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Seismic Deformation and Landslide Assessment Using Iterative DInSAR Analysis of the 2022 Mw 6.1 Pasaman Earthquake in Indonesia

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ABSTRACT

Earthquakes, particularly those along active tectonic boundaries such as Indonesia's Semangko Fault, often trigger cascading hazards like landslides. Accurate monitoring of earthquake-induced surface deformation and secondary hazards remains critical for disaster risk reduction, especially in mountainous regions. Using a multi-sensor geospatial approach, this study investigates the spatial and temporal evolution of ground deformation and landslide activity associated with the 2022 Mw 6.1 Pasaman earthquake. We apply an Iterative Observation Differential Interferometric Synthetic Aperture Radar (IO-DInSAR) technique to Sentinel-1A imagery, enabling the reconstruction of true vertical displacements across pre-seismic, co-seismic, and post-seismic phases. The results reveal progressive interferometric fringe development and vertical deformation preceding the mainshock, followed by widespread post-seismic landslides, particularly on the slopes of Mount Talamau. Coherence change detection (CCD), Normalized Difference Vegetation Index (NDVI) analysis from Sentinel-2, and derived landslide velocity models further corroborate spatial patterns of slope failure. Validation against CORS geodetic data yields a root mean square error (RMSE) of 0.0097 m, confirming the reliability of vertical displacement estimates. Unlike traditional DInSAR, the IO-DInSAR approach captures temporally continuous deformation patterns, offering deeper insights into the development of earthquake-related instability. These findings highlight the utility of iterative DInSAR analysis for enhancing our understanding of cascading seismic hazards and inform early warning strategies in tectonically active regions.

Keywords earthquake, geological landslide, DInSAR, IO-DInSAR, earthquake prediction, Sentinel 1A

1. INTRODUCTION

Indonesia is located at the convergence of the Indo-Australian, Eurasian, and Pacific tectonic plates, making it one of Earth's most seismically active regions [1]. The region experiences frequent earthquakes; for example, over 11,600 earthquakes were recorded in Indonesia in 2019 alone [2]. This intense seismicity is driven by the complex tectonics of the area, including the Sunda megathrust subduction zone and numerous active crustal faults, which together produce a remarkable diversity in faulting, including subduction, extension, thrusting, and strike-slip faulting [1]. Western Sumatra faces a high seismic hazard due to the combined influence of the offshore Sunda subduction interface and the onshore Great Sumatran Fault system. The Great Sumatran Fault itself is a ~1900-km-long strike-slip fault zone divided into multiple segments (60–200 km in length) that accommodate the oblique convergence in this region [3], [4]. These tectonic conditions have been reflected in Indonesia's probabilistic seismic hazard assessments, consistently ranking Sumatra among the regions with the highest earthquake risk. Major historical earthquakes, such as the 2004 Mw 9.1 Sumatra–Andaman and the 2009 Mw 7.6 Padang earthquake, underscore the destructive potential of this seismicity [5].

A significant secondary hazard associated with Indonesia's frequent earthquakes is the triggering of landslides in the country's rugged, high-relief terrains. Earthquake-induced landslides are among the most damaging secondary effects of strong ground shaking[6], [7] . Globally, these events have demonstrated devastating potential: the 2008 Wenchuan and 2015 Gorkha earthquakes triggered tens of thousands of landslides, while the 2016 Kumamoto earthquake caused about 1,500 landslides [8]. In tropical regions like Indonesia, the risk is compounded by intense monsoonal rainfall and deeply weathered volcanic soils, which lower slope thresholds[9] . When seismic shaking acts as a trigger on such saturated slopes, cascading hazards often ensue . For example, the 2022 Mw 6.1 Pasaman earthquake in West Sumatra led to widespread landslides around Mount Talamau, affecting over 1,200 hectares [10].

Remote sensing techniques have become indispensable for characterizing hazard cascades, especially in inaccessible regions. Synthetic Aperture Radar (SAR) interferometry, particularly Differential InSAR (DInSAR), allows for sub-centimeter ground deformation tracking regardless of weather or lighting conditions [11]. Time-series InSAR methods such as Persistent Scatterer Interferometry (PSI) and Small Baseline Subset (SBAS) have improved deformation monitoring even in vegetated tropical zones [12]. Recent work by Kuang et al. (2022) and Cai et al. (2020) demonstrated the integration of time-series SAR data and optical imagery for tracking spatiotemporal evolution of landslides. However, conventional DInSAR still faces challenges monitoring episodic deformation due to temporal decorrelation in densely vegetated and mountainous areas like West Sumatra [13], [14].

To address these limitations, the Iterative Observation Differential Interferometric Synthetic Aperture Radar (IO-DInSAR) method has emerged as a promising approach to enhance landslide detection in tropical, tectonically active environments. IO-DInSAR involves iterative stacking and refinement of interferometric pairs to improve the reliability of displacement estimates, even under low-coherence conditions [15]. This technique enables more robust tracking of pre-failure ground

75 motions and post-seismic slope instabilities across seismic phases. Its utility has been demonstrated
76 in recent studies applying it to fault zone dynamics in West Java [16], supporting its potential for
77 broader landslide risk applications. The present research leverages the IO-DInSAR approach to
78 iteratively monitor surface displacements associated with seismic events in Pasaman, offering a
79 refined lens for understanding ground deformation with probabilistic seismic hazard.

80 While probabilistic seismic hazard analysis (PSHA) and remote sensing techniques have each
81 advanced significantly, their integration remains underexplored, particularly in tropical, tectonically
82 complex regions. PSHA provides a framework to quantify the likelihood of various levels of ground
83 shaking across a region [17], while most landslide susceptibility models rely on static factors [18]
84 and often treat seismic inputs as deterministic rather than probabilistic [19]. This disconnection leads
85 to underrepresenting cascading hazard dynamics [20]. Some recent efforts, like Maharjan et al.
86 (2021), have integrated geotechnical modeling with high-resolution DEMs to estimate critical
87 acceleration for slope failure. Still, few studies directly link seismic strain accumulation with evolving
88 landslide susceptibility in a probabilistic framework [21].

89 To address these limitations, this study proposes an integrated approach that combines PSHA
90 with IO-DInSAR monitoring to evaluate the evolution of landslide susceptibility in Pasaman, West
91 Sumatra. Using Sentinel-1A (S1A) time-series radar data, the study aims to detect coseismic and
92 aseismic deformation, identify threshold strain values related to slope failure, and enhance PSHA
93 outputs with spatial evidence of ground instability. The approach also leverages Indonesia-specific
94 tectonic datasets [16], [22] and landslide inventories [9], [23] to develop a robust multi-hazard risk
95 assessment framework. By integrating dynamic seismic strain modeling and remote sensing, the
96 study contributes to more realistic risk estimates and improved disaster preparedness for
97 tectonically active and topographically complex regions.

98 2. RESEARCH METHODS

99 Methods for detecting and monitoring ground movements are continuously advancing through
100 the use of remote sensing imagery, including both optical and Synthetic Aperture Radar (SAR)
101 technologies [24]. Remote sensing via active satellites equipped with radar sensors, utilizing SAR,
102 is an evolving approach for investigating surface deformation. Synthetic Aperture Radar (SAR) is a
103 microwave-based imaging system capable of penetrating cloud cover due to its use of microwaves.
104 As an active system, SAR operates both day and night [25]. An 'interferometric configuration' such
105 as Interferometric SAR (InSAR) enables precise measurements of the path traveled by radar
106 signals, as it maintains coherence. By tracking variations in satellite position and acquisition time,
107 measurements can generate a Digital Elevation Model (DEM) and quantify surface deformations at
108 the centimeter scale [26]. The use of interferometry allows high-precision detection of surface
109 displacements, with accuracy down to millimeters, and is particularly useful for monitoring urban
110 subsidence, landslides, and other terrain displacements in seismic, coastal, and flood-prone
111 regions. SAR operates by reflecting signals off the target area and measuring the signal's travel time
112 back to the satellite.

Synthetic Aperture Radar (SAR) is a microwave imaging system capable of penetrating cloud cover due to its use of microwaves. This system operates effectively both during the day and at night, as it is an active system. Consequently, an interferometric configuration, such as Interferometric SAR (InSAR)[27], [28], [29], [30], [31], [32], enables precise measurements of the radiation travel path due to its coherent nature. By utilizing variations in the satellite's path as a function of its position and acquisition time, it is possible to generate a Digital Elevation Model (DEM) and measure surface deformations with centimeter-scale accuracy [16], [26]. Differential Interferometric Synthetic Aperture Radar (DInSAR) is a technique that obtains a pair of SAR images (primary and secondary images), which are combinations of complex data from the same spatial location (baseline) (in the case of differential SAR) or from slightly different locations. In this context, the elevation of the terrain, derived from InSAR, is analyzed for the same area to perform double conjugate multiplication, yielding data on surface displacement or a Digital Elevation Model [33]. In both Single Look Complex (SLC) SAR images, the first image (primary) represents the initial data before any surface displacement, while the second image (secondary) serves as a reference for the condition after migration. An additional external DEM is used to convert the initial pair of data into phase values [11], [34]. This study utilizes level 1 products from S1A SLC IW for SAR data[15], [35], [36], [37], [38], as these products contain one image per sub-swath, per channel, and polarization, facilitating interpretation and reducing the workload on the system workspace. The polarization used is VV, which refers to vertical polarization for both the transmitted and received transverse waves, as the goal is to observe vertical deformation specifically.

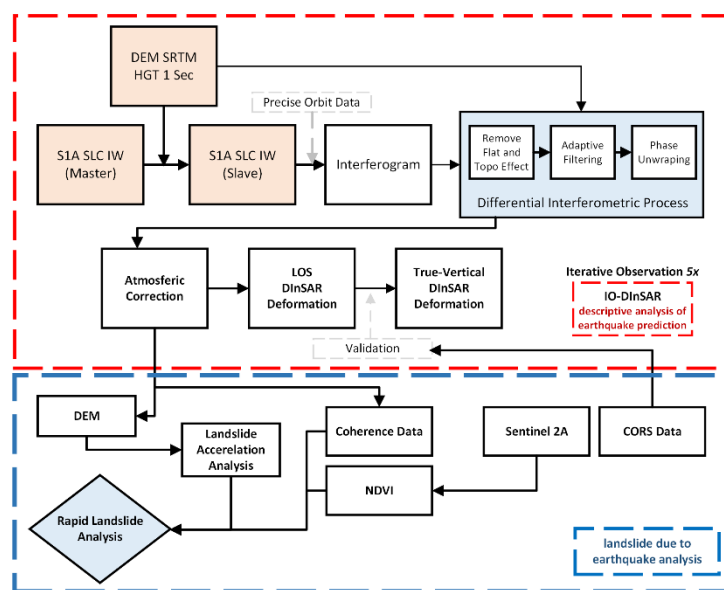


Fig. 1 Research Workflow

Guided by previous research, this study adopts several methods and analyses deemed necessary and effective for the case study of renewable earthquake deformation. Additionally, we incorporate observations using IO-DInSAR, the methods employed and analyses conducted include the DInSAR technique [15], [16], [39], which examines displacement between two S1A SLC images [40] combined with IDW interpolation for each earthquake epicenter recorded. However, in this study,

the verification technique using SRTM elevation data [41] is replaced with a DTM derived from S1A, as SRTM data is no longer valid due to its outdated temporal version. The surface phase is removed and converted into terrain to enhance vertical accuracy. Eliminating the phase of surface objects is essential to obtain a pure ground surface representation. Additionally, Sentinel-2A (S2A) is used to highlight the spatial geographic aspects of the study area through RGB and NDVI analysis. The initial result of displacement obtained from this processing is the LOS (Line of Sight) displacement [42], which is not entirely vertical. Therefore, it is necessary to derive a displacement component that is fully perpendicular to the Earth's surface, eliminating the influence of satellite incidence angles. Using geodetic mathematics, the LOS displacement is converted into true vertical deformation [15], [43]. Finally, the coherence results are integrated with NDVI values to analyze the magnitude, patterns, and distribution of landslides triggered by earthquakes.

2. Introducing IO-DInSAR

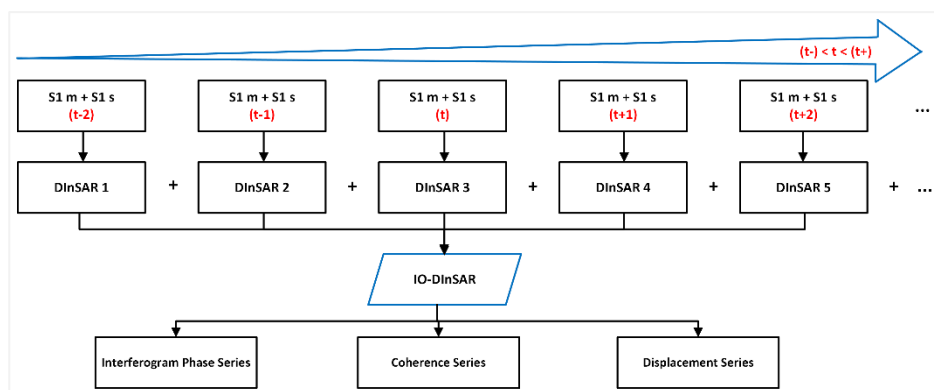


Fig. 2 IO-DInSAR Workflow

Repeated DInSAR observations were conducted in this study, which we refer to as the Iterative Observation DInSAR technique, abbreviated as IO-DInSAR, a DInSAR observation was conducted over multiple time intervals, with the requirement that all images be acquired from the same orbital path, with 100% spatial overlap and strictly sequential acquisition dates, no temporal gaps were permitted. In this study, the observation period spanned from January 2022 to April 2022. From 14 S1A acquisitions, seven temporally consecutive DInSAR datasets were generated. This sequence enabled the analysis of deformation patterns occurring both before and after the main earthquake event on 25 February 2022. This approach was implemented to facilitate the analysis of the distribution and pattern of each DInSAR analysis per observation time unit. It is expected that this analysis will reveal a consistent pattern in terms of quantity, shape, and distribution of deformation caused by the earthquake. The steps followed are outlined in Fig. 2, highlighted in a red strip box. Two SAR image observations with different acquisition times were used, with the earliest date serving as the Master and the most recent as the Slave.

The data used in this analysis consists of level-1 Single Look Complex (SLC) products from S1A, with spatial resolutions that vary depending on the acquisition mode. We selected the Interferometric Wide Swath Mode (IW) for data acquisition due to its use of TOPSAR, a variant of ScanSAR imaging. In the TOPSAR mode, the radar beam alternates cyclically between three sub-

swaths, capturing one azimuthal look per beam for all points. The satellite is equipped with a C-SAR instrument, featuring an active phased array antenna designed for rapid scanning in various elevations and azimuths. It operates at a frequency of 5.041 GHz, with a central wavelength of 6 cm and a halfwavelength of 3 cm. For polarization, we utilized VV polarization, which represents vertical polarization for both transmission and reception.

The methodology applied in this study to model earthquake-induced deformation is Differential Interferometry Synthetic Aperture Radar (DInSAR), which calculates the phase difference between two SAR images taken from the same orbit. DInSAR processing was carried out using the SNAP software. The steps involved in this process are outlined in Fig. 2, assuming a dataset of S1A SLC IW SAR images was collected at designated times (before and after the earthquake) covering the study area. The first step involves generating and merging the SLC IW imagery with external Digital Elevation Model (DEM) data, specifically the SRTM HGT 1 dataset, and accurate orbit information. The interferogram is then generated, with constraints on perpendicular and temporal baselines, and the DEM data is used to correct for topographic effects. After this, adaptive filtering and unwrapping phases are applied to produce an unwrapped differential interferogram dataset. A simple linear model is then applied to remove topography-related atmospheric phases, as expressed in the formula [13], [15], [16], [44], [45], [46]. The deformation phase consists of multiple components, including topographic effects, atmospheric artifacts, decorrelation, thermal noise, and ground

deformation along the radar's Line of Sight (LoS). Once the non-deformation phase components are subtracted, the remaining unwrapped differential interferometric phase represents the deformation phase, which can then be converted into displacement, yielding the DInSAR results. In DInSAR, the phase difference is calculated by comparing two SAR images pixel by pixel, resulting in an interferogram that shows phase differences. These phase differences correspond to variations in SAR signals caused by deformation. It is important to note that the values in the interferogram typically range from 0 to 2π , or one wavelength cycle, determined by the sensor's specific characteristics [11].

$$\phi_{diff} = \phi_{def} + \phi_{topo_{res}} + \phi_{atm_{res}} + \phi_{noise}$$

Equation 1

The formula represents the decomposition of the interferometric phase difference (ϕ_{diff}) observed in synthetic aperture radar (SAR) interferometry into its constituent components. Specifically, ϕ_{def} denotes the phase contribution associated with surface deformation. $\phi_{topo_{res}}$ corresponds to the residual topographic phase due to inaccuracies in the digital elevation model (DEM) used during interferogram generation. $\phi_{atm_{res}}$ represents atmospheric delay artifacts caused by variations in tropospheric and ionospheric conditions between acquisitions. Lastly, ϕ_{noise} encompasses random noise introduced by system limitations, temporal decorrelation, and other unmodeled errors.

Accurate interpretation of SAR interferograms requires isolating and minimizing these non-deformation components to reliably retrieve ground displacement. Following the interferogram process, overlapping information is present in each burst, both in the range and azimuth directions. This overlap is crucial for achieving continuous ground coverage. At this stage, each burst has been processed as an individual SLC image. To merge these bursts seamlessly, especially in the azimuth direction, and maintain the phase information, a merging procedure is used. Additionally, in the overlapping range region, merging is performed between sub-swaths. To facilitate this, Topographic Phase Removal is implemented to estimate and subtract the topographic phase from the deburst interferogram. Afterward, a "Multilooking" process is carried out to reduce speckle noise inherent in SAR images, resulting in square pixels and improved data quality. Phase filtering is then applied to reduce phase noise, which is essential for enhancing the accuracy of phase unwrapping in subsequent stages. At this point, coherence information is derived by interfering the two images through InSAR (Interferometric Synthetic Aperture Radar). Coherence values, which typically range from 0 to 1, represent the quality of the interference. The coherence value information is displayed in Fig. 8 and 10. Phase unwrapping is necessary to convert phase values into physical displacement units. It involves recovering unambiguous phase data from a 2-D array of phase values, which are initially known only modulo 2π radians. These unwrapped phase results are then converted into displacement data, enabling precise quantification of ground movements. Based on Equation 1, where the deformation phase consists of, topo-res, atmospheric-res and noise which represent the deformation phase of the ground, topographical faults, residual atmospheric artifacts, decorrelation and thermal noise, respectively, along the LOS (line of sight) radar [47]. After reducing the other phase components, the differential interferometric phase that is unwrapped only remains the deformation phase, so it can be converted into a displacement, the DInSAR results [1].

The SAR phase difference data, once the absolute values are obtained, is referred to as displacement data. This data results in Line of Sight (LOS) observations, representing the vertical height difference between two images, which have not yet been oriented perpendicular to the Earth's surface. Therefore, it is necessary to correct these values to the actual vertical (true vertical). In this study, we employ the formula [48], as follows:

$$vertical\ displacement = \frac{LoS}{\cos \theta}$$

Equation 2

Where θ represents the incident angle of the S1A SLC IW image. Due to the satellite's observation angle, the displacement must be adjusted to be perpendicular to the ellipsoid, a process referred to as the true vertical displacement [15], [47]. By dividing the LoS displacement by the cosine of the incidence angle, the equation compensates for angular distortion, thereby isolating the vertical motion component. This transformation is critical for accurate quantification of surface deformation in geodetic and geophysical applications, including land subsidence analysis, tectonic displacement monitoring, and infrastructure stability assessment.

2.1 Rapid Landslide Analysis

2.1.1 Coherent Change Detection Method

Coherent Change Detection (CCD) utilizes the correlation and decorrelation of interferometric signals estimated between interferometric pairs of SAR images [49], [50], [51]. Cross-correlation analysis can provide information on changes in scattering properties, including dielectric and structural variations. The CCD technique has demonstrated excellent performance in detecting subtle changes caused by natural hazards and human activities. By leveraging interferometric phase information, the Coherent Change Detection (CCD) technique enables not only surface displacement measurements but also the detection of landslides. The Coherent Change Detection method, based on coherence measurements, has been developed and applied to various natural disasters, including wildfires, volcanic ash events, earthquakes, and tsunamis [52]. This technique can reveal the location, magnitude, and pattern of landslides triggered by earthquakes. However, for broader-scale applications, landslide susceptibility analysis is necessary to assess potential future landslides in the study area by incorporating landslide physics into spatial analysis. For instance, in the case of the 2022 Pasaman earthquake, landslides reached residential areas shortly after the earthquake. Hence, this study will focus on analyzing landslide travel velocity to enhance future mitigation strategies. CCD analysis provides spatial representation of landslide patterns and distribution, but it is also crucial to examine the physical processes underlying landslide dynamics. Cliff slides, as a physical process, can be represented by a simplified model that describes the potential flow volume of a landslide mass, assuming that the landslide mass remains constant along the landslide path [53]. The frictional force between debris material and the sliding surface acts as a resisting factor below the critical slope angle. However, above the critical angle, mass acceleration follows Newton's Second Law. Therefore, if a landslide mass possesses potential energy H and moves a distance x , the energy lost during movement is given by:

$$E_f = mg \int_0^x \cos \alpha \tan \phi_p \frac{dx}{\cos \alpha}$$

Equation 3

with m = mass of the soil block (kg), g = gravitational acceleration (m/s^2), x = horizontal distance (m), ϕ_p = imaginary friction angle ($^\circ$), μ = friction coefficient, $\tan \alpha$ = slope inclination (degree).

The energy of a landslide is influenced by the slope height, as energy is divided by gravitational force. The sliding velocity follows the equation $\frac{v^2}{2g}$, where it is proportional to gravity. This relationship is determined by the height difference between the energy line and the center of mass of the moving debris, representing the total energy affecting the landslide [54]. A landslide stops when its height approaches the flat topographic surface ($h \sim 0$) forming an inclination angle ϕ_p . As a result, the gradient of the energy line depends on the angle ϕ_p , which allows the estimation of both travel distance and velocity when this angle is known.

The movement of debris along a slip surface, which extends over a distance ℓ and has a height H , is affected by forces acting in horizontal and vertical directions. These forces are influenced

by slope angle, friction coefficient, and travel distance $\Delta\ell$ [53]. Based on the energy equilibrium principle, the relationship is expressed as:

$$\Delta\frac{1}{2}mv^2 = mg \sin \alpha \Delta\ell - \mu mg \cos \alpha \Delta\ell$$

Equation 4

Here, $\sin \alpha$ corresponds to Δh , while $\cos \alpha \Delta\ell$ represents Δx . By simplifying, the total landslide path length can be expressed as:

$$L = \frac{H}{\mu} = \frac{H}{\tan \phi_p}$$

Equation 5

A moving landslide mass experiences both potential and kinetic energy, which together form the total mechanical energy. This total energy remains constant, though potential and kinetic energy may fluctuate as the landslide progresses. However, energy loss due to friction (E_f) occurs along the sliding surface, where μ represents the roughness coefficient of the slope [54]. In this study, rotational energy is not considered. Thus, for a landslide mass with initial height H moving a distance x along the landslide path, the conservation of energy is expressed as:

$$mgH_2 - mgh(x) = \frac{1}{2}mv(x)^2 + mgx\mu$$

Equation 6

Rearranging this equation, the velocity of debris at position x is given by:

$$v(x) = \sqrt{2g(H - (x) - x \tan \phi_p)}$$

Equation 7

From this equation, if the velocity $v(x)$ remains constant at a slope angle $\alpha = \phi_p$, the debris will decelerate when $\alpha < \phi_p$ and accelerate when $\alpha > \phi_p$. When considering rotational effects, Gerber's (1994) findings [55] indicate that the rotational energy accounts for approximately 5% of the total kinetic energy, with an equivalent factor between 0.95 and 0.97. Under these conditions, the velocity expression is modified to:

$$v(x) = f_v \sqrt{2g\Delta h} = 0.97 \sqrt{2g\Delta h}$$

Equation 8

For landslides that travel in a straight path at an angle α , the velocity can be estimated using Masuya's (2008) equation 9 [55]:

$$v(x) = \chi \sqrt{2g\Delta h}$$

Equation 9

Here, $\chi = \sqrt{1 - \frac{\mu}{\tan \alpha}}$ serves as the straight-line coefficient. In this study, however, it is assumed that $\chi = 1$, meaning the landslide is modeled as an ideal case without resistance to simplify the analysis. This equation will be applied using band math within SNAP software, utilizing DEM data derived from InSAR and converted into a vector slope format.

2.1.1 NDVI Method

In this study, an NDVI analysis is required to spatially map landslides, as landslide activity removes vegetation, leading to a measurable decline in vegetation index values. The Normalized Difference Vegetation Index (NDVI) is a ratio-based measure of reflectance in the near-infrared (NIR) and red spectral bands [56], [57], [58]. It is one of the most widely used spectral indices in both research and agriculture, providing a rapid and efficient method for detecting vegetation and assessing overall plant health [56], [59]. This measurement is based on the principle that leaf cellular structures strongly reflect NIR radiation due to minimal absorption by plant pigments, whereas chlorophyll pigments exhibit strong absorption in the red spectrum. The NDVI formula is as follows:

$$NDVI = (DCS_{NIR} - DCS_{RED}) / (DCS_{NIR} + DCS_{RED})$$

Equation 10

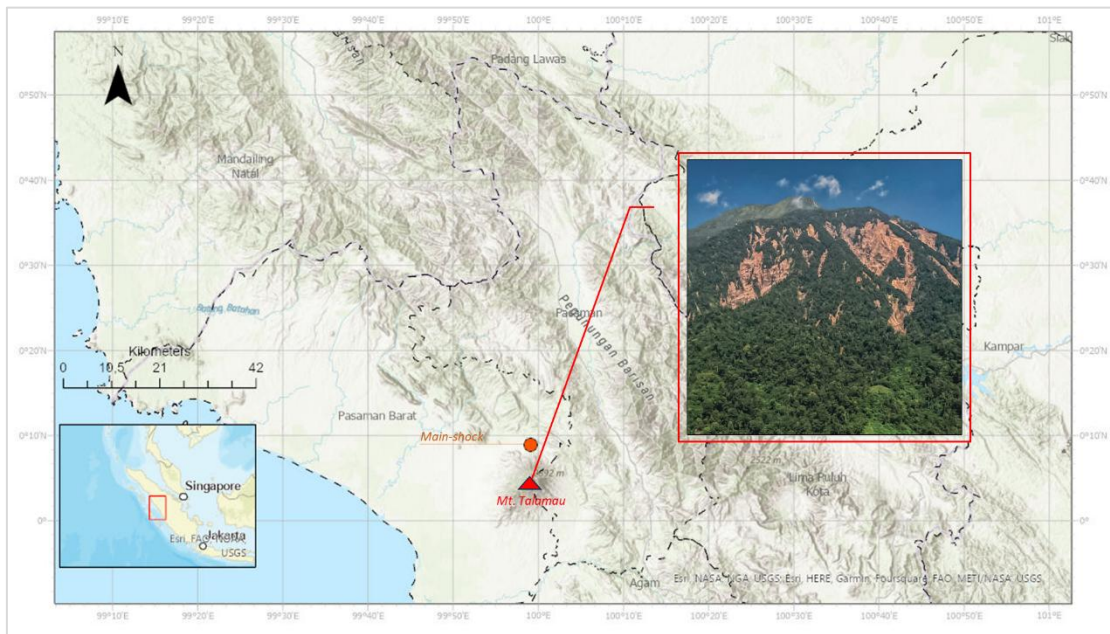


Fig. 3 Research location and Landslide at the Summit of Mount Talamau Following the 2022 Pasaman Earthquake

The formula represent the digital count values captured in the near-infrared and red spectral bands, respectively. Vegetation exhibits high reflectance in the near-infrared region and strong absorption in the red region due to chlorophyll activity, making this spectral contrast an effective proxy for plant vitality. Healthy vegetation, characterized by high chlorophyll content, absorbs more red light while reflecting a higher proportion of NIR, resulting in higher NDVI values. The NDVI scale is normalized between -1 and 1, where positive values indicate a greater NIR reflectance compared to red reflectance. For healthy vegetation, chlorophyll absorbs red light more effectively than NIR, leading to NDVI values approaching 1 [60], [61]. Conversely, when chlorophyll levels decline due to stress or aging, NDVI approaches 0, indicating reduced red light absorption [62]. NDVI is calculated using the equation above, where NIR and red reflectance values range from 0 to 100% [56]. In mountainous regions, landslides result in NDVI values approaching zero due to the complete loss of vegetation during these events (Fig. 3,8,and 10).

3. RESULT

3.1 Interferogram Phase Pattern

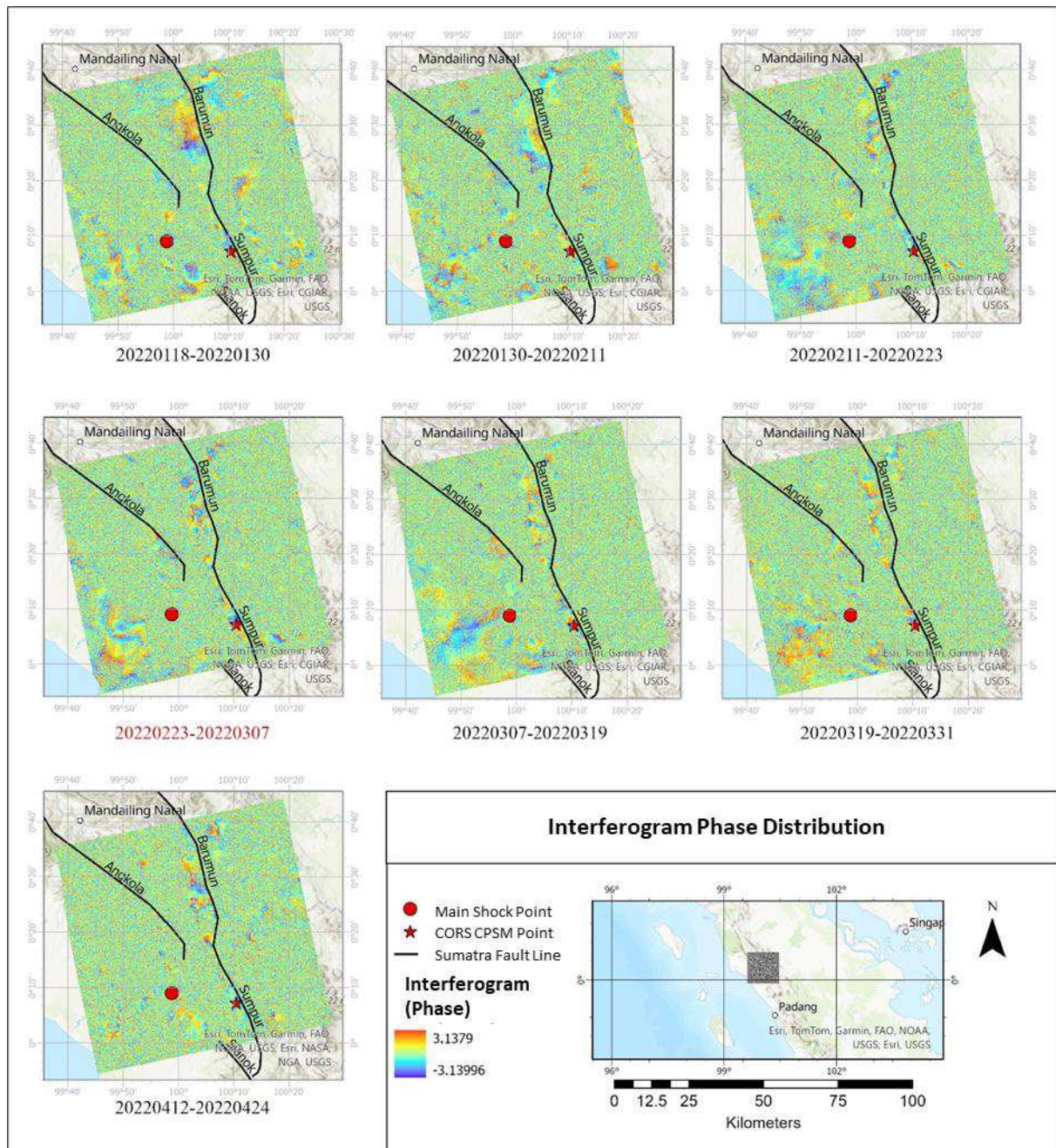


Fig. 4 the interferometric phase analysis conducted during the IO-DInSAR process

Phase data analysis yields phase difference values ranging from -3.112 to 3.117 radians. Regions experiencing deformation are characterized by repeating phase patterns forming fringes. These fringes represent variations in ground displacement between two satellite passes. Each interferometric phase cycle corresponds to a complete color spectrum transition, typically from purple to red. The displacement indicated by a single fringe cycle is equivalent to half the wavelength of the SAR instrument's operating band. To determine the total displacement, the number of fringes is counted and multiplied by the appropriate scale factor.

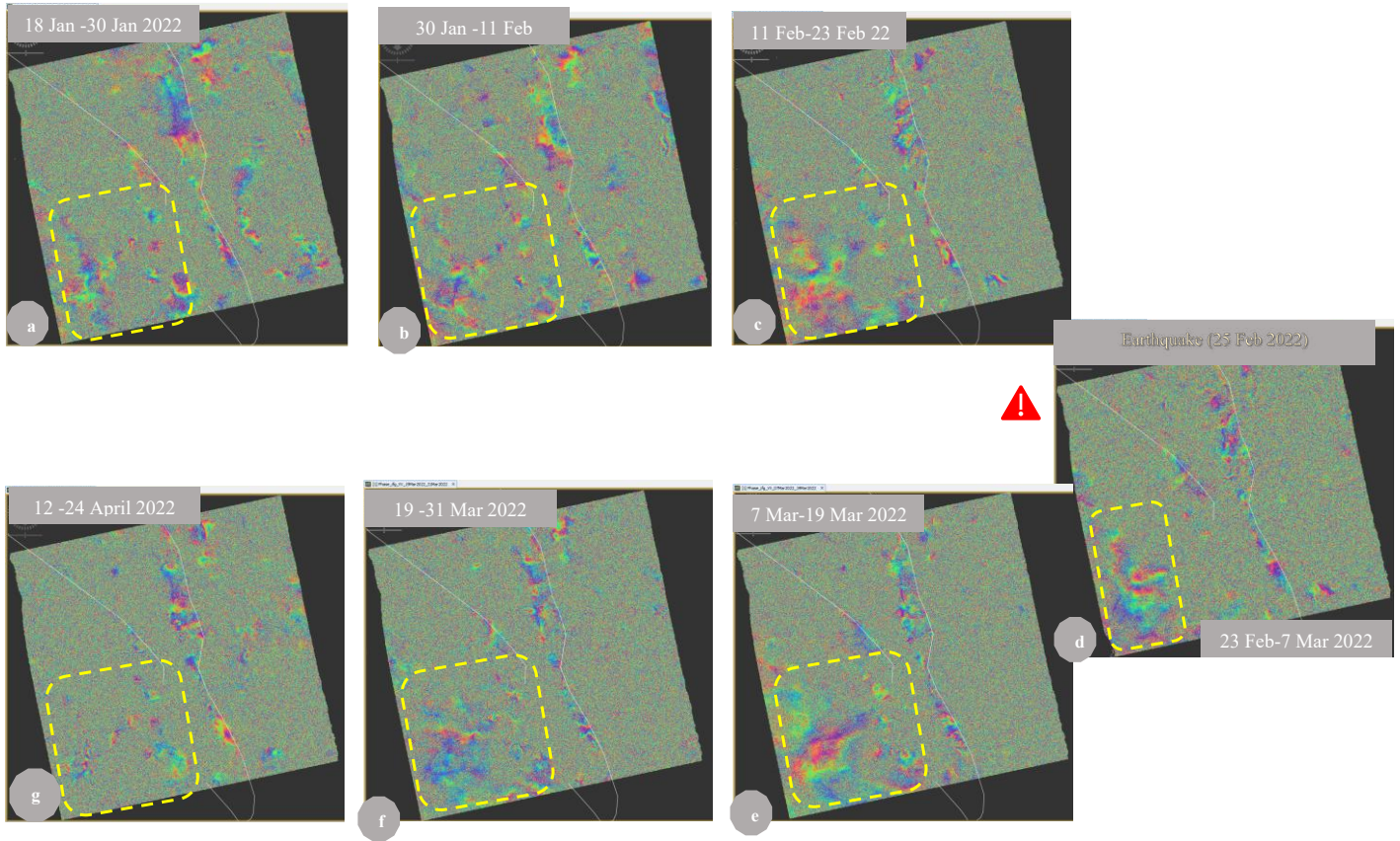


Fig. 5 Descriptive visual analysis (highlighted by the dashed yellow box) of the interferogram results as part of the IO-DInSAR process

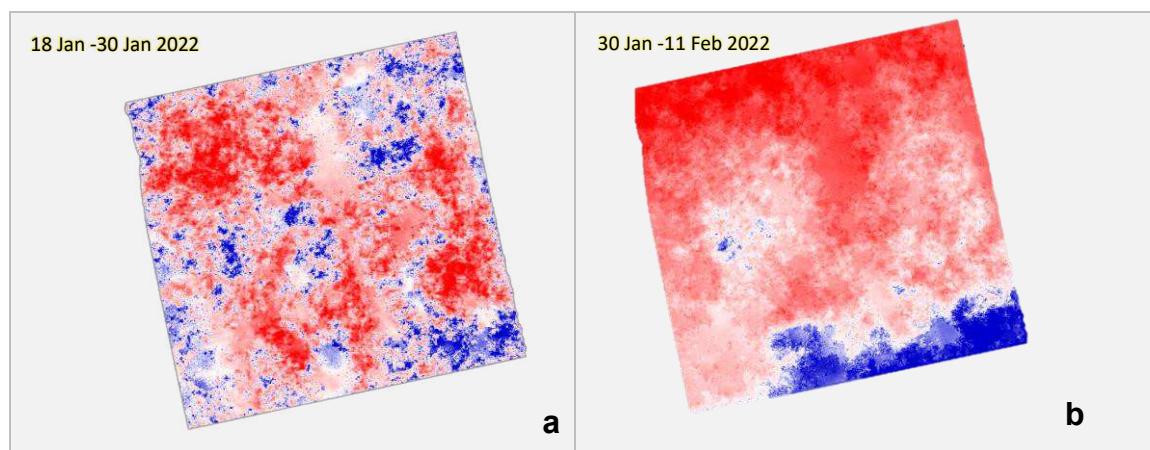
The yellow dashed box in Fig. 5 highlights an area exhibiting significant changes in phase distribution and pattern. In this context, the interferogram phase shifts according to the color spectrum: when fringes transition from red to purple, it indicates that the ground has moved closer to the satellite, resulting in a negative phase change, and vice versa. The upper section of Fig. 5 presents the phase evolution across seven observations in this study. The lower left region of the figure displays a fringe pattern with random, increasing, and significant intensity from Fig. 5a to 5c. This pattern then transitions into a wave-like fringe formation in Fig. 5d corresponding to the 2022 Pasaman earthquake period. The intensity then gradually diminishes until nearly disappearing in Fig. 5g. These observations suggest that earthquake intensity patterns do not form instantaneously at the moment of the earthquake but instead develop progressively as accumulated energy builds up. An earthquake serves as a mechanism for energy release, unlocking stored seismic stress over time.

The significance of phase fringe repetition in the area surrounding the Pasaman earthquake during the observation period from February 23, 2022 (master image) to March 7, 2022 (slave image) is analyzed to obtain information on the main shock event on February 25, 2022, this can be observed in Fig. 5d. Meanwhile, Fig. 4 presents the geographically mapped interferogram phase, allowing for a clear visualization of the spatial distribution and geographic location of the observed phase changes. Based on the distribution of the interferogram observed in the IO-DInSAR analysis

within the yellow box in Fig. 5, it is evident that the recorded deformation does not align with the fault line previously mapped by BMKG in 2017 (indicated by the white line in the Fig. 5). This may indicate the formation of a new fault or fracture in the area surrounding the yellow box, warranting further investigation. The consistent interferogram phase fringes along the Sumatra Fault Zone (white line) indicate surface instability in the region. Additionally, the growth of interferogram phase fringes at the future main-shock location was observed as early as three periods before the earthquake (January 2022). This growth continued significantly, reaching its peak during the earthquake period (20220223-20220307) before gradually decreasing until it nearly disappeared by the end of the observation period. This finding is highly significant, as it demonstrates that interferogram phase fringe patterns formed even before the earthquake occurred. This insight represents a breakthrough in the advancement of earthquake prediction methodologies.

3.2 Displacement Distribution Pattern

The deformation caused by the earthquake is measured in absolute values with meters as the unit, allowing for an analysis of displacement magnitude. This displacement can occur both vertically and horizontally, however, this study focuses on vertical displacement to assess the vertical deformation resulting from the earthquake within the study area. The research employs DInSAR observations over seven monitoring periods, yielding seven displacement events along the Line of Sight (LOS), which are subsequently corrected to obtain the true vertical displacement. LOS measurements are subject to errors due to the satellite's observation angle relative to the target, leading to the formation of an incidence angle. The distribution and pattern of vertical deformation in the study area remain fluctuating, indicating high tectonic activity. The deformation pattern and distribution can be observed in Fig. 6.



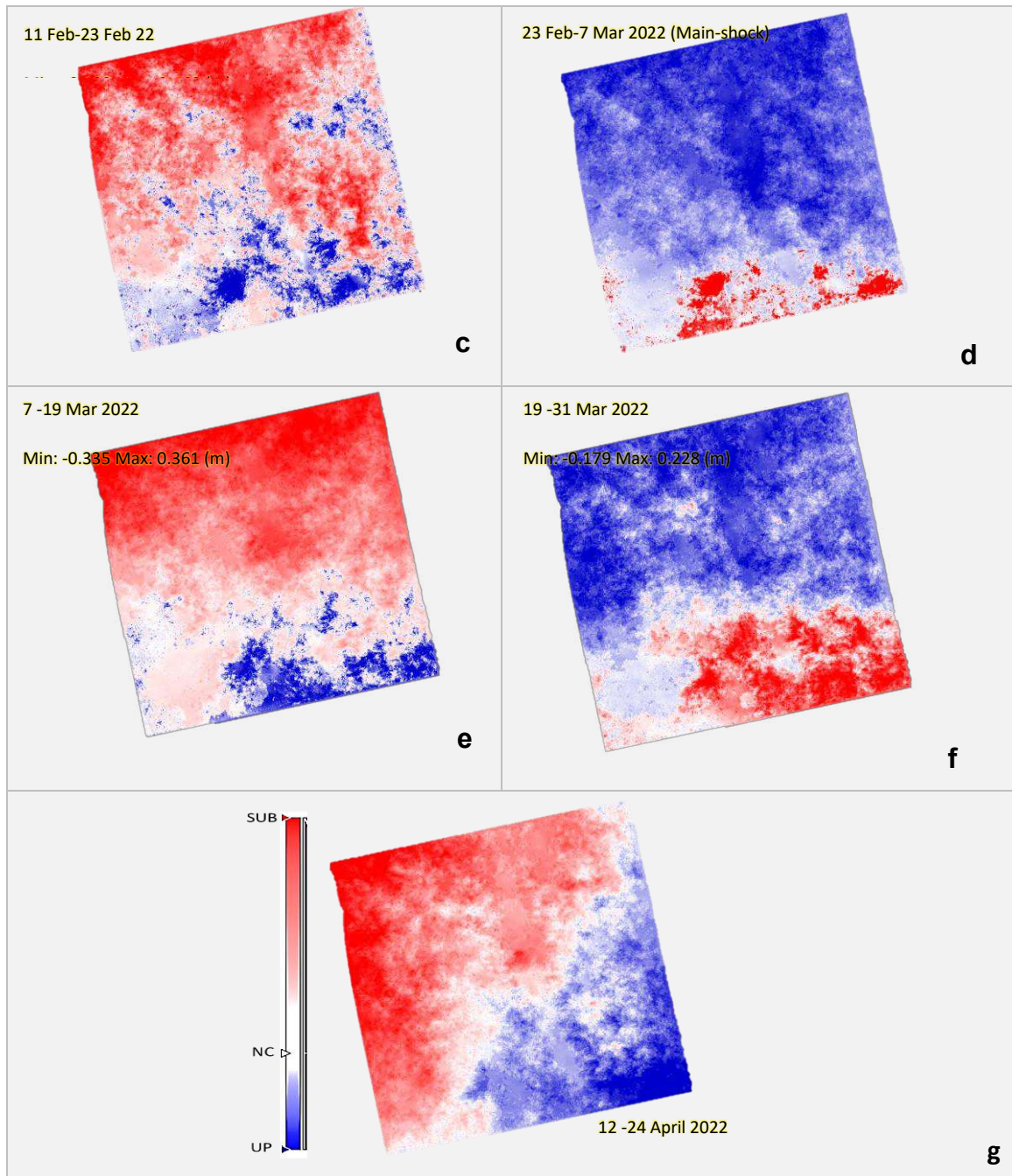


Fig. 6 Spatiotemporal model of true-vertical displacement derived from iterative observation DInSAR (IO-DInSAR) across seven observation periods in the Pasaman study area, expressed in meters. Blue tones represent apparent uplift, whereas red tones indicate apparent subsidence. The displacement patterns exhibit considerable spatial and temporal variability, characterized by alternating uplift and subsidence signals across successive observation periods.

Fig. 6 presents the displacement values (in meters), which highlight the instability within the study area, characterized by periodic and irregular vertical ground movements. The color red indicates vertical subsidence (SUB), white denotes areas with no significant change (NC), and blue represents vertical uplift (UP). The most significant range of vertical displacement (Δ displacement)

404 is observed at point E in Fig. 6, spanning from -0.335 m (subsidence) to +0.361 m (uplift), indicating
 405 localized deformation dynamics potentially linked to subsurface geological processes.

406 The significance of the difference between the line-of-sight (LOS) and true vertical
 407 displacement measurements at the CORS observation point with ID CPSM, located at coordinates
 408 100° 10' 25.71937" E, 00° 07' 12.45185" N in Pasaman Regency, Lubuk Sikaping District, over the
 409 observation period from January 1, 2022, to April 30, 2022 (seven satellite observation periods), is
 410 presented in Table 1. The observed discrepancy ranges from 0.1 mm to 0.9 mm, which is statistically
 411 significant for mathematical displacement measurements.

412 *Table 1. Correlation between true vertical displacement and CORS data from the Geospatial*
 413 *Information Agency for validation purposes*

Period	Activity	CORS Data (m)	Delta CORS (a-b)	Satellite True Vertical (m)
20220118	Pra 3 (a)	451.6456	0.01327	-0.027232
20220130	Pra 3 (b)	451.6323		
20220130	Pra 2 (a)	451.6323	-0.00603	-0.037672
20220211	Pra 2 (b)	451.6384		
20220211	Pra 1 (a)	451.6384	0.00447	0.006719
20220223	Pra 1 (b)	451.6339		
20220223	Eq 1 (a)	451.6339	0.00367	0.039016
20220307	Eq 1 (b)	451.6302		
20220307	Pas 1 (a)	451.6302	-0.01532	-0.035287
20220319	Pas 1 (b)	451.6455		
20220319	Pas 2 (a)	451.6455	0.00994	0.008445
20220331	Pas 2 (b)	451.6356		
20220412	Pas 3 (a)	451.6448	-0.00935	0.072473
20220424	Pas 3 (b)	451.6541		
RMSE = 0.009760212			Very Strong	

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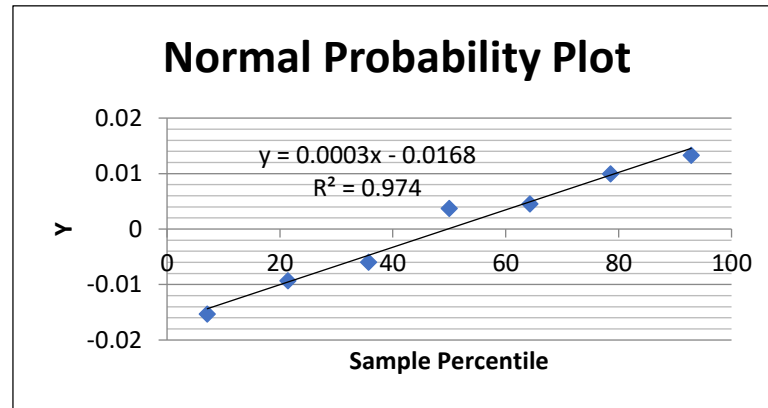


Fig. 7 Normal Probability Plot based on Table 1

The validation analysis of SAR displacement from S1A satellite data against CORS observation data provided by the Geospatial Information Agency demonstrates strong agreement. The RMSE value of 0.009760212 falls within the "very strong" category. A normal probability plot was utilized to evaluate the distribution of residuals between the measured true vertical displacements and the validation data obtained from CORS (Continuously Operating Reference Stations). The results demonstrated a strong linear relationship, with a coefficient of determination (R^2) of 0.974 and a fitted regression equation of $y=0.0003x-0.0168$, indicating minimal deviation between the two datasets. The alignment of data points along the fitted line suggests that the residuals are approximately normally distributed, fulfilling an important assumption for subsequent statistical evaluations. Furthermore, the Root Mean Square Error (RMSE) value of 0.00976 confirms the low magnitude of residuals, reinforcing the high precision and accuracy of the displacement measurements. Collectively, these findings validate the robustness and reliability of the proposed method for monitoring vertical ground movements with high statistical confidence.

3.3 Coherent Change Detetction

The InSAR processing generates an Interferogram Phase, which also includes coherence data. This data ranges from 0 to 1, where values closer to 1 indicate a high degree of similarity between the processed SAR image pair, while values approaching 0 signify a lack of similarity. In other words, significant differences between the master and slave images are interpreted as zero coherence by Coherence Change Detection (CCD) analysis. Fig. 8 presents the CCD observations over seven satellite observation periods, illustrating the temporal variations in coherence values.

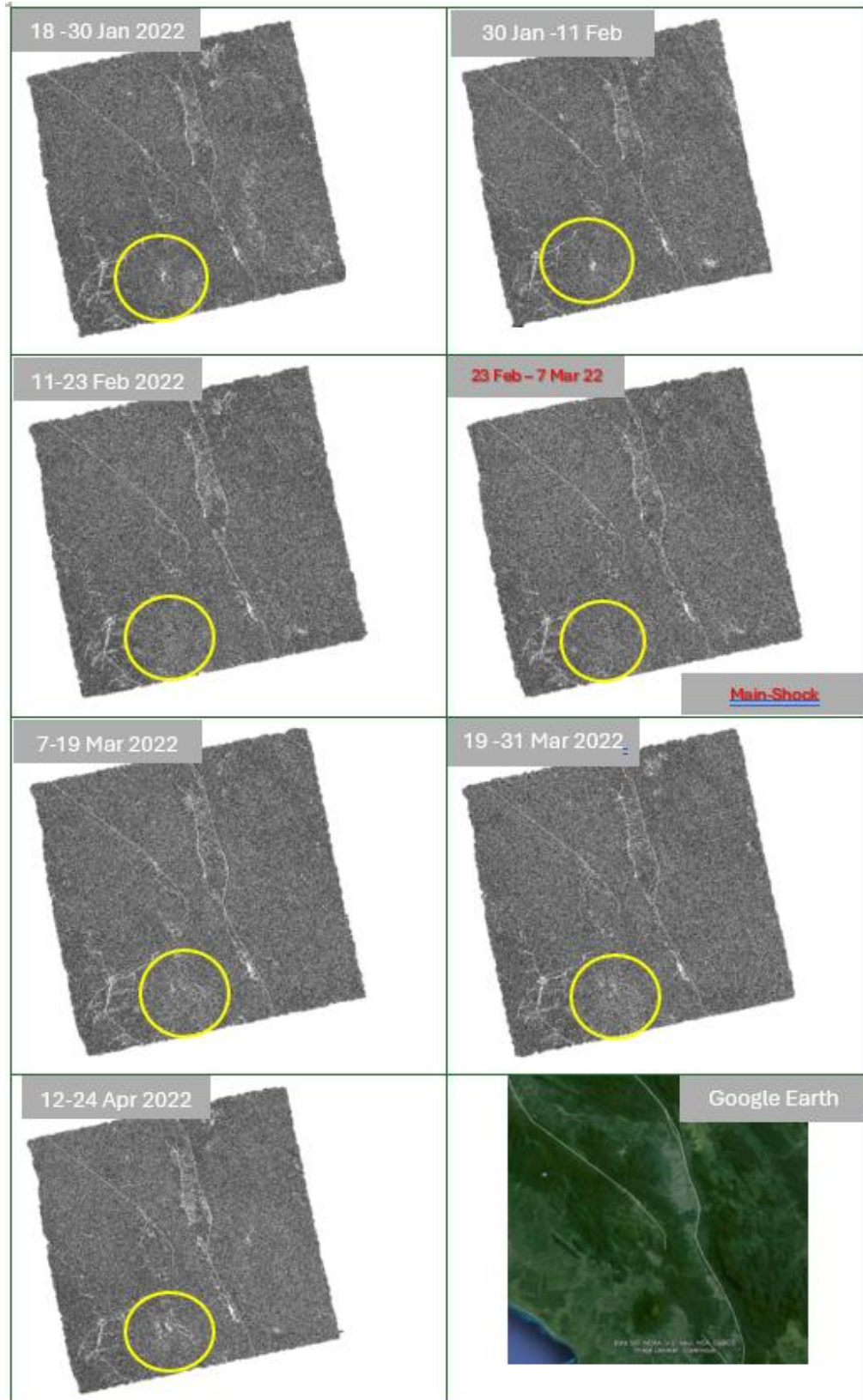


Fig. 8 Temporal evolution of SAR coherence during the seven observation periods. The landslide area exhibits low coherence immediately following the mainshock due to rapid surface disturbance. In the subsequent post-seismic interferometric pairs, the landslide scar progressively

regains coherence, forming a distinguishable landslide pattern as the newly exposed surface becomes relatively stable

Fig. 8 illustrates that post-earthquake landslides began forming during the first post-earthquake phase (March 7 – April 19, 2022). Notably, during the earthquake period (February 23 – March 7, 2022), no coherence values near 1 were recorded. This is because, on February 23, 2022, landslides caused by the earthquake had not yet occurred, whereas by March 7, they had already taken place. As a result, no similar topographic conditions existed between the master and slave images to generate high coherence values. The yellow-circled area in Fig. 8 highlights the continuous expansion of landslides in the post-earthquake period. The ground shaking from the earthquake destabilized soil masses, which, when combined with high rainfall in the study area, exacerbated the situation. The landslide continued expanding until all unstable soil had completely collapsed. Once no further collapses occurred, vegetation began to regrow and cover the affected area. Fig. 8 further presents the landslide conditions during the second post-earthquake phase (March 19 – March 31, 2022), demonstrating the progressive development of the affected region.



Fig. 9 On-site documentation of damage caused by the 2022 Pasaman earthquake

3.4 Multi-Analysis due to Seismic Activity

The occurrence of the earthquake in an area traversed by active fault lines, followed by landslides on Mount Talamau and structural damage to residential buildings and public facilities (Fig.

9) located outside the previously mapped fault zone, necessitated a multi-parameter analytical approach. Based on Fig. 10, significant landslide activity is observable at the summit of Mount Talamau, as indicated by the fringe patterns in the interferometric phase data, the coherence loss, and vegetation cover reduction seen in the NDVI imagery, all of which suggest deforestation due to landslide events.

During the Pasaman earthquake disaster on February 25, 2022, a destructive event known locally as a “galodo” occurred—an avalanche of landslide material mixed with river water struck residential areas near Mount Talamau (Fig. 3). The post-earthquake landslides were extensive, as illustrated in the 1:130,000 scale map in Fig. 10, showing both the areal extent and distribution. NDVI analysis was used to enhance the interpretation of landslide events, revealing that the lowest NDVI values correspond to landslide-affected areas due to the absence of healthy vegetation and the spectral reflectance of debris. These findings support the conclusion that landslides were a secondary hazard triggered by the earthquake.

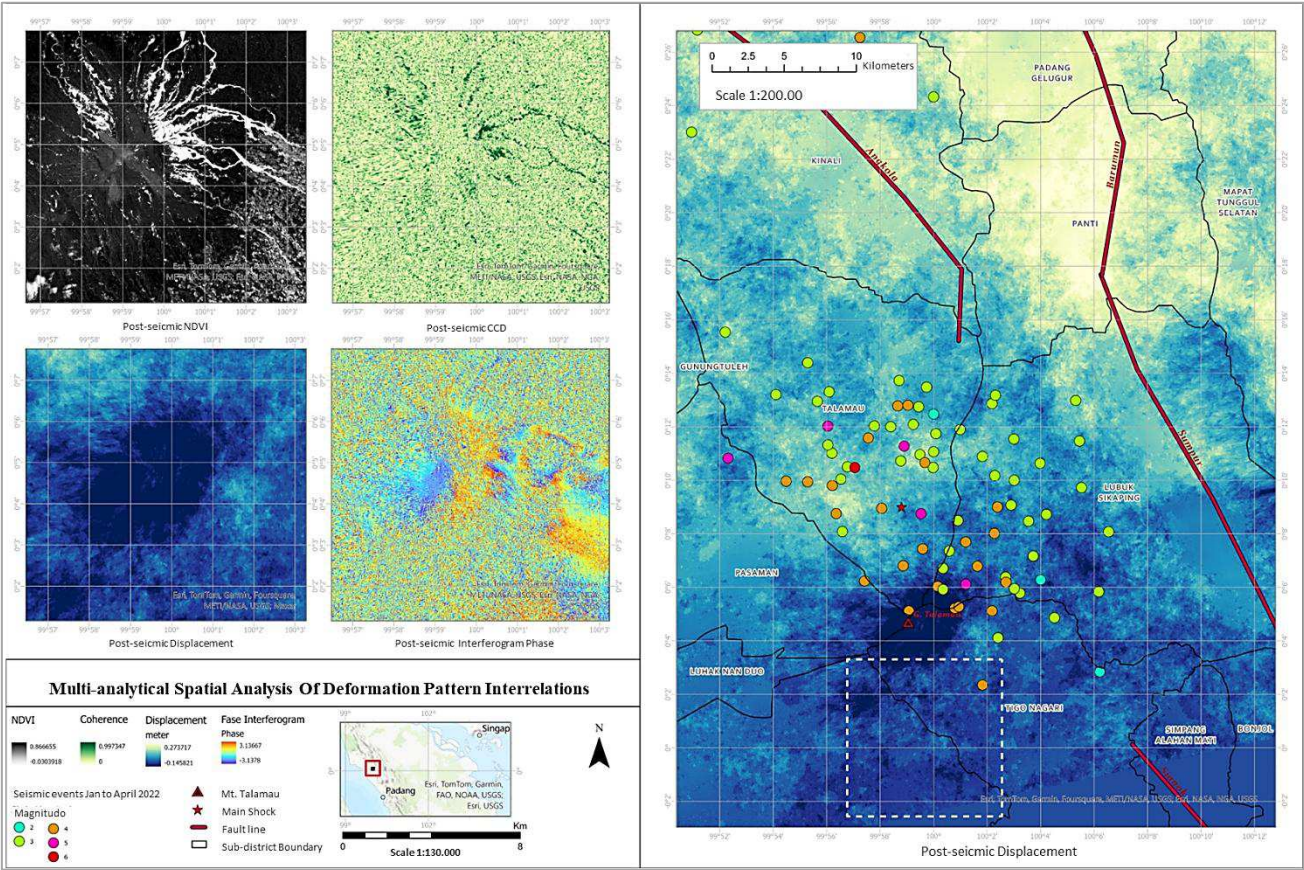


Fig. 10 Multi-analytical assessment of earthquake-induced landslides in the 2022 Pasaman event

A comprehensive multi-parameter analysis was also conducted for the landslide zone, as illustrated in Fig. 10 NDVI, true vertical displacement, coherence, phase interferograms, and Digital Elevation Models (DEM) were integrated to identify the affected areas. Additionally, slope-derived data from the DEM were used to estimate potential landslide velocities. Low NDVI values delineated landslide patterns, extents, and distribution. High coherence loss was effective in indicating landslide

locations and their spatial coverage. Displacement maps revealed vertical ground movement associated with slope failure. Phase fringe patterns further supported the detection of vertical displacement in the landslide-affected zones. DEM analysis confirmed that landslide events predominantly occurred in areas of high elevation and steep slope gradients.

The integration of NDVI and post-landslide coherence products reveals a linear relationship useful for analyzing landslide hazard distribution. In the event of a landslide, vegetation is typically removed, resulting in a near-zero NDVI value due to minimal or absent vegetation reflectance. Concurrently, coherence values tend to approach 1, indicating a high degree of similarity between the master and slave SAR images, characteristic of surface changes such as landslides. This demonstrates an inverse relationship between NDVI and coherence: as NDVI decreases, coherence increases, and vice versa. These observations suggest that combining passive (NDVI) and active (SAR coherence) remote sensing data provides a robust and complementary approach for detecting and mapping landslide events.

Furthermore, an Inverse Distance Weighting (IDW) interpolation was applied to earthquake epicenter data, interpolating low to high magnitude values based on shallow crustal earthquake depths ranging from 1 to 20 km. This interpolation aimed to estimate values at unsampled locations using surrounding seismic data. As shown in Fig. 11, the IDW interpolation revealed that earthquake activity from January to April 2022 was highly concentrated in the Mount Talamau region and its vicinity.

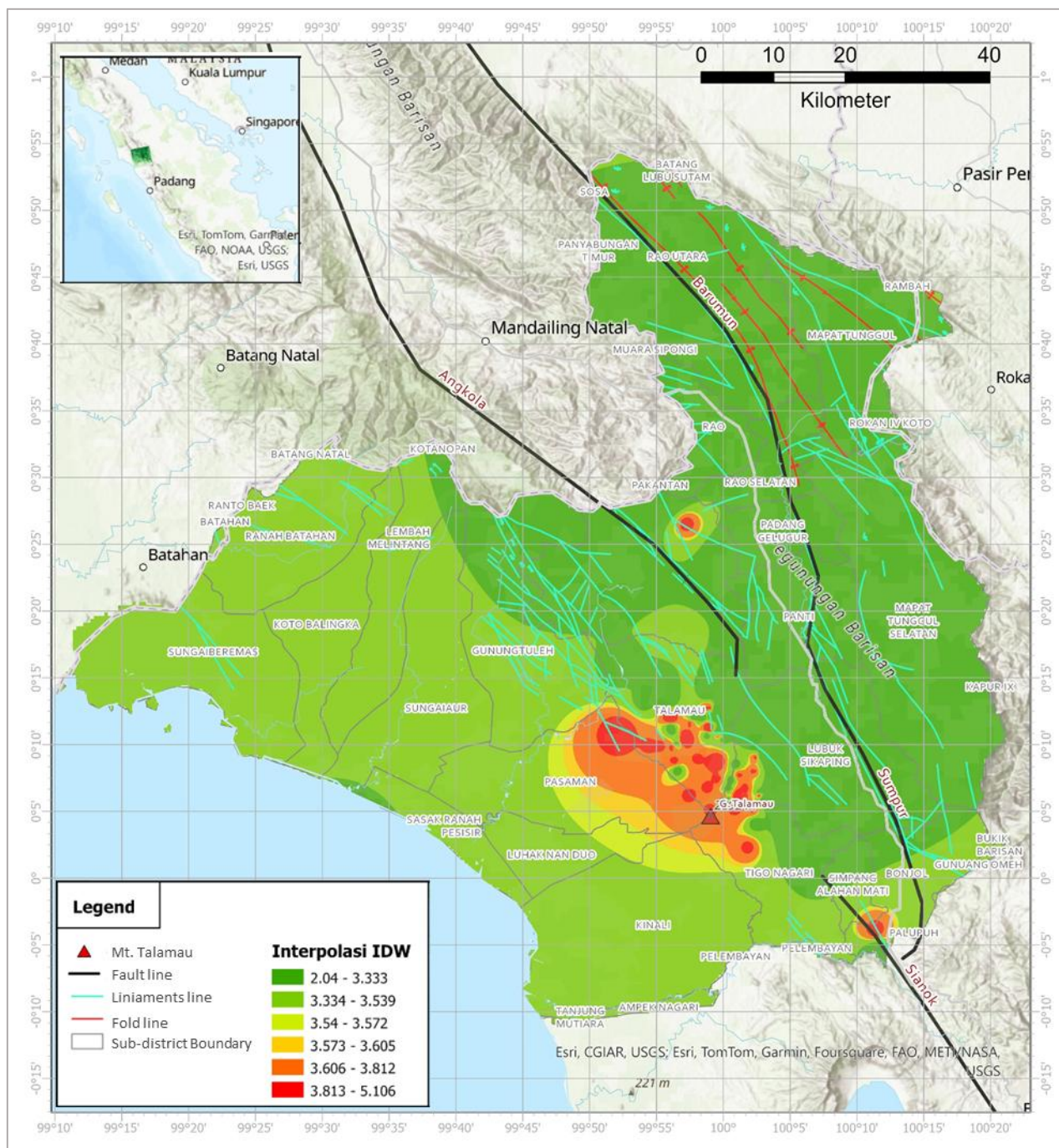
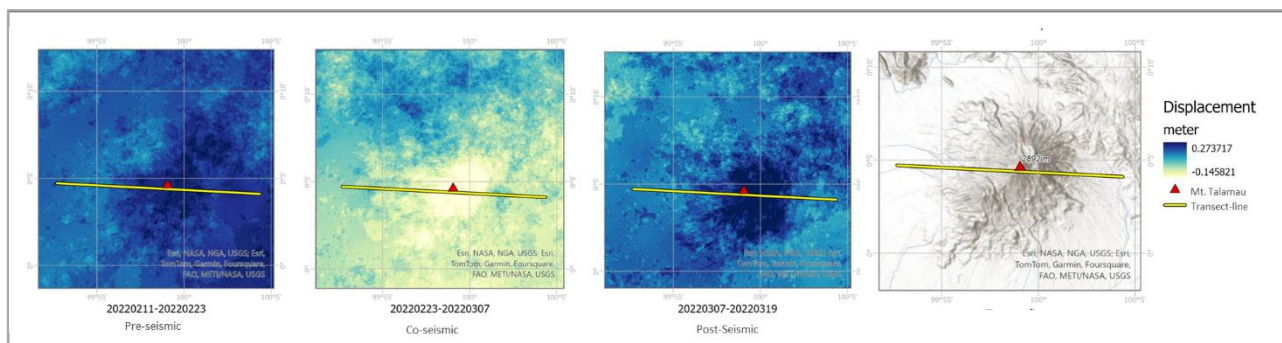


Fig. 11 Inverse Distance Weighting (IDW) interpolation applied to the 2022 Pasaman earthquake region

Displacement data obtained from IO-DInSAR observations were further analyzed through a cross-sectional approach along a defined transect encompassing the summit and surrounding areas of Mount Talamau. This method facilitated the assessment of both the magnitude and spatial pattern of vertical ground deformation by examining displacement time-series profiles across three key periods: the pre-seismic phase (11–23 February 2022), the co-seismic phase (23 February–7 March 2022), and the post-seismic phase (7–19 March 2022) of the 2022 Pasaman earthquake. As

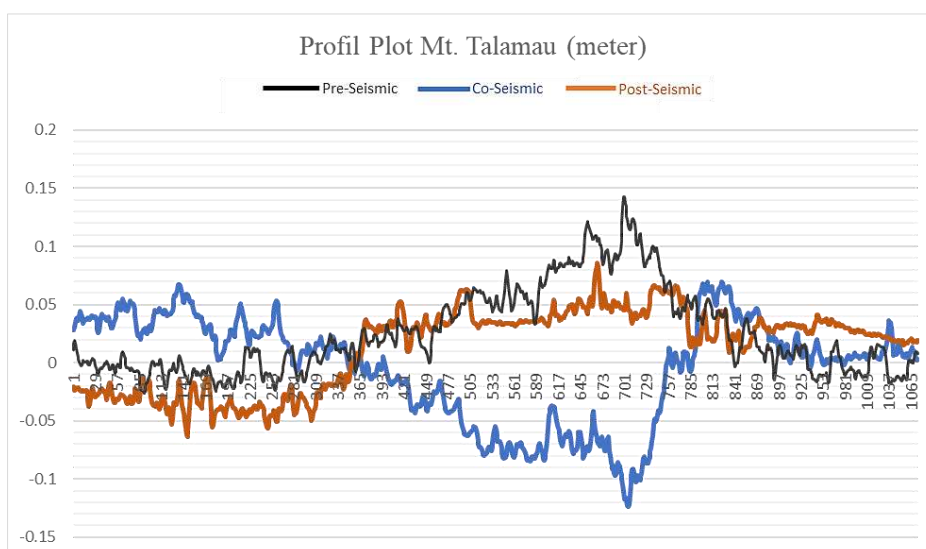
507 depicted in Fig. 12, the transect line was applied consistently across the three temporal datasets,
 508 revealing distinct variations in vertical deformation that are clearly observable when comparing the
 509 spatial profiles over time.



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Fig. 12 Cross-section along the transect line derived from IO-DInSAR displacement data



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Fig. 13 Graphical representation of the cross-section results from Fig. 11. The x-axis indicates vertical displacement in meters, while the y-axis represents pixel positions along the transect line

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The profile plots of each time-series transect line are presented in Fig. 13, illustrating the occurrence of vertical displacement resulting from the 2022 Pasaman earthquake. A notable deformation is observed across the summit region of Mount Talamau, particularly between pixels 361 and 781, where both subsidence and uplift were detected. In accordance with the landslide analysis methodology, an estimation of debris flow velocity can be derived. Assuming the landslide travels along a straight path on a slope with an inclination angle of α , the simplified calculation of debris mass velocity follows the approach proposed by Masuya (2008), as referenced in Equation 9.

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The physical landslide equation (Equation 11) was subsequently implemented using the Band Math function within the SNAP software environment, and interpreted as follows:

$$v(x) = \text{pow}((2 \times 9.78 \times \text{elevation}_{VV}), 0.5)$$

Equation 11.

The calculated landslide velocity $v(x)$ is influenced by the elevation_{VV} variable, which represents elevation data derived from a DEM constructed using S1A imagery. Additionally, the gravitational acceleration specific to the equatorial region, measured at 9.78 m/s^2 (Meena, 2019), was incorporated into the velocity model. As shown in Fig. 14, the resulting landslide velocity values across the study area range from 0.009 m/s to 237.505 m/s . The velocity distribution model presented in Fig. 14 indicates that the highest velocities depicted in black are concentrated at higher elevations, particularly around the summit of Mount Talamau and the peak of the Bukit Barisan range to the east of Lubuk Sikaping District. These results suggest that the extensive post-seismic landsliding observed at the summit of Mount Talamau was primarily driven by a loss of soil cohesion triggered by the earthquake, particularly in areas characterized by steep and elevated terrain.

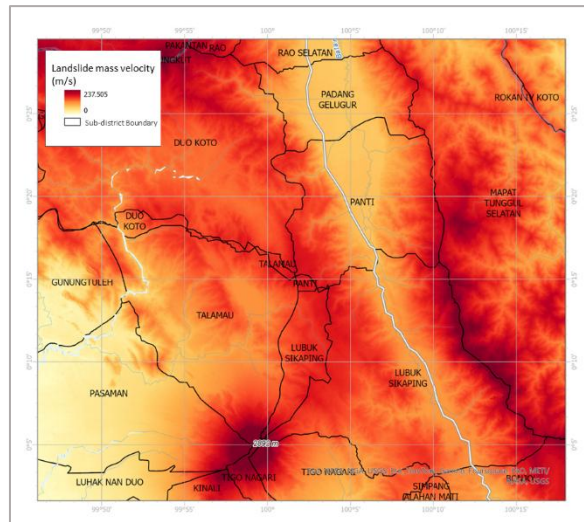


Fig. 14 Predicted Landslide Velocity Potential Map Triggered by the 2022 Pasaman Earthquake

Monthly CHIRPS rainfall data for the observation period from January to April 2022 (Fig. 15) indicate that the Mount Talamau region experienced lower accumulated rainfall in February 2022 coinciding with the timing of the Pasaman earthquake compared to surrounding areas. However, a significant increase in rainfall accumulation was observed in April 2022, which may have intensified erosion processes following the landslide events. The earthquake likely weakened soil cohesion, making the landscape more susceptible to slope failures. The dominant soil type in the Mount Talamau area is Andosol, which is naturally loose and friable. Combined with the region's steep and elevated topography, these factors significantly exacerbate the likelihood and severity of post-seismic landslides.

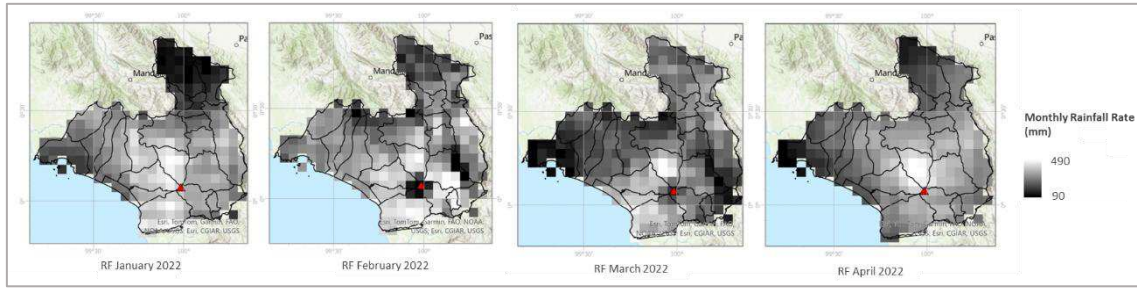


Fig. 15 CHIRPS Monthly Rainfall Data from January to April 2022 in the Study Area

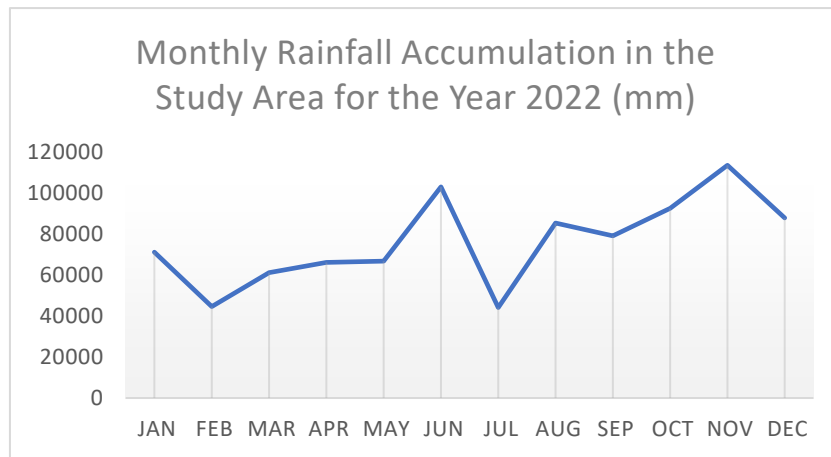


Fig. 16 Monthly Rainfall Graph Based on CHIRPS Data

As illustrated in Fig. 15 and Fig. 16, rainfall during February 2022 was observed to be lower than in other observation periods, ranging between 90 and 281 mm. Spatially, the area surrounding Mount Talamau marked by a red triangle recorded the lowest rainfall within the region. The significant increase in precipitation observed in April 2022 is likely a contributing factor to the expansion of landslide-affected areas during that month, which in turn influenced the spatial distribution of Coherence Change Detection (CCD) results. Therefore, seismic activity associated with the earthquake is identified as the primary triggering factor for landslides in the affected region.

4. DISCUSSION

A case study from research by Xiao, Z. (2022) about the case of landslides triggered by earthquake. On September 5, 2022, a magnitude 6.8 earthquake occurred in Luding County, Ganzi Tibetan Autonomous Prefecture, Sichuan, China. The death toll and economic losses from the earthquake were enormous. Most of the landslides triggered by this earthquake were small to medium-sized rockfalls and destructive debris flows, with a small number of large-scale landslides. In other events, nearly 200,000 landslides were induced by the Wenchuan earthquake in 2008, with a total area of 1160 km². Coseismic landslides cause more than 20,000 deaths, about a quarter of the total. In 2013, the Ms7.0 Lushan earthquake triggered more than 1,000 landslides, which caused many roads in mountainous areas to be completely blocked, and seriously affected people's transportation [63], [64], [65], [66]. The Ms6.5 Ludian earthquake in 2014 not only caused major

landslides such as Ganjiazhai, Wangjiapo, and Hongshiyan but also caused a sharp increase in geological hazard potential [67]. The geological environment is also one of the important factors influencing the development of coseismic landslides. In a study by Xiao, Z et al. (2022) lithology, distance from active faults, vegetation cover, and land use type were selected as geological factors in the analysis of the characteristics of coseismic slide development. The seismic factor is a reflection of the triggering factors and landslide initiation mechanisms, while the topographical factor is a manifestation of a disaster-prone environment. In his research, elevation, slope, and aspect were selected as representative topographical factors to analyze the influence of topographical characteristics on the distribution of coseismic slides. Similarly, as discussed in detail in the Results section, the 2022 Pasaman earthquake was followed by coseismic landslides occurring in regions with comparable geological characteristics. This observation indicates that geological landslides can be triggered by seismic activity, particularly in areas with mountainous or hilly topography, highlighting the critical role of terrain and lithological conditions in the manifestation of earthquake-induced slope failures.

This study employing the IO-DInSAR technique approach represents a novel contribution to the understanding, analysis, and the potential of earthquakes prediction and their secondary hazards. Previous studies have not explored the development of pattern-based models for earthquake prediction efforts. DInSAR utilizes microwave sensors capable of achieving centimeter-level measurement precision [39]. Displacement and coherence results are subsequently analyzed to determine the magnitude of the incoherent delta; areas with the highest incoherence are suspected to correspond to landslide events. Once the distribution pattern is identified, these analyses can be spatially mapped. Accordingly, the IO-DInSAR method proves to be effective for this type of case. Further research is required, particularly in the area of descriptive visual analysis, to enhance the potential for earthquake prediction by providing absolute quantitative values.

A recent study indicates that the Mw 6.1 Pasaman earthquake in 2022 resulted from slip along the newly identified 20 km long dextral strike-slip Kajai Fault, which has been recognized as a segment of the broader Great Sumatran Fault system. Notably, adjacent segments of the Great Sumatran Fault specifically the Angkola and Sumpur sections underwent a substantial increase in stress without producing any associated aftershocks. This stress accumulation may elevate the likelihood of future rupture along these fault segments [68], consistent with the IDW interpolation analysis presented in this study (Fig. 11). However, this study has not yet accounted for the pulsation activity of Mount Talamau, which we have interpreted in Fig. 13 and 14. The true vertical displacement analysis using IO-DInSAR reveals vertical deformation along the cross-section of Mount Talamau before, during, and after the earthquake. Therefore, further research is warranted to investigate the potential relationship between the formation of new fractures and possible volcanic activity associated with Mount Talamau.

6. CONCLUSION

There is a correlation between surface deformation patterns observed using the DInSAR method and the occurrence of landslides, land cover characteristics, and nearby fault segments

during the 2022 Pasaman earthquake event. Surface deformation can be identified through the distribution of interferogram fringe phases, coherence patterns, and the magnitude of absolute true vertical displacement. A secondary disaster triggered by the 2022 Pasaman earthquake was the occurrence of widespread landslides on Mount Talamau. There is a notable correlation indicating that the Mount Talamau area, located near the mainshock epicenter and serving as the focal point for the distribution of 92 earthquakes over a four-month observation period, experienced significant vertical displacement.

The displacement pattern is accompanied by high coherence values aligned with interferometric fringe patterns and low NDVI values, enabling the delineation of landslide patterns, extent, and spatial distribution. Furthermore, the landslide-prone areas are characterized by loose Andosol soil types and steep elevations, both of which contribute significantly to landslide susceptibility. However, the landslides on Mount Talamau triggered by the 2022 Pasaman Earthquake were solely attributed to seismic activity, with no contribution from rainfall, as February 2022 was recorded as the driest month of the year based on climatological data. In general, the spatiotemporal distribution of true vertical displacement in the study area indicates vertical surface deformation resulting from the 2022 Pasaman Earthquake. The magnitude of displacement varied over seven observation periods, ranging from -0.181 cm to 0.365 cm. Surface instability in the study area is further supported by observational data from Indonesia's Geospatial Information Agency (BIG) through the CORS station with ID CPSM. The accuracy of the true vertical displacement data was validated against this CORS dataset, yielding a Root Mean Square Error (RMSE) of 0.0097, R^2 value from the normal distribution plot was 0.974, with a regression line equation of $y = 0.0003x - 0.0168$, indicating high data reliability. This study identified a patterned distribution of interferometric fringes that progressively intensified prior to the earthquake (January 2022), became dense and widespread during the seismic event (February 2022), then gradually declined (March 2022), and ultimately disappeared after the earthquake (by late April 2022). These findings highlight the utility of iterative DInSAR analysis for enhancing our understanding of cascading seismic hazards and inform early warning strategies in tectonically active regions. However, further systematic investigation is warranted to refine the methodology and validate its applicability across diverse geological settings.

7. ACKNOWLEDGMENT

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Author Contributions

All authors contributed substantially to the conception, development, and finalization of this manuscript, and have read and approved the final version.

Demi Stevany led the study by formulating the research design, conducting data collection and analysis, and preparing the initial draft of the manuscript.

Masita Dwi Mandini Manessa contributed to the research design, participated in data analysis and manuscript drafting, and was primarily responsible for critical revision, refinement, and final approval of the manuscript.

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