

Article

Characterization and Geomorphic Change Detection of Landslides Using UAV Multi-Temporal Imagery in the Himalayas, Pakistan

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Abstract: Multi-temporal unmanned aerial vehicle (UAV) imagery and topographic data were used to characterize and evaluate the geomorphic changes of two active landslides (Nara and Nokot) in Pakistan. Ortho-mosaic images and field-based investigations were utilized to assess the geomorphological changes, including the Topographic Wetness Index, slope, and displacement. Volumetric changes in specific areas of the landslides were measured using the Geomorphic Change Detection (GCD) tool. The depletion zone of the Nara landslide was characterized by failures of the main scarps, resulting in landslides causing erosional displacements exceeding 201.6 m. In contrast, for the Nokot landslide, the erosional displacement ranged from −201.05 m to −64.98 m. The transition zone of the slide experienced many slow earth flows that re-mobilized displaced material from the middle portion of the landslide, ultimately reaching the accumulation zone. Volumetric analysis of the Nara landslide indicated overall erosion of landslide material with a volume of approximately 4,565,274.96 m³, while the accumulated and surface-raising material volume was approximately 185,544.53 m³. Similarly, for the Nokot landslide, the overall erosion of landslide material was estimated to be 6,486,121.30 m³, with an accumulated volume and surface-raising material of 117.98 m³. This study has demonstrated the efficacy of the GCD tool as a robust and repeatable method for mapping and monitoring landslide dynamics with UAVs over a relatively long time series.

Keywords: unmanned aerial vehicle (UAV); GCD; surface movement; point cloud; orthomosaic; DSM; landslide



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1. Introduction

Landslides with increasing frequency and impact have caused significant economic losses and human fatalities in mountainous regions [1]. Physical and environmental settings largely influence their spatial distribution and intensity, and they are widely triggered by earthquakes and precipitation [2]. Anthropogenic activities, including road cutting, excavation, and mining, contribute to slope destabilization and landslides [3,4]. For the characterization, displacement monitoring, volume estimation, and hazard assessment of landslides, unmanned aerial vehicles (UAVs) that derive very high-resolution (VHR) images and topographic data with their intrinsic capabilities and control have gained momentum

in the recent past [5]. UAV-based landslide monitoring is instrumental in understanding the triggering mechanism, early warning, risk assessment, and management.

Landslides are monitored by assessing their extent, displacement rate, surface topography, and fissure structures. Measuring vertical and horizontal displacements assists in understanding the triggering mechanism of landslides. Three-dimensional (3D) data, such as digital surface models (DSMs), enable the evaluation of surface displacement in space and time domains. Since the early 2000s, technological advances in the availability of a range of topographic data with varying resolutions have transformed DSM data collection, analysis, and applications. Key technologies used include differential GPS, robotic total stations, airborne LiDAR, and terrestrial laser scanners. However, ground surveys are time consuming and have limited spatial coverage, leaving out fine-scale terrain structures. TLS has line-of-sight limitations, while airborne LiDAR is generally too expensive for individual research. Landslide studies at a regional scale focusing on landslide inventory, monitoring, hazard, and risk assessment have effectively utilized a range of space-borne remote sensing platforms, i.e., MODIS [6], Landsat [7,8], Worldview [9], ASTER [10], SPOT [11], and Sentinel [12]. However, their coarse spatial resolution, extended temporal resolution, and dependency on weather conditions limit their application for monitoring and characterizing a specific landslide [13,14]. Fine-resolution remote sensing data, including IKONOS, Digital Globe, Quickbird, and Pleiades, are effective for local-scale mapping. However, their limited coverage and high costs limit their application for regional-scale landslide mapping and monitoring.

In contrast to spaceborne and airborne remote sensing, UAVs, with their expanding capabilities, provide a wide range of effective applications for landslide mapping and monitoring [5]. UAVs are effective remote sensing platforms capable of producing high-resolution aerial photographs [15]. UAV-derived VHR ortho-mosaic and topographic data are frequently and effectively utilized for the detailed displacement of landslides and monitoring through the analysis of multi-temporal topographic data [16]. To evaluate ground displacement, a variety of tools, i.e., COSI Corr [17], Mic Mac [18], and the differential DSM method [19], have widely been used on satellite images. Geomorphic change detection (GCD) provides a topographic data analysis tool to monitor and measure surface changes using multi-temporal topographic data [20,21]. By generating spatially explicit metrics, including elevation change rates, sediment budgets, and morphological indices, it is effective in identifying and quantifying geomorphic processes, such as erosion, deposition, channel migration, and landform evolution [22–24].

Balakot, located in the Himalayan Mountains of Pakistan, has a rugged topography, fragile geology, active tectonics, and climatic conditions and is exposed to a high density of landslides. Climate change-induced erratic rainfall patterns, increasing temperatures in the area, and human intervention, including deforestation, excavation, and land use changes, have increased the frequency of landslides and pose a significant risk to the communities and infrastructure [25]. A comprehensive understanding of the underlying slope failure mechanism is required to characterize large-scale landslide deformation and potential triggers [4]. Besides the region being highly susceptible to landslide hazards, existing studies have focused mainly on regional-scale landslide susceptibility in the Balakot and Muzaffarabad regions [3,26–28]. In contrast, studies on the UAV-based assessment of landslide deformation are rarely implemented in northern Pakistan and ignored in the Balakot region [16]. This complexity has resulted in the need to integrate UAVs' high-resolution data and advanced analytical techniques, i.e., GCD, to study temporal and spatial variability and understand the complex interactions between triggering factors, deformation patterns, and the cascading effects on communities, infrastructure, and landscapes [29,30].

This study aims to employ UAVs' technological capabilities in conjunction with innovative analytical methodologies, such as GCD, and conduct a thorough morphometric analysis encompassing the geomorphological changes in various parts of the landslides. The GCD Tool_v8.0 is an innovative software program that provides topographic data analysis and scientifically rigorous terrain morphology change detection for researchers

and practitioners [21]. Using a variety of sophisticated algorithms and analytical methods, the GCD Tool makes it possible to compare digital elevation models (DEMs) that were methodically obtained at different times [22]. By generating spatially explicit metrics, including elevation change rates, sediment budgets, and morphological indices, it is easier to identify and quantify geomorphic processes, such as erosion, deposition, channel migration, and landform evolution [19]. The GCD tool is employed in various geoscience disciplines, especially landslide dynamics, using high-resolution UAV-based DEMs [23]. This in-depth analysis, which primarily focuses on the Nara and Nokot landslides in the Balakot region, tries to understand the complex dynamics of large-scale landslides within northern Pakistan's unique geological and geomorphological environment. By bridging the knowledge gap, this study aims to understand the dynamics of the Nara and Nokot landslides and their impact on the community. It will provide detailed high-resolution UAV and field-based data analysis to mitigate the hazard properly by policymakers.

Study Area

The selected landslides for the study, comprising the Nara and Nokot landslides, are situated east of the Kunhar River in Balakot Valley in the district of Mansehra (Figure 1). The elevation of the Nara and Nokot landslides ranges from 905 to 1320 m above the mean sea level. The temperature of the area ranges from 3.2 °C to 15.9 °C in winter and 20 °C–37.6 °C in summer, with annual 1588 mm precipitation [28]. The Nara and Nokot landslides, initially triggered by the 2005 Kashmir earthquake, remained active afterward and posed a significant hazard to the surrounding settlements and infrastructure. The settlements on the Nara landslide's scarp region are particularly at high risk (Figure 1). Similarly, the consistent displacement on the Nokot landslide threatens the surrounding houses, population, schools, and hospitals. Debris from the landslide was deposited into nearby rivers, elevating the channel level. The lithology of the area is largely composed of sedimentary rocks, including shale, limestone, and fractured sandstone, contributing to the instability of the slopes. The study area is seismically active, comprising the Main Boundary Thrust (MBT), Kashmir Boundary Thrust (KBT), and the Balakot–Bagh Fault [29]. The brittle nature of shale and fractured sandstone are susceptible to erosion and slope failures due to rainfall [31]. Moreover, the anthropogenically induced excavation of the landslides for construction materials is destabilizing the landslide.

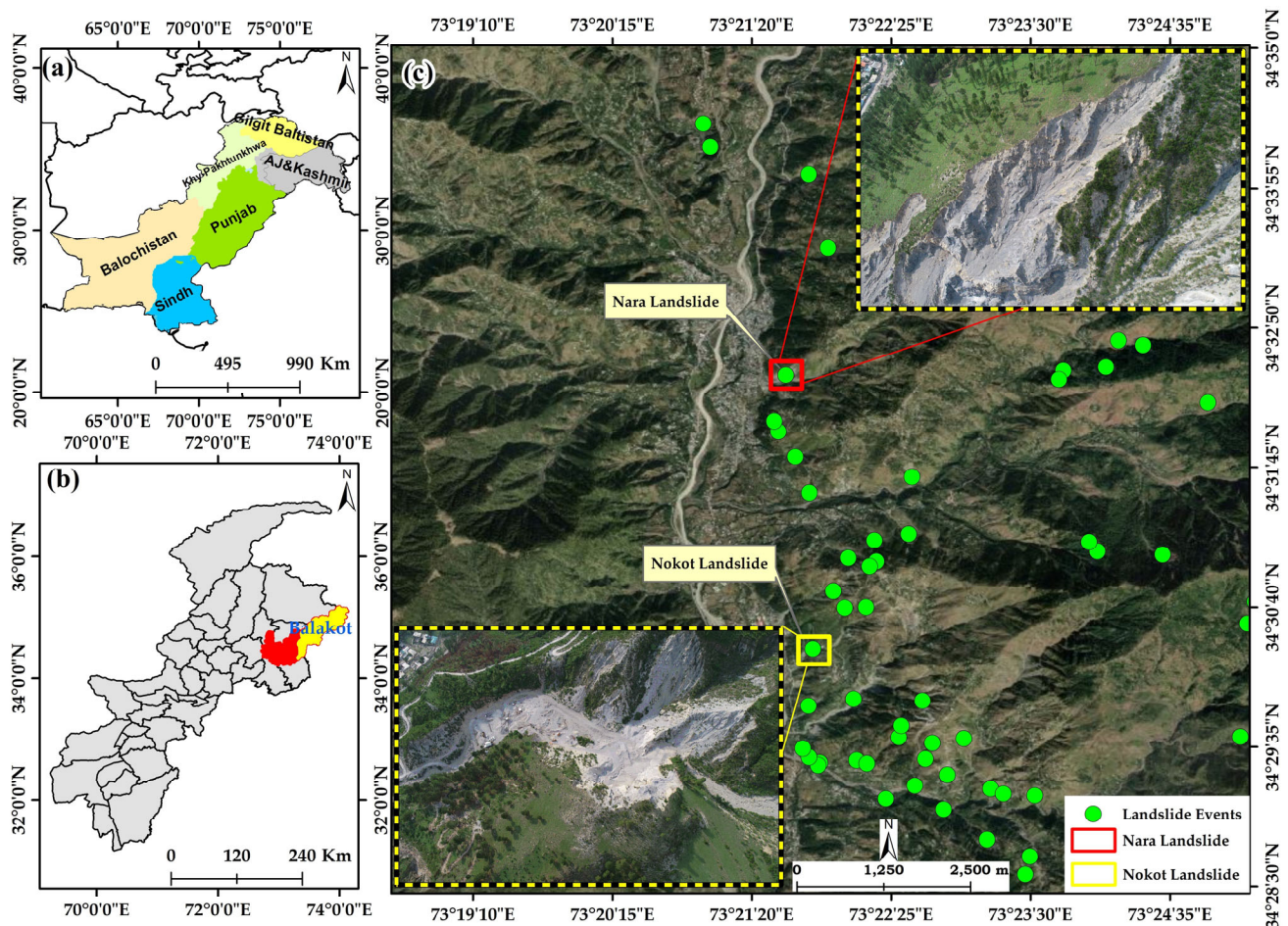


Figure 1. Location map of the Nara and Nokot landslides: (a) Pakistan boundary with the KP administrative boundary, (b) Mansehra and Balakot, and (c) the Nara and Nokot landslides along with other landslide events in the study area.

2. Materials and Methods

2.1. Data Acquisition

A remotely controlled Quadcopter, i.e., DJI Inspire II and Mavic II Dual Enterprise (Figure 2a) by Da-Jiang Innovations Science and Technology Co., Ltd. (DJI), Nanshan District, Shenzhen, China, was used for mapping the Nara and Nokot landslides. The UAV has a take-off weight of 1.28 kg (camera and battery included for increased stability in the air) with a Xemuse X4 gimbal having a 120° tilt range. The DJI Mavic II Dual Enterprise, Nanshan District, Shenzhen, China, has a take-off weight of 905 g (camera and battery included for increased stability in the air), with a gimbal having a 135 ± 45 tilt range. The gimbal holds the UAV's camera and harmonizes with the movement of the UAV for image acquisition. Besides this, the Inspire II and Mavic II Dual Enterprise are mounted with ordinary GPS/GLONASS [28], which positions the grid path and takeoff and landing accurately [4]. The visual positioning system (VPS) attached below the UAVs consists of ultrasonic sensors and a monocular camera, which enhances the XYZ accuracies up to 0.1 to 0.5 cm [4]. For this study, we utilized DGPS (Figure 2b) to collect the GCPs (Figure 2c) to enhance the precision of data obtained from the UAV. The wooden tiles of 18×18 Inches with black and white painting and the centroid visible in black were used as GCPs. PPS (precise positioning service) mode was used to conduct a geodetic survey to collect GCPs [29–32]. PPS achieved high accuracy in UAV-based landslide mapping and geodetic surveys for gathering GCPs. First, GPS devices were positioned at selected survey markers and GCP locations, remaining static for an extended period to obtain stable satellite signal data. This initial phase was critical in gathering the raw positional data required for

post-processing. The gathered GPS data were then retrieved and analyzed for corrections for various problems, such as air delays and satellite clock discrepancies, by comparing the recorded signals to data from a network of reference stations. The post-processed data had a high level of accuracy, which was critical for the orthorectification of the UAV's orthomosaic and DSMs and ensuring the precision of the landslide displacement analysis. For the UAV survey, the single and double grid missions (waypoint mode) were used in the DJI Go 4 application (Figure 2d). The frontal and side overlap of 85% is used for SfM-based mapping techniques [17,33–35]. The ISO was fixed at 100 for noise reduction [36]. The UAV was set to 2 s to capture all images at a 4.6 m/s speed. The data were acquired in April 2019, August 2019, and July 2022.

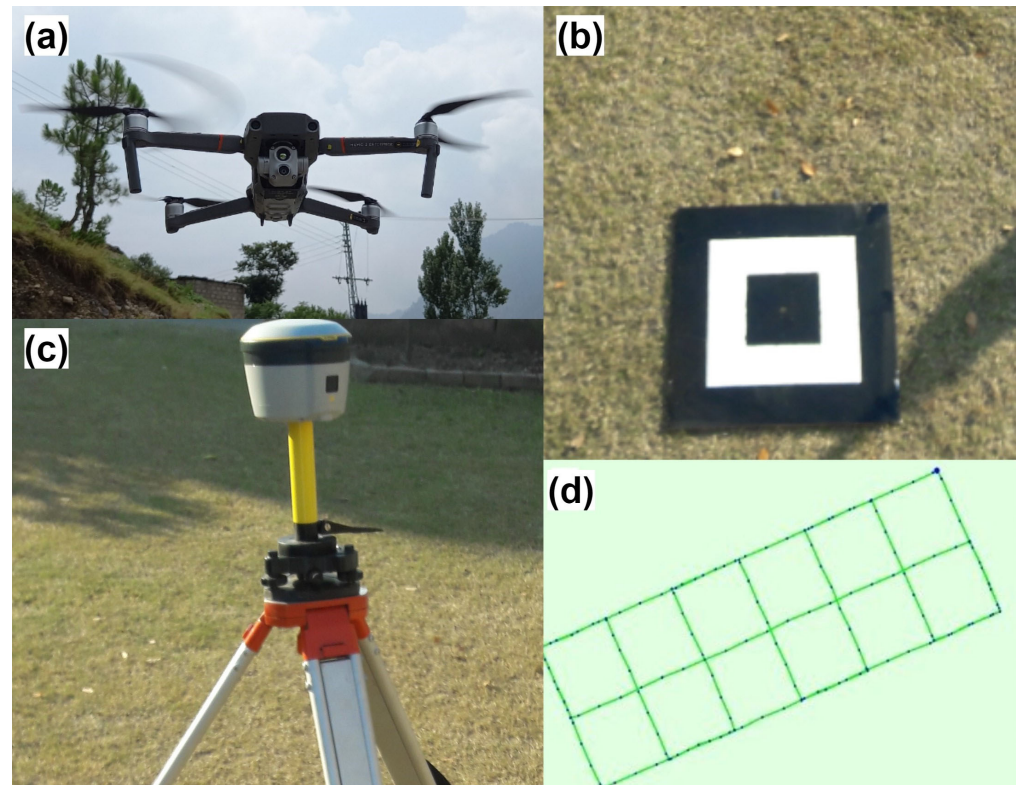


Figure 2. Figure showing (a) the gridded mission for the UAV aerial survey, (b) the ground control points, (c) the DPGS for geodetic surveying, and (d) the DJI Mavic II dual enterprise.

2.2. Method

2.2.1. Data Pre-Processing

Pix4D Mapper 4.8.0, an advanced form of photogrammetric software specifically developed to process large datasets, was utilized to compute the DSM and ortho-mosaic images. The procedure commences by automatically identifying shared features among photos and creating a dense three-dimensional point cloud to develop a DSM and ortho-mosaic (Figure 3). The computed DSM was subsequently analyzed with the DGPS GCPs' data (Figure 3a,b) to enhance the accuracy of the DSM. The DGPS data were also utilized as reference data for the accuracy assessment of the derived DSM. The integration rectifies any possible geometric distortions that arise during the first image-stitching process, such as variations in scale, rotational impacts, or errors in elevation. The pre-and post-DSMs and ortho-mosaics, i.e., April 2019, August 2019, and July 2022 for the three temporal periods generated (Table 1), were resampled to the exact resolution to map the surface displacement accurately. These time points were chosen due to the availability of resources and favorable weather conditions and to understand the low and high temporal changes in the landslides.

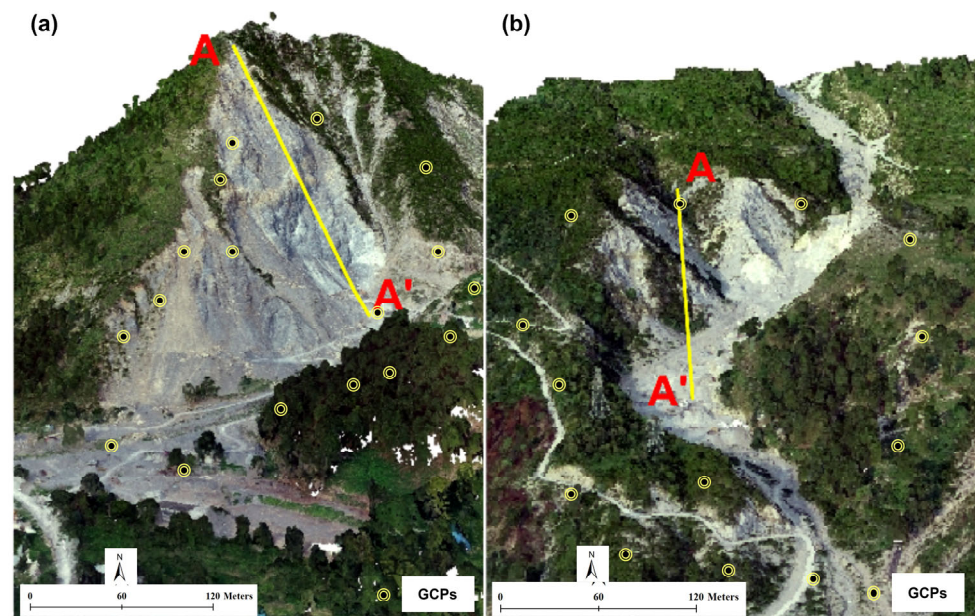


Figure 3. The 3D point cloud with AA's cross-section along the Nara (a) and Nokot (b) landslides and the GCPs used for the orthorectification of the UAV images.

Table 1. Acquisition date and spatial and temporal resolution with weather conditions.

S. No	Landslide	Date of Acquisition	Spatial Resolution (cm)
1	Nara	04-04-19	8
2	Nara	15-08-19	7
3	Nara	28-07-22	8
4	Nokot	04-04-19	7
5	Nokot	15-08-19	8
6	Nokot	27-07-22	8

To compute the root mean square error (RMSE), DSM elevation values were extracted at the precise locations of the validation points, calculating the elevation differences, squaring these differences, summing them, dividing by the number of points, and taking the square root of the results. The RMSE for the landslides was calculated using Equation (1) [32,33], i.e.,

$$RMSE = \frac{\sqrt{\sum (GNSS - DSM)^2}}{N} \quad (1)$$

where GNSS represents the GCPs' true position during the geodetic survey. The DSM represents the predicted values of the DSM. N represents the total number of points taken.

This formula calculated the vertical accuracy (Z) for the Nara and Nokot landslides. For this, the GCPs used to co-register the ortho-mosaic and DSM in the SfM algorithm were plotted over the ortho-mosaic and were located correctly [37]. The RMSE is a statistical measure used to quantify the accuracy of a model by calculating the average magnitude of the errors between predicted and observed values [38,39]. In the context of UAV-derived DSMs, the RMSE assesses the difference between the elevation values from the DSM and the corresponding ground truth elevations obtained from [5]. The RMSE is computed by taking the square root of the average squared differences between these sets of values. A lower RMSE indicates higher accuracy, signifying that the DSM closely matches the precise measurements [40]. After this positional verification, the points were plotted on the DSMs of the Nara and Nokot landslides. The elevation values were extracted to the GCP file. The Nara landslide has 4.58 cm of RMSE aided with 17 GCPs, and the Nokot landslide has 13 GCPs plotted with an RMSE of 4.24 cm.

In situ observations, field photographs, and high-resolution ortho-mosaics generated by the UAV aerial survey were used to assess the morphometric analysis of the landslides. This resulted in the generation of the landslide inventory map of the Nara and Nokot landslides, indicating the active, dormant, and suspended areas of the Nara and Nokot landslides. The Nara and Nokot slope maps were also generated to study the changing topographic conditions of the landslides using the high-resolution DSMs generated from the Nara and Nokot aerial survey data. To assess the water content in the landslides, a Topographic Wetness Index (TWI) map was created using high-resolution DSMs in ArcGIS 10.7, with flow accumulation and slope data from the Nara and Nokot landslides. To compute the TWI from a DSM, it is necessary to first estimate the specific catchment area (SCA) by calculating flow accumulation with flow direction algorithms. The slope angle was then estimated from the DSM using the gradient method [41–43]. Finally, the ratio of the specified catchment area to the tangent of the slope angle was utilized to calculate the TWI values for each cell. The precipitation data were acquired from the Pakistan Meteorological Department (PMD) meteorological observatory at Peshawar, and the data are represented graphically to evaluate their correlation with the TWI and UAVs' data-based landslide deformation information [44,45].

2.2.2. Geomorphic Change Detection Model

The multi-temporal DEMs were analyzed using Geomorphic Change Detection (GCD) 7.0 software to evaluate the landslide deformation (Figure 4). The vertical differences between two temporally distinct DEMs indicate the potential areas of geomorphic changes. Given the inherent uncertainties in DEMs' surface representation—stemming from possible errors over space and time—it was crucial to quantify these volumetric changes accurately. To address this, a non-parametric signed-rank test was incorporated into the workflow, offering a probabilistic evaluation of the difference of DEMs (DoD) [46,47]. This statistical approach helped to affirm the significance of observed changes by assessing the probability that observed differences in elevation were due to actual geomorphic activity rather than random variation or noise [48]. Furthermore, the analysis involved extracting geomorphological surface features to study variations within each DEM grid cell. The GCD analysis recognized two scenarios in the variability of the DoD: basic and complex. For basic DoD scenarios, where uncertainty is less pronounced, a minimum detection level (minLoD) was employed to filter out minor changes within the noise threshold. In contrast, complex scenarios required a more nuanced approach where spatial variability of DoD uncertainty was considered [49–52]. This involved determining spatial variability and applying a spatially consistent elevation uncertainty to each DEM, ensuring that these uncertainties were accurately propagated into the DoD calculation. A fuzzy inference system (FIS) generated an elevation uncertainty estimate if the spatial variability was significant. To mitigate any potential geometric errors in the data, the DSMs were resampled to 1 m resolution [53,54]. The final step in GCD-based change detection involved setting a minimum detection threshold of 0.20 m for the three temporal DSMs. This threshold was strategically chosen to ensure that only significant geomorphic changes were considered, thereby avoiding the inclusion of minor alterations that might not be relevant to the broader geomorphological analysis, including areal, volumetric, vertical averages, and percentages (by volume). The inter-comparison between the two change-detected surfaces generated from the temporal DSMs resulted in the cross-comparison of the changes.

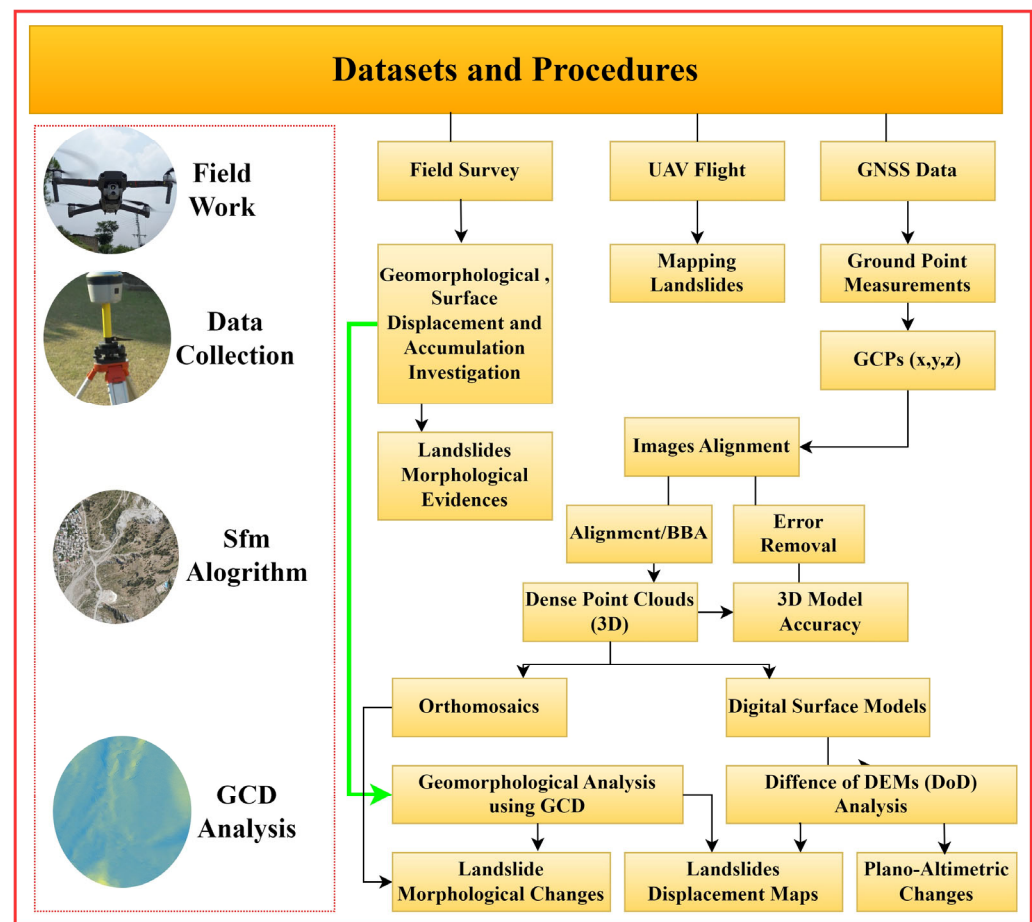


Figure 4. The methodology flow chart for assessing landslide displacement using the geomorphic change detection model.

3. Results

3.1. Accuracy Assessment

The Nara landslide has 4.58 m of RMSE aided with 17 GCPs, and the Nokot landslide has 13 GCPs plotted with an RMSE of 4.24 m.

3.2. Morpho Dynamics of Nara and Nokot Landslides

Based on the observed geomorphic features, a landslide is categorized into three distinct zones: depletion, transition, and accumulation. The delineation of these zones involves a combination of quantitative methods, such as topographic and movement data, and qualitative assessments based on field observations of geomorphological and depositional characteristics. In the case of the Nara landslide (Figure 5a), the depletion zone corresponds to the scarp region where the landslide originated during the 2005 earthquake, resulting in material detachment [54–56]. Continuous erosion characterizes the transition zone, with the northwestern part experiencing the highest erosion rates. The accumulation zone of the Nara landslide is where the eroded material from the depletion and transition zones is deposited. For the Nokot landslide (Figure 5b), the depletion zone consists of two elongated source areas with a disorganized distribution of surface irregularities, indicating ongoing sliding affecting the slopes. Within the depletion zone of the Nokot landslide, the main and secondary scarps exhibit an accurate form, and the ground surface is tilted backward, suggesting rotational or roto-translational slides that evolve into earth flows downslope. Detailed field investigations revealed the presence of extensional cracks and trenches often filled with collapsed material. Moreover, tension cracks and lateral fissures

were observed at the top of the slope, highlighting the retrogressive evolution of the main scarps in the Nokot landslide.

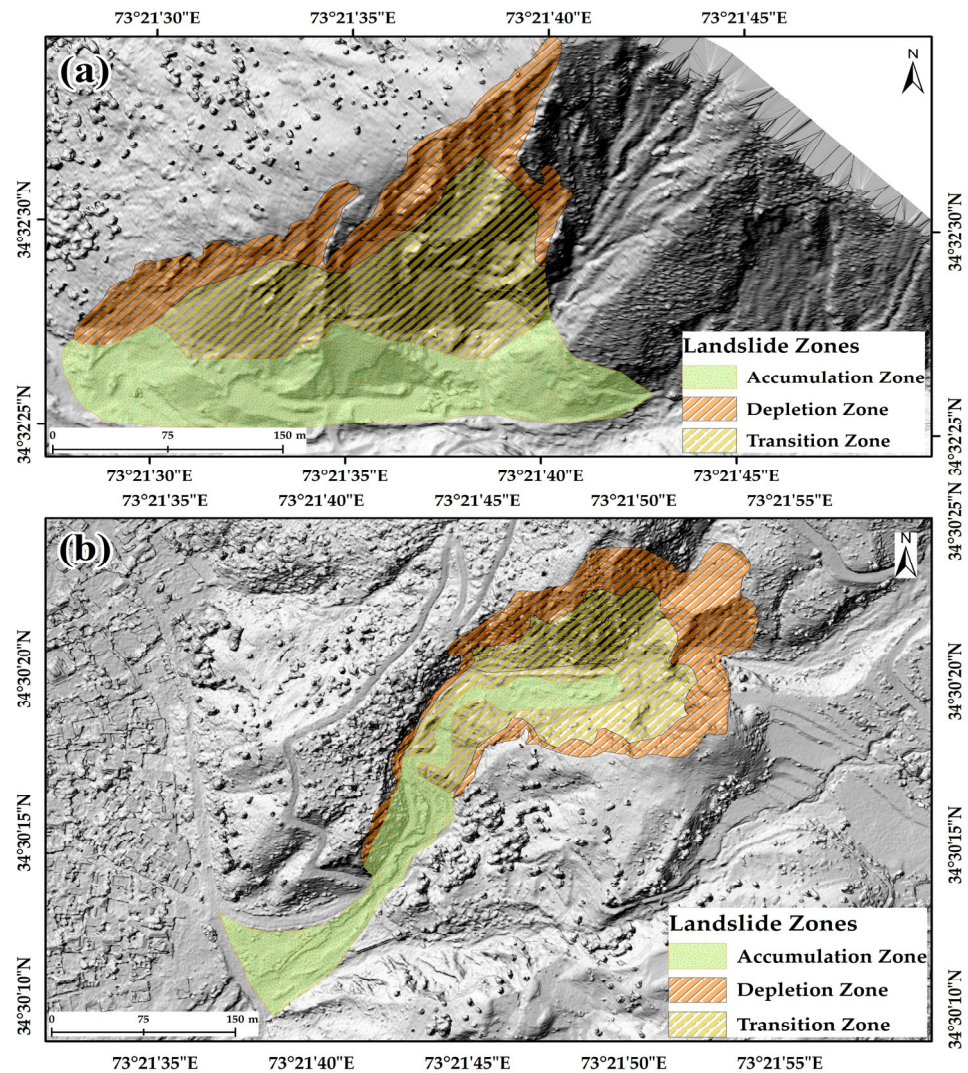


Figure 5. The (a) Nara and (b) Nokot landslides are divided into depletion, transition, and accumulation zones.

3.3. Nara and Nokot Landslide Geomorphological Changes

The geomorphological investigation of the Nara landslide in Balakot shows considerable changes between 2019 (Figure 6a) and 2022 (Figure 6b). The data are divided into three categories, active, dormant, and suspended zones, with each demonstrating significant fluctuations over the study period. In 2019, the active area of the Nara landslide was 69,428.04 m² (Figure 6), which decreased to 55,700.63 m² in 2022. The dormant area representing temporarily inactive zones has the potential for future activity to increase from 9621.22 m² in 2019 to 19,480.58 m² in 2022. This growth shows that some previously active areas have fallen inactive and may reactivate. The suspended area, including transit materials, has also significantly increased. The suspended area has increased from 12,306.27 m² in 2019 to 35,433.36 m² in 2022. The rise in suspended material indicates increased movement of debris and materials, which contributes to the overall dynamic changes inside the landslide. The observed variations in the Nara landslide's active, dormant, and suspended zones between 2019 and 2022 highlight the landslide's dynamic nature. The change of sections from active to dormant and suspended phases emphasizes the need for ongoing monitoring and analysis (Table 2).

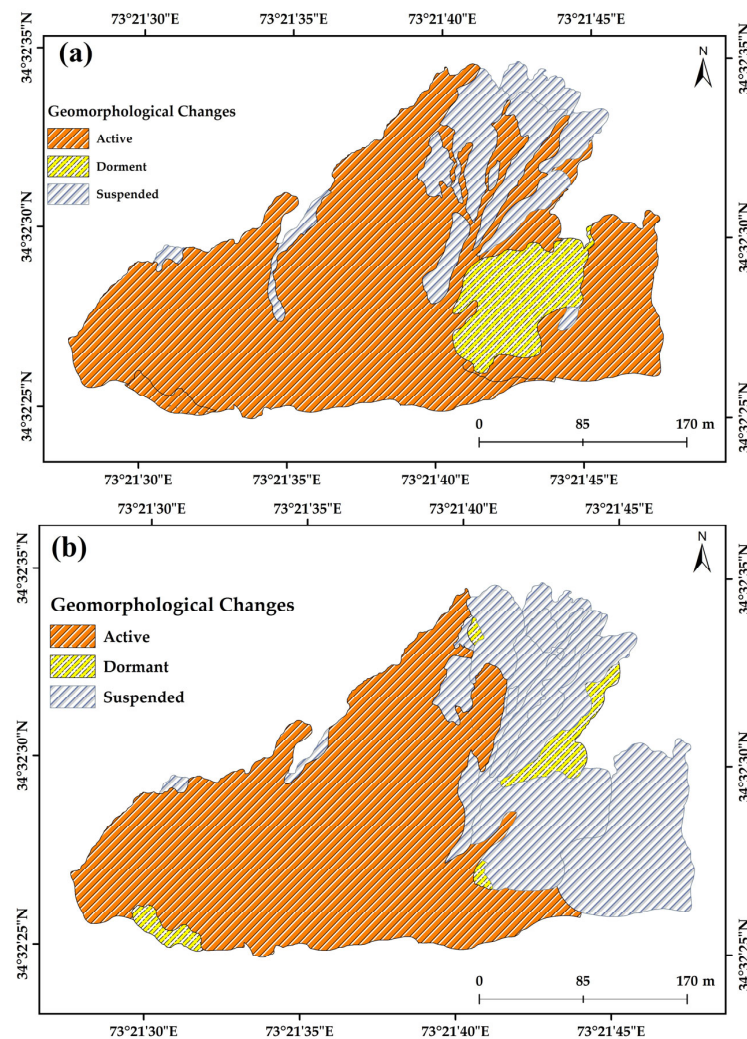


Figure 6. Figure showing the geomorphological changes in the Nara Landslide for the temporal period (a) 2019 and (b) 2022, showing the overview of the reduction in the active and dormant zones and the expansion of the suspended zone.

Table 2. The landslide geomorphological changes in the Nara and Nokot landslides (2019–2022).

Nara Landslide Geomorphological Change Analysis		
Conversion	Area (m ²)	Changes in the Landslide Zones
Active to Dormant	2222.11	Vegetated area along the transition zone
Dormant to Suspended	7570.20	The area along the main scarp and its surrounding
Dormant to Active	585.55	Secondary scarp and transition area
Suspended to Active	2367.43	Secondary scarp and transition area
Suspended to Dormant	727.06	The area along the secondary scarp
Intact Active	10,132.88	The main and secondary scarp region
Intact Dormant	51,210.01	Stabilizing region over the main scarp and transition zone
Intact Suspended	451.47	The vegetated portion of the landslide
Nokot Landslide Geomorphological Change Analysis		
Active to Dormant	3371.20	Around the transition zone
Dormant to Suspended	710.65	Near the accumulation and toe
Active to Suspended	649.99	Near the accumulation and WE scarp region
Dormant to Active	1482.07	In the NW and SW scarp region
Suspended to Active	2372.65	NS scarp
Suspended to Dormant	861.30	Accumulation and transition zone
Intact Active	41,265.65	Along the scarp
Intact Dormant	861.30	Along the transition zone
Intact Suspended	1566.95	Along the accumulation zone, specifically the NE part

The ortho-mosaic-based geomorphological map of the Nokot landslide in Balakot was created to divide the landslide mass into active, dormant, and suspended zones between 2019 (Figure 7a) and 2022 (Figure 7b). The research yielded significant and intriguing results. In 2019, the active component of the landslide, representing the actively moving and unstable area, measured roughly 47,252.21 m² (see Figure 7). By 2022, the active component increased to 48,260 m². The dormant portion, which includes sections that are temporarily inactive but have the potential to revive, grew significantly between 2019 and 2022. In 2019, the dormant area covered 7744.30 m², indicating stable areas of the landslide. However, in 2022, the dormant section reached 13,263.83 m². This expansion suggests the potential for future activity and highlights the need for continued monitoring and assessment to understand the triggers and dynamics of the landslide in Balakot.

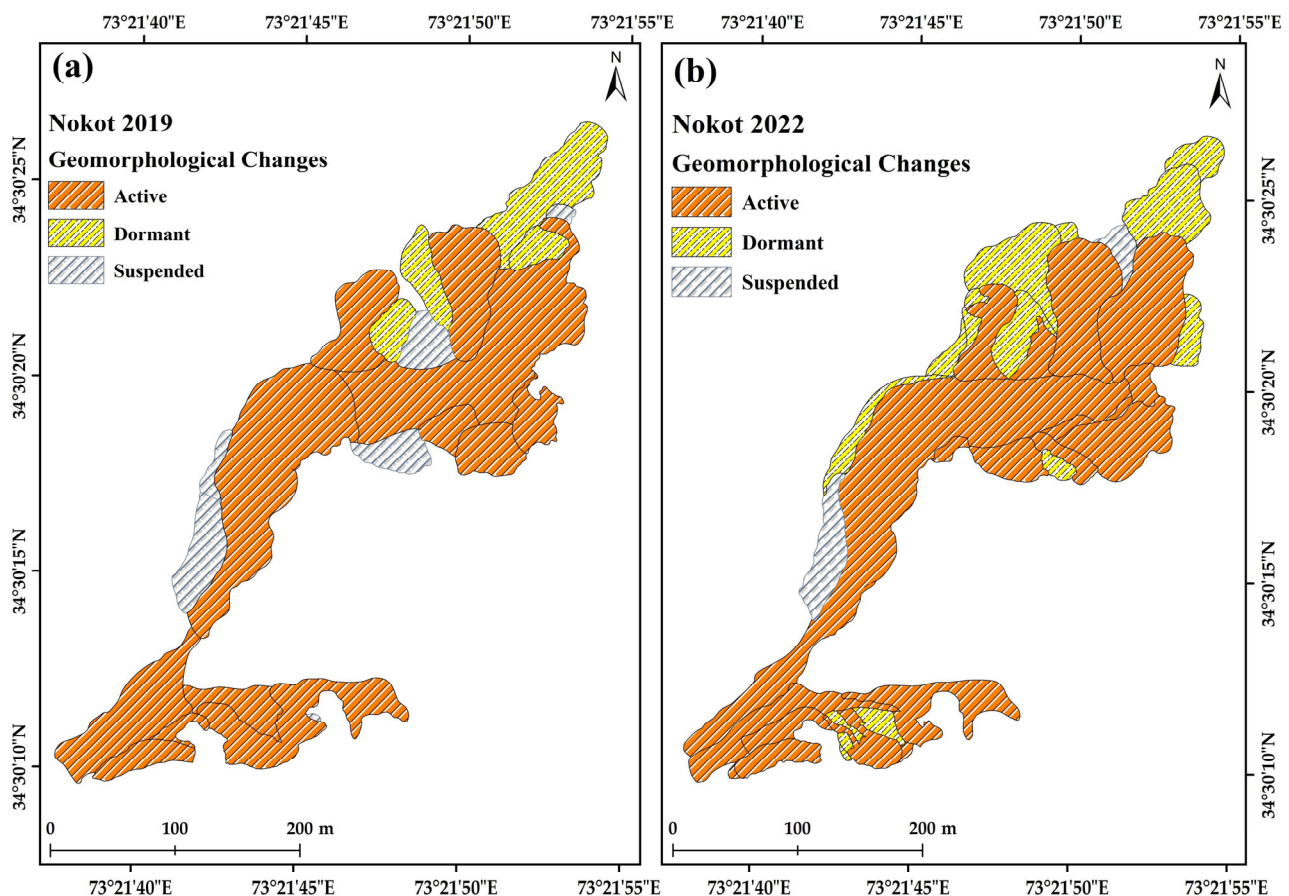


Figure 7. Figure showing the changes in the geomorphology of the Nokot Landslide over the period of (a) 2019 and (b) 2022.

On the other hand, the suspended area, representing material in transit and suspended in the gravitational mass movement, displayed an exciting trend. In 2019, the suspended portion was estimated to be approximately 5782.35 m², indicating a significant volume of unstable material transported within the landslide. However, in 2022, the suspended area shrank to 2927.78 m², indicating that some active areas are dormant or have been halted.

3.4. Slope Analysis of the Nara and Nokot Landslides

The Nara landslide has been excavated for raw construction materials, and there has been a volume loss in different regions over the landslides. This excavation has made the particular zone highly dynamic (Figure 8a) at the area (a) of the Nara landslide. The area has a significantly displaced depression (Figure 8a–c) at area (b) identified above the toe at area (a). The July 2022 slope (Figure 8c) at area (b) shows the lowest slope due to the unmapped above-scarp area in the field for DSM generation during the aerial survey and

processing in the SfM algorithm. It can be observed that there are also other significant changes in the slope map across the main scarp, secondary scarp, and the toe region. The scarp portion (Figure 8a) at location (a) is stable with movement in the material, but there are very few slope changes of less than 1 degree. The secondary scarp to the NW side to the point (Figure 8a–c) at area (b), which is highly active, shows stability and lesser changes in the slope, although it is also upright-faced and covered with loose debris. The leading toe at the area (c) has only been excavated, reducing the slope to 15 degrees. Based on these dynamics, the lateral leading to the (c) portion may surge again shortly.

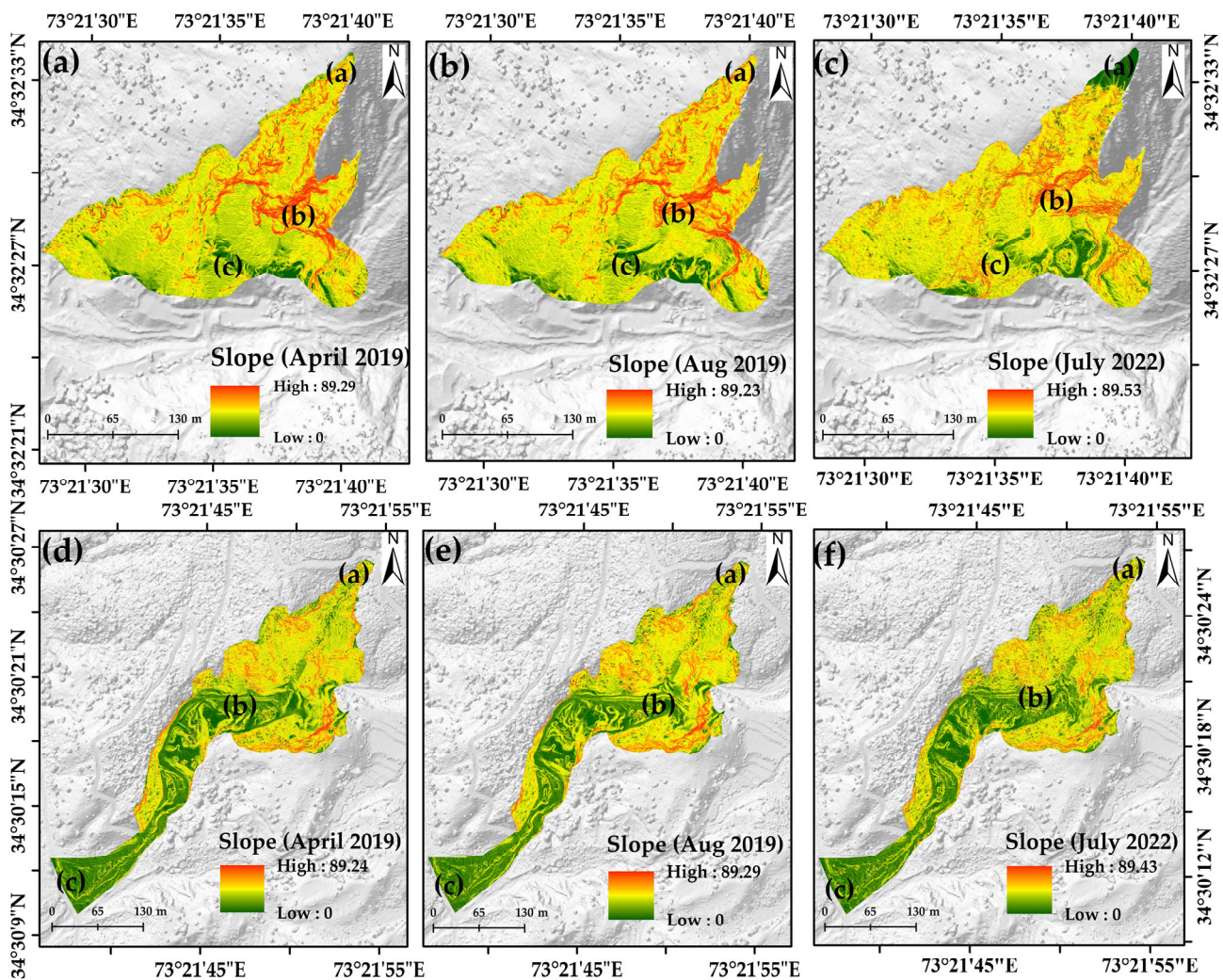


Figure 8. The temporal slope maps of the Nara landslide in (a) April 2019, (b) August 2019, and (c) July 2022 and the Nokot landslide for the periods of (d) April 2019, (e) August 2019, and (f) July 2022.

The Nokot landslide slope map (Figure 8d–f) shows a surge in the NS scarp (a) with white ranging from 3 to 4 degrees. These changes in the slope indicate the possibility of a surge in the NS scarp (a). The lower portion, i.e., the valley floor and the toe (b) of the landslide, resembles small changes. These variations represent the changing slope scenario in the valley floor of the Nokot landslide. There has been a 2–3-degree change in the landslide’s lower regions (b) and (c).

3.5. Cross-Sectional Investigation of DSM-Based Landslide Slope Changes

The slope measurements in the Nara landslide in April 2019, August 2019, and July 2022 show significant variations (Figure 9). Slope values fluctuate throughout the measured

periods, suggesting that landmass movement is active and that the land is prone to a landslide. A noticeable change in the slope values between April 2019 and July 2022, with some regions exhibiting considerable rises and declines, as encircled in blue, confirms severe erosional activity; these variations indicate the terrain's susceptibility to landslides and imply ongoing geological processes. The deviation in the slope over the temporal period identifies the Nara landslide's active nature.

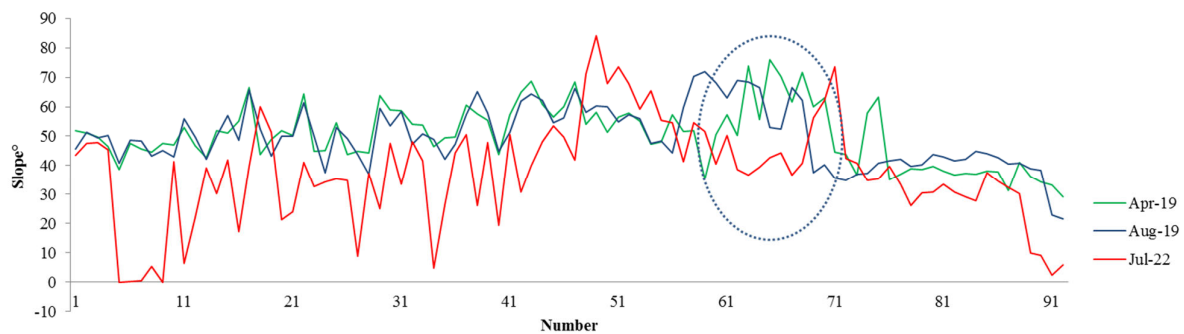


Figure 9. The cross-section AA's slope changes: Change for the temporal period of April 2019, August 2019, and July 2022 of the Nara landslide, where the Y-axis shows the changing slope values and the x-axis shows the number of points taken along the AA profile used for extracting the slope values from the DSM derived slope data.

The examination of Nokot landslide slope data from April 2019, August 2019, and July 2022 (Figure 10) reveals significant variations in slope values over time, indicating the active landslide erosional activity. The mean slope numbers exhibit a noticeable increase from July 2022 (mean slope: 36.15°) to April 2019 (mean slope: 35.62°), suggesting a progressive rise in the steepness of the terrain. The mean slope numbers, for example, exhibit a noticeable increase from July 2022 (mean slope: 36.15°) to April 2019 (mean slope: 35.62°), suggesting a progressive rise in the steepness of the terrain. Specific data points, such as the slope values for places, which show varying patterns during the studied period, further confirm this trend. For instance, between April 2019 and July 2022, slope values at several sites changed significantly, with noticeable increases or decreases in slope angle. These variations in slope values demonstrate the dynamic nature of landslides in Nokot and emphasize the necessity of ongoing observation and thorough risk assessment to reduce potential dangers successfully. The deviation in the slope over the temporal period identifies the active nature of the Nokot landslide.

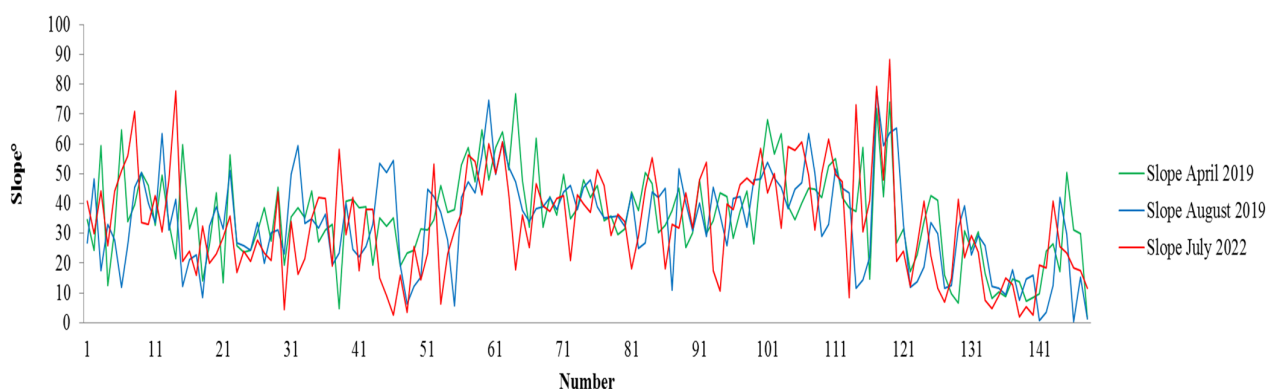


Figure 10. The cross-section AA's slope changes: Change for the temporal period of April 2019, August 2019, and July 2022 of the Nokot landslide, where the Y-axis shows the changing slope values and the x-axis shows the number of points taken along the AA profile used for extracting the slope values from the DSM derived slope data.

3.6. Topographic Wetness Index Map

The TWI derived from the DSM for the Nara landslide (Figure 11a) varies between -1 and 1.09 . Positive TWI readings indicate that the area is more humid. The TWI number increases the likelihood of water buildup or absorption in the terrain. As a result, this area may have a greater likelihood of soil moisture. The TWI values for a point at area (b) and its surroundings range from 1.93 to 7.47 . This suggests that the moisture conditions are similar to point (a). The TWI values at point (c) and the surrounding areas range from 1.93 to 4.01 . Point (d) and its surrounding areas possess TWI values varying from 1.08 to -1.08 . The point (e) is from 1.09 to 1.93 . The existence of positive and negative numbers can show a change from wetter to drier circumstances. The positive TWI values (e.g., 1.93), though less strongly than in points (a), (b), and (c), still allude to some degree of potential water accumulation. The negative TWI values indicate the lower soil moisture content or drier circumstances, i.e., -1.08 in the Nara landslide.

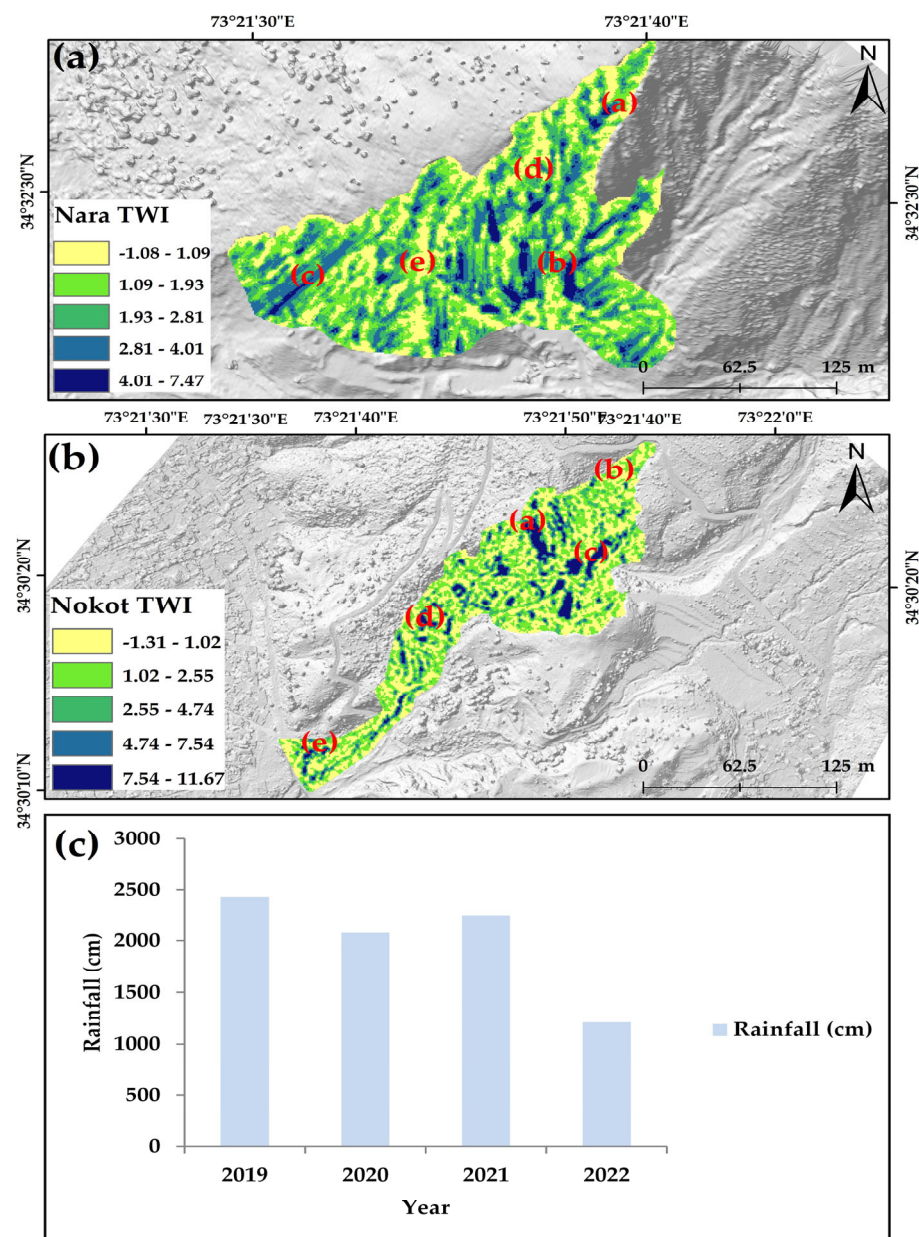


Figure 11. The Topographic Wetness Index map of the (a) Nara and (b) Nokot landslides (c) shows the rainfall pattern from 2019 to 2022, which is in agreement with the TWI results.

The TWI values range from 4.74 to 11.87 for the Nokot landslide at sites shown (Figure 11b) at points (a), (b), and (c), as well as the areas surrounding areas, indicating wetter conditions for soil moisture content. Points (d) and (e), on the other hand, and the area around them, have TWI values ranging from 2.66 to -1.31 , indicating a change to drier circumstances with less water retention or the amount of moisture in the soil. The variations in wetness inside the Nokot landslide location and its near surroundings are widely understood due to the TWI values.

The Balakot area experienced varying levels of rainfall from 2019 to 2022, providing valuable insights into precipitation and its correlation with the TWI results. In 2019, the rainfall measured 2430.79 cm (Figure 11c), followed by 2075.45 cm in 2020, 2250.03 cm in 2021, and 1208.06 cm in 2022. These rainfall measurements offer important information on the moisture patterns in the region during those years. The interaction between these rainfall values and the TWI (landslide topographic wetness index) values can significantly influence the moisture conditions and potential landslide hazards in both the Nara and Nokot landslide areas.

3.7. The Areal and Volume Changes in the Nara and Nokot Landslides

The areal changes for the temporal period August–April 2019 for the Nara landslide show a total area of about 2613.73 m² of surface lowering with a total of 35,124.83 m² of surface raising with the total area of interest as 3778.5 m² (Table 3). The DSM areal changes for the temporal period July 2022–August 2019 show the total surface lowering as 37,726.63 m² with a total surface raising m² of 9.59 m². The total area of interest was 37,736.22 m². The DSM areal changes for the temporal period July 2022–April 2019 DSM changes have 37,739.64 m² of surface lowering areas with 4.53 m² of total surface raising. The total area of interest recorded is 37,744.1 m².

Table 3. The Areal changes in the Nara and Nokot landslide.

DEM of Difference	Total Area of Surface Lowering (m ²)	Total Area of Surface Raising (m ²)	Total Area of Detectable Change (m ²)	Total Area of Interest (m ²)
Nara Landslide				
August–April 2019	2613.71	35,124.83	NA	37,738.55
July 22–August 2019	37,726.63	9.59	NA	37,736.22
July 22–April 2019	37,739.64	4.53	NA	37,744.1
Nokot Landslide				
August–April 2019	56,904	61	NA	56,965
July 22–August 2019	56,978	0	NA	56,978
July 22–April 2019	57,005	0	NA	57,005

The DSM areal changes for the temporal period of August–April 2019 show that the Nokot landslide has a total surface lowering of 56,904 m² with a total area of surface raising acquired 61 m². The total area of interest for the August–April 2019 temporal period landslide is 56,965 m². The DSM areal changes for the temporal period of July 2022–August 2019 DSM changes show the total area of surface lowering as 56,978 m² with no surface raising. The total area of interest recorded is 56,978 m². The July 2022–April 2019 DSM changes show the total area of surface lowering as 57,005 with no area surface raising.

The volumetric changes for the Nara landslide in the August–April 2019 temporal period DSM changes show a total volume of surface lowering of 17,392.22 m³ with the total volume of surface raising of 184,432.99 m³ (Table 4). The July 2022–August 2019 temporal period DSM changes shows a total volume of surface lowering of 2,357,482.13 m³ with a total volume of surface raising of 812.71 m³. The July 2022–April 2019 temporal period DSM changes show a total volume of surface raising of 219,000.37 m³ with the total volume of surface raising of 298.82 m³.

Table 4. The volume changes in the Nara and Nokot landslides.

DEM of Difference	Total Volume of Surface Lowering (m ³)	Total Volume of Surface Raising (m ³)
Nara Landslide		
August–April 2019	17,392.44	184,432.99
July 22–August 2019	2,357,482.13	812.71
July 22–April 2019	2,190,400.37	298.82
Nokot Landslide		
August–April 2019	651,471.13	117.98
July 22–August 2019	2,590,821.21	0
July 22–April 2019	3,243,829	0

The Nokot landslide DSM changes for August–April 2019 show a total volume of surface lowering of 651,471.13 m³ with a volume surface raising of 117.98 m³. The July 2022–August 2019 DSM changes show the total volume of surface lowering of 2,590,821.21 m³ with no volume surface raising. Similarly, the July 2022–April 2019 temporal period DSM changes show a total volume of surface lowering of 3,243,829 m³ with no surface raising.

3.8. Plano-Altimetric Changes of the Nara and Nokot Landslides

The Nara landslide geomorphic change detection for the temporal period August–April 2019 (Figure 12) shows the elevation changes in the NW part of the landslides where there is a certain level of erosion detected with displacement ranging from −1 to 68.41 m. The NE part of the landslide along the secondary scarp also shows some erosion with displacement ranging from 1.98 to 25.45 m (Figure 12). The main scarp is channelized toward the accumulation zone in the NW direction (Figure 12), and some surface deposition occurs where the material detached from the NE part of the scarp is deposited (Figure 12a–c). The NE part of the main scarp (a) shows some erosion with displacement ranging from −11.62–1.91 m with some deposition ranging from 1.911 m to 7.20 m (a). The accumulation zone of the main landslide body (b) and the accumulation and deposition zone of the secondary landslide body show some deposition with surface deposition ranging from 1 to 68.41 m (c).

The NW part (Figure 12b) at point (b) of the Nara landslide shows the highest erosion, with displacement ranging from −174 to −68.88 m. The lower NS part, i.e., the toe (c), shows erosion, with displacement ranging from −68 m to −17.74 m. The primary scarp (a) shows high erosion, with displacement ranging from −77.78 to −94.92 m. The secondary scarp accumulation and toe (c) region show high deposition values ranging from 0 to 600 m.

The DSM changes of the Nara landslides for the temporal period of June 2022–April 2019 show high erosion values in the primary scarp region (Figure 12c) at point (a), ranging from −65.39 to −96.28 m. The toe region also shows high erosion with displacement ranging from −18.21 to −74.86 m. The accumulation region of the landslide body (b) shows the highest erosion with displacement ranging from −83.61 to −201.60 m. The accumulation and toe region of the secondary part of the landslide shows high deposition values ranging from −18.18 to −81.67 m.

The Nokot landslide DSM changes for the temporal period August–April 2019 (Figure 13a) at point (a) show that the Northern part of the scarp shows high deposition values ranging from 1 to 5 m. The NW scarp (b) also shows a high deposition level ranging from 0 to 6 m. The valley's lateral part (c) and NE scarp (a) show high erosion values with displacement ranging from 6.93 to −21 m.

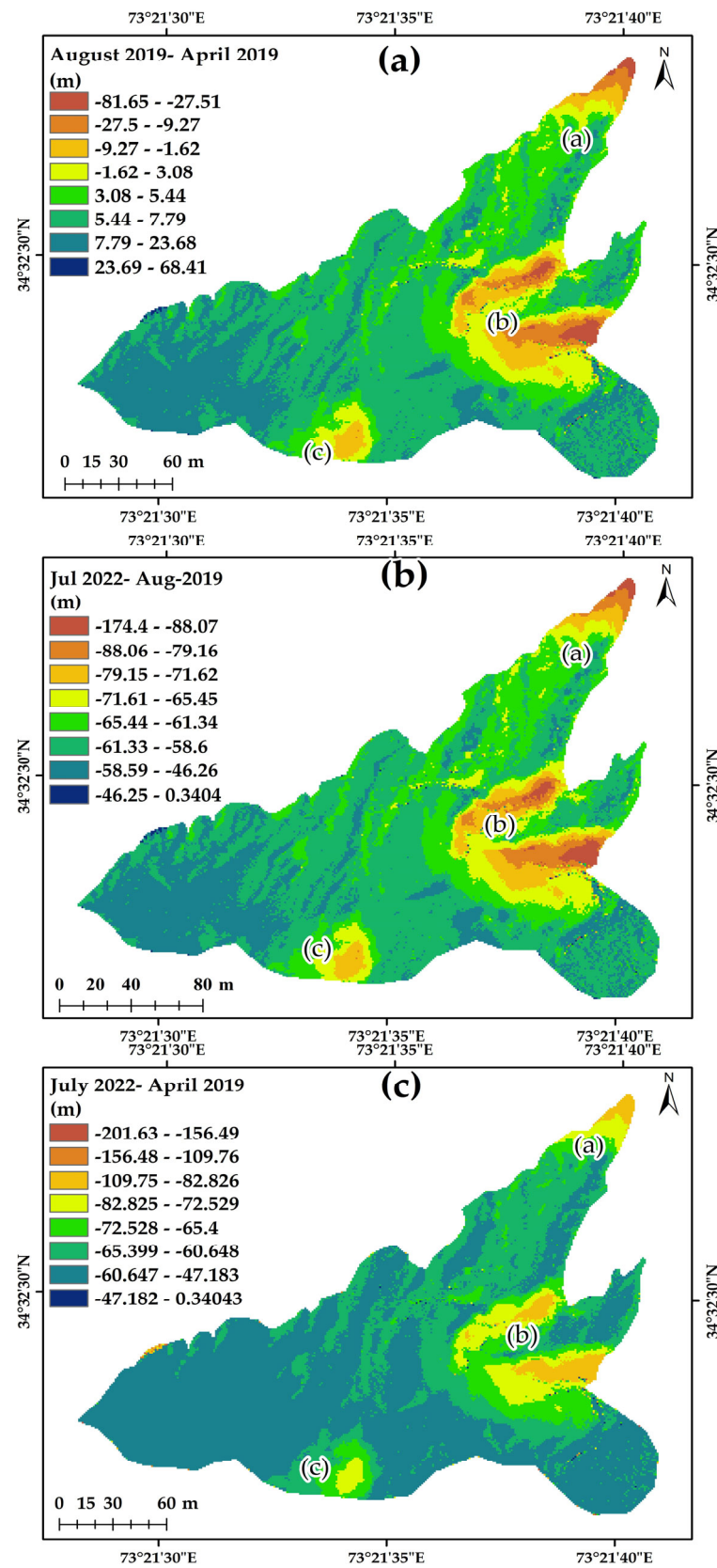


Figure 12. The temporal DSM changes using the GCD for the temporal periods of (a) August 2019–April 2019, (b) July 2022–August 2019, and (c) July 2022–April 2019 of the Nara landslide.

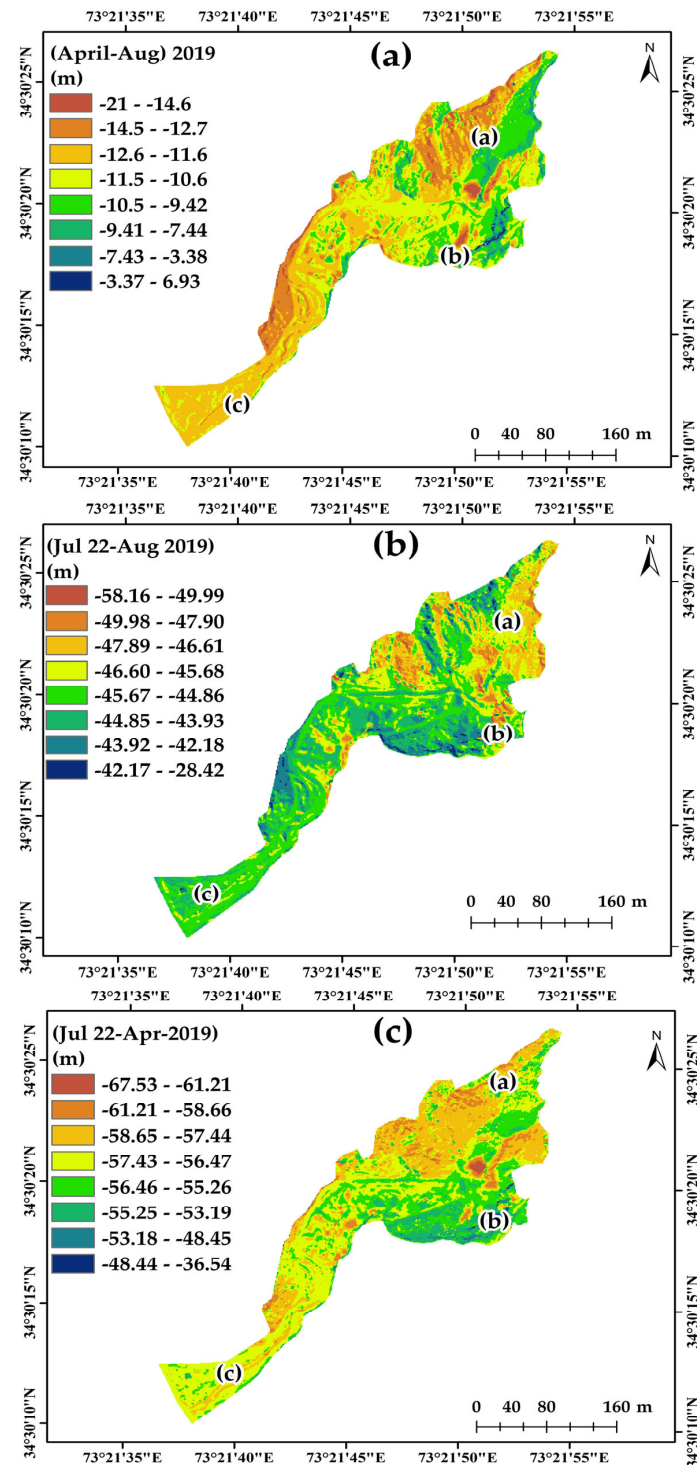


Figure 13. The temporal DSM changes using the GCD for the temporal periods of (a) August 2019–April 2019, (b) July 2022–August 2019, and (c) July 2022–April 2019 of the Nokot landslide.

The Nokot landslide DSM changes for the temporal period of July 2022–August 2019 show high erosion (Figure 13b) at point (a) with displacement ranging from 0 to −58 m. The NW scarp (b) also shows high erosion with displacement ranging from −28 to −58 m. The NE scarp (b) and the lateral valley floor until the lower toe show high levels of erosion with displacement ranging from −14 to −58 m.

The Nokot landslide DSM changes for the temporal period of July 2022–April 2019 also show high erosion values (Figure 13c). The landslides' northern and NE scarp areas show high erosion with displacement ranging from −1 to −67 m. The lateral part of the

valley and valley floor shows significant material loss with displacement ranging from -2 to 50 m. The NE scarp, however, shows some erosion with displacement ranging from -51 to -68 m.

3.9. Inter-Comparison of the Temporal DSMs Generated

The inter-comparison analysis between all of the temporal datasets for the Nara landslide DSM changes shows that a total of all compared $78,079.99$ m² of the area have surface lowering and a total of $35,138.96$ m² of the area have surface raising m² in the Nara landslide (Table 5).

Table 5. The areal changes inter-comparison of the different temporal DSM changes of the Nara and Nokot landslides.

DEM of Difference	Total Area of Surface Lowering (m ²)	Total Area of Surface Raising (m ²)
Nara Landslide		
August–April 2019	37,739.64	4.53
July 22–August 2019	37,726.63	9.59
July 22–April 2019	2613.71	35,124.83
Total of All Compared	78,079.99	35,138.96
Nokot Landslide		
August–April 2019	56,904.00	61.00
July 22–August 2019	57,005.00	0.00
July 22–April 2019	56,978.00	0.00
Total of All Compared	170,887.00	61.00

The Nokot landslide, however, shows that of the entire total area, there has been significant surface lowering over an area of 7807.99 m² over the three temporal DSMs changes analysis. However, the total surface raising area is 61 m² for all of the temporal periods of the Nokot landslide.

Similarly, the total volume loss for the Nara landslide over three temporal periods recorded is $4,565,274.96$ m³ (Table 6), with a total surface raising of $185,544.53$ m³. Similarly, the Nokot landslide has a total volume loss of $6,486,121.30$ m³ with a total volume raising of 117.98 m³.

Table 6. The volumetric changes inter-comparison of the different temporal DSM changes of the Nara and Nokot landslides.

DEM of Difference	Total Volume of Surface Lowering (m ³)	Total Volume of Surface Raising (m ³)
Nara Landslide		
August–April 2019	2,190,400.37	298.82
July 22–August 2019	2,357,482.13	812.71
July 22–April 2019	17,392.44	184,432.99
Total of All Compared	4,565,274.96	185,544.53
Nokot Landslide		
August–April 2019	651,471.13	117.98
July 22–August 2019	3,243,828.95	0.00
July 22–April 2019	2,590,821.21	0.00
Total of All Compared	6,486,121.30	117.98

4. Discussion

Recently developed and widely accessible UAV equipment with high-resolution cameras has been effectively used for the characterization and monitoring of landslides and offers a useful tool for assessing the risk of landslides. To assess and characterize the displacement of the Nara and Nokot landslides in Balakot, northern Pakistan, the current

study used multi-temporal UAV surveys. Overall elevation (Z) error between the DSMs generated using the DGPS GCPs was obtained (RMSE 85% and 86%, respectively) during the processing of each set of photos, confirming the high accuracy of 3D models. These RMSE values are also comparable to those found in other studies, e.g., [57–59]. Eker et al. [4] used a geodetic survey and acquired an accuracy of XYZ 5–10 cm. Ma et al. [35] acquired an XYZ 2–4 cm accuracy using 24 BBA and 39 independent GCPs. Eker et al. [4], acquired an XYZ accuracy of 6–10 cm. To acquire information about the landslides' topographic changes, we needed large displacement values relative to the computed errors; lesser values were inconclusive [60–64].

The 3D models created permitted the production of ortho-mosaics and DSMs with high spatial resolution. They proved suitable for multi-temporal landslide displacement studies, as demonstrated by several research studies [5,34,35,37,38]. Many researchers have focused on using the DSMs to assess landslide displacement using DoD analysis techniques, e.g., [5,35,38–40]. Using the structure from motion (SfM) technique, the DSMs were produced. As a result, the DoD analysis was completed using the DSMs, allowing for more accurate assessments of the landslides' displacements and volumes. It was possible to obtain specific information about morphological changes, deformation, and vertical displacements within the Nara and Nokot landslides between April 2019, August 2019, and July 2022 by analyzing multi-temporal ortho-mosaics and DSMs. By conducting field surveys, the gathered data were validated and enhanced.

Through the study of multi-temporal ortho-mosaics and DSMs, the acquisition of detailed information about morphological changes and vertical displacements that occurred within the Nara and Nokot landslide area between April 2019, August 2019, and July 2022 was possible. Field investigations and multiple aerial surveys were used to validate and enhance the acquired data.

The combination of ortho mosaic interpretation and frequent field surveys revealed geomorphological evidence of the ongoing activities in the Nara and Nokot landslides. Mass movements of various sizes and levels of activity, therefore, affected the landslides, resulting in swift changes in morphology, particularly in the depletion and transition zones of the landslide. The upper part of the source area is said to have chaotic dynamics, with numerous landslide scarps, tension cracks, trenches, and counter slopes. Additionally, the multi-temporal study showed that different parts of the landslide region were active at various points, which is typical behavior of massive landslides. The Nara and Nokot landslides demonstrate a complex morphodynamic and composite organization of activity, as evidenced by the information gathered.

An extensive multi-temporal morphometric analysis of the aerial surveys conducted in April 2019, August 2019, and July 2022 revealed that the active area of the Nara landslide had gradually decreased from 69,428.04 m³ to 5,570,063 m³ and that of the Nokot landslide increased from 47,252.21 m³ to 48,260 m³ due to active tectonics, rainfall patterns, and excavation of the material anthropogenically. The dormant area of the Nara landslide, however, increased from 9621.22 m³ to 19,480.58 m³, and for the Nokot landslide, the dormant area increased from 7744.30 m³ to 13,263.83 m³. This expansion was determined to result from the Nara and Nokot landslide scarps gradually moving uphill, causing a progressive change in the landscape. Notably, sliding occurred repeatedly in the top part of the transition zone of the Nara landslide and in the depletion zone of the Nokot landslide, which helped to continuously lower the elevation of the landslide. Additionally, the forward movement of the landslide's mass from the degraded depletion zone to the transitional and, eventually, accumulation zones justified the minimal elevation rise in particular designated points due to rainfall events washing out the loose material to the water channel and the river. The accumulation zone of the Nara and Nokot landslides' DSMs revealed substantial and apparent variations in the topographic characteristics. This detailed analysis revealed the dynamic and constantly changing nature of the Nara and Nokot landslides.

Huntley's findings [34], including two sets of DEMs and orthophoto mosaics, taken on 16 July 2011, and 10 November 2011, were compared to analyze landslide dynamics. The COSI-Corr image correlation technique was employed to measure and map terrain displacements. The results indicated that the technique effectively mapped the displacement vectors of the landslide's toes, soil chunks, and vegetation patches but was unsuccessful in mapping the main scarp's retreat. Similarly, Ahmad et al. [23] explored the application of DTA on loess landslides in China using high-resolution terrain data from low-cost UAVs. Focusing on a high-speed, long-runout landslide on the Bailu Loess Tableland, the research examined the landslide's fundamental characteristics and spatial patterns through hydrology analysis, geomorphic change detection, hypsometric integral (HI) and stability analysis, morphology analysis, and structure analysis. The results demonstrated that DTA enhances the understanding of landslide geomorphology and structure, detects geomorphic changes, reveals landform evolution principles, and offers advantages in predicting landslide stability. Mao et al. [22] investigated the reactivation of the Jiangdingya landslide near the Bailong River in Nanyu Township, Zhouqu County, Gansu Province, China. Approximately 10,000 m³ of material slid into the river, causing flooding and destruction of infrastructure [36,41,42]. Using GCD, researchers used field investigations, UAV photography, InSAR traces, historical records, and remote sensing images to analyze the landslide's geometry and geomorphic parameters. High-resolution topographic data helped assess geomorphological changes, stability, and precursory motion [43–47].

The Google Earth-based temporal analysis (2010, 2014, and 2022) of the visual records for the Nara landslide revealed a serious issue as communities grow dangerously above the landslide scarp (Figure 14) [48–51]. This circumstance causes a great deal of concern regarding landslide hazards [52–55]. The images emphasize the changing terrain over time and the progressive expansion of these towns. The need for a detailed risk assessment and the creation of practical mitigation methods in this area is made more urgent by the settlements' closeness to the scarp [56–61].

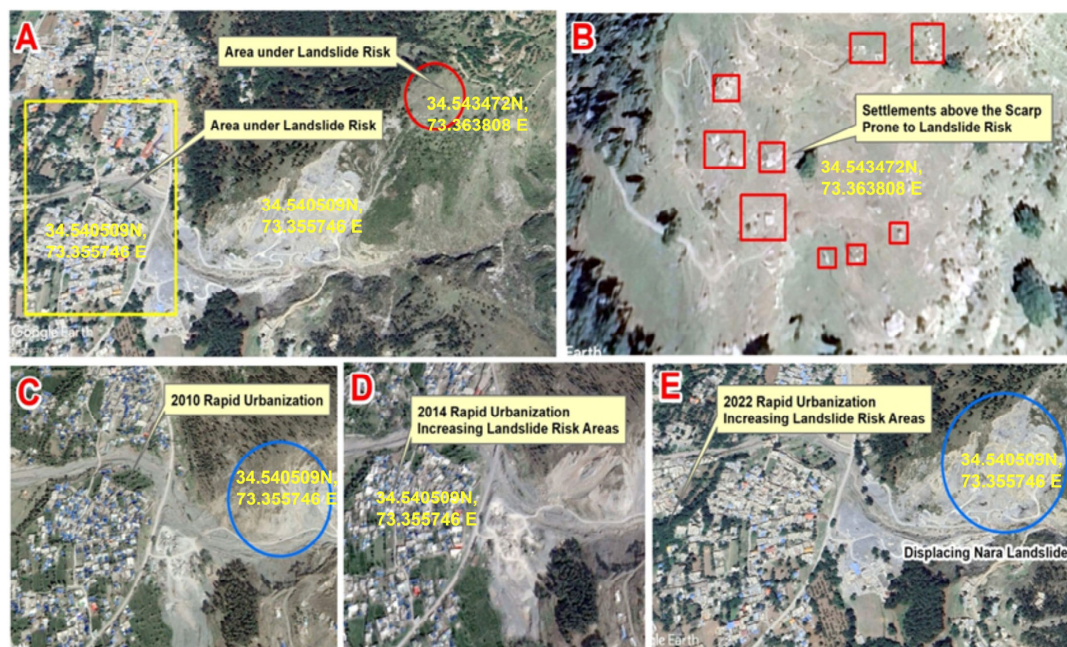


Figure 14. Progression of Nara Landslide Impact and Community Expansion; (A) Houses at risk (red circle) and landslide scarp (red squares), (B) Landslide above scarp living community, (C) Landslide extent(encircled in blue) in 2010, (D) Rapid community expansion by 2014, (E) Increased risk: to community and landslide expansion (encircled in blue) by 2022.

Turning to the Nokot landslide, our examination of 2010, 2012, 2016, and 2022 suggests a clear cause for concern. Settlements below the landslide-prone area are at increased risk

in this situation. This risk is increased by the undeniable proof of the landslide's elevation of the flow channel and the continual deposition of debris into the adjoining Kunhar River and, therefore, there is an urgent need for thorough land-use planning and efficient risk mitigation strategies in these susceptible areas. Given these changing landslide dynamics, ongoing monitoring is crucial for making informed decisions [62–64]. The community living above the scarp and below the landslides, as evidenced by Figures 14 and 15 is on the verge of the impending landslide risk [65,66]. The timely mitigation and stabilization of the landslide through engineering and bioengineering is needed for the Nara and Nokot landslides [67].

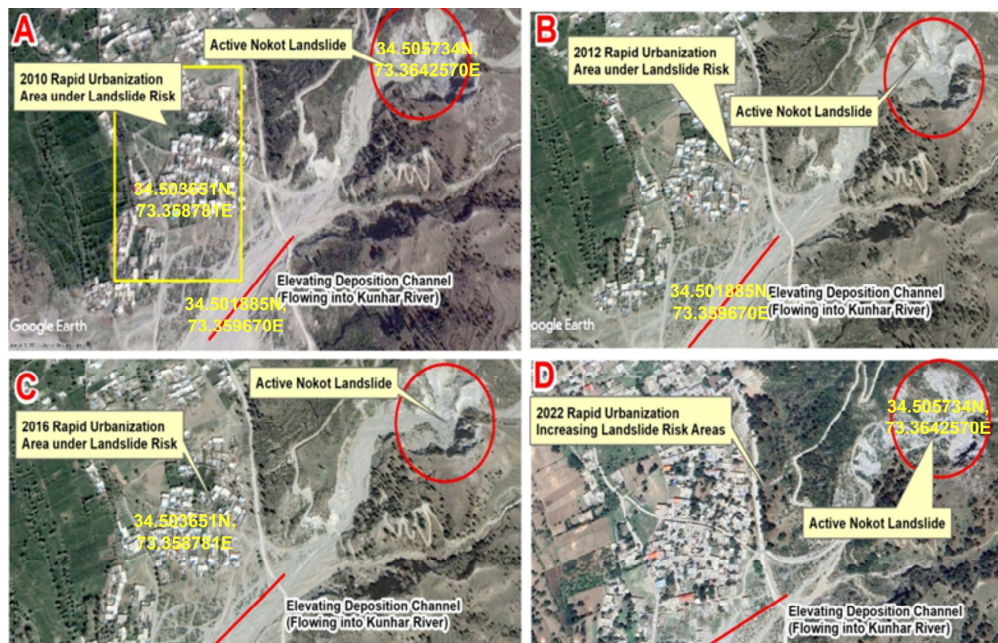


Figure 15. Progression of Nokot Landslide Impact and Community Expansion Visual records of landslide risk to settlements and displacement of the Nokot landslide using Google Earth data for the temporal years; (A) Houses at risk and landslide scarp in 2010, (B) Community expansion and scarp growth in 2014, (C) Continued expansion and scarp growth in 2016, (D) Further expansion, scarp growth, and rising water channel (red line) posing increased risk to Nokot village by 2022.

Figures 14 and 15 detail the progression of landslide impacts and community expansion in the Nara and Nokot regions, respectively. Figure 14A depicts the community at risk from the Nara landslide, with a red circle indicating houses above the landslide scarp, which are shown as red squares in Figure 14B. Figure 14C illustrates the Nara landslide's extent in 2010, while Figure 14D highlights the rapid expansion of community houses by 2014. By 2022, Figure 14E shows further expansion of both the community and the landslide body, emphasizing the increased risk.

Similarly, Figure 15A presents the community at risk from the Nokot landslides in 2010. Figure 15B–D show the community's expansion in 2014, 2016, and 2022, respectively, with red circles marking the scarp region's growth. Additionally, a red line in the toe region indicates the rising water channel draining into the Kunhar River, posing multiple hazards and increased risks to the Nokot village. These figures collectively underscore the growing vulnerability of the communities due to ongoing landslide activity and residential expansion.

The detailed analysis and field-based interpretations revealed that the compaction of the landslide mass and deep erosive processes, primarily gullies that work along the flanks of the accumulation zone, can both be credited with contributing to a portion of the volume losses in the Nara and Nokot landslides.

The results of this study confirm previous findings by [36,41,42] and highlight the effectiveness and practicality of using UAVs as a robust and near real-time platform for mapping significant landslide events [68,69]. The quick on-demand repeatability capability of UAVs, providing them with an edge over other surveying and remote sensing platforms, i.e., terrestrial laser scanners, satellite imagery, etc., boasting high-resolution results while preserving cost-efficiency, stands out as a major benefit [38,70,71]. Additionally, choosing the 90° angle of UAV flights over ground-level photography (capturing images at a nearly horizontal angle) makes it easier to acquire high-resolution imagery quickly and uniformly over vast areas, minimizing shadow-induced gaps in the resulting 3D models. These research results support using multi-temporal UAV photography in conjunction with field data. The way forward of this research is that all landslides should be continuously monitored to study the movement pattern. Multi-temporal UAV-based monitoring is a very useful and cost-effective technique for mapping landslide activities. Aerial photographs and high-resolution satellite imagery are also helpful for the monitoring of landslide displacement due to their high temporal resolution.

5. Conclusions

UAV systems have emerged as a simple, effective, and repeatable method for monitoring and surveying landslide areas, facilitating the identification, mapping, and monitoring of their spatial and temporal evolution, thus enhancing landslide risk management practices. The study integrated data from three drone flights and field surveys conducted between April 2019 and July 2022 to detect the short-term evolution of a slow-moving earth flow. We effectively delineated geomorphological changes, identified landslide types and activity states, and conducted detailed spatial and volumetric analysis using GCD, showcasing the approach's efficacy. Specifically, during the study period, the depletion zone exhibited signs of activity due to multiple slides evolving into earth flows, resulting in localized collapses of the main scarps of the Nara and lower edges of the Nokot with retrogressive fail upslope exceeding 100 m. The transition zone was affected by numerous slow earth flows that re-mobilized displaced material from the middle portion of the landslide, subsequently reaching the accumulation zone. The accumulation zone predominantly appeared active. Volumetric analysis of the Nara landslide indicated overall erosion of landslide material with a volume of approximately 4,565,274.96 m³, while the accumulated and surface-raising material volume was approximately 185,544.53 m³. Similarly, for the Nokot landslide, the overall erosion of landslide material was estimated at 6,486,121.30 m³, with an accumulated volume and surface-raising material of 117.98 m³. The high-resolution topographic data derived from UAVs, coupled with field surveys, contribute to an enhanced understanding of landslide dynamics and enable quantification of displacement distribution within the landslide area, which is crucial for comprehending the response of landslide activity to climatic conditions. Future research might focus more on optimizing UAV flying parameters, developing sophisticated algorithms that can overcome the performance of GCD and provide better results for automated landslide change detection, and looking at integrating data from many sources for improved landslide monitoring and mitigation techniques. Considering these factors, we can improve the viability and practicality of UAV technology for landslide displacement detection, ultimately leading to more efficient planning for hazard mitigation and disaster relief operations.

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References

1. Yin, Y.; Guo, Y.; Su, Q.; Wang, Z. Task Allocation of Multiple Unmanned Aerial Vehicles Based on Deep Transfer Reinforcement Learning. *Drones* **2022**, *6*, 215. [\[CrossRef\]](#)
2. Solaimani, K.; Mousavi, S.Z.; Kavian, A. Landslide susceptibility mapping based on frequency ratio and logistic regression models. *Arab. J. Geosci.* **2013**, *6*, 2557–2569. [\[CrossRef\]](#)
3. Li, J.; Han, L.; Zhang, C.; Li, Q.; Liu, Z. Spherical Convolution Empowered Viewport Prediction in 360 Video Multicast with Limited FoV Feedback. *ACM Trans. Multimed. Comput. Commun. Appl.* **2023**, *19*, 1–23. [\[CrossRef\]](#)
4. Eker, R.; Aydın, A.; Hübl, J. Unmanned aerial vehicle (UAV)-based monitoring of a landslide: Gallenzerkogel landslide (Ybbs-Lower Austria) case study. *Environ. Monit. Assess.* **2017**, *190*, 28. [\[CrossRef\]](#)
5. Li, J.; Zhang, C.; Liu, Z.; Hong, R.; Hu, H. Optimal Volumetric Video Streaming With Hybrid Saliency Based Tiling. *IEEE Trans. Multimed.* **2023**, *25*, 2939–2953. [\[CrossRef\]](#)
6. Ali, M.Z.; Ullah, S.; Ali, A. Impact assessment of spatial resolution on landslide inventories: A case study of Muzaffarabad city. *J. Himal. Earth Sci.* **2017**, *50*, 114–124.
7. Asghar, U. *Landslide Mapping from Analysis of UAV-SfM Point Clouds in the College of Graduate Studies*; The University of British Columbia: Vancouver, BC, Canada, 2017.
8. Mercuri, M.; Conforti, M.; Ciurleo, M.; Borrelli, L. UAV Application for Short-Time Evolution Detection of the Vomice Landslide (South Italy). *Geosciences* **2023**, *13*, 29. [\[CrossRef\]](#)
9. Zhou, S.; Zhou, S.; Tan, X. Nationwide susceptibility mapping of landslides in Kenya using the fuzzy analytic hierarchy process model. *Land* **2020**, *9*, 535. [\[CrossRef\]](#)
10. Gorum, T.; Fan, X.; van Westen, C.J.; Huang, R.Q.; Xu, Q.; Tang, C.; Wang, G. Distribution pattern of earthquake-induced landslides triggered by the 12 May 2008 Wenchuan earthquake. *Geomorphology* **2011**, *133*, 152–167. [\[CrossRef\]](#)
11. Parkash, S. Earthquake Related Landslides in the Indian Himalaya: Experiences from the Past and Implications for the Future. In *Landslide Science and Practice: Volume 5: Complex Environment*; Margottini, C., Canuti, P., Sassa, K., Eds.; Springer: Berlin/Heidelberg, Germany, 2013; pp. 327–334.
12. Perera, E.N.C.; Jayawardana, D.T.; Ranagalage, M.; Dissanayake, D.M.S.L.B.; Wijenayaka, H.M.D.S. Introduce a framework for landslide risk assessment using geospatial analysis: A case study from Kegalle District, Sri Lanka. *Model. Earth Syst. Environ.* **2020**, *6*, 2415–2431. [\[CrossRef\]](#)
13. Zhu, W.; Chen, J.; Sun, Q.; Li, Z.; Tan, W.; Wei, Y. Reconstructing of High-Spatial-Resolution Three-Dimensional Electron Density by Ingesting SAR-Derived VTEC Into IRI Model. *IEEE Geosci. Remote Sens. Lett.* **2022**, *19*, 4508305. [\[CrossRef\]](#)
14. Hong, H.; Shahabi, H.; Shirzadi, A.; Chen, W.; Chapi, K.; Bin Ahmad, B.; Roodposhti, M.S.; Hesar, A.Y.; Tian, Y.; Bui, D.T. Landslide susceptibility assessment at the Wuning area, China: A comparison between multi-criteria decision making, bivariate statistical and machine learning methods. *Nat. Hazards* **2019**, *96*, 173–212. [\[CrossRef\]](#)
15. Wang, X.; Huang, J.; Feng, Q.; Yin, D. Winter Wheat Yield Prediction at County Level and Uncertainty Analysis in Main Wheat-Producing Regions of China with Deep Learning Approaches. *Remote Sens.* **2020**, *12*, 1744. [\[CrossRef\]](#)
16. Khaliq, A.H.; Basharat, M.; Riaz, M.T.; Riaz, M.T.; Wani, S.; Al-Ansari, N.; Le, L.B.; Linh, N.T.T. Spatiotemporal landslide susceptibility mapping using machine learning models: A case study from district Hattian Bala, NW Himalaya, Pakistan. *Ain Shams Eng. J.* **2023**, *14*, 101907. [\[CrossRef\]](#)
17. Huang, J.; Gómez-Dans, J.L.; Huang, H.; Ma, H.; Wu, Q.; Lewis, P.E.; Liang, S.; Chen, Z.; Xue, J.-H.; Wu, Y.; et al. Assimilation of Remote Sensing into Crop Growth Models: Current Status and Perspectives. *Agric. For. Meteorol.* **2019**, *276–277*, 107609. [\[CrossRef\]](#)
18. Ramirez, R.; Lee, S.-R.; Kwon, T.-H. Long-Term Remote Monitoring of Ground Deformation Using Sentinel-1 Interferometric Synthetic Aperture Radar (InSAR): Applications and Insights into Geotechnical Engineering Practices. *Appl. Sci.* **2020**, *10*, 7447. [\[CrossRef\]](#)
19. Casagli, N.; Frodella, W.; Morelli, S.; Tofani, V.; Ciampalini, A.; Intrieri, E.; Raspini, F.; Rossi, G.; Tanteri, L.; Lu, P. Spaceborne, UAV and ground-based remote sensing techniques for landslide mapping, monitoring and early warning. *Geoenviron. Disasters* **2017**, *4*, 250–282. [\[CrossRef\]](#)
20. Chen, G.; Zhang, K.; Wang, S.; Xia, Y.; Chao, L. IHydroSlide3D v1.0: An Advanced Hydrological-Geotechnical Model for Hydrological Simulation and Three-Dimensional Landslide Prediction. *Geosci. Model Dev.* **2023**, *16*, 2915–2937. [\[CrossRef\]](#)
21. Hu, J.P.; Wu, W.B.; Tan, Q.L. Application of Unmanned Aerial Vehicle Remote Sensing for Geological Disaster Reconnaissance along Transportation Lines: A Case Study. *Appl. Mech. Mater.* **2012**, *226–228*, 2376–2379. [\[CrossRef\]](#)

22. Zheng, X.; Sarwar, A.; Islam, F.; Majid, A.; Tariq, A.; Ali, M.; Gulzar, S.; Khan, M.I.; Sardar Ali, M.A.; Israr, M.; et al. Rainwater Harvesting for Agriculture Development Using Multi-Influence Factor and Fuzzy Overlay Techniques. *Environ. Res.* **2023**, *238*, 117189. [\[CrossRef\]](#)
23. Ahmad, N.; Shafique, M.; Hussain, M.L. Landslide assessment by using multi-temporal UAV datasets: A case study in northern Pakistan. *Arab. J. Geosci.* **2021**, *14*, 1855. [\[CrossRef\]](#)
24. Cao, B.; Li, M.; Liu, X.; Zhao, J.; Cao, W.; Lv, Z. Many-Objective Deployment Optimization for a Drone-Assisted Camera Network. *IEEE Trans. Netw. Sci. Eng.* **2021**, *8*, 2756–2764. [\[CrossRef\]](#)
25. Liu, W.; Zhou, H.; Zhang, S.; Zhao, C. Variable Parameter Creep Model Based on the Separation of Viscoelastic and Viscoplastic Deformations. *Rock Mech. Rock Eng.* **2023**, *56*, 4629–4645. [\[CrossRef\]](#)
26. Turner, D.; Lucieer, A.; Watson, C. An Automated Technique for Generating Georectified Mosaics from Ultra-High Resolution Unmanned Aerial Vehicle (UAV) Imagery, Based on Structure from Motion (SfM) Point Clouds. *Remote Sens.* **2012**, *4*, 1392–1410. [\[CrossRef\]](#)
27. Zhou, G.; Wang, Z.; Li, Q. Spatial Negative Co-Location Pattern Directional Mining Algorithm with Join-Based Prevalence. *Remote Sens.* **2022**, *2103*. [\[CrossRef\]](#)
28. Shi, B.; Liu, C. UAV for landslide mapping and deformation analysis. In Proceedings of the International Conference on Intelligent Earth Observing and Applications 2015, Guilin, China, 23–24 October 2015; SPIE: Bellingham, WA, USA, 2015.
29. Xu, J.; Zhou, G.; Su, S.; Cao, Q.; Tian, Z. The Development of A Rigorous Model for Bathymetric Mapping from Multispectral Satellite-Images. *Remote Sens.* **2022**, *14*, 2103. [\[CrossRef\]](#)
30. Zhang, Y.; Li, S.; Wang, S.; Wang, X.; Duan, H. Distributed Bearing-Based Formation Maneuver Control of Fixed-Wing UAVs by Finite-Time Orientation Estimation. *Aerosp. Sci. Technol.* **2023**, *136*, 108241. [\[CrossRef\]](#)
31. Fernández, T.; Pérez, J.L.; Cardenal, J.; Gómez, J.M.; Colomo, C.; Delgado, J. Analysis of Landslide evolution affecting olive groves using UAV and photogrammetric techniques. *Remote Sens.* **2016**, *8*, 837. [\[CrossRef\]](#)
32. Wheaton, J.M.; Pérez, J.L.; Cardenal, J.; Gómez, J.M.; Colomo, C.; Delgado, J. Linking geomorphic changes to salmonid habitat at a scale relevant to fish. *River Res. Appl.* **2010**, *26*, 469–486. [\[CrossRef\]](#)
33. Ye, B.; Qiu, H.; Tang, B.; Liu, Y.; Liu, Z.; Jiang, X.; Yang, D.; Ullah, M.; Zhu, Y.; Kamp, U. Creep Deformation Monitoring of Landslides in a Reservoir Area. *J. Hydrol.* **2024**, *632*, 130905. [\[CrossRef\]](#)
34. Mohamad, N.; Ahmad, A.; Din, A.H.M. Estimation of surface elevation changes at bare earth riverbank using differential DEM technique of UAV imagery data. *Malays. J. Soc. Space* **2021**, *17*, 339–352. [\[CrossRef\]](#)
35. Ma, S.; Qiu, H.; Hu, S.; Yang, D.; Liu, Z. Characteristics and geomorphology change detection analysis of the Jiangdingya landslide on July 12, 2018, China. *Landslides* **2021**, *18*, 383–396. [\[CrossRef\]](#)
36. Hu, S.; Qiu, H.; Pei, Y.; Cui, Y.; Xie, W.; Wang, X.; Yang, D.; Tu, X.; Zou, Q.; Cao, P.; et al. Digital terrain analysis of a landslide on the loess tableland using high-resolution topography data. *Landslides* **2019**, *16*, 617–632. [\[CrossRef\]](#)
37. Wei, W.; Gong, J.; Deng, J.; Xu, W. Effects of Air Vent Size and Location Design on Air Supply Efficiency in Flood Discharge Tunnel Operations. *J. Hydraul. Eng.* **2023**, *149*, 4023050. [\[CrossRef\]](#)
38. Wheaton, J.M.; Brasington, J.; Darby, S.E.; Sear, D.A. Accounting for uncertainty in DEMs from repeat topographic surveys: Improved sediment budgets. *Earth Surf. Process. Landf. J. Br. Geomorphol. Res. Group* **2010**, *35*, 136–156. [\[CrossRef\]](#)
39. Fu, X.; Ren, M. Sustainable and Low-AoI Cooperative Data Acquisition in UAV-Aided Sensor Networks. *IEEE Sens. J.* **2024**, *24*, 9016–9031. [\[CrossRef\]](#)
40. Kulsoom, I.; Hua, W.; Hussain, S.; Chen, Q.; Khan, G.; Shihao, D. SBAS-InSAR based validated landslide susceptibility mapping along the Karakoram Highway: A case study of Gilgit-Baltistan, Pakistan. *Sci. Rep.* **2023**, *13*, 3344. [\[CrossRef\]](#)
41. Basharat, M.U.; Khan, J.A.; Khalil, U.; Tariq, A.; Aslam, B.; Li, Q. Ensuring Earthquake-Proof Development in a Swiftly Developing Region through Neural Network Modeling of Earthquakes Using Nonlinear Spatial Variables. *Buildings* **2022**, *12*, 1713. [\[CrossRef\]](#)
42. Tian, J.; Wang, B.; Guo, R.; Wang, Z.; Cao, K.; Wang, X. Adversarial Attacks and Defenses for Deep-Learning-Based Unmanned Aerial Vehicles. *IEEE Internet Things J.* **2022**, *9*, 22399–22409. [\[CrossRef\]](#)
43. Hussain, A.; Khan, M.R.; Malik, N.A.; Amin, M.; Shah, M.H.; Tahir, M.N. GIS based mapping and analysis of landslide hazard's impact on tourism: A case study of Balakot valley, Pakistan. *Int. J. Adv. Geosci.* **2017**, *5*, 116–120. [\[CrossRef\]](#)
44. Soomro, A.S.; Rajput, A.Q.K.; Solangi, S.H. GIS-based fast moving landslide risk analysis model using qualitative approach: A case study of Balakot, Pakistan. *J. Eng. Technol.* **2011**, *30*, 307–317.
45. Liu, L.; Zhang, S.; Zhang, L.; Pan, G.; Yu, J. Multi-UUV Maneuvering Counter-Game for Dynamic Target Scenario Based on Fractional-Order Recurrent Neural Network. *IEEE Trans. Cybern.* **2023**, *53*, 4015–4028. [\[CrossRef\]](#)
46. Riaz, M.T.; Basharat, M.; Brunetti, M.T.; Riaz, M.T. Semi-quantitative landslide risk assessment of district Muzaffarabad, northwestern Himalayas, Pakistan. *Stoch. Environ. Res. Risk Assess.* **2023**, *37*, 3551–3570. [\[CrossRef\]](#)
47. Basharat, M.U.; Khan, J.A.; Abdo, H.G.; Almohamad, H. An integrated approach based landslide susceptibility mapping: Case of Muzaffarabad region, Pakistan. *Geomat. Nat. Hazards Risk* **2023**, *14*, 2210255. [\[CrossRef\]](#)
48. Dai, Z.; Li, X.; Lan, B. Three-Dimensional Modeling of Tsunami Waves Triggered by Submarine Landslides Based on the Smoothed Particle Hydrodynamics Method. *J. Mar. Sci. Eng.* **2023**, *11*, 2015. [\[CrossRef\]](#)
49. Ahmad, M.N.; Shao, Z.; Aslam, R.W.; Ahmad, I.; Liao, M.; Li, X.; Song, Y. Landslide hazard, susceptibility and risk assessment (HSRA) based on remote sensing and GIS data models: A case study of Muzaffarabad Pakistan. *Stoch. Environ. Res. Risk Assess.* **2022**, *36*, 4041–4056. [\[CrossRef\]](#)

50. Yin, L.; Wang, L.; Li, J.; Lu, S.; Tian, J.; Yin, Z.; Liu, S.; Zheng, W. YOLOV4_CSPBi: Enhanced Land Target Detection Model. *Land* **2023**, *12*, 1813. [\[CrossRef\]](#)
51. Hussain, A.; Yeats, R.S.; Lisa, M. Geological setting of the 8 October 2005 Kashmir earthquake. *J. Seismol.* **2009**, *13*, 315–325. [\[CrossRef\]](#)
52. Thomas, O.; Stallings, C.; Wilkinson, B. Unmanned aerial vehicles can accurately, reliably, and economically compete with terrestrial mapping methods. *J. Unmanned Veh. Syst.* **2019**, *8*, 57–74. [\[CrossRef\]](#)
53. Yin, L.; Wang, L.; Keim, B.D.; Konsoer, K.; Yin, Z.; Liu, M.; Zheng, W. Spatial and Wavelet Analysis of Precipitation and River Discharge during Operation of the Three Gorges Dam, China. *Ecol. Indic.* **2023**, *154*, 110837. [\[CrossRef\]](#)
54. Lucieir, A.; Jong, S.M.D.; Turner, D. Mapping landslide displacements using Structure from Motion (SfM) and image correlation of multi-temporal UAV photography. *Prog. Phys. Geogr.* **2013**, *38*, 97–116. [\[CrossRef\]](#)
55. Sheng, H.; Wang, S.; Yang, D.; Cong, R.; Cui, Z.; Chen, R. Cross-View Recurrence-Based Self-Supervised Super-Resolution of Light Field. *IEEE Trans. Circuits Syst. Video Technol.* **2023**, *33*, 7252–7266. [\[CrossRef\]](#)
56. Turner, D.; Lucieir, A.; Jong, S.M.D. Time Series Analysis of Landslide Dynamics Using an Unmanned Aerial Vehicle (UAV). *Remote Sens.* **2014**, *7*, 1736–1757. [\[CrossRef\]](#)
57. Mateos, R.M.; Azañón, J.M.; Roldán, F.J.; Notti, D.; Pérez-Peña, V.; Galve, J.P.; Pérez-García, J.L.; Colomo, C.M.; Gómez-López, J.M.; Montserrat, O.; et al. The combined use of PSInSAR and UAV photogrammetry techniques for the analysis of the kinematics of a coastal landslide affecting an urban area (SE Spain). *Landslides* **2017**, *14*, 743–754. [\[CrossRef\]](#)
58. Hirano, A.; Welch, R.; Lang, H. Mapping from ASTER stereo image data: DEM validation and accuracy assessment. *ISPRS J. Photogramm. Remote Sens.* **2003**, *57*, 356–370. [\[CrossRef\]](#)
59. Yang, D.; Cui, Z.; Sheng, H.; Chen, R.; Cong, R.; Wang, S.; Xiong, Z. An Occlusion and Noise-Aware Stereo Framework Based on Light Field Imaging for Robust Disparity Estimation. *IEEE Trans. Comput.* **2024**, *73*, 764–777. [\[CrossRef\]](#)
60. Zhang, K.; Gann, D.; Ross, M.; Robertson, Q.; Sarmiento, J.; Santana, S.; Rhome, J.; Fritz, C. Accuracy assessment of ASTER, SRTM, ALOS, and TDX DEMs for Hispaniola and implications for mapping vulnerability to coastal flooding. *Remote Sens. Environ.* **2019**, *225*, 290–306. [\[CrossRef\]](#)
61. Yordanov, V.; Truong, Q.X.; Brovelli, M.A. Estimating Landslide Surface Displacement by Combining Low-Cost UAV Setup, Topographic Visualization and Computer Vision Techniques. *Drones* **2023**, *7*, 85. [\[CrossRef\]](#)
62. Teo, T.-A.; Fu, Y.-J.; Li, K.-W.; Weng, M.-C.; Yang, C.-M. Comparison between image-and surface-derived displacement fields for landslide monitoring using an unmanned aerial vehicle. *Int. J. Appl. Earth Obs. Geoinf.* **2023**, *116*, 103164. [\[CrossRef\]](#)
63. Huntley, D.; Rotherham-Clarke, D.; MacLeod, R.; Cocking, R.; LeSueur, P.; Lakeland, B.; Wilson, A. Scalable Platform for UAV Flight Operations, Data Capture, Cloud Processing and Image Rendering of Landslide Hazards and Surface Change Detection for Disaster-Risk Reduction. In *Progress in Landslide Research and Technology*; Springer: Berlin/Heidelberg, Germany, 2023; Volume 1, pp. 49–61.
64. Melis, M.T.; Da Pelo, S.; Erbi, I.; Loche, M.; Deiana, G.; Demurtas, V.; Meloni, M.A.; Dessì, F.; Funedda, A.; Scaioni, M.; et al. Thermal Remote Sensing from UAVs: A Review on Methods in Coastal Cliffs Prone to Landslides. *Remote Sens.* **2020**, *12*, 1971. [\[CrossRef\]](#)
65. Bentley, M.J.; Foster, J.M.; Potvin, J.J.; Bevan, G.; Sharp, J.; Woeller, D.J.; Take, W.A. Surface displacement expression of progressive failure in a sensitive clay landslide observed with long-term UAV monitoring. *Landslides* **2023**, *20*, 531–546. [\[CrossRef\]](#)
66. Aslam, R.W.; Shu, H.; Tariq, A.; Naz, I.; Ahmad, M.N.; Quddoos, A.; Javid, K.; Mustafa, F.; Aeman, H. Monitoring Landuse Change in Uchhali and Khabeki Wetland Lakes, Pakistan Using Remote Sensing Data. *Gondwana Res.* **2024**, *129*, 252–267. [\[CrossRef\]](#)
67. Ma, S.; Qiu, H.; Zhu, Y.; Yang, D.; Tang, B.; Wang, D.; Wang, L.; Cao, M. Topographic Changes, Surface Deformation and Movement Process before, during and after a Rotational Landslide. *Remote Sens.* **2023**, *15*, 662. [\[CrossRef\]](#)
68. Liu, Z.; Qiu, H.; Zhu, Y.; Liu, Y.; Yang, D.; Ma, S.; Zhang, J.; Wang, Y.; Wang, L.; Tang, B. Efficient identification and monitoring of landslides by time-series InSAR combining single-and multi-look phases. *Remote Sens.* **2022**, *14*, 1026. [\[CrossRef\]](#)
69. Mao, Z.; Hu, S.; Wang, N.; Long, Y. Precision evaluation and fusion of topographic data based on UAVs and TLS surveys of a loess landslide. *Front. Earth Sci.* **2021**, *9*, 801293. [\[CrossRef\]](#)
70. Giordan, D.; Adams, M.S.; Aicardi, I.; Alicandro, M.; Allasia, P.; Baldo, M.; De Berardinis, P.; Dominici, D.; Godone, D.; Hobbs, P.; et al. The use of unmanned aerial vehicles (UAVs) for engineering geology applications. *Bull. Eng. Geol. Environ.* **2020**, *79*, 3437–3481. [\[CrossRef\]](#)
71. Karantanellis, E.; Marinos, V.; Vassilakis, E.; Christaras, B. Object-Based Analysis Using Unmanned Aerial Vehicles (UAVs) for Site-Specific Landslide Assessment. *Remote Sens.* **2020**, *12*, 1711. [\[CrossRef\]](#)

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