
1 Early Identification of Reservoir-Bank Landslides in Deeply 2 Incised Mountain Canyon Areas with Interferometric Baseline 3 Optimization

4 Wenfei XI^{1,2,3}, Wenyu HONG¹, Zhiquan YANG⁴, Guangcai HUANG^{5,6}, Junqi GUO¹, Kunwu
5 YANG¹, Tingting JIN¹

6 ¹Faculty of Geography, Yunnan Normal University, Kunming Yunnan 650500, China;

7 ²Key Laboratory of Highland Geographic Processes and Environmental Change in Yunnan Province, Kunming,
8 Yunnan 650500, China;

9 ³Key Laboratory of Early Rapid Identification, Prevention and Control of Geological Diseases in Traffic Corridor of
10 High Intensity Earthquake Mountainous Area of Yunnan Province, Kunming, Yunnan 650093 China;

11 ⁴School of Public Safety and Emergency Management, Kunming University of Science and Technology, Kunming,
12 Yunnan 650093, China;

13 ⁵Guizhou Geological Survey, Guiyang, Guizhou 550081, China;

14 ⁶Engineering Tecmology Innovation Center of Mineral ResoureesExploraions in Bedroek Zones, Ministry of Naur
15 Resources, Guiyang 550081

16 *Correspondence to:*Wenfei XI(wenfeixi@ynnu.edu.cn) and Wenyu HONG(2323130105@ynnu.edu.cn)

17
18 **Abstract:** The complex geological conditions in deeply incised mountainous canyon areas make reservoir-bank
19 landslides a frequent hazard. Accurate interferogram selection and baseline network configuration are crucial for
20 SBAS-InSAR-based landslide monitoring, yet are severely challenged by seasonal vegetation decorrelation. To
21 overcome this limitation, this study proposes a novel Vegetation-Adaptive WCTM that integrates time-series
22 vegetation dynamics into interferometric baseline optimization. This approach establishes a vegetation-coherence
23 coupling model to dynamically adjust coherence thresholds based on quantified vegetation coverage levels and
24 synergizes ERA5 meteorological data with tropospheric delay modeling for atmospheric correction.The results
25 demonstrate significant advancements: (1) The deformation rate standard deviation is reduced by 0.520 and 0.192
26 compared to traditional short-temporal baseline and average coherence threshold methods, respectively, corresponding
27 to a 29.1% improvement (1.2668 vs. 1.7865). (2) The proposed method improves phase-unwrapping robustness
28 and the spatial continuity of the deformation field under vegetation-induced decorrelation, thereby enhancing
29 landslide detectability in densely vegetated canyon slopes, particularly during low-coherence vegetation
30 seasons. (3) 39 landslides were successfully identified, representing a 22% increase compared to conventional methods
31 (32 landslides), with 7 new high-risk sites discovered even during low-coherence vegetation seasons. Based on field
32 verification with drone surveys, typical landslides were selected to analyze their spatial distribution and temporal

33 evolution patterns, demonstrating the applicability of the method in deeply incised mountainous canyon areas. These
34 findings provide theoretical and technical support for regional disaster prevention and mitigation efforts.

35 **Keywords:** SBAS-InSAR; WCTM Method; Interferometric baseline; Reservoir Bank Landslide; Early
36 Identification

37 **1 Introduction**

38 Landslides along reservoir banks are a common geological hazard during the construction and operation of hydraulic
39 and hydropower engineering projects(Liu et al., 2022; Li et al., 2021). These landslides are typically concentrated on
40 the steep slopes on both sides of deeply incised mountain canyon reservoir banks(Zhu et al., 2024; Lu et al., 2019).
41 Early identification of reservoir-bank landslides is a crucial component of geological hazard prevention and risk
42 assessment.

43 Traditional technologies, such as Global Navigation Satellite Systems (GNSS) (Guo et al.,2025; Mao et al.,2024)and
44 optical remote sensing(Cai et al.,2024; Guo et al., 2016), are unable to meet the current demands for landslide detection.

45 In contrast, Synthetic Aperture Radar Interferometry (InSAR) has shown significant potential(Li et al., 2020; Li et al.,
46 2022; Zhou et al., 2022). Deformation monitoring technology based on InSAR baseline optimization has become a key
47 method for high-precision early landslide identification(Ferretti et al., 2001; Pepe, 2021; Liao et al., 2021). However,
48 SBAS-InSAR technology requires high-quality interferograms and a well-constructed baseline network. Incorrect or
49 inaccurate selection of interferograms and baseline network configurations may introduce decorrelation errors and
50 systematic errors, reducing the accuracy of deformation inversion or even preventing correct inversion of deformation
51 results(Zebker et al., 2021; Zhang et al., 2022). Additionally the accuracy of landslide monitoring is influenced by
52 multiple factors, such as decorrelation caused by complex terrain, coherence fluctuations due to land cover changes,
53 and the rational configuration of interferometric baseline optimization parameters(Liu et al., 2024; Ren et al., 2022;
54 Wang et al., 2023; Zhang et al., 2022). Selecting high-quality interferograms and optimizing the interferometric
55 baseline network in the extreme natural conditions of deeply incised mountain canyon regions has become an important
56 research topic for large-scale reservoir bank landslide identification and monitoring.

57 Currently, the methods for interferogram selection and baseline optimization can generally be divided into three
58 categories: The first category is expert knowledge-based manual selection of interferograms. In this approach, expert
59 knowledge is used to conduct empirical analysis of all acquired interferograms. The interferograms with higher
60 coherence are selected through manual judgment based on coherence comparisons. For example, Shi et al., (2019)
61 manually selected interferograms with higher coherence based on empirical knowledge to study the surface response
62 and underground characteristics during the groundwater extraction restriction period in Suzhou. Although this method
63 can effectively reduce the impact of spatiotemporal decorrelation in forested areas with extremely low coherence, it is

64 highly subjective due to reliance on expert knowledge, and is time-consuming and labor-intensive. Additionally, it
65 fails to meet the deformation monitoring requirements for long-term time-series landslide detection in large-scale
66 reservoir banks.

67 The second category of methods involves selecting interferograms by simultaneously setting temporal baseline and
68 spatial baseline thresholds. During the SBAS-InSAR processing, interferograms are selected based on short time
69 baseline and spatial baseline thresholds, which are determined through pre-experimental comparative analysis or prior
70 knowledge. For example, Zhao et al., (2012) used ALOS PALSAR2 data for large-scale landslide detection in Southern
71 California and Oregon, while Zhou et al., (2023) utilized Sentinel-1 data to monitor permafrost changes in the XiaoTuo
72 River region, both of which set short time and space baseline thresholds for interferogram selection. Although setting
73 short time and spatial baseline thresholds is the most widely used method for interferogram selection, this approach is
74 based on the empirical assumption that ground objects undergo minimal changes over short time intervals, which will
75 not induce spatiotemporal decorrelation. However, this assumption does not guarantee that all interferogram pairs will
76 exhibit good coherence. On the contrary, setting excessively short time and spatial baseline thresholds can introduce
77 decorrelation and systematic errors, reducing the accuracy of deformation inversion results.

78 The third category of methods is based on coherence coefficient for interferogram selection, where interferograms are
79 chosen by setting a coherence coefficient threshold and optimizing the interferometric baseline network. For example,
80 Tao et al.,(2021)used a custom coherence coefficient threshold for interferogram selection; Wang et al.,(2022); Wang
81 et al.,(2023)et al. directly used the average coherence between SAR images as a baseline constraint indicator to
82 optimize interferogram selection; Zhang et al.,(2024)used average segmented coherence threshold coefficients to select
83 interferograms in landslide creep identification and monitoring in the Xiaojiang River Basin. The coherence coefficient
84 of InSAR interferograms is influenced by the spatiotemporal baseline of SAR images and external environmental
85 coupling, which can accurately reflect the quality of the interferogram. Setting a coherence coefficient threshold is a
86 reliable method for generating a robust interferometric baseline network. Custom coherence coefficient thresholds are
87 often established through prior knowledge or comparative pre-experiments. However, this method is highly subjective
88 and suffers from issues such as insufficient interferogram samples for pre-experiments. Moreover, the set thresholds
89 cannot account for the intermittent coherence problems caused by vegetation changes, while the average coherence
90 coefficient threshold overly relies on simple statistical patterns and fails to consider the impact of vegetation cover
91 changes on the coherence of interferograms.

92 In summary, compared to other interferometric baseline optimization methods, expert knowledge-based manual
93 selection of interferograms is the most time-consuming and labor-intensive approach, making it unsuitable for long-
94 term landslide deformation monitoring along reservoir banks. Although methods based on simultaneous setting of
95 temporal/spatial baseline thresholds and those using coherence coefficient for interferogram selection have improved
96 upon traditional expert-based approaches, these methods remain highly subjective and fail to cover all potential
97 baseline selection errors. They may also introduce decorrelation and systematic errors, thereby affecting the accuracy
98 of deformation inversion and limiting their applicability in complex environments. Furthermore, they inadequately
99 account for the impacts of external environmental conditions on coherence(Dai et al., 2022; Westerhoff et al., 2020;
100 Zhang et al., 2023). For instance, the application of InSAR in low-coherence areas such as mountainous canyon regions
101 and vegetated zones faces considerable limitations(Lemmetynen et al., 2022) The combination of temporal and spatial
102 baselines is critical in deformation monitoring; ideally, baseline combinations should maintain high coherence while
103 ensuring the precision of deformation signal extraction. However, certain temporal and spatial baseline combinations
104 may exhibit superficially high coherence but result in distortion of deformation information due to terrain shielding,
105 vegetation changes, or other interfering factors, ultimately failing to produce ideal interferograms(Chen et al., 2021;
106 Santoro et al., 2009).

107 This issue of neglecting the impact of vegetation coverage changes on coherence can be addressed by considering the
108 variation in vegetation coverage over time and introducing a weighted average coherence coefficient to optimize the
109 interferometric baseline network. For example, during InSAR processing, it is observed that vegetation coverage is
110 relatively sparse in winter, leading to good coherence between SAR images even over longer temporal intervals.
111 Conversely, in summer, when vegetation coverage is dense, coherence between SAR images may be poor even over
112 shorter temporal intervals. We propose that such anomalous baseline combinations represent potential issues in
113 interferometric baseline optimization. First, vegetation coverage is calculated over time. Then, interferograms are
114 categorized into grades, and using the weighted average coherence of the categorized interferograms
115 as the coherence coefficient threshold, it is possible to optimize the interferometric baseline network. Additionally
116 analyzing the low-frequency anomalous patterns in baseline combinations can effectively mitigate decorrelation issues
117 in interferograms, thereby providing a more reliable baseline optimization strategy for the early identification of
118 landslides along deeply incised mountainous reservoir banks.

119 The primary objective of this study is to address the limitation of conventional SBAS-InSAR techniques, which often
120 fail to adequately account for the effects of seasonal vegetation variations in interferometric baseline network

121 configuration, leading to poor interferogram coherence. To overcome this, we propose a Weighted Coherence
122 Threshold Method (WCTM) that incorporates time-series vegetation coverage dynamics to optimize the
123 interferometric baseline. The main work and contributions of this research can be summarized as follows: (1) A
124 vegetation-adaptive WCTM is proposed, which establishes a vegetation-coherence coupling model to dynamically
125 adjust coherence thresholds, thereby effectively mitigating the impact of seasonal vegetation decorrelation on
126 interferogram quality; (2) ERA5 high-resolution meteorological reanalysis data are integrated with tropospheric delay
127 modeling, significantly reducing atmospheric delay errors in complex terrain and improving deformation inversion
128 accuracy; (3) High-precision early identification of reservoir landslides was achieved in the deeply incised alpine gorge
129 area of the Baihetan reservoir region, with a 22% increase in detection rate compared to conventional methods,
130 validating the method's applicability and effectiveness under extreme topographic conditions.

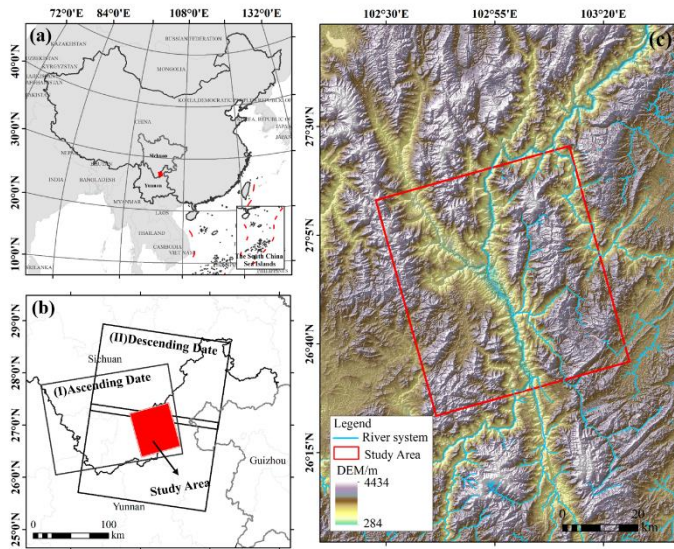
131 **2. Study Area and Research Data**

132 **2.1 Study Area**

133 The Baihetan Reservoir is located in the lower reaches of the Jinsha River, at the confluence of Sichuan and Yunnan
134 provinces, and is one of China's key hydropower projects (Fig.1a). The reservoir area is situated at the northeastern
135 edge of the Hengduan Mountains and the southeastern margin of the Tibetan Plateau. characterized by complex
136 geographical and geological features. The reservoir covers approximately 7,285.72 km², with a linear distribution. The
137 terrain is primarily dominated by deeply incised river valleys and high mountain gorges, with diverse
138 geomorphological types(Li et al., 2022), including river erosion, tectonic, and glacial erosion landforms(Xi et al.,2020).
139 The region exhibits significant elevation variation, ranging from a minimum elevation of 284 m to a maximum of
140 4,434 meters, with a relative elevation difference of up to 3,950 meters. (Shi et al.,2022; Zhu et al.,2021), typical of a
141 deeply incised alpine gorge region(Xie et al., 2012).

142 The climate of the area is classified as a subtropical plateau monsoon climate, characterized by distinct wet and dry
143 seasons, with an average annual precipitation of 822.7 mm. Precipitation is predominantly concentrated in the wet
144 season, while the dry season is relatively arid. Due to the unique climatic conditions and abundant water resources, the
145 stratigraphy of the reservoir area is complex, spanning multiple geological periods, including the Quaternary, Permian,
146 and Carboniferous, with predominant rock types such as gravelly mixed soil, basalt, limestone, and sandstone(Yang et
147 al., 2021) (Fig.1b). The region is extensively covered by weak rock formations and loose materials, and the area has

148 undergone multiple tectonic movements, leading to fractured and jointed bedrock. Active fault zones, such as the
149 Zemuhe and Xiaojiang fault zones, are also present in the region(Dun et al., 2023) (Fig.1c), with a predominantly
150 north-south orientation and left-lateral strike-slip motion. After the reservoir impoundment, fluctuations in water levels,
151 prolonged immersion of the slopes by reservoir water, and seasonal dry-wet cycles contribute to the formation of a
152 high-risk environment for geological hazards, including landslides, collapses, and debris flows.



153 **Figure 1: Overview of the Study Area**

154 **2.2 Research Data**

155 **2.2.1 HyP3 InSAR Data**

156 This study uses the HyP3 interferometric data stack, produced by the Alaska Satellite Facility (ASF) cloud platform,
157 as the experimental dataset for interferometric baseline optimization and atmospheric error correction. The data can be
158 accessed and freely applied for online retrieval through the ASF website (<https://search.asf.alaska.edu/#/>), with the
159 application submitted on May 18, 2023. HyP3 is primarily used for processing Sentinel-1 data provided freely by the
160 European Space Agency (ESA). Based on the ASF data platform, users can retrieve and query the Sentinel-1 SAR data
161 archive. The main interferometric products available include wrapped and unwrapped interferograms, coherence maps,
162 amplitude images, water mask images, DEMs, and look vector maps, etc. HyP3 utilizes Amazon's infrastructure
163 services, including Amazon Elastic Compute Cloud (EC2) and Amazon Simple Storage Service (S3). It provides users
164 with customized, on-demand synthetic aperture radar (SAR) processing services, eliminating the need for users to
165 purchase or install complex SAR processing software and acquire advanced SAR processing skills. After the user

166 submits an application through the ASF Vertex website or using the HyP3 Python SDK, the system automatically
167 processes the interferometric data using GAMMA software hosted by Amazon Web Services (AWS). The process uses
168 the Copernicus GLO-30 DEM to remove terrain phases and applies the minimum cost flow (MCF) method for phase
169 unwrapping, ultimately generating interferometric products suitable for coherence analysis and with moderate pixel
170 spacing. HyP3 data effectively addresses the issues associated with traditional interferometric processing methods,
171 which require significant disk space, computational resources, and processing time, offering a new approach for large-
172 scale reservoir bank landslide detection and monitoring.

173 The HyP3 platform supports customizable temporal and spatial baseline settings. Considering the monthly variation in
174 vegetation coverage in deep-cut mountain canyon areas, and to avoid phase unwrapping issues and the introduction of
175 additional errors, this study sets the temporal baseline threshold to 36 days. Notably, the Sentinel-1 satellite has a
176 relatively short revisit cycle, and it revisits the same location multiple times over short spatial distances, making the
177 impact on coherence negligible. Therefore, no spatial baseline threshold is set. Long-term interferograms from July
178 2019 to May 2023 were obtained using the baseline tool provided by the HyP3 online service platform (**Appendix A**
179 **Figure A1**)

180 **2.2.2 Auxiliary Datasets**

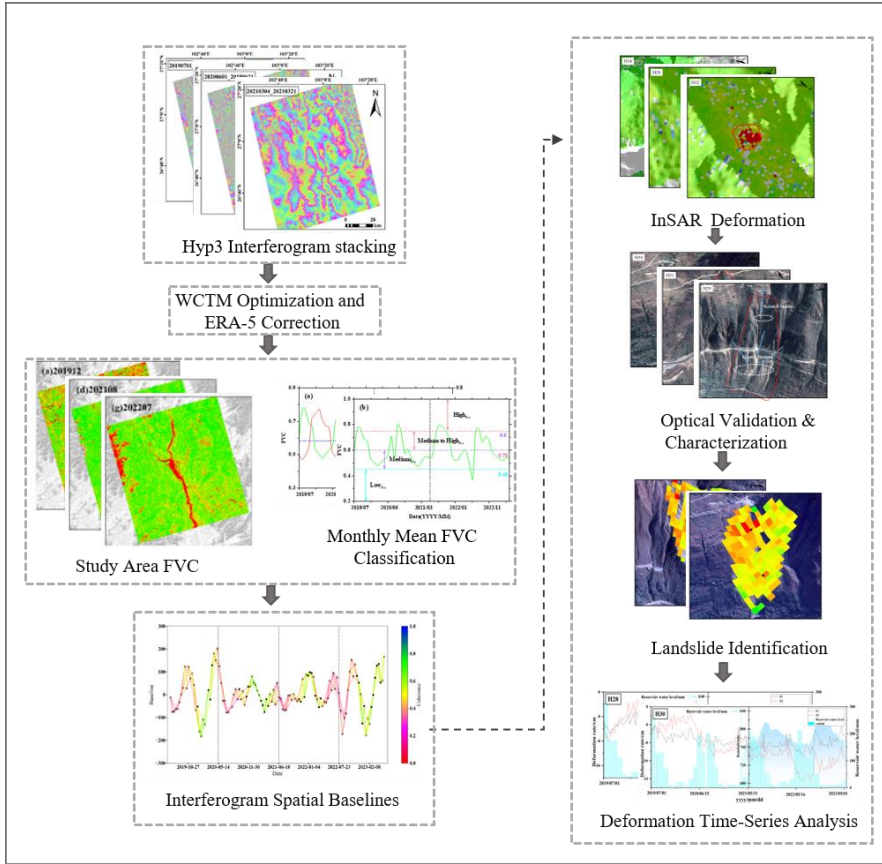
181 The auxiliary datasets used in this study include several key sources. Sentinel-2 data (Level 2A) with a 10-meter spatial
182 resolution, including red, blue, and green bands, was utilized to refine the estimation of surface vegetation coverage
183 (Fraction of Vegetation Coverage, FVC) in the study area. This data was accessed online from Copernicus on June 18,
184 2023. Additionally a 30-meter resolution Digital Elevation Model (DEM) from the ALOS WORLD 3D dataset,
185 provided by the Japan Aerospace Exploration Agency (JAXA), was used to calculate topographic features like
186 mountain shadow, slope, aspect, and curvature. This dataset was accessed on July 1, 2023, from ALOS.High-resolution
187 Google Earth imagery with a 0.2-meter spatial resolution was employed for location annotation of reservoir-bank
188 landslides and for overlaying the acquired InSAR deformation results. This data was accessed on July 10, 2023, from
189 Google Earth. Drone aerial imagery with a 0.1-meter resolution was also used for field surveys to validate landslide
190 identification results and to observe the Optical Characteristics of typical reservoir-bank landslides, with the imaging
191 conducted on May 14, 2023. Precipitation data, acquired from the precipitation processing system on July 15, 2023,
192 were used to analyze rainfall patterns, and Reservoir water-level elevation data were measured in the field during the
193 research period. These datasets, summarized in Table. 1, provided comprehensive support for the research.

194 **Table 1: Data sources and specifications**

Data Name	Data Phase	Data Type	Data Scale	Data Source
HyP3 Interferogram Stacking	2019-07~2023-05	Raster	40 m	ASF
Sentinel-2	2019-07~2023-05	Raster	10 m	ESA
FVC	2019-07~2023-05	Raster	30 m	Band Calculation
Elevation	-	Raster	30 m	JAXA
Google Maps imagery	2023	Raster	0.2 m	Google Earth
Drone Aerial Imagery	2023	Raster	0.02 m	Measured
Precipitation	2019-07~2023-05	-	-	PPS
Reservoir water-level elevation	2021-04~2023-05	-	-	Measured

195 **3 Research Methods and Data Processing**

196 The main technical process of this study is as follows Fig. 2: (1) calculation of vegetation coverage and classification
 197 of interferogram stacks; (2) interferometric baseline optimization and atmospheric error correction; (3) surface
 198 deformation information acquisition and reservoir bank landslide identification and monitoring.



200 **Fig. 2: The technical flowchart of this study**

201 3.1 Vegetation Coverage Calculation Based on the Pixel Dichotomy Method

202 This study utilizes Sentinel-2 optical imagery from July 2019 to May 2023 and employs the Band Math tool to calculate
 203 the Normalized Difference Vegetation Index (NDVI) across the study area. To minimize the influence of non-
 204 landslide-related surface features, NDVI values were processed based on the pixel dichotomy model (Pi et al., 2021)
 205 to derive the Fractional Vegetation Cover (FVC) on a monthly scale (**Appendix A Figure A2**, as expressed in
 206 Eq.(3) presents the spatial and temporal variations in FVC, clearly reflecting seasonal vegetation dynamics—higher
 207 vegetation coverage is observed in summer months (e.g., August 2020 and July 2022), while markedly lower values
 208 appear during winter periods (e.g., December 2019 and December 2022). These seasonal changes in vegetation
 209 coverage significantly impact interferometric coherence and phase unwrapping performance in SBAS-InSAR
 210 processing. The vegetation temporal patterns revealed in FVC maps serve as a critical foundation for the development
 211 of the proposed Vegetation-Adaptive WCTM, enabling dynamic adjustment of coherence thresholds to mitigate
 212 decorrelation effects associated with vegetation growth cycles in deeply incised mountainous canyon environments.

$$213 \quad FVC = \begin{cases} 0 & , NDVI \leq NDVI_{soil} \\ \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} & , NDVI_{soil} \leq NDVI \leq NDVI_{veg} \\ 1 & , NDVI \geq NDVI_{veg} \end{cases} \quad (1)$$

214 In the Eq.: FVC represents the monthly average vegetation coverage, $NDVI$ represents the total value of the vegetation
 215 index for the pixel, $NDVI_{soil}$ represents the $NDVI$ value of pixels with no vegetation coverage, and $NDVI_{veg}$
 216 represents the $NDVI$ value of pixels fully covered by vegetation.

217

218 3.2 WCTM Optimization of Interferometric Baseline

219 The WCTM considers the monthly variation of vegetation coverage in the time series and divides the interferogram
 220 into different coherence segments based on the vegetation coverage levels. The number of interferograms in each
 221 coherence segment is calculated, and the coherence coefficient is assigned a weight according to the number of
 222 interferograms in each segment. The final coherence coefficient optimization threshold is determined using a weighted
 223 averaging model. The process of optimizing the interferometric baseline using WCTM is as follows:

224 (1) Calculate the point coherence and average coherence for each interferogram. Coherence is an important indicator
 225 for describing the quality of the interferometric phase. It is defined by the cross-correlation function during the
 226 registration of two complex images. The coherence at a pixel point (i, j) in the interferogram is defined as:

$$227 \quad r_{(i,j)} = \frac{\left| \sum_{i=1}^m \sum_{j=1}^n M(i,j) S^*(i,j) \right|}{\sqrt{\sum_{i=1}^m \sum_{j=1}^n |M(i,j)|^2 \sum_{i=1}^m \sum_{j=1}^n |S(i,j)|^2}} \quad (2)$$

228 In the formula: (i, j) represents the pixel coordinates of the interferogram at a certain point in the radar slant range
 229 coordinates, m and n represent the local window sizes for coherence calculation, and M and S represent the
 230 acquisition of two different Synthetic Aperture Radar (SAR) data. $*$ represents the complex conjugate of a given
 231 complex number.

232 After calculating the pixel coherence point by point, the coherence for each interferogram in the study area can be
 233 calculated using Eq. (3):

$$234 \quad r_{avg} = \frac{\sum_{i=1}^P \sum_{j=1}^Q r_{(i,j)}}{P * Q} \quad (3)$$

235 In the formula, (i, j) represents the coherence coefficient of each interferogram, with a value range from 0 to 1.

236 (i, j) denotes the pixel coordinates of the interferogram at a specific point in radar slant-range coordinates. $r_{(i,j)}$
 237 represents the coherence at the pixel point (i, j) , and P and Q represent the length and width of the interferogram
 238 image, respectively.

239 (2) Classify the vegetation coverage levels of the time series.

240 (3) Divide the interferograms into different coherence segments.

241 (4) Assign weights to the coherence coefficients and use the weighted average model to optimize the coherence
 242 coefficient threshold. Calculate the number of interferograms under different vegetation coverage levels, assign

243 weights to each coherence segment, and calculate the optimized interferometric baseline threshold based on the weights
 244 of different coherence segments:

$$245 \quad r_{WCTM} = \sum_{i=1}^I \frac{m_i r_i}{n} \quad (4)$$

246 In the Eq.: r_{WCTM} represents the optimized interferometric baseline threshold using the WCTM method, I represents
 247 the total number of coherence segments, m_i represents the number of interferograms in each coherence segment, r_i
 248 represents the average coherence of the interferograms in each coherence segment, n represents the total number of
 249 interferograms generated from all SAR acquisitions during the study period.

250 3.3 Correction of Atmospheric Delay Errors Using ECMWF ERA-5 Products

251 SAR signals are influenced by changes in atmospheric pressure, temperature, and humidity during propagation, leading
 252 to tropospheric delay effects (Li et al., 2023; Yang et al., 2023). The fifth-generation meteorological reanalysis dataset
 253 provided by European Centre for Medium-Range Weather Forecasts (ECMWF) offers high temporal resolution (hourly)
 254 and high spatial resolution (0.1), providing numerical weather model data on temperature, humidity, and pressure
 255 across 37 atmospheric pressure levels. This information can be effectively used to calculate atmospheric hydrostatic
 256 delay and correct atmospheric delay errors (Mandal et al., 2021; Soares et al., 2020).

$$257 \quad N = \left(k_1 \frac{P}{T} \right)_{hydro} + \left(k_2 \frac{e}{T} + k_3 \frac{e}{T^2} \right)_{wet} = N_{hydro} + N_{wet} \quad (5)$$

258 In the Eq.: N_{hydro} represents the fluid static refractive component of the atmospheric refractive index, N_{wet} represents
 259 the wet refractive component of the atmospheric refractive index, P is the total atmospheric pressure, T is the
 260 temperature in Kelvin, e is the water vapor pressure, and k is the empirical constant. At this point, the integral value
 261 of the refractive index between the tropospheric zenith direction h_{top} and the height along the radar line of sight h is:

$$262 \quad \varphi_{tropo} = -\frac{4\pi}{\lambda} \cdot \frac{10^{-6}}{\cos\theta} \int_h^{h_{top}} (N_{hydro} + N_{wet}) dh \quad (6)$$

263 In the Eq., φ_{tropo} represents the bidirectional tropospheric delay phase, λ denotes the radar center wavelength,
 264 and θ is the satellite incidence angle.

265 For InSAR measurements, the tropospheric delay phase in the interferogram is the difference in tropospheric delay
 266 between the imaging points of the master and secondary images. Due to slight differences in atmospheric conditions
 267 between the two acquisitions, the tropospheric delay error for two imaging points (q, p) at times m and n can be
 268 expressed as:

$$269 \quad \Delta\varphi_{tropo} [(p, q), (t_m, t_n)] = [\varphi_{tropo}(p, t_n) - \varphi_{tropo}(p, t_m)] - [\varphi_{tropo}(q, t_n) - \varphi_{tropo}(q, t_m)] \quad (7)$$

270 3.4 SBAS-InSAR Processing

271 SBAS-InSAR technology efficiently synthesizes all available small baseline interferograms, selects coherent target
 272 points for modeling and calculation, and removes atmospheric delays via temporal filtering to obtain high spatial
 273 density surface deformation results(Fan et al., 2016; Zhang et al., 2012). In this study, we use the open-source software
 274 package Mintpy (The Miami InSAR Timeseries Software in Python) for SBAS-InSAR processing(Zhang et al., 2019).
 275 We load the selected ascending track interferogram stack from July 2019 to May 2023 into the Mintpy software. A
 276 reference pixel with high coherence (we set the threshold) is chosen from a region far from the deformation area. Then,
 277 the initial phase value θ_n and estimated phase value φ_n are used to evaluate the quality of each pixel in the raw
 278 phase time series, as shown in Eq. (8):

$$279 \quad r = \frac{1}{N^2 - N} \sum_{n=1}^N \sum_{k \neq n}^N e^{i\theta_{nk}} e^{-i(\varphi_n - \varphi_k)} \quad (8)$$

280 In the Eq., N represents the number of SAR images, i refers to a single SAR image, and n and k represent the
 281 wrapped phase interferograms collected at corresponding times. To ensure data quality and the accuracy of InSAR
 282 measurements, the root mean square error (RMSE) of the residual phase is used to estimate the noise present in the
 283 time series:

$$284 \quad RMSE_i = \sqrt{\frac{1}{N_\Omega} \sum_{p \in \Omega} \left(-\hat{\varphi}_{resid}^i(p) \cdot \frac{\lambda}{4\pi} \right)^2} \quad (9)$$

285 In the Eq., $i = [1, \dots, N]$ and Ω represent reliable pixels selected from the temporal coherence mask, λ is the
 286 radar center wavelength, and $\hat{\varphi}_{resid}^i$ represents the redundant phase at time i . After applying the noise mask, the
 287 average deformation rate in the study area is estimated from the time series using Eq. (10):

$$288 \quad v_{los} \cdot t_i + c = -\hat{\varphi}_{disp}^i \cdot \frac{\lambda}{4\pi} \quad (10)$$

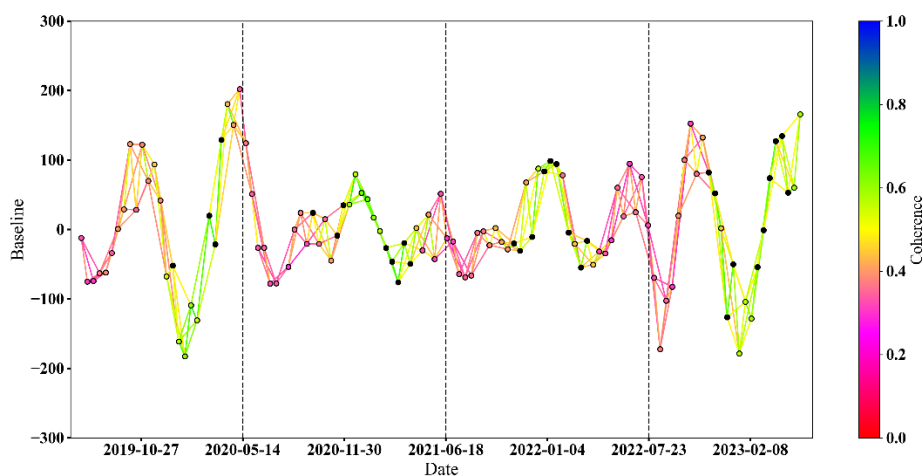
289 In the Eq., v_{los} represents the average deformation rate in the radar line-of-sight direction, t_i denotes the time of SAR
 290 acquisition at time i , c is the unknown deformation offset constant, and $\hat{\varphi}_{disp}^i$ represents the displacement time series.

291 4. Results and Analysis

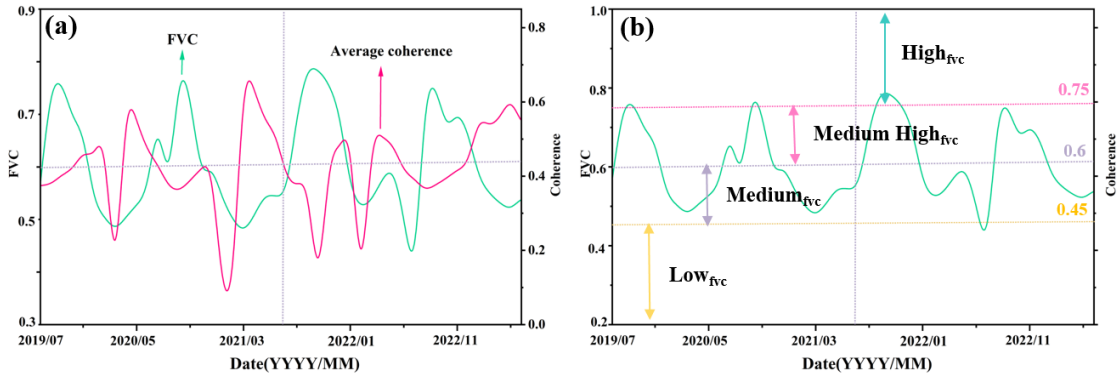
292 4.1 Results of Interference Baseline Optimization Using WCTM

293 Based on the 345 HyP3 interferograms from July 2019 to May 2023, with July 3, 2019, as the reference image date,
 294 the baseline connection map for all interferograms was obtained (Fig.3). It can be observed that the average coherence
 295 coefficient in the Baihetan Reservoir area exhibits distinct seasonal variation, specifically with higher average
 296 coherence during the winter and lower average coherence during the summer. This pattern aligns with seasonal changes
 297 in vegetation and the regional dry-wet climate cycle.

298 To further explore the relationship between the average coherence coefficient and vegetation coverage in the Baihetan
 299 Reservoir area, monthly average vegetation coverage was calculated based on the pixel binary model (Eq (1)), and a
 300 time series curve was established between the monthly average coherence of the interferograms and the vegetation
 301 coverage (Fig.4a). The variation in the average coherence coefficient in the study area shows a significant correlation
 302 with changes in vegetation coverage. The WCTM method proposed in this study was used to optimize the
 303 interferometric baseline threshold. Based on the objective distribution characteristics of the FVC data and with
 304 reference to classification criteria used in similar regions, this study establishes a vegetation-based categorization
 305 scheme. Accordingly, the monthly average vegetation coverage in the study area was classified into four levels
 306 [49]: low vegetation coverage (<45%), medium vegetation coverage (45%-60%), medium-high vegetation coverage
 307 (60%-75%), and high vegetation coverage (>75%). Based on the classified vegetation coverage levels, the monthly
 308 average coherence coefficient was divided into four coherence segments (Fig.5b). These segments accounted for 2.1%,
 309 57.5%, 23.4%, and 17.0% of the total interferograms, respectively. These proportions were used as weights to calculate
 310 the optimized interferometric baseline threshold ($\lambda_{WCTM} = 0.4882$) using the WCTM method. Interferograms with
 311 average coherence coefficients below this threshold were excluded, and the remaining 146 optimized interferograms
 312 were retained for SBAS-InSAR processing.



313 **Figure 3: Spatio-Temporal Baseline Network of All Interferograms (The red dashed line represents a spatial baseline value**
 314 **of 0, the black dashed lines indicate December 31 of each year, and the red-to-blue gradient represents the average coherence**
 315 **of each interferogram).**
 316



317
 318 **Figure 4: Monthly Average Vegetation Coverage Time Series (a shows the relationship between monthly average vegetation**
 319 **coverage and monthly average coherence coefficient; b presents the classification results of monthly average vegetation**
 320 **coverage levels. The black dashed line represents the midpoint date of the study period).**

321 **Note: The red polygons represent the geological boundaries of historical landslides delineated based on geomorphic features**
 322 **such as rear scarps and frontal bulging; the InSAR monitoring results characterize the current surface deformation during**
 323 **the study period. The reasons for the discrepancy between them are as follows: ① The deformation rate of some landslides**
 324 **is below the detection limit of InSAR; ② Severe decorrelation (coherence < 0.2) caused by slope vegetation cover interferes**
 325 **with deformation signal extraction; ③ Radar geometric distortion induced by steep terrain impairs signal monitoring**
 326 **effectiveness.**

327 Due to the inherent limitations of C-band radar wavelength, coherence significantly deteriorates in areas with
 328 vegetation coverage exceeding 75% (particularly during summer, as shown in Figure 4a). This results in the omission
 329 of small-scale landslides within steep canyon slopes (>45° inclination). Analysis using 30m-resolution ALOS DEM
 330 data indicates such terrain accounts for approximately 12.7% of the total study area. Future investigations could
 331 enhance detection capabilities through integration with L-band SAR data.

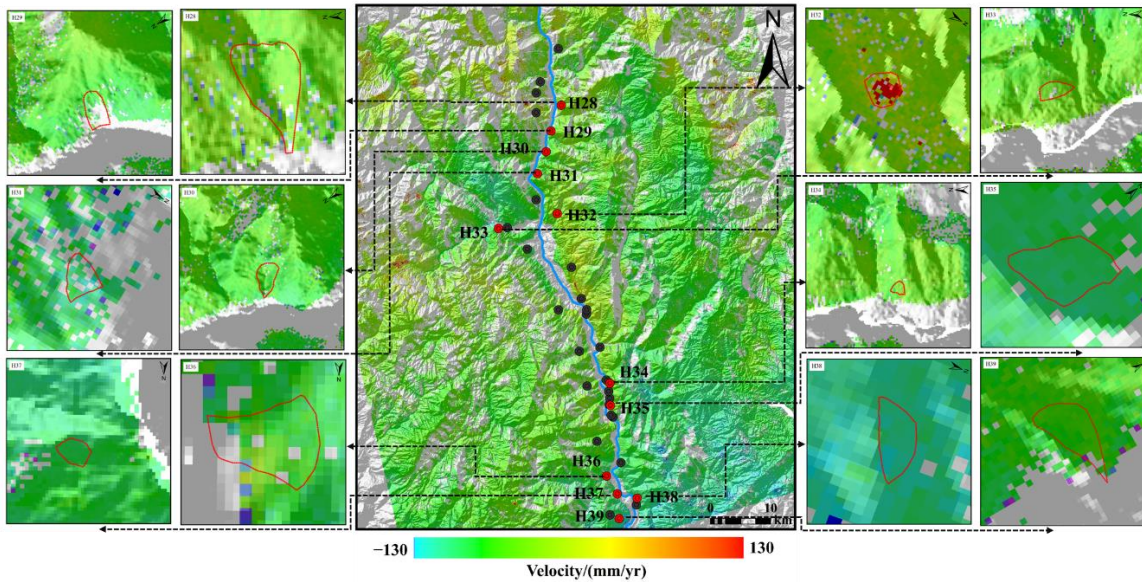
332 **4.2 Early Detection Results of Reservoir-bank landslides**

333 The SBAS-InSAR processing was performed on the HyP3 interferometric stack optimized using the WCTM method
 334 with the open-source software MintPy 1.5.1. Additionally atmospheric delay errors in the interferometric stack were
 335 corrected using the ECMWF ERA-5 product. As a result, radar line-of-sight surface deformation information from
 336 July 2019 to May 2023 was successfully obtained. Positive deformation values indicate motion towards the sensor,
 337 while negative values indicate motion away from the sensor. The absolute value of the deformation rate represents the
 338 magnitude of the deformation rate.

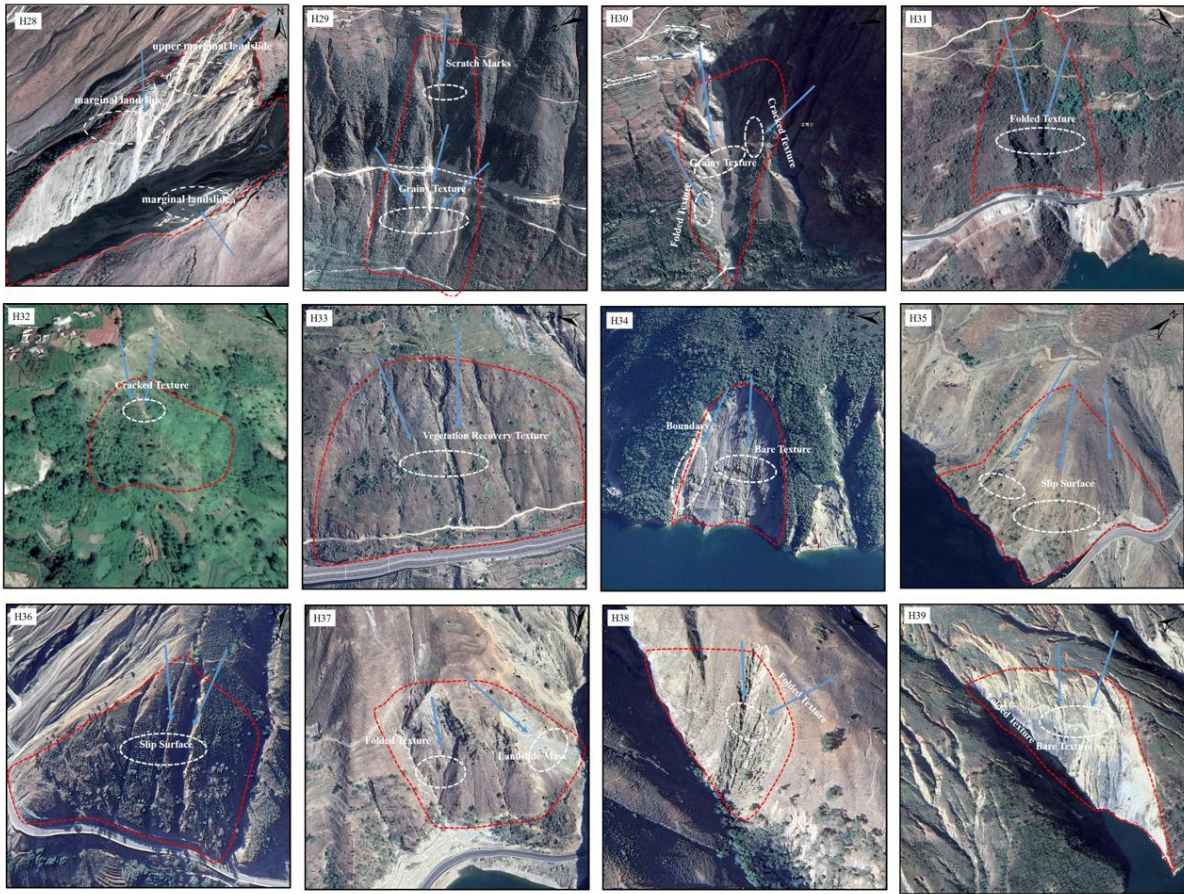
339 Based on relevant literature and the complex geological conditions in the Baihetan Reservoir area, C-band SAR data
 340 can be used to monitor slope deformation. In this region, if the annual deformation rate of a slope exceeds 16 mm, it
 341 is considered to indicate potential landslide hazards. In this study, considering factors such as resettlement activities,

342 frequent human activities, and deformation signal errors within the reservoir area, a threshold of 16 mm/yr was set for
343 identifying potential reservoir-bank landslides. Specifically, when the deformation rate of a slope exceeds 16 mm/yr,
344 it is considered a suspected landslide area. To further assess landslide risks, this study combined SAR deformation
345 signals with the established threshold to initially delineate suspected landslide areas. Additionally high-resolution
346 optical images (e.g., Google Earth imagery) were used to conduct a detailed analysis of features such as color, structure,
347 topographic morphology, landslide boundaries, and cracks for early detection and localization of reservoir-bank
348 landslides(Fig.5).

349 A total of 39 potential reservoir-bank landslides were identified in the Baihetan Reservoir area Among the early
350 identified landslides, 27 were historical landslide hazards, numbered H1-H27; 12 new landslides were identified,
351 numbered H28-H39. The interpretation of the remote sensing images is shown in(Fig.8).



352
353 **Figure 5: Localized InSAR deformation signals for the early identification of reservoir-bank landslides.**



355 **Figure 6: Optical characteristics of representative reservoir-bank landslides based on Google Earth imagery.**
 356 (Image source: © Google; Landsat / Copernicus; U.S. Navy; National Geospatial-Intelligence Agency (NGA); General
 357 Bathymetric Chart of the Oceans (GEBCO).)d

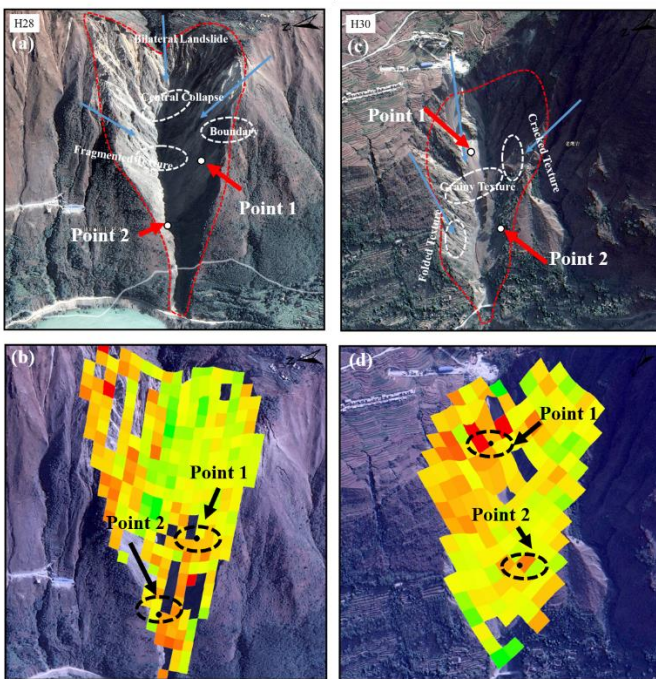
358 4.3 Analysis of Typical Reservoir Bank Landslide Deformation Trend Evolution

359 Based on the early identification results of reservoir-bank landslides presented in Section 4.2, the H28 and H30
 360 landslides were selected from the Baihetan Reservoir catchment for detailed analysis of their deformation evolution
 361 characteristics using Google Earth imagery. High-resolution images clearly reveal typical landslide features, including
 362 cracks, frontal bulging, subsidence, and slope fragmentation.

363 The H28 landslide, situated in Miansha Village, Qiaojia County on the eastern bank of the upper Jinsha River reservoir
 364 section, demonstrates two distinct deformation zones in the InSAR deformation signals (Fig. 7b)—one along the right
 365 slip surface and another at the slope toe. Google Earth imagery interpretation indicates bilateral sliding toward the
 366 center, forming an irregularly shaped "bidirectional landslide" characterized by a wider upper section and narrower
 367 lower extent. The steep slope exhibits significant surface subsidence with rough textures (Fig. 7a), while granular

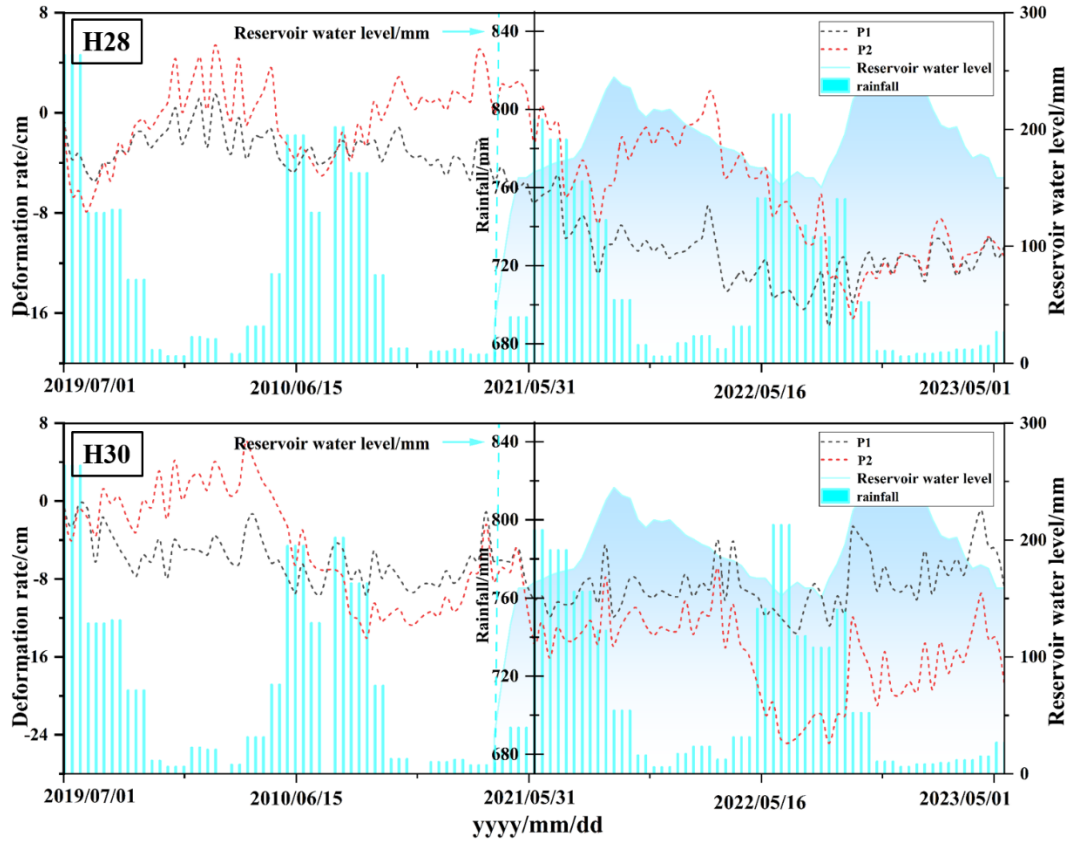
368 accumulations are visible in the basal trough. More pronounced displacement traces on the right slope compared to the
369 left suggest the landslide is likely in a state of prolonged sliding activity.

370 Located on the western bank of the lower Baihetan Reservoir area in Shuicaozi Village, Huidong County, the H30
371 landslide displays a tongue-shaped irregular boundary with prominent concave morphology. The slope deformation
372 manifests primarily as compressional displacement from both sides toward the center (Fig.7c), with greater
373 deformation intensity observed on the right slip surface. Fractures and debris deposits identified in the central portion
374 of the landslide body, coupled with pronounced deformation zones at the upper-left and lower-right sections (Fig. 7d),
375 further confirm its active deformation state.



376
377
378 **Figure 7: Remote sensing interpretation of typical reservoir-bank landslides based on optical features derived from Google**
379 **Earth imagery and corresponding InSAR deformation signals.**
380 **(Image source: © Google; Landsat / Copernicus; U.S. Navy; National Geospatial-Intelligence Agency (NGA); General**
381 **Bathymetric Chart of the Oceans (GEBCO).)**

382 This study analyzed the temporal evolution characteristics of reservoir-bank landslide deformation. Characteristic
383 points with significant deformation (H28 P1, H28 P2, H30 P1, and H30 P2) were selected from the H28 and H30
384 landslide areas in the Baihetan Reservoir, and time-series deformation curves were constructed (Figure 8).



385
386 **Figure 8: Time Series Deformation Curves of Typical Landslide Feature Points**

387 As observed from the time-series deformation curves, the deformation of characteristic points is not synchronized with
388 reservoir water level variations, exhibiting an obvious time-lag effect. To accurately quantify this lag relationship, this
389 study employs the signal cross-correlation analysis method, with the core calculation formulas presented as follows:

390 (1) Cross-Correlation Coefficient Calculation Formula

$$391 \quad R_{xy}(\tau) = \frac{E[(X_t - \mu_X)(Y_{t+\tau} - \mu_Y)]}{\sigma_X \sigma_Y} \quad (11)$$

392 Where: $R_{xy}(\tau)$ is the cross-correlation coefficient corresponding to the lag step τ ; $R_{xy}(\tau)$ is the landslide
393 deformation observation value at time t ; $Y_{t+\tau}$ is the reservoir water level observation value at time $t + \tau$; μ_X and μ_Y
394 are the means of the deformation sequence and water level sequence, respectively; σ_X and σ_Y are the standard
395 deviations of the two sequences, respectively; $E[\cdot]$ denotes the mathematical expectation operator.

396 (2) Optimal Lag Time Determination Formula

$$397 \quad \tau_{opt} = \arg \max_{\tau \in [-\tau_{max}, \tau_{max}]} |R_{xy}(\tau)|$$

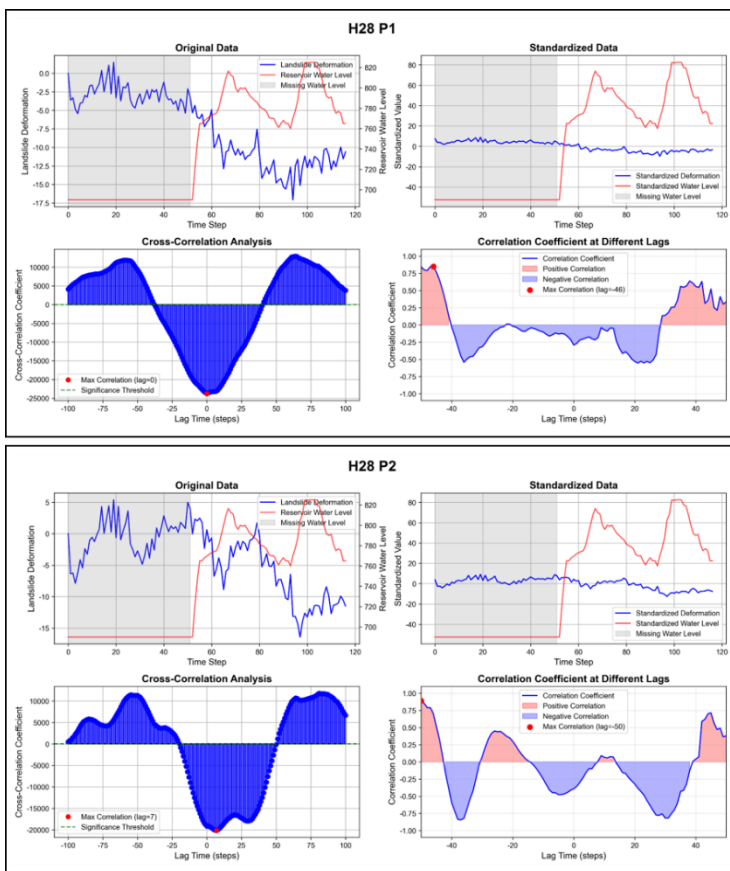
398 Where: τ_{opt} is the optimal lag time (a negative value indicates that deformation precedes water level changes);
399 $\arg \max$ is the operator that takes the independent variable corresponding to the maximum value; τ_{max} is the preset
400 maximum lag step (100 steps in this study).

401 In the H28 landslide, P1 is located in the upper-middle part of the landslide, while P2 is situated in the lower part. Both
402 points exhibit deformation moving away from the satellite along the radar line of sight. Precipitation and reservoir
403 water level variations at the Baihetan Reservoir are identified as the primary controlling factors for landslide
404 deformation. During the 2021 impoundment period, when the water level reached the maximum elevation of 816.5
405 meters, the cumulative deformation of both characteristic points before and after impoundment exceeded 10
406 centimeters, indicating a strong response of the H28 landslide to reservoir water level changes. After the completion
407 of phased impoundment, P2 in the lower part showed a more stable deformation trend, which is inferred to stem from
408 slope structure compaction and reduced looseness induced by rising water levels.

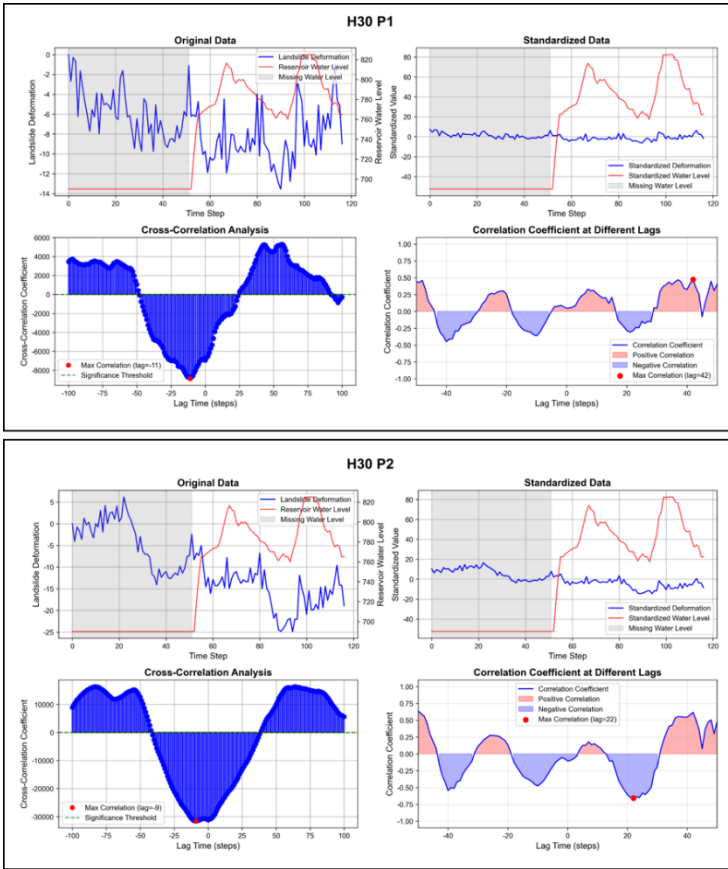
409 Throughout the two impoundment cycles, the deformation of P1 and P2 was asynchronous with water level fluctuations.
410 The time-lag effect was quantified via signal cross-correlation analysis (Figure 9). For H28 P1, the maximum
411 correlation between deformation and reservoir water level corresponded to a lag time of -40 steps, meaning
412 deformation preceded water level changes by 40 time units. For H28 P2, the maximum correlation lag time was -50
413 steps. Both correlation coefficients exceeded the statistical significance threshold, confirming the statistical
414 significance of the time-lag effect.

415 For the H30 landslide, P1 is located at the middle elevation of the left sliding surface, and P2 at the lower elevation of
416 the right sliding surface. Both points exhibited deformation trends away from the satellite before and after
417 impoundment. Compared with P2, P1 displayed a more stable deformation trend, implying the H30 landslide may
418 possess rotational sliding characteristics, with sliding directions varying by elevation. During the 2021-2022
419 impoundment periods, the deformation peaks of P1 and P2 did not coincide with the water level peaks of 816.5 meters
420 and 825 meters. Further quantification through cross-correlation analysis (Figure 10) revealed that the maximum
421 correlation lag time for H30 P1 was -42 steps and -22 steps for H30 P2. Both results passed the significance test, further
422 verifying the time-lag response of the landslide to water level variations. After the conclusion of impoundment, the
423 cumulative deformation of P2 exceeded 10 centimeters, suggesting that water level changes may intensify landslide
424 activity in this region.

425 In summary, reservoir-bank landslide deformation is significantly affected by water level variations. Signal cross-
 426 correlation analysis enables clear quantification of this time-lag effect: the lag steps for characteristic points in the H28
 427 area range from 40 to 50 steps, while those in the H30 area range from 22 to 42 steps. These quantified results provide
 428 data support for understanding the temporal response patterns of landslide deformation. Furthermore, they emphasize
 429 the importance of real-time monitoring and dynamic updates of reservoir-bank landslides for regional geological
 430 hazard prevention and mitigation.
 431



432 **Figure 9:** Analysis of Time-Lag Effect Between Deformation and Water Level for Characteristic Points of the H28 Landslide



434 **Figure 10:** Analysis of Time-Lag Effect Between Deformation and Water Level for Characteristic Points of the H30 Landslide

435 **5 Discussion and Conclusion**

436 **5.1 Discussion**

437 **5.1.1 Baseline Optimization Performance Evaluation**

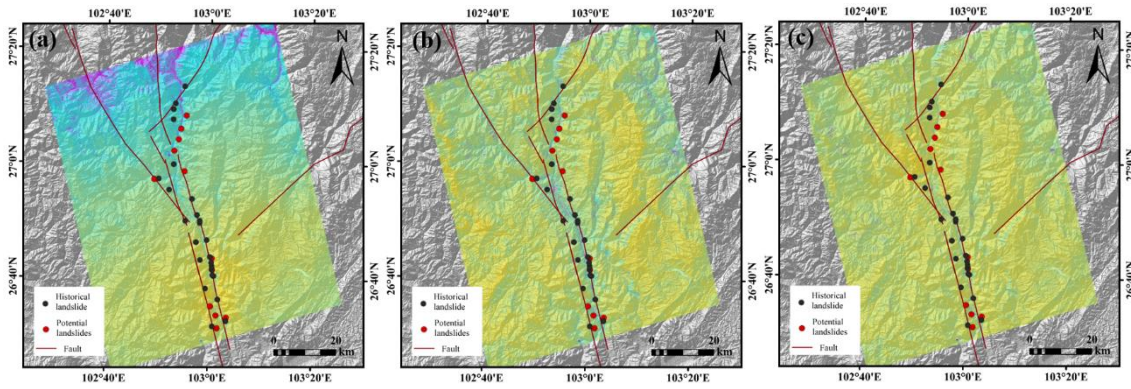
438 The WCTM method proposed in this paper takes into account the relationship between the InSAR coherence and the
 439 monthly variation in vegetation cover, which represents a specific improvement over previous studies. By comparing
 440 the WCTM method with traditional interference baseline selection methods (short time-space baseline threshold and
 441 average coherence threshold), the performance of the optimized interferometric baseline is evaluated through the
 442 calculation of deformation rate standard deviation (Fig.11 and Fig.12) and the full-phase ambiguity of the loop closure
 443 error (Fig.13). As shown in Fig 10, the deformation rate standard deviation with the short time-space baseline threshold
 444 (time baseline threshold: 36d, space baseline threshold: 200m) exhibits an irregular and uneven spatial distribution
 445 along the Jinsha River (from south to north), with maximum and minimum deformation rate standard deviations

446 observed in the northern and southern parts of the study area, respectively (Fig.11a). This indicates that the short time-
 447 space baseline threshold is prone to introducing decorrelation errors, making it ineffective for obtaining stable InSAR
 448 deformation signals. The use of the average coherence threshold effectively improves the overall Stability of the InSAR
 449 signals, but some anomalies were still observed outside the reservoir banks of the Baihetan Reservoir (Fig.11b). This
 450 suggests that simply setting an average coherence threshold through basic statistical methods does not reflect the
 451 seasonal variation in coherence caused by interference, and is not suitable for InSAR deformation signal detection in
 452 deeply-cut mountain canyon areas. The WCTM method, which optimizes the interferometric baseline by considering
 453 the relationship between coherence and vegetation cover, reduces the redundancy of low-coherence interferograms,
 454 effectively improving overall coherence, and avoids the subjectivity caused by expert experience and simple statistical
 455 methods. The deformation rate standard deviation shows a more uniform and Stable distribution (Fig.11c). Furthermore,
 456 the statistical analysis of the deformation rate standard deviation distribution (Fig.12) also confirms this, with the
 457 average deformation rate standard deviations for the short time-space baseline method, average coherence threshold
 458 method, and WCTM method being 1.7865, 1.4587, and 1.2668, respectively, and with quartile medians of 1.6802,
 459 1.3831, and 1.1667. This demonstrates that the WCTM method, which optimizes interferometric baseline thresholds
 460 significantly reduced the time-series noise contained in the InSAR deformation signals, resulting in more effective and
 461 stable deformation rates.

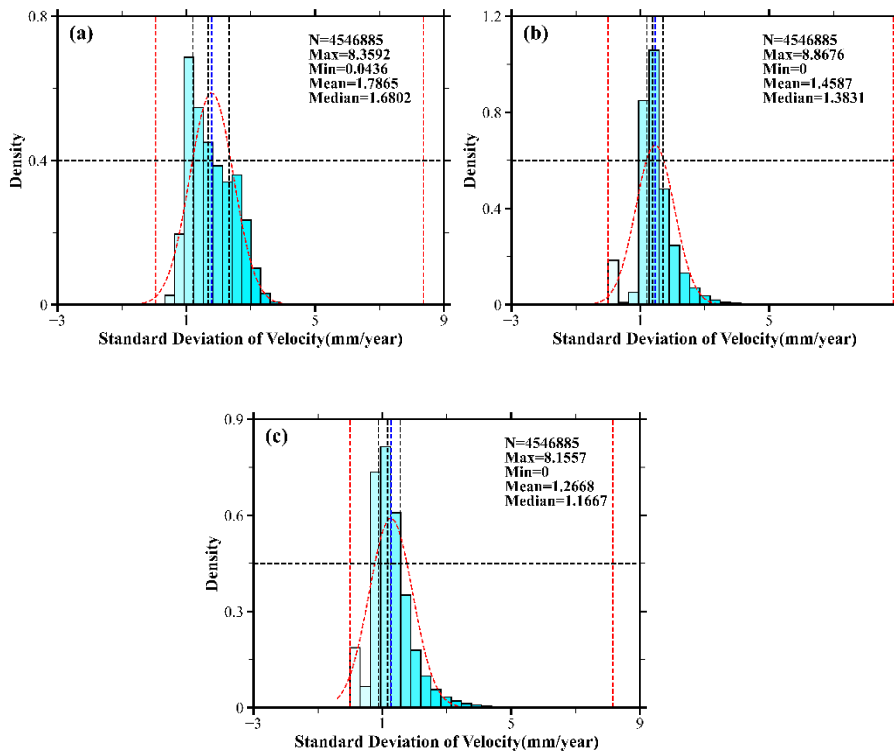
462 The WCTM method optimizes interferometric baseline thresholds, substantially reducing temporal noise in InSAR
 463 deformation signals, thereby yielding more reliable and stable deformation rate estimates. The relative reduction in the
 464 deformation rate standard deviation achieved by the WCTM method compared to the conventional short temporal
 465 baseline threshold method is quantitatively expressed as:

$$466 \quad Reduction = \frac{\sigma_{shortbaseline} - \sigma_{WCTM}}{\sigma_{shortbaseline}} \times 100\% \quad (12)$$

467 Where $\sigma_{shortbaseline}$ and σ_{WCTM} denote the mean deformation rate standard deviations obtained by the short
 468 temporal baseline threshold method and the proposed WCTM method, respectively. This result quantitatively
 469 demonstrates that the WCTM method reduces the deformation rate standard deviation by approximately 29.1%,
 470 confirming its superior capability in improving the accuracy and stability of deformation measurements in complex
 471 mountainous canyon environments.



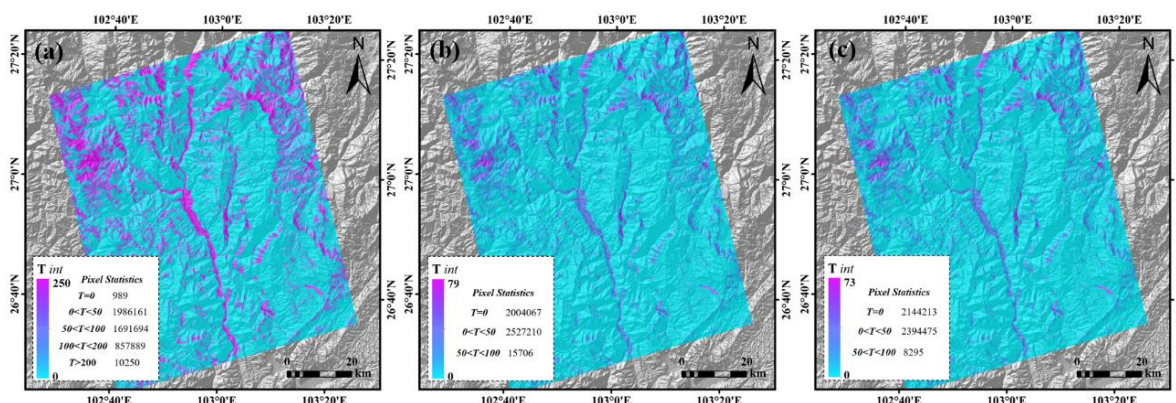
472
 473 **Figure 11: Standard Deviation of Deformation Rates: (a) Results without interferometric baseline threshold optimization,**
 474 **(b) Results with interferometric baseline optimization based on average coherence, (c) Results with interferometric baseline**
 475 **optimization using the WCTM method**



476
 477
 478 **Figure12: Statistical Distribution of Deformation Rate Standard Deviation**
 479

480 In addition, the full-phase ambiguity results of the loop phase closure check for phase unwrapping also validate the
 481 performance of the optimized interferometric baseline using the WCTM method proposed in this paper. The full-phase
 482 ambiguity of the loop closure describes the "periodicity" or "ambiguity" of radar phase during the phase unwrapping
 483 process in time-series InSAR technology, and is used to evaluate the quality of phase unwrapping and possible phase
 484 unwrapping errors. Fig.13 shows the full-phase ambiguity of the loop closure obtained using the three methods. It is
 485 not difficult to observe that, compared to the short time-space baseline threshold method, the optimization of
 486 interferometric baseline threshold using the coherence coefficient of the interferogram yields more robust phase

487 unwrapping results, with a significant improvement in the quality of phase unwrapping. The non-zero values of the
 488 full-phase ambiguity of the loop closure are effectively reduced. By considering the monthly variation of InSAR
 489 coherence and vegetation cover, the WCTM method leads to an increase of 140,146 good unwrapping results ($T_{int} =$
 490 0) compared to the average coherence threshold method, while the unwrapping errors with closure differences greater
 491 than 50 ($50 \text{ times } 2\pi$) are reduced by 7,411, indicating that the WCTM method effectively reduces the noise level
 492 detected by time-series InSAR technology and demonstrates good applicability in deeply-cut mountain canyon areas.
 493

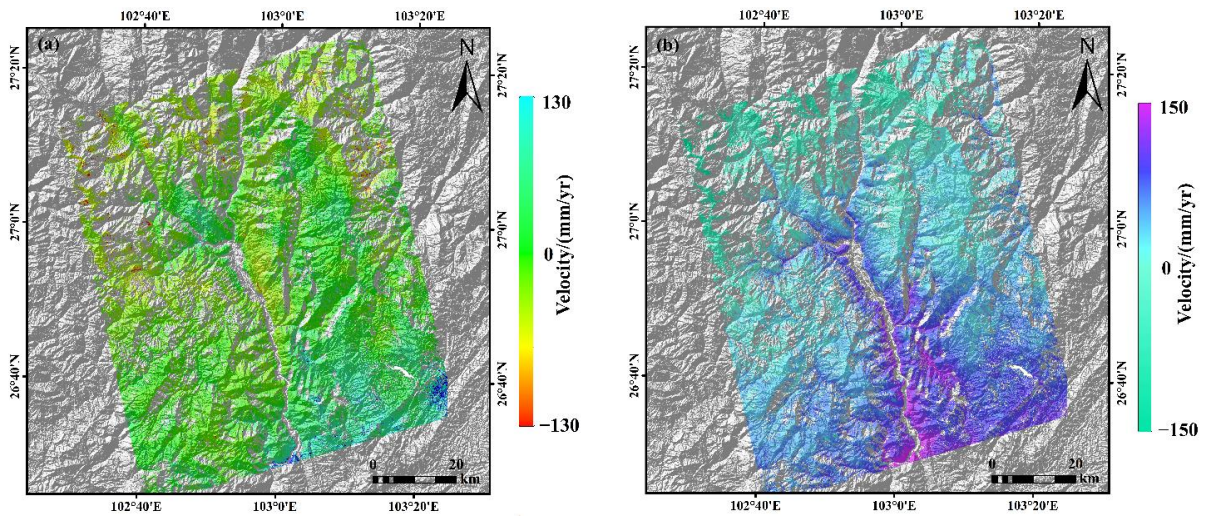


494
 495 **Figure 13: Integer Ambiguity of Circular Phase Closure Errors**

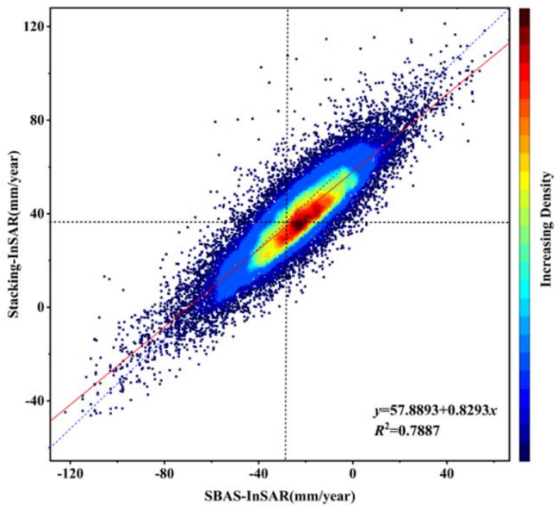
496 5.1.2 SBAS-InSAR Deformation Signal Accuracy Verification and Error Analysis

497 This paper describes a method for optimizing the interferometric baseline threshold of the HyP3 interferogram stack
 498 using the proposed WCTM method to obtain InSAR deformation signals for deeply incised high mountain canyon
 499 areas. The accuracy of the deformation signals is limited by the HyP3 interferogram stack products processed and
 500 released by the ASF. Due to the special terrain and topography of the Baihetan Reservoir area, the descending track
 501 data experiences significant geometric distortion. To improve the accuracy of the InSAR deformation signals and
 502 reduce the impact of geometric distortion on reservoir bank landslide identification results, we selected ascending track
 503 data from the HyP3 interferogram stack as the experimental dataset for the WCTM method. By comparing with
 504 historical landslide data from 2021, the spatial locations of the early-identified reservoir-bank landslides showed a high
 505 degree of similarity to the historical landslides, indirectly validating the accuracy of the InSAR results. However, due
 506 to the lack of GNSS observational data in the study area, we were unable to compare the detected InSAR deformation
 507 signals with GNSS data on a time-series scale. To quantitatively analyze the reliability of the InSAR results, we
 508 performed cross-validation by comparing deformation results obtained using different techniques on the same track.
 509 We used the HyP3 interferogram stack mentioned in Section 2.2 for Stacking-InSAR processing, obtaining the average

510 phase velocity for the study period(Fig.14b), and then performed a combined analysis with the deformation rates
 511 obtained using the SBAS-InSAR technique in Section 4.3. We randomly selected 25,141 deformation points from areas
 512 with consistent deformation trends (Fig.14) for regression analysis (Fig.15). The cross-validation results between
 513 SBAS-InSAR and Stacking-InSAR show an R^2 value of 0.79, which demonstrates that the surface deformation
 514 information obtained from both SBAS-InSAR and Stacking-InSAR methods is reliable on both temporal and spatial
 515 scales. Additionally, the cross-validation results also verify the accuracy and reliability of the time-series InSAR data
 516 optimized using the WCTM method proposed in this study.



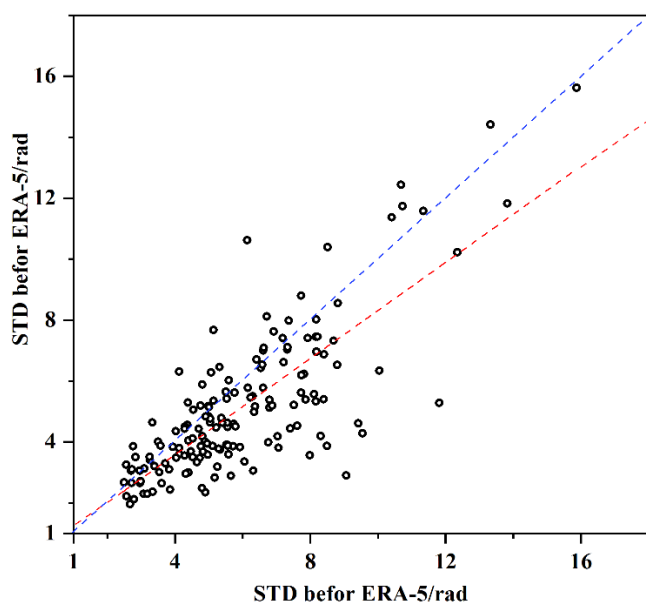
517
 518 **Figure 14: Deformation Information from SBAS-InSAR and Stacking-InSAR in the Study Area**



519
 520 **Figure 15: Cross-validation Results between Stacking-InSAR and SBAS-InSAR**

521 The SBAS-InSAR deformation inversion results are often affected by phase unwrapping errors and atmospheric delay
 522 errors. Optimizing these errors can significantly improve monitoring accuracy. The above experiments demonstrate
 523 that by adjusting the coherence threshold and optimizing the full-wavelength ambiguity of the phase closure, the

524 WCTM method effectively improves the stability of phase unwrapping. Based on this, this study combined the ERA-
 525 5 meteorological reanalysis product released by the ECMWF to correct atmospheric delay errors, and compared the
 526 phase standard deviation of interferograms before and after correction (Fig.16). The results show that after ERA-5
 527 correction, the phase standard deviation significantly decreased, with the maximum phase standard deviation reduced
 528 from 11.81 rad to 5.27 rad. Notably, 71.2% of the interferogram phase standard deviations showed significant
 529 improvement, while only 28.8% of interferograms were negatively affected, with the maximum negative standard
 530 deviation being -4.48 rad. This indicates that the ERA-5 product, with its high spatiotemporal resolution, can
 531 effectively eliminate atmospheric delay errors in InSAR monitoring, and is particularly well-suited for deep-cut
 532 mountain canyon areas.

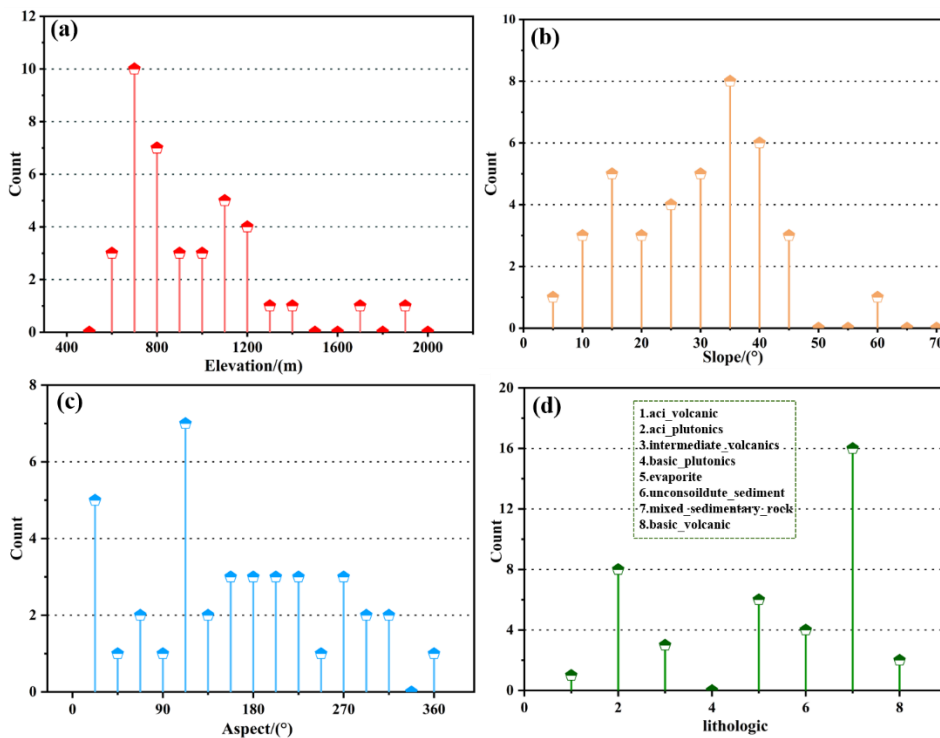


533
 534 **Figure 16: Correlation Analysis of Phase Standard Deviation Before and After ERA-5 Atmospheric Correction**

535 **5.1.3 Distribution Patterns of Reservoir-bank landslides and the Impact of Reservoir Water Level Changes on**
 536 **Landslide Deformation**

537 There are many factors that influence reservoir-bank landslides. Considering the geomorphological conditions of the
 538 Baihetan Reservoir, this study analyzes the distribution patterns of reservoir-bank landslides based on the 39 landslides
 539 identified in Section 4.2, using statistical methods and examining terrain factors such as elevation, slope, aspect, and
 540 lithology (Fig.17). From Fig16, it can be seen that the identified reservoir-bank landslides are primarily concentrated
 541 within the elevation range of 600m to 1400m and widely developed in slopes ranging from 30° to 45° . This indicates
 542 that slopes that are too gentle are not enough to induce slope movement, while steeper reservoir banks are more
 543 conducive to landslide development. The landslides identified in the early stages are mostly distributed in the northeast,

544 east, and northwest directions, similar to the findings of Dun et al., with fewer landslides identified in the north-south
545 direction. This could be due to the sensitivity of the Sentinel-1 satellite to deformation in the north-south direction
546 being affected by its flight path. Additionally, the lithology of the reservoir-bank landslides mainly consists of mixed
547 sedimentary rocks, carbonate rocks, and neutral volcanic rocks, which are generally located in incompetent strata.
548 Previous studies suggest that the increase or decrease in pore water pressure on the sliding surface caused by changes
549 in the reservoir water level is the primary factor triggering instability in reservoir-bank landslides. Moreover, under
550 different reservoir water level change patterns, the deformation signals of the landslides show significant differences.
551 Notably, in Section 4.3, the analysis of landslide deformation trend evolution indicates that the peak of landslide
552 deformation does not coincide with the peak of the reservoir water level, suggesting a time-lag response of landslide
553 deformation to the water level changes in the Baihetan Reservoir. This phenomenon is similar to previous research. The
554 time-lag effect includes a time delay in the deformation process of the landslide and irreversible plastic deformation
555 of the landslide's geological structure during the water level change process. As the pore water pressure in the landslide
556 changes, it affects the stability of the slope. The stress state of the soil also needs time to adjust to and adapt to the new
557 pressure conditions. Therefore, when the reservoir water level changes, the moisture within the landslide requires a
558 certain period to reach a new equilibrium state, which is why the deformation of the reservoir-bank landslides shows
559 a clear lag response to water level fluctuations.



560
561 **Figure 17: Statistical Chart of the Distribution Pattern of Reservoir-bank landslides**

562 In summary, the WCTM method proposed in this study demonstrates effectiveness in the early identification of
563 reservoir landslides in deeply incised alpine gorge areas. The core advantage of this approach lies in its ability to
564 resolve the decorrelation problem caused by seasonal vegetation changes – a challenge prevalent in numerous surface
565 deformation monitoring scenarios. Consequently, the methodology can be extended to the following application
566 scenarios: monitoring of other types of reservoir landslides, identification of geological hazards such as landslides and
567 collapses in vegetated mountainous areas, and stability monitoring of engineering structures in regions with significant
568 seasonal vegetation variations.

569 **5.2 Conclusion**

570 This study focused on the Baihetan Hydropower Station reservoir area, utilizing Sentinel-1A ascending and descending
571 track data from July 2019 to May 2023. The Vegetation-Adaptive WCTM was employed to optimize interferometric
572 baseline thresholds, combined with atmospheric delay correction using the ERA-5 meteorological reanalysis product.

573 The main conclusions are as follows:

- 574 (1) Compared with the traditional short temporal-spatial baseline threshold method and the average coherence
575 threshold method, the WCTM approach achieved an average reduction of 0.520 and 0.192 in the STD of deformation
576 signals, and median reductions of 0.514 and 0.216, respectively, significantly improving phase unwrapping quality.
577 After atmospheric delay correction, 71.2% of the interferograms exhibited a substantial decrease in phase STD, with
578 the maximum phase STD was reduced from 11.81 rad to 5.27 rad. These results demonstrate the superiority of the
579 proposed method in enhancing data quality.
- 580 (2) Using the InSAR deformation signals optimized by the WCTM, early identification of reservoir-bank landslides in
581 deeply incised mountainous canyon areas was successfully achieved, with a total of 39 landslides detected. Field
582 validation via drone surveys confirmed the applicability and robustness of the method, and detailed analyses of the
583 spatial distribution and temporal evolution of landslides were conducted.
- 584 (3) Statistical analysis revealed that most reservoir-bank landslides in the Baihetan area occur within an elevation range
585 of 600 m to 1400 m and on slopes between 30° and 45°. The predominant slope aspects are northeast, east, and
586 northwest. Lithologically, these landslides mainly develop on carbonate rocks, intermediate volcanic rocks, mixed
587 sedimentary rocks, and siliceous clastic sedimentary rocks.

588 In summary, the WCTM method provides an effective technical means for high-precision monitoring of reservoir-
589 bank landslides in complex mountainous regions, offering significant theoretical and practical value for regional
590 landslide disaster prevention and mitigation.

591

592 **Code and data availability**

593 The dataset supporting this study has been deposited in a public repository and assigned a Digital Object Identifier
594 DOI: <https://doi.org/10.57760/sciencedb.28757> The data of this study are available upon request from any author.
595 Please refer to the author information in the article for contact details.

596

597 **Authorship contribution statement**

598 All authors have made significant contributions to various aspects of this research. The specific contributions are as
599 follows: XI Wenfei was responsible for writing, reviewing, and editing the manuscript; HONG Wenyu handled data
600 management; YANG Zhiqian was responsible for conceptualization of the study; HUANG Guangcai was responsible
601 for software development; GUO Junqi managed the project; YANG Kunwu performed formal analysis; JIN Tingting
602 managed resources; All authors participated in various stages of the research and have approved the final version of
603 the manuscript.

604

605 **Competing interests**

606 The authors declare that there is no competing interest related to the publication of this paper.

607

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612 Copernicus program, and Google Earth for providing high-resolution satellite imagery that facilitated landslide
613 interpretation. We also appreciate the use of the Hybrid Pluggable Processing Pipeline (HyP3) developed by Hogenson
614 et al. (2020), which offered a cloud-native infrastructure for SAR data processing and greatly facilitated our work.

615

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624

625 **Review statement**

626 No potential conflict of interest was reported by the author(s).

627

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