

High-Resolution Subsurface Mapping Using SBAS-InSAR and Multilayer Compaction Monitoring Wells for Land Subsidence Mitigation

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Abstract

Land subsidence from excessive groundwater extraction has long affected the Choushui River Fluvial Plain (CRFP) in Taiwan, increasing flood risks and threatening infrastructure like the Taiwan High Speed Rail (THSR). A network of multilayer compaction monitoring wells (MLCWs) aids in understanding subsidence mechanisms, but their high installation costs limit dense deployment. This study integrates SBAS-InSAR surface deformation data with MLCW measurements using geographically weighted regression (GWR) to map layer-wise compaction regionally. This approach enables cost-effective, high-resolution monitoring to inform groundwater management and infrastructure protection.

Keywords: land subsidence; mitigation; layer-wise compaction

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1 Introduction

2 Study Area Background

The CRFP belongs to the western coastal region of central Taiwan. CRFP has an area of approximately 2000 km^2 , which belongs to the regions of Changhua, Yunlin, and the northern part of the Chiayi counties, with a surface elevation ranging from 0 m to 100 – 150 m above sea level. The CRFP boundary is shaped by Douliu Hill and Bagua Tableland on the eastern side, the Wu River to the north, the Beigang River to the south, and the Taiwan Strait to the west (Figure 1). The hydrogeological structures of the study area are divided into three sections from the east to the west, namely proximal fan, middle fan, and distal fan [Survey, 1999]. Each section was comprised of various sedimentary materials, with the average grain sizes decreasing from hilly regions to coastal areas. The sedimentary materials in the CRFP are divided into four primary groups, grading from very coarse grains to very fine grains: gravel, coarse sand, fine sand, and clay or silt [Survey, 1999]. These materials are weathered products of rock formations located in the upstream watershed of the study area, such as slate, quartzite, shale, sandstone, and mudstone [Liu et al., 2004, Hung et al., 2015]. The borehole profiles suggest that gravel and coarse sand are primarily present at the proximal fan and part of the middle fan, whereas the distal fan mainly witnesses fine-grain materials, including fine sand, clay, and silt (Figure 2).

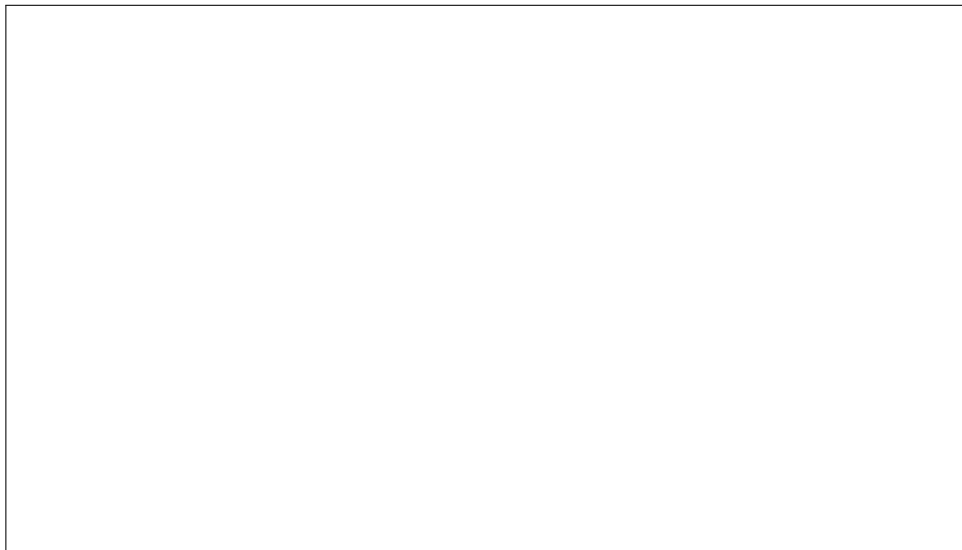


Figure 1: The location of the study area (bounded by a gray line) and the coverage of Sentinel-1's SAR images (blue rectangle). The green triangles and black squares stand for GPS stations and leveling benchmarks, respectively. The hydrogeological structures are roughly separated by purple lines.



Figure 2: Cross-section showing the distribution of sedimentary materials along profile AA'.

3 Data Sets

3.1 Multilayer Compaction

A multilayer compaction monitoring well (MLCW) is a specialized borehole extensometer that captures the subtle subsurface compaction by reading measurements at magnetic rings, strategically installed at boundaries between significant aquifers, or transitions between fine and coarse sedimentary materials, as defined by the Geological Survey and Mining Management Agency (GSMMA). The depth of each MLCW often extends up to 300 m, with 21 to 26 magnetic rings anchored throughout the profile. Based on hydrogeological properties, aquifer units at each well are determined, each containing a number of corresponding magnetic rings, providing measurements of aquifer-specific compaction. The installation and measurement approaches of the MLCWs have been comprehensively described by [Hung et al., 2021]. In this study, 29 MLCWs were employed, with monthly data collected from April 2016 to November 2021.

3.2 Cumulative vertical displacement

This study derived cumulative vertical displacement from an 8-year dataset of Sentinel-1 SAR images (2016 - 2024), acquired from both ascending and descending orbits; the image properties are summarized in Table 1. First, the images from each acquisition orbit were processed separately applying the *hyp3-isce2* plugin, part of the Hybrid Pluggable Processing Pipeline (HyP3) [Hogenson et al., 2025]. For interferogram formation, each SAR image was paired with up to four subsequent consecutive images to minimize temporal decorrelation. Next, each image pair was analyzed using the InSAR Scientific Computing Environment 2 (ISCE2) TOPS workflow, which sequentially performs burst-level coregistration of Single Look Complex (SLC) images, interferogram generation, waterbody masking and topographic phase correction with the Copernicus GLO-30 DEM, phase unwrapping via the SNAPHU algorithm, and geocoding to produce unwrapped interferograms suitable for further time-series InSAR analysis. A detailed description of the ISCE2 workflow is available in [Rosen et al., 2012, Yagüe-Martínez et al., 2016, Fattahi et al., 2017].

Table 1: Summary of the Sentinel-1A datasets used in this study.

Parameters	Ascending	Descending
Relative Orbit (Path)	69	105
Acquisition Period	4/2016 – 11/2021	
Number of Images	266	264
Acquisition Mode	Interferometric Wide (IW)	
Polarization	VV	
Incidence Angles	32° – 38°	38° – 43°
Satellite Headings	347.63°	192.37°

Subsequently, a time-series analysis was conducted on the unwrapped interferograms from ascending and descending orbits separately using the small baseline subset approach, provided by Miami InSAR Time-series software (MintPy) [Yunjun et al., 2019]. The valid interferogram network was formed through a two-stage selection. The minimum spanning tree (MST) [Perissin and Wang, 2012] first identified the most coherent interferograms to connect all SAR images, by using the inverse of the average spatial coherence of all interferograms as weight. After this, any interferograms not included in the MST were excluded if their average spatial coherence was lower than 0.3. After network formation, the optimal values of the interferometric phase timeseries were estimated through a network inversion using the inverse of the phase variance as weight [Tough et al., 1995]. The temporal coherence, as a product of the network inversion process, was utilized to evaluate the reliability of the estimated value at each pixel [Pepe and Lanari, 2006]. Pixels with temporal coherence (γ_{temp}) below 0.65 were then masked from further processing. Regarding atmospheric correction, the tropospheric delay components were removed based on the empirical linear relationship between InSAR phase delay and elevation [Doin et al., 2009]. All interferograms from both ascending and descending orbits were referenced to a single stable point, which was located far from the subsiding area (Figure 3a). Finally, the line-of-sight deformation (d_{LOS}) was decomposed into the east-west (d_{E-W}) and vertical (d_U) components, assuming the deformation in north-south direction (d_{N-S}) was negligible. The decomposition employed the incidence angles (θ) and satellite heading angles (α) from both ascending (asc) and descending ($desc$) images [Hanssen, 2001]:

$$\begin{bmatrix} d_U \\ d_{E-W} \end{bmatrix} = \begin{bmatrix} \cos(\theta^{asc}) & \sin(\theta^{asc}) \cos(\alpha^{asc}) \\ \cos(\theta^{desc}) & \sin(\theta^{desc}) \cos(\alpha^{desc}) \end{bmatrix}^{-1} \begin{bmatrix} d_{LOS}^{asc} \\ d_{LOS}^{desc} \end{bmatrix}. \quad (1)$$

Validation of the vertical displacements was performed against precise leveling survey, with benchmarks locations shown in Figure 1. First, reliable measurement points ($\gamma_{temp} \geq 0.65$) within a 200 m radius of each benchmark were selected. Average velocities were then derived for these points from both the InSAR and annual leveling survey time series, calculated as the slope of the best-fitting line to their respective displacement time series. Such a comparison

69 based on rates was required due to the different temporal sampling intervals of the two datasets
 70 Figure 3.

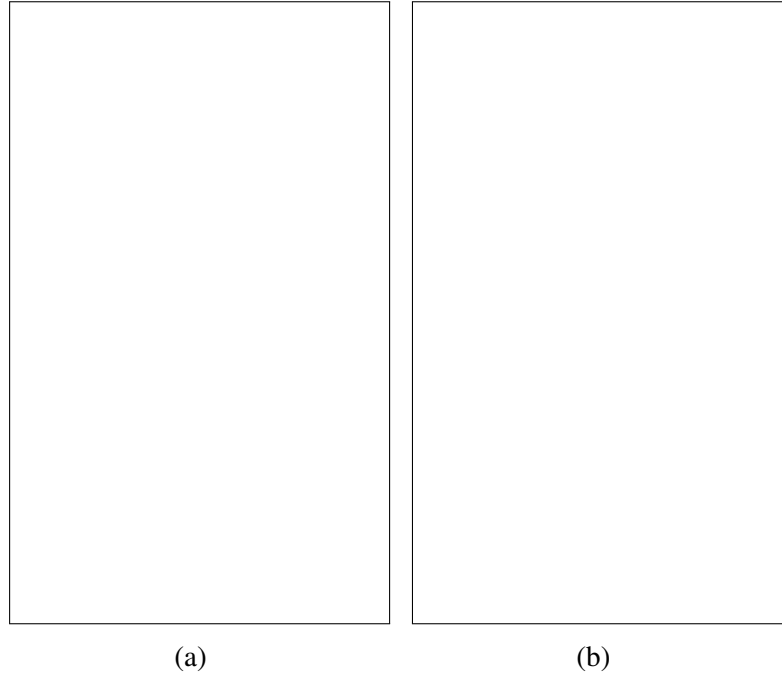


Figure 3: Comparison of InSAR results and leveling data. (a) The results from InSAR processing.
 (b) The ground truth data from leveling surveys.

71 4 Methodology

72 4.1 Geographically Temporally Weighted Regression

73 4.1.1 Model Calibration

74 Before discussing the GTWR model, it is useful to review the fundamental concepts of
 75 ordinary least squares (OLS) regression and geographically weighted regression (GWR). The
 76 OLS models the relationship between a dependent variable and one or more predictors, under
 77 the assumption that the relationships being modeled are spatially stationary, represented as:

$$y_i = \sum_{k=0}^p \beta_k x_{ik} + \varepsilon_i \quad (2)$$

78 where y_i denotes the dependent variable at the i -th location; x_{ik} represents the independent
 79 variables (or predictors), with $x_{i0} = 1$ at the intercept β_0 ; β_k indicates the regression coefficient
 80 corresponding to the k -th predictor; ε_i is the random error at the i -th point, and p is the number
 81 of independent variables (excluding the intercept). The OLS assigns a single set of coefficients to
 82 all observations regardless of their geographical locations, which deliberately neglects potential
 83 spatial variation and might cause model misspecification [Fotheringham et al. \[2017\]](#). The GWR
 84 approach allows the relationships to vary spatially, Prior to discussing the GTWR model, it

is useful to recap the fundamental concept of the geographically weighted regression (GWR) approach [Brunsdon et al., 1996, Fotheringham, 2002], defined as:

$$y_i = \sum_{k=0}^p \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (3)$$

where $x_{i0} = 1$ for the intercept, (u_i, v_i) are the spatial coordinates of the i -th point, $\beta_k(u_i, v_i)$ and x_{ik} are the coefficient and observed value for the k -th independent variable, respectively; ε_i is the random error, and p is the number of independent variables (excluding the intercept). Equation 3 indicates that the relationships between dependent and independent variables are spatially nonstationary, which provides a more effective model than the global regression, which assumes spatially constant relationships. However, the environmental quantities not only exhibit spatial but also temporal relationships. Therefore, Huang et al. [2010] introduced the GTWR model to account for spatiotemporal nonstationarity. The general form of the GTWR model can be expressed as:

$$y_i = \sum_{k=0}^p \beta_k(u_i, v_i, t_i) x_{ik} + \varepsilon_i \quad (4)$$

Here, the terms mirror those in GWR, adding the temporal dimension t_i . The GTWR model is calibrated based on the assumption that observations closer to the i -th point in spatiotemporal coordinate system have greater influence on the estimation of $\beta_k(u_i, v_i, t_i)$ than more distant ones. The estimated parameters $\hat{\beta}(u_i, v_i, t_i)$ can be obtained by:

$$\hat{\beta}(u_i, v_i, t_i) = (\mathbf{X}^T \mathbf{W}(u_i, v_i, t_i) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(u_i, v_i, t_i) \mathbf{y} \quad (5)$$

where $\mathbf{W}(u_i, v_i, t_i)$ is a diagonal matrix with elements denoting the spatiotemporal weights assigned to the observations associated with the i -th point. The weights are usually obtained through a kernel function that implement either a fixed bandwidth (using specific distance thresholds) or an adaptive bandwidth (seeking an optimal number of nearest observations), as described by Páez et al. [2002]. A fixed bandwidth can introduce estimation bias dependent on observation density. More specifically, in regions with dense observations, an excessive number of neighbors might lead to over-smoothing, while an insufficient number is more likely to cause uncertain estimates. The adaptive bandwidth ensures each regression point is informed by exactly the same number of neighbors, regardless of data density. Due to the sparse distribution of the MLCW stations across the study area, this study employed the adaptive bi-square kernel function, defined as:

$$W_{ij} = \begin{cases} [1 - (d_{ij}^{ST}/h_i)^2]^2, & \text{if } d_{ij}^{ST} < h_i \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where d_{ij}^{ST} denotes the spatiotemporal distances between location i and j , and h_i is the adaptive bandwidth. Since spatial and temporal distances are measured in different units and exhibit different scale effects, [Wu et al. \[2014\]](#) proposed an integrated formulation, expressed as:

$$\begin{cases} d_{ij}^{ST} = \lambda d_{ij}^S + (1 - \lambda) d_{ij}^T + 2\sqrt{\lambda(1 - \lambda) d_{ij}^S d_{ij}^T} \cos(\xi), & t_j < t_i \\ d_{ij}^{ST} = \infty, & t_j > t_i \end{cases} \quad (7)$$

where t_i and t_j are sampled times at locations i and j ; λ and $\xi \in [0, \pi]$ are adjustment parameters. Noticeably, Equation 7 implies that the GTWR model will simplify to GWR (eq. 3) when $\lambda = 1$, and space-time interaction effects reach their maximum when $\xi = 0$. In practice, the bandwidths h_i , λ , and ξ can be determined and optimized using a corrected version of the Akaike Information Criterion (AICc) [[Hurvich et al., 2002](#)], defined as:

$$\text{AICc} = 2n \log_e(\hat{\sigma}) + n \log_e(2\pi) + n \left\{ \frac{n + \text{tr}(\mathbf{S})}{n - 2 - \text{tr}(\mathbf{S})} \right\} \quad (8)$$

where n is the sample size, $\hat{\sigma}$ is the estimated standard deviation of the error term, and $\text{tr}(\mathbf{S})$ denotes the trace of the hat matrix \mathbf{S} . The hat matrix \mathbf{S} is defined as:

$$\mathbf{S} = \{S_{ij}\}, \text{ where } S_{ij} = \mathbf{x}_i^T (\mathbf{X}^T \mathbf{W}(u_i, v_i, t_i) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(u_i, v_i, t_i) \quad (9)$$

where \mathbf{x}_i^T represents the values of independent variables at the i -th point. The hat matrix \mathbf{S} transforms observed values into fitted values through spatiotemporal weightings, as in $\hat{\mathbf{y}} = \mathbf{S}\mathbf{y}$, with its trace representing the effective number of parameters in the model [Hoaglin and Welsch \[1978\]](#). The detailed information of these components can be found in [Fotheringham \[2002\]](#).

4.1.2 Posterior Uncertainty Assessment

When the optimal bandwidth is obtained through the calibration process, the fitted value $\hat{\mathbf{y}}$ at any unsampled location can be calculated using the hat matrix relationship as previously mentioned. The prediction error variance for each fitted value $\hat{\mathbf{y}}$ is defined as:

$$\sigma_i^2 = \hat{\sigma}^2 \left(1 + \mathbf{x}_i^T (\mathbf{X}^T \mathbf{W}(u_i, v_i, t_i) \mathbf{X})^{-1} \mathbf{x}_i \right) \quad (10)$$

where $\hat{\sigma}^2$ represents the overall model error variance, which is defined as:

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{n - 2\text{tr}(\mathbf{S}) + \text{tr}(\mathbf{S}^T \mathbf{S})} \quad (11)$$

The first term in Equation 10 accounts for the intrinsic model residual variance, while the second term assesses the additional uncertainty that arises when estimating local relationships from limited neighboring observations.

4.2 Curve Fitting

5 Results

6 Discussion

7 Conclusion

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