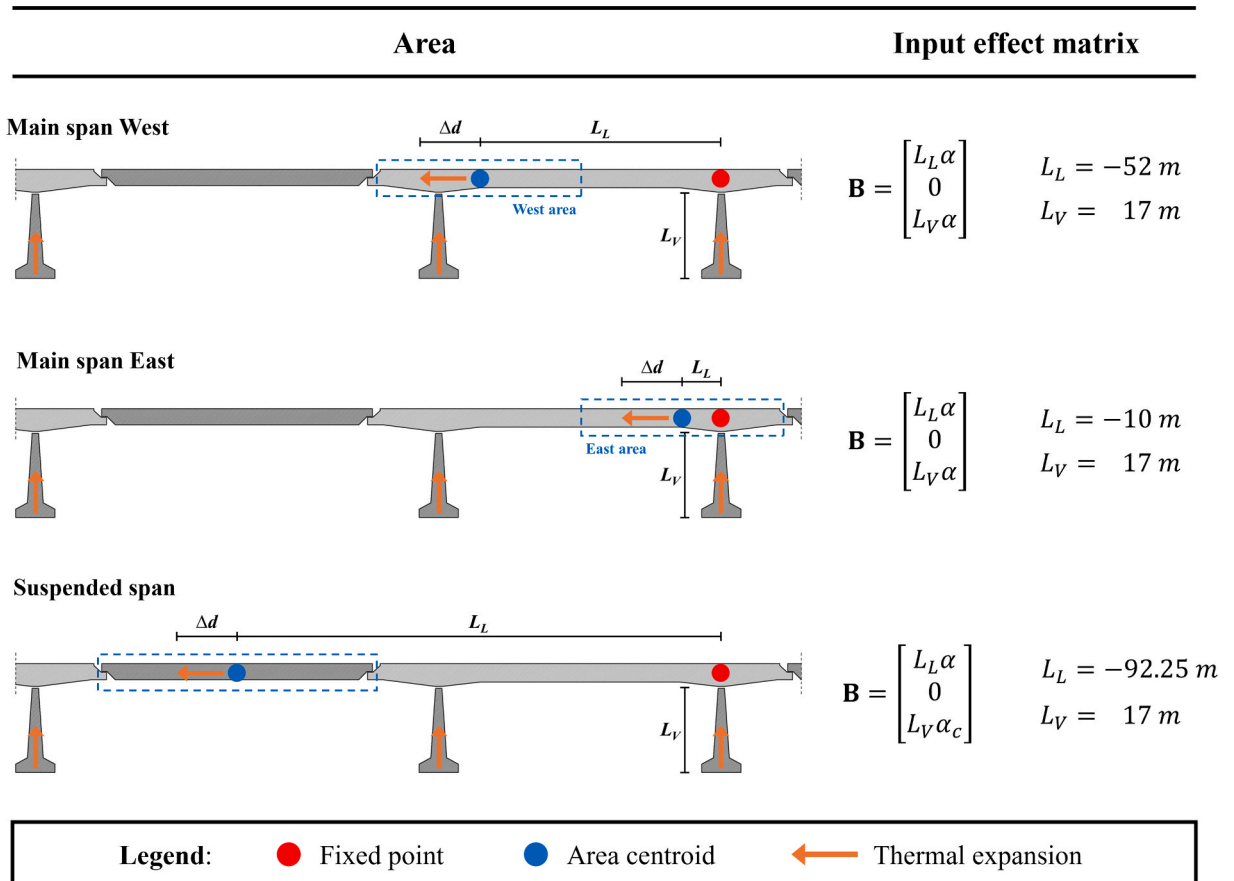


Fig. 18. Definition of the input-effect matrices.

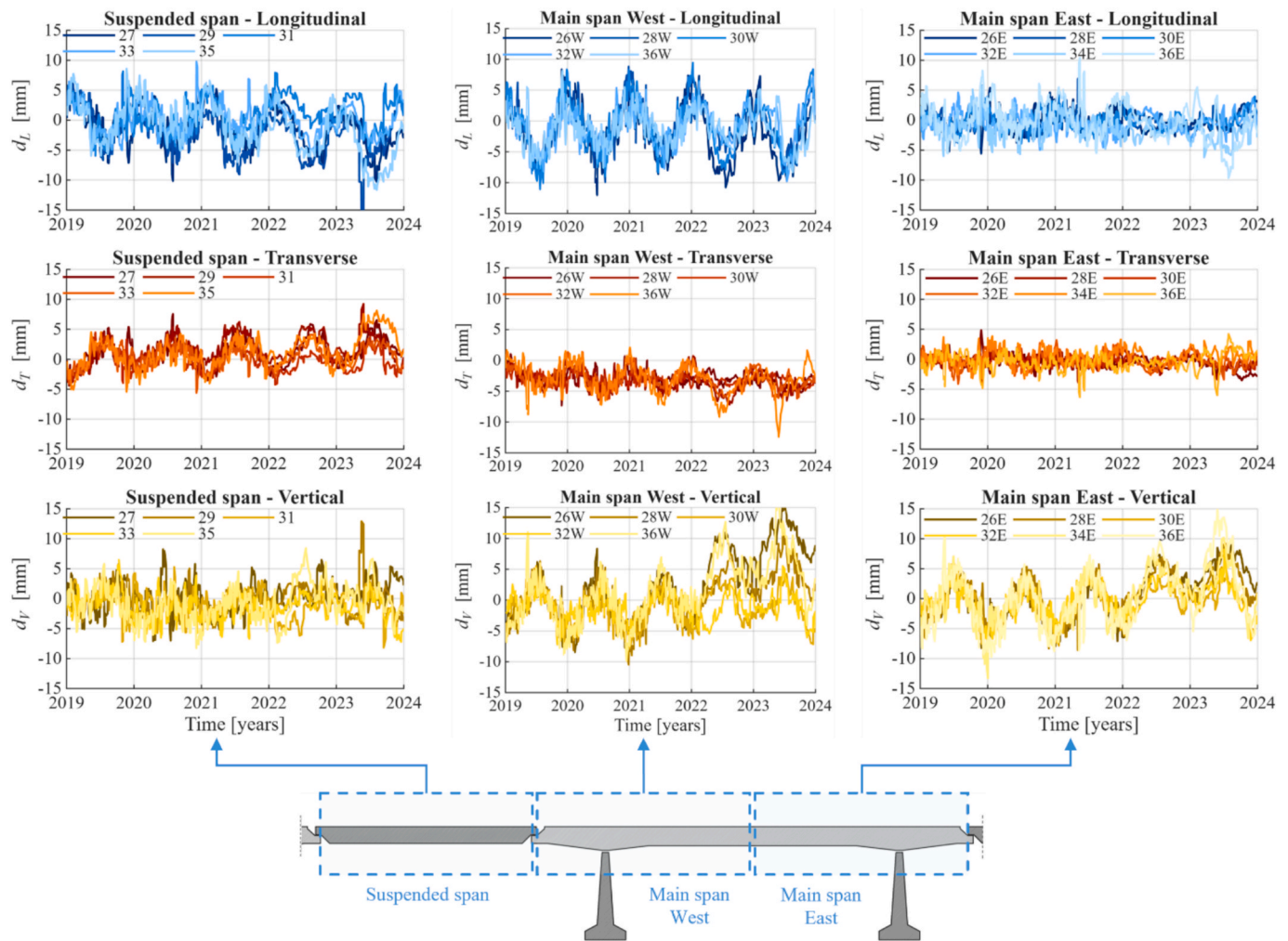


Fig. 19. Displacement results for different span types.

time series are normalised by removing their mean displacement. GNSS data from antennas PON2 and POS1 are considered in the analysis, while measurements from antenna POS2 are excluded due to the presence of anomalous trends that compromise their reliability.

Fig. 20 presents the (a) longitudinal, (b) transverse, and (c) vertical displacements for Area 36W, corresponding to the left side of span 36, using GNSS measurements from the PON2 antenna, which operated between 2019 and 2022. For the KF reconstruction, the figure also reports the associated confidence intervals, expressed as the estimate plus or minus one standard deviation derived from the covariance matrix. RMSE values are shown in Fig. 21 for the (a) longitudinal, (b) transverse, and (c) vertical displacements. For the longitudinal displacement, the estimates obtained with the KF show a closer agreement with the GNSS data than those from the conventional method. The variances of the KF estimates remain stable for all displacement components. Among them, the transverse displacement is associated with the highest uncertainty, whereas the vertical displacement exhibits the lowest variance. It should be noted that, since the variance terms are governed by the filter model, the covariance matrix is identical for all areas and does not depend directly on the InSAR measurements.

With regard to the interpretation of the results, it should be noted that the GNSS antenna is mounted on the pier, which in practice follows the motion of the deck where the PSs are located, since the roller support is not activated. This behaviour reflects a broader structural issue already documented for the bridge bearings. The bearings have been studied and monitored through visual inspections, which revealed two main problems: oxidation of the roller devices at the Gerber saddles,

preventing their proper functioning, and end-of-travel conditions in some cases, where bearings are in direct contact with the stoppers. It is unclear whether this condition originates from an incorrect initial setting or from subsequent degradation. In any case, it is plausible that all bearings currently behave as hinges, preventing relative displacements between the connected elements. Remarkably, this malfunction of the rollers can also be detected from space through the InSAR analysis. The transverse displacement can only be reconstructed with the KF and shows very good agreement with the GNSS data, with a minimal RMSE. Similarly, for the vertical displacement, the KF results are closer to the GNSS data than those obtained with the conventional approach.

Fig. 22 shows the results for Area 34E, corresponding to the right side of span 34. Specifically, Fig. 22(a), 22(b), and 22(c) show the longitudinal, transverse, and vertical displacement components, respectively. The GNSS record exhibits a sudden drop at the beginning of 2022; therefore, RMSE values are computed only for the period preceding this event and are shown in Fig. 23. In particular, Fig. 23(a), 23(b), and 23(c) report the RMSE values for the longitudinal, transverse, and vertical displacement components, respectively. For consistency, the mean displacement used for normalisation is also computed in this interval. The longitudinal and transverse displacements observed by GNSS at this location are very small and largely dominated by noise, and the InSAR results are correspondingly small. For the vertical displacement, all three methods provide similar results.

While the horizontal displacements vary depending on the selected area, the vertical displacements are consistent across all areas. A closer inspection of the vertical displacement time series reveals that InSAR

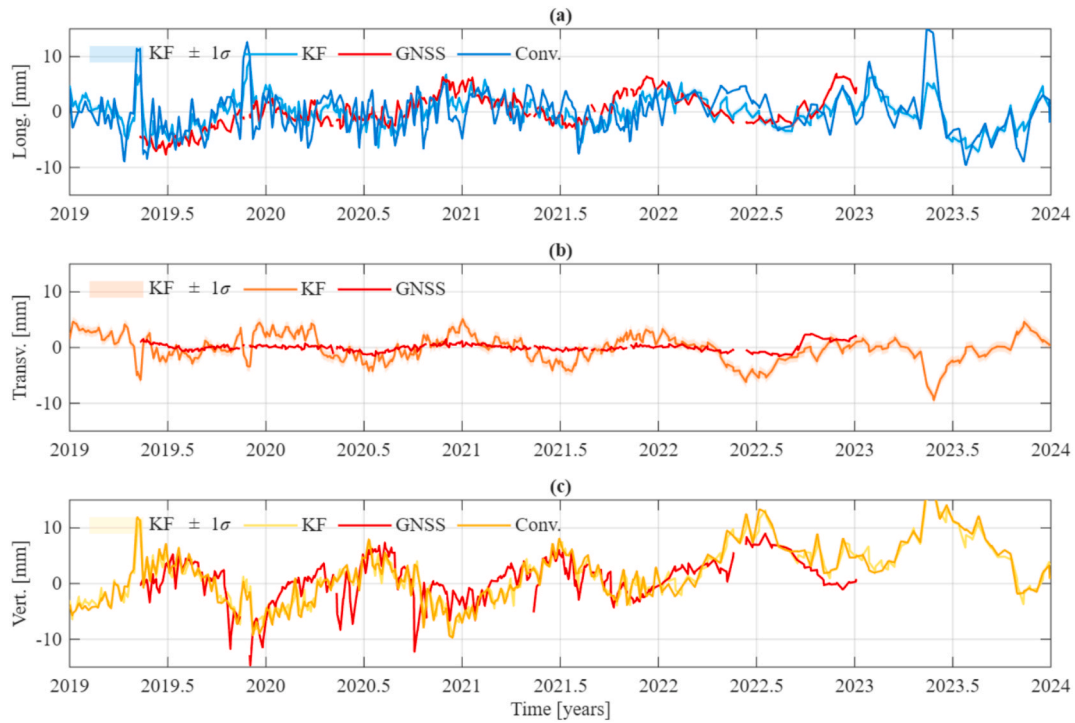


Fig. 20. Comparison between GNSS measurements from station PON2 and the reconstructed displacements for Area 36W, obtained using the KF and the conventional inversion approach.

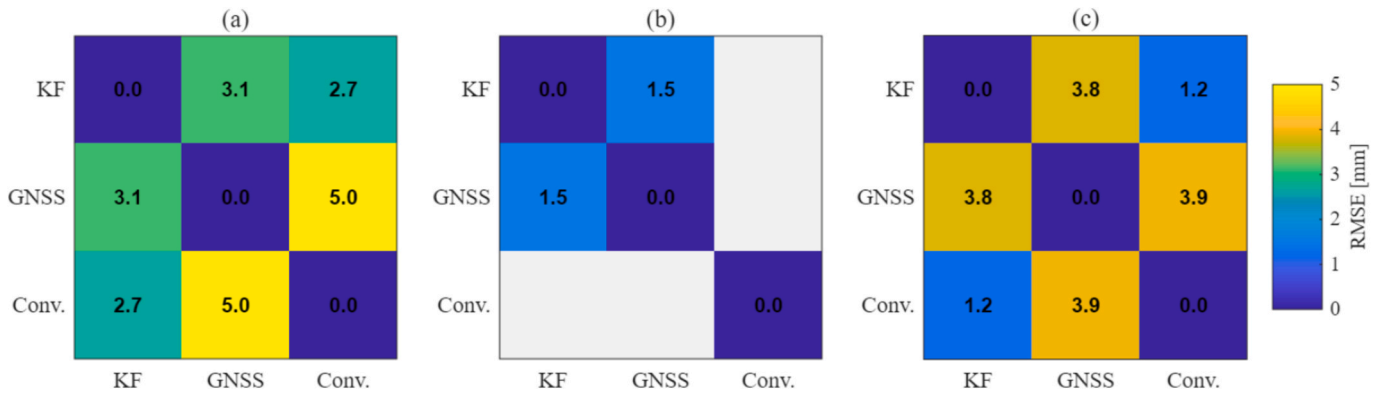


Fig. 21. RMSE among displacement time series for Area 36W (GNSS-PON2).

data are unable to reproduce abrupt variations not related to temperature but rather associated with water level changes. In turn, displacements due to water level changes are tracked by GNSS data as shown in Fig. 24. This behaviour suggests that elevated river levels induce an elastic response of the soil, leading to negative vertical displacements of the bridge. A similar behaviour for bridges crossing the Po River was observed in other studies [39,58].

5. Discussion

The numerical experiments provide useful insights into the performance of the proposed KF framework in comparison with the conventional inversion approach. A first observation is that the conventional method, which reconstructs longitudinal and vertical displacements by solving a reduced system under the assumption of null transverse motion, is highly sensitive to the structural orientation ϕ with respect to the satellite LOS. Reliable results are obtained when ϕ is close to 0° or 180° , i.e., when the neglected transverse displacement contributes only marginally to the LOS projection. By contrast, for orientations around

90° and 270° , the errors become substantial, exceeding 200 mm for the longitudinal component and propagating to the vertical reconstruction. Furthermore, the transverse component remains entirely unobservable within this framework. These results clearly show that structural orientation plays a crucial role in determining the observability of the displacement components and, consequently, the accuracy of the reconstruction. In particular, for unfavourable values of ϕ , the LOS measurements contain little or no information on the longitudinal displacement, so that the corresponding estimates are only weakly constrained by the data. Within this context, the application of the KF improves displacement reconstruction in several respects. Even when the null-transverse-displacement assumption is retained, the filter significantly reduces errors at unfavourable orientations (90° and 270°), achieving considerably better performance than the standard method. When the assumption of null transverse displacement is relaxed, the KF is able to reconstruct both horizontal components, though their accuracy decreases under certain orientations. Notably, the vertical component is consistently reconstructed with high reliability across all tested orientations. However, the numerical analyses also confirm that the KF

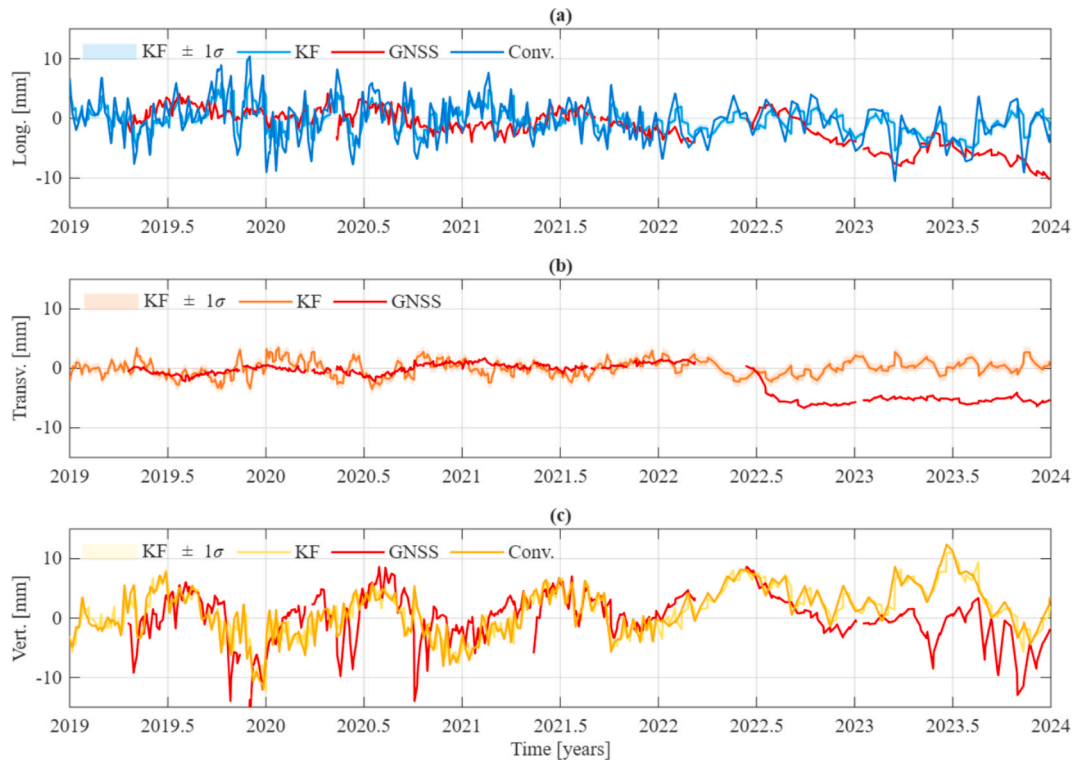


Fig. 22. Comparison between GNSS measurements from station POS1 and the reconstructed displacements for Area 34E, obtained using the KF and the conventional inversion approach.

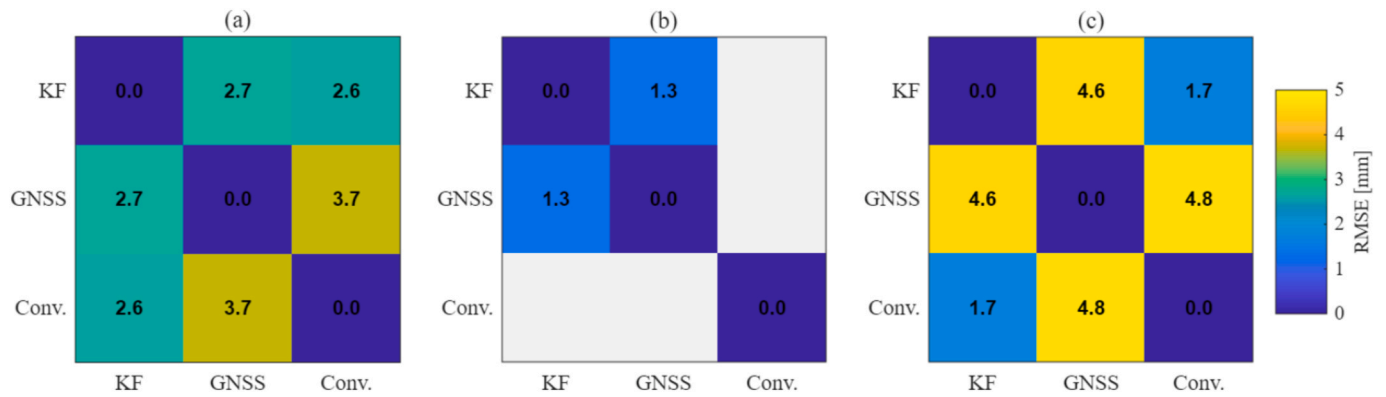


Fig. 23. RMSE among displacement time series for Area 34E (GNSS-POS1).

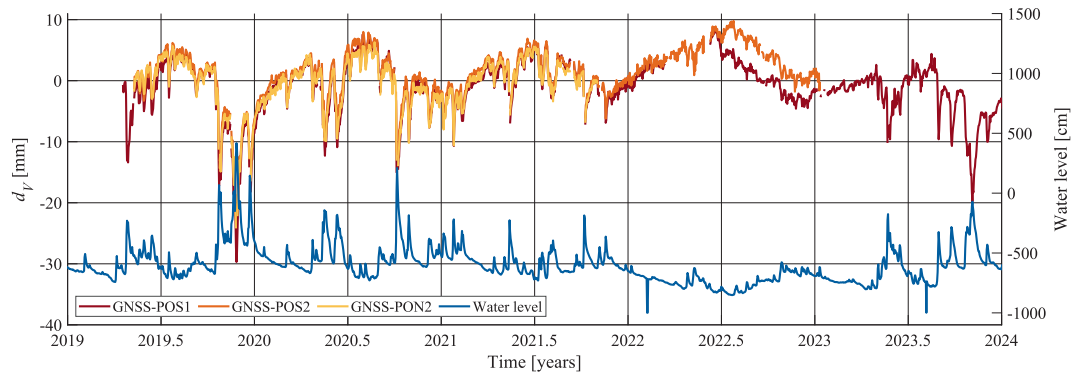


Fig. 24. GNSS displacement and water level data.

formulation alone does not resolve the fundamental observability limitations imposed by the measurement geometry. Rather, it provides a framework for optimally combining the information contained in the measurements with prior knowledge, so that components that are weakly observable from InSAR data alone can still be estimated more robustly when additional information is introduced. Regarding the estimated uncertainties, without additional priors, the variances of the estimated components tend to increase linearly in time, reflecting the random-walk nature of the state model and the limited observability of certain directions. The introduction of environmental data and minimal structural information, together with the incorporation of a soft constraint on the transverse displacement, substantially improves the filter's behaviour. Regarding parameter tuning, the results suggest that process and measurement noise variances should be chosen to ensure that the posterior covariance matrix remains stable over time. It should be emphasised, however, that these findings are derived from controlled simulations. Real-world applications will inevitably involve additional uncertainties, such as unmodeled environmental effects, structural nonlinearities, and higher noise levels.

The application of the proposed framework to the A21 viaduct over the Po River confirms and extends the findings of the numerical experiments. The joint use of ascending and descending EGMS datasets provided dense spatial coverage of the structure, enabling the definition of representative areas for displacement reconstruction. The comparison with GNSS data highlighted the ability of the KF to reproduce the main trends of longitudinal and vertical displacements with higher fidelity than the conventional inversion approach. In particular, for Area 36W, the KF estimates were closer to the PON2 GNSS records than those obtained with the standard method, both in terms of longitudinal and vertical components. Moreover, the KF enabled the estimation of transverse displacements, which are not accessible through the conventional formulation, and these estimates showed good agreement with GNSS measurements, especially for the PON2 antenna. The analysis of vertical displacements further demonstrated both the potential and the limitations of the KF approach. The GNSS system captured abrupt variations associated with high water level events, whereas the InSAR-only reconstructions were not sensitive to such short-term phenomena. This result is consistent with a general limitation of InSAR-based monitoring. In the present case, the vertical displacements induced by water-level variations are not clearly captured by the processed InSAR time series and, moreover, water level was not included among the input variables of the state-space model. Consequently, this effect could neither be directly observed nor indirectly modelled within the proposed formulation. For the investigated bridge, the adopted linear thermal model proved sufficient to capture the dominant seasonal component of the structural response; however, the proposed KF framework is general and can accommodate more refined input formulations, including spatial temperature gradients or delayed thermal effects, when more detailed information is available.

It should be emphasised, however, that the definition of the input-effect matrix adopted in this study is specific to the investigated bridge, its Gerber static scheme, the selected spatial discretisation, and the dominant quasi-static thermal behaviour observed in this case. Therefore, it should not be interpreted as a universally applicable formulation for all bridge typologies or monitoring scenarios. In general, the input-effect matrix should be adapted to the structural scheme of the monitored bridge, the location of the analysed areas, and the prior information available on the expected deformation mechanisms. Different applications may require more refined input models, for example to account for restrained thermal expansion, deck temperature gradients, or additional environmental and operational drivers.

Finally, the selection of grid size and shape remains a relevant source of uncertainty. In this study, the representative position of each cell was defined by its geometric centroid, consistently with common grid-subsampling approaches. However, when the PS distribution inside a cell is strongly non-uniform, the centroid of the PSs may provide a more

appropriate representation of the effective measurement location. This aspect is particularly relevant when structural quantities depending on the representative position are computed, such as the effective expansion length used to model thermal elongation.

6. Conclusion

This paper presented a Kalman Filter (KF)-based framework for the reconstruction of three-dimensional structural displacements from multi-geometry InSAR data, enhanced by the integration of environmental parameters and minimal structural information. The method was first evaluated through numerical simulations and then applied to the A21 viaduct over the Po River in Italy with validation against independent GNSS measurements.

More generally, the study addresses a measurement problem in which the measurand of interest is not directly observed, but inferred from partial LOS observations through a model-based fusion procedure. In this sense, the paper presents an uncertainty-aware estimation framework for structural displacement reconstruction under incomplete observability.

The numerical experiments demonstrated the main limitations of the conventional inversion approach, which relies on restrictive assumptions about the displacement field. In particular, the conventional method provides acceptable results only for favourable orientations of the structure with respect to the satellite LOS, while producing large errors for other configurations and leaving the transverse component unobservable. In contrast, the proposed KF formulation proved more robust, achieving lower errors across all tested orientations and enabling the estimation of all displacement components within a unified data-fusion framework, without requiring additional on-site instrumentation in the investigated case. The integration of environmental data and structural information, together with the use of soft constraints on poorly observable directions, further improved the results. At the same time, the study also highlighted a fundamental limitation of InSAR-based reconstruction: displacement components having null projection along the available LOS directions remain unobservable from InSAR measurements alone and therefore cannot be reliably reconstructed without introducing modelling assumptions or auxiliary information.

The case study confirmed these findings in a real-world setting. The KF results reproduced the longitudinal and vertical displacements of the A21 bridge with higher fidelity than the conventional inversion, as verified against GNSS records. Importantly, the framework also provided estimates of the transverse component, which compared well with in-situ measurements. By incorporating temperature data through the input-effect matrix, the method successfully captured the seasonal thermal trends of the structure, while GNSS remained crucial for detecting short-term effects such as elastic pier settlements during high water level events. A remarkable aspect of the case study is that the malfunctioning of the bridge supports, already identified by visual inspections and GNSS results, could also be observed from space using freely available InSAR data.

Overall, the study shows that the proposed KF approach significantly extends the applicability of InSAR to Structural Health Monitoring (SHM). Beyond routine monitoring, the proposed approach is particularly valuable for forensic analysis, as it allows the reconstruction of historical displacement patterns that can shed light on the progression of structural anomalies and the conditions preceding critical events. It should be emphasised, however, that its applicability remains conditioned by the reliability of the underlying InSAR observations, including the availability of coherent scatterers and displacement evolutions compatible with the temporal sampling and interferometric processing limits.

The proposed framework is flexible and can be extended in several directions. Future work will focus on its application to other bridge typologies, the inclusion of additional environmental drivers, and its integration into operational monitoring systems for large-scale

infrastructure networks. Further developments will also address the joint use of multiple InSAR datasets to improve the reliability and temporal resolution of displacement reconstructions. More advanced nonlinear or adaptive state-space formulations may also be explored to better represent complex structural behaviours.

CRediT authorship contribution statement

Pier Francesco Giordano: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Riccardo Liuzzo:** Writing – review & editing, Visualization, Validation, Software, Investigation. **Maria Pina Limongelli:** Writing – review & editing, Validation, Resources, Investigation. **Andrea Piscini:** Writing – review & editing, Validation, Data curation. **Massimo Gammino:** Writing – review & editing, Validation, Data curation.

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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Data availability

EGMS data available online

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