remote sensing

Review

Remote Sensing-Based 3D Assessment of Landslides: A Review of the Data, Methods, and Applications

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Abstract: Remote sensing (RS) techniques are essential for studying hazardous landslide events because they capture information and monitor sites at scale. They enable analyzing causes and impacts of ongoing events for disaster management. There has been a plethora of work in the literature mostly discussing (1) applications to detect, monitor, and predict landslides using various instruments and image analysis techniques, (2) methodological mechanics in using optical and microwave sensing, and (3) quantification of surface geological and geotechnical changes using 2D images. Recently, studies have shown that the degree of hazard is mostly influenced by speed, type, and volume of surface deformation. Despite available techniques to process lidar and image/radar-derived 3D geometry, prior works mostly focus on using 2D images, which generally lack details on the 3D aspects of assessment. Thus, assessing the 3D geometry of terrain using elevation/depth information is crucial to determine its cover, geometry, and 3D displacements. In this review, we focus on 3D landslide analysis using RS data. We include (1) a discussion on sources, types, benefits, and limitations of 3D data, (2) the recent processing methods, including conventional, fusion-based, and artificial intelligence (AI)-based methods, and (3) the latest applications.

Keywords: 3D data; 3D geometric analysis; lidar; elevation maps; DEM; DSM; DTM

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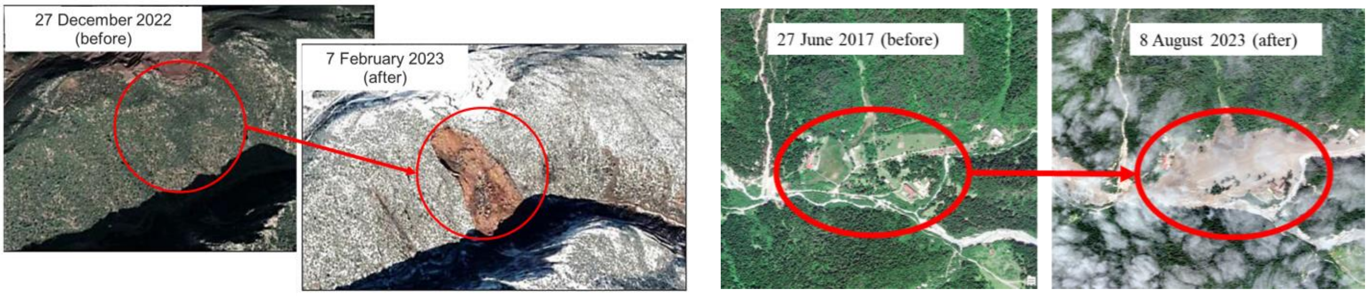
1. Introduction

1.1. Background about the History of Landslides and Remote Sensing

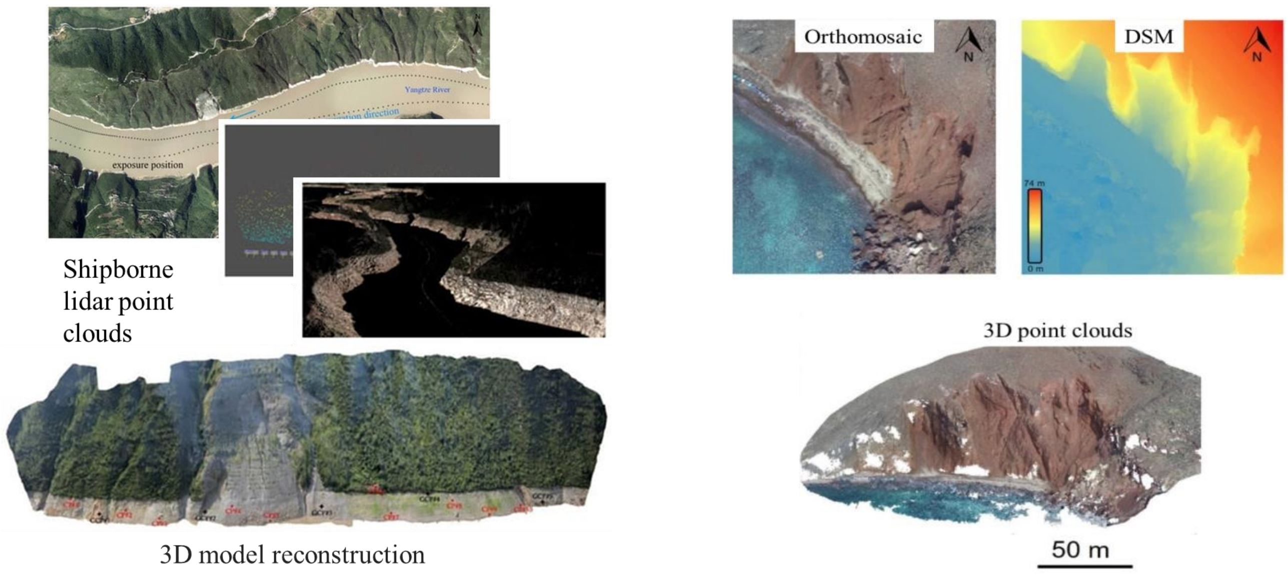
Landslides are caused by earth masses (such as rock, soil, and debris) falling downslope due to the different actions of gravitational forces on segregated layers [1]. These deadly geohazards frequently occur worldwide on local, regional, and global scales. They are often triggered by natural forces such as rainfall, glacier melt, and seismic activity. (Figure 1), or human activities such as deforestation, construction, and excavation [2,3]. Landslides can have substantial socioeconomic and environmental impacts when they lead to fatalities, injuries, and damage to property and infrastructure. Preventing natural disasters such as landslides is impossible; however, mitigating the risks and negative impact through informed planning and evacuation is extremely effective at mitigating landslide risks. This can be achieved by identifying danger zones and continuously monitoring and updating the progress of subtle surface movement before it turns into a life and infrastructure-threatening landslide [2–4].

Remote sensing (RS) techniques have played a major role in studying landslides. By gathering earth observations (EO) from a distance in real-time or near real-time, scientists and authorities may detect, monitor, and predict these deadly events without expensive and time-consuming field surveys like boreholes or in-site measurements of dimensions and slope [5]. This facilitates obtaining a detailed inventory of landslides on local, regional, and global scales to indicate their state (i.e., active or inactive), location, distribution, movement speed and type, etc. Studying landslides using RS technology requires knowledge of the complex nature of landslides and the types of RS sensors, platforms, and data used to study them. The complex nature of landslides refers to understanding the causes, mechanisms, topological changes, and surface deformations. The leading causes can be divided into natural events (e.g., rain and earthquakes), human activities (e.g., construction and excavation), and morphological (e.g., waves) or geological (e.g., lithology and layers materials) causes [1–3,6,7]. The mechanism and kinematics of landslides describe the speed and style of movement of earth masses. According to [1], there are five types of movement: flow, slide, fall, topple, and spread, which can have varying speeds and can be used to determine the hazard level. The topological changes refer to the vertical displacement, terrain profile changes, and the volume of eroded or deposited materials. Figure 1 shows four examples of landslides by different causes (i.e., trigger factors, failure mechanism, etc.). For instance, Turkey's earthquake in February 2023 triggered thousands of landslides due to co-seismic ground movement [8]. Figure 1a shows one of the biggest landslides (near Islahıye, Gaziantep, Turkey) blocking the river channels due to a rockslide from the snowmelt that fell on limestone after ground shaking. The landslide in Shovi, Georgia, also occurred due to glacial/snowmelt; however, this was triggered by heavy rainfall that led to a large mudflow down the valley (Figure 1b). On the other hand, the landslide in the Three Gorges Reservoirs in China resulted from an increased water level from heavy rainfall, leading to steep slopes along the valley (Figure 1c). Figure 1d shows a rockslide and rockfall from a cliff in Red Beach, Greece, due to coastal erosion of weak unconsolidated soils and volcanic materials. Effective investigation of the landslides' variations requires knowledge of the depth or elevation, which should be computed from the scene (Figure 1c,d). Understanding the 3D motion by the landslides can be beneficial to recognize surface deformations over time, which may include changes in size, shape, volume, content (e.g., land use land cover (LULC)), and properties of the surface (e.g., soil moisture).



(**a**) (**b**)

Figure 1. *Cont.*



(**c**) (**d**)

Figure 1. Examples of landslides where (**a**) a landslide triggered by an earthquake in Turkey [9]; (**b**) GeoEye images (Copyright 2023 Maxar) show a mudflow site in a mountainous area in Shovi, Georgia; (**c**) Shipborne lidar and 3D model showing a landslide in Three Gorges reservoir China due to heavy rainfall [10]; and (**d**) A DSM and 3D point clouds showing rock slide in Red Beach, Greece that occurred due to lithology and coastal erosion [11].

Remote sensing technology can collect data from spaceborne, airborne, or terrestrial platform sensors. The choice of RS data, sensor, and processing method is based on the unique characteristics of a given landslide or landslide-prone region. For example, an indicator of landslides in rainy areas is an increase in soil moisture content, which can weaken soil strength due to water pressure and lead to slope failures [12]. RS, optical, thermal, or microwave images can record soil moisture content and indicate saturated areas with potential slope failure [12–14]. Optical images, such as multispectral images, can compute the normalized difference vegetation index (NDVI) and normalized difference water index (NDWI), indicating strongly vegetated and wet areas. Thermal imaging devices installed on unmanned aerial vehicles (UAVs) can correlate the wetness levels by inspecting the temperature of areas because warmer soils are often more saturated than colder soils. Radar images obtained from satellites (such as the Advanced Microwave Scanning Radiometer) offer direct measurements of soil moisture content by operating on different frequency levels, where they can penetrate the soil (and vegetation cover) at varying depths and measure the variations in soil water content. In general, there are numerous ways to examine landslides through RS technology.

1.2. The Importance of 3D Data for Studying Landslides in Remote Sensing

Remote sensing data can be categorized based on their structure and encapsulated physical information into two types, two-dimensional (2D) or three-dimensional (3D) data, where both have advanced landslide studies [3,6,7] (Table 1). In RS, 2D data are derived from optical images that capture panchromatic, multispectral, or hyperspectral images from space and airborne sensors, including UAV devices (Figure 2). In landslide research, 2D data are often used to determine apparent spatial, spectral, and temporal changes on the surface, such as vegetation removal, cracks, and inconsistency in the distribution of materials (e.g., deposition) [3,15–18]. Processing 2D data has been established for decades because of its low cost, simple 2D analysis, frequency of data collection, and large area coverage [3,15–17]. However, as 2D data analysis relies only on color information, they can be limited by spectral distortions from varying acquisition conditions (e.g., atmospheric or sun angle) [19,20]. This can lead to noisy and spectrally heterogeneous images that result in difficulty separating landslide areas from the surrounding environment and inaccurate comparison of multitemporal images. Most sensors collecting this type of 2D data are restricted in their viewing angles, scale, and temporal and spatial resolutions, which may prevent the analysis from capturing intricate or subtle cues related to landslides. For example, medium-resolution (15–30 m) Landsat 8 images cannot be used to identify small-scale changes or fine details like small cracks that help detect landslides [13,21,22]. Finally, 2D data cannot obtain information about the sub-surface deformations of a terrain, which can indicate the severity of slope failures [17,20,23]. Conversely, 3D data has proven more effective in studying landslides over the years [24–32]. This is because of their ability to compute the 3D geometric information of terrains (i.e., elevation/depth) and use it as the main parameter to detect and inform the severity and extent of landslides [18,33–37]. The 3D data can be generated directly from the light detection and ranging (lidar) and radar sensors or processed using photogrammetric stereo methods [20]. These approaches can provide full or partial representation of the 3D data. For example, point clouds are considered full 3D data. In contrast, digital elevation models (DEMs), digital surface models (DSMs), and digital terrain models (DTMs) are considered a simplified representation of the 3D data and are often referred to as 2.5D (Figure 2). 3D data are more consistent, robust, and less susceptible to unwanted changes (e.g., radiometric artifacts) over time than 2D data [20,23,38]. Moreover, studies have shown that the 3D geometric and topographic features are strongly associated with landslides [33,35,39,40]. These features can be measured directly from point clouds and elevation maps such as 2.5D DEMs, including elevation, slope, aspect, hill shade, curvature, etc. [33,35,39,40]. Therefore, they can be used to compute more meaningful metrics such as volume of deposition or erosion, vertical displacements, steep slopes, etc., improving the detection and assessment of landslide areas. Sensors collecting 3D data can be installed on various platforms, including spaceborne, airborne, or terrestrial. They can be calibrated or set up based on the characteristics of the study area and the intended applications. For example, the accuracy of data generated by microwave satellite sensors (i.e., RADAR) can be impacted by densely vegetated areas [41], so using terrestrial lidar can be more suitable for accessing these areas and collecting 3D data [26,31,42]. Unfortunately, 3D data can be very expensive and complex to collect. Their area coverage can also be limited in terms of space and time. They may be unavailable in some areas worldwide, such as in developing countries. Other studies have also noted that collecting 3D data can be difficult in unreachable and inaccessible regions such as deep valleys and high mountains [43–45].

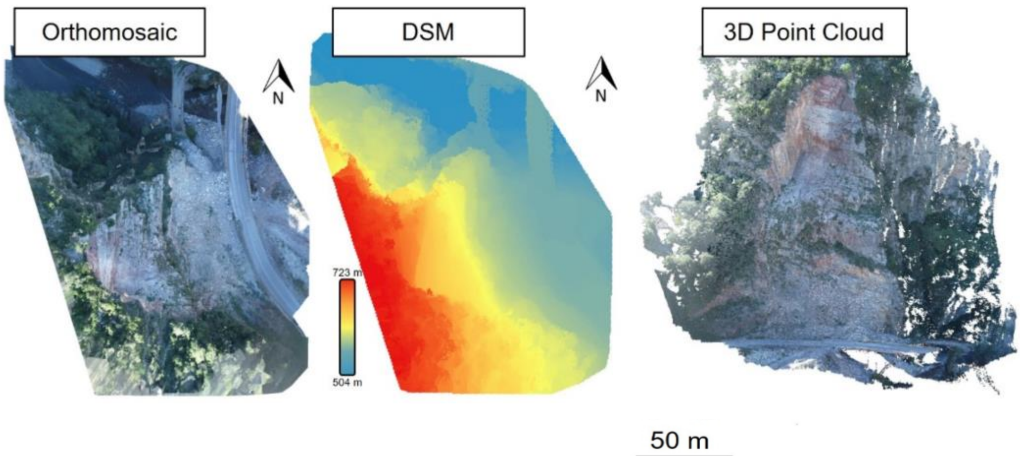


Figure 2. An example from [11] of a landslide in Proussos in Evritani, Greece, showing a spectral UAV image, a DSM from photogrammetry, and the reconstructed 3D model from point clouds embedded with color.

Table 1. A comparison between 2D and 3D data for landslide studies.

Type of Data	2D Data	3D Data
Description	Refers to data produced by imaging sensors installed on a more sensing platform, such as airborne, UAV-borne, and spaceborne platforms. The data of interest may have panchromatic, multispectral, or hyperspectral optical image data and 2D microwave images.	Refers to data containing 3D geometric information like depth or elevations acquired from RADAR, lidar, or photogrammetric stereo methods.
Metrics to study landslides	• Change in spectral information (e.g., NDVI, NDWI, and MSI) • Brightness and intensity differences • Texture differences (e.g., entropy) • Planimetric 2D shapes	• Vertical displacement • Volumetric differences • Changes in topographic features, e.g., slope, aspect, and hill-shade • Full 3D geometric change
Advantages	• Wide area coverage • Large availability of data over time with a variety of costs • Simple 2D analysis approaches, e.g., image differencing • Capture surface changes, e.g., LULC changes, surface cracks, and deposited materials	• Consistent measurements of 3D data over time • Determination of mechanism (i.e., movement type) and kinematics (i.e., speed and volume) of landslides to indicate danger level. • Detect sub-surface deformations, e.g., topography, terrain profile, and 3D displacements.
Challenges	• Radiometric distortions due to acquisition conditions, e.g., weather, sun angle, and season. • Restricted angle of view, coverage, and spatial resolution • Cannot detect sub-surface deformations, e.g., vertical displacements. • Difficult to separate between landslide areas and the surrounding environment.	• Costly and time-consuming to collect and process. • Complex processing algorithms. • Limited archive • Small area coverage • Difficult to assess uncertainties in inaccessible areas such as high mountains.

In general, the analysis of 2D data is suited to detecting landslides at a large granular level, e.g., binary detection of significant landslides at coarse resolution. However, due to the many challenges of using 2D image data (Table 1), researchers have combined 2D and 3D data to understand landslide events better and potentially develop more effective strategies to monitor them [24,46–50]. The 3D geometric analysis can provide detailed estimates of the terrain's surface and sub-surface characteristics. This includes elevation, slope, change in volume, speed of fall, type of vertical movements, 3D displacements in the vertical and horizontal directions, 3D deformations, and change in geometry in areas that have exhibited or are prone to landslides [3,4,6,7].

1.3. Scope of the Review and Paper Organization

This review focuses on the 3D geometric analysis of landslides in RS, emphasizing the full or partial use of 3D data. These 3D data could be collected from laser scanning sensors (i.e., lidar) or generated using a pair of images and photogrammetric stereo methods. The review is divided into three parts, as depicted in Figure 3. First, we present a thorough description of the latest advancements in 3D data, where we discuss their sources, types, benefits, and limitations (Section 2). Second, we discuss the most recent processing methods and algorithms to detect, monitor, and predict landslides (Section 3). These include conventional 3D geometric analysis, fusion, and state-of-the-art learning methods, i.e., artificial intelligence (AI). Third, we describe the latest landslide applications that benefit from 3D data and their geometric analysis, which can be used for either qualitative or quantitative 3D geometric assessment of landslides (Section 4). The qualitative assessment is concerned with landslide existence, state, and type [51], whereas the quantitative assessment applies mathematical modeling to estimate the 3D displacement, change in volume, and speed of falls [22,52,53]. Finally, Section 5 summarizes this review by discussing the opportunities, challenges, and suggestions for future work in the 3D geometric assessment of landslides.

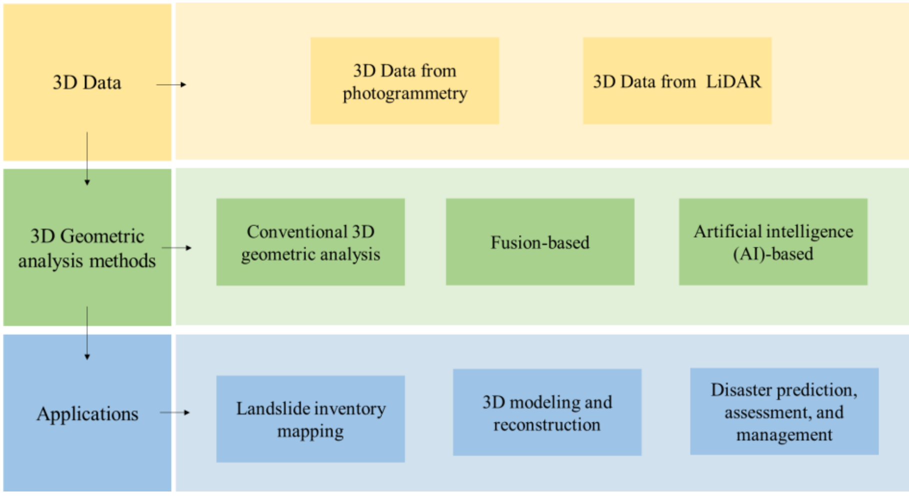


Figure 3. The workflow of this review.

2. The 3D Data Used for Landslide Studies

The choice of 3D data is critical to landslide investigation in RS due to the variety of landslide patterns, causes, areas, types, and impact periods. Therefore, determining the suitable type of 3D data is necessary. Factors of concern can be data availability, cost, coverage, occlusions (e.g., mountains), level of data uncertainty, etc. Typically, two forms of 3D data are used for 3D geometric analysis: image-derived elevation maps (i.e., DEMs, DSMs, and DTMs) and lidar-based 3D point clouds [3]. Point clouds record the X, Y, and Z coordinates of objects and surfaces, which can be acquired from lidar or stereo matching. Lidar can be installed on various platforms; the most common for landslide studies are airborne and terrestrial platforms. Spaceborne lidar, on the other hand, is rarely used for landslides or general topographical and geomorphological studies. This is because flying at high altitudes limits the characterization of internal structures, thus not being able to separate between ground and non-ground points (i.e., DTM) [54,55]. Photogrammetric elevation data are generally preferred due to their relatively low cost and availability from all platforms, including satellite, aerial, UAV, and terrestrial systems. Methods used to study landslides can drastically vary based on the data collection platform. Table 2 summarizes different photogrammetry and lidar data characteristics lidar for use in landslide studies.

2.1. 3D Data from Photogrammetry

Photogrammetry can generate both 3D point clouds and 2.5D elevation data. It relies on stereo-matching methods, which require at least two overlapping images acquired from optical sensors. The process of photogrammetry follows georeferencing and dense matching steps to generate point clouds. Elevation maps can then be derived [38,56–58]. As mentioned earlier, photogrammetry is preferred because images are much cheaper to capture and available on all platforms. However, as shown in Table 2, the generated point clouds' granularity and accuracy level significantly vary with the platform. Thus, in the following subsections, we entail their respective characteristics.

Table 2. Sources and characteristics of 3D data for 3D geometric analysis of landslides.

Source of 3D Data	**Photogrammetry**			**Lidar**	
Platform	**Spaceborne**	**Airborne**	**Terrestrial**	**Airborne**	**Terrestrial**
Type of 3D data	Derived point clouds Derived DEM, DSM, DTM			Point clouds Derived DEM, DSM, DTM	
Spatial resolution	Several meters to tens of meters	Several meters to Sub meters (<1 m)		Several meters to Sub meters (<1 m)	
Temporal resolution	Frequent (daily, weekly, monthly)	By demand		By demand	
Area coverage	Large	Small		Small	
Cost	Low-high	Low-high		High	
Setup	Fixed	Flexible		Flexible	
Viewing angle	Vertical	Vertical to oblique	Side view	Vertical to oblique	Side view
Areas best suited for	-Open areas without obstructions from buildings or vegetation	-Hazardous areas -Mountains -High-relief areas -Urban areas	-Obscured areas (e.g., mines, sea notches, and caves) -Dense vegetated or forested areas	-Hazardous areas -Mountains -Urban areas	-Obscured areas and side views (e.g., mines, sea notches, and caves)
Preprocessing	-Radiometric correction -Geometric correction -Photogrammetry methods	-Geometric correction -Photogrammetry methods -Mosaic/image stitching	-Geometric correction -Photogrammetry methods -Mosaic -GCPs setup	-Projection of point clouds to image-derived elevation maps -Registration and alignment of point clouds -GCPs setup	
Factors influencing the accuracy of 3D data	-Radiometric distortions -Spatial resolutions -Type of photogrammetry algorithm	-Terrain complexity and occlusions -Sensor type -Type of photogrammetry algorithm	-Radiometric distortions -Terrain complexity and occlusions -Type of photogrammetry algorithm -Sensor type and motion	-Terrain complexity and occlusions -Sensor type and motion	
Generation time	Fast	Fairly slow	Slow	Fairly slow	Slow

2.1.1. Spaceborne Sensors

Spaceborne sensors capture images with large area coverage due to orbiting the Earth at high altitudes, and they provide repeating observations, sometimes almost daily. For landslide studies, obtaining high-resolution and reliable 3D data is necessary to extract the terrain's detailed and precise topographical and morphological variation over time. The spaceborne sensors can provide images with resolution ranging at the sub-meter level (e.g., QuickBird, Worldview-3, and Pleiades) [16,33,59–74]. The cost of 3D data from these sensors varies with the number of images required to generate accurate 3D models. Choosing the images for use in generating 3D data may be a sophisticated process, and it may leverage orbital factors that lead to certain intersection angles and sun radiometry to decide the number of overlaps for accurate 3D modeling [75]. Moreover, the photogrammetry algorithms used for dense matching (or stereo matching) may also be a concern [38,75]. For example, a study by [38] indicates that deep learning methods (such as MC-CNN, GCNet, and PSMNet) are robust in handling variations in sun and viewing angles but may be slower to process large-scale satellite images. On the other hand, non-learning-based methods such as Census semi-global matching are less demanding in terms of time and data requirement, thus providing 3D data at a lower cost, but are more sensitive to variations among stereo images, thus requiring more images.

2.1.2. Airborne Sensors

Sensors installed on UAVs and aircraft have a high potential to detect and characterize landslides [55,76–79]. Early studies used their 3D data as ground truth reference data to validate the results through visual inspection or to extract training and testing features for machine and deep learning methods [7,38,56,57,80]. The lower flight altitudes and very high spatial resolution (<0.5 m) of UAVs result in data that captures features such as fissures and small deformations and provides better spectral separation between the landslide area and its surrounding environment [78]. Images captured using airborne platforms are flexible due to flexible air-platform maneuvers and flight designs. Thus, the airborne acquisition system can provide data with access to difficult regions, such as mountains with high reliefs, and can be acquired under cloud cover [78,81]. The airborne platform also has full control over the viewing angle of cameras, providing vertical or oblique views of the scene [78,79]. The level of flexibility of the airborne platform enables landslide detection and identification of its types, for example, falls, slides, flows, etc. Nevertheless, flying airborne sensors must be scheduled ahead of time and can be costly; thus, their data are not always available for a given area of interest [55,76–79]. They may also require expertise to operate the sensors and calibrate the sensors and data to ensure accurate acquisition of the 3D data. Compared to satellite images, aerial images can provide images with area coverage at a medium to large site level, which is often sufficient in landslide studies [55,76–79]. Similar to satellite sensors, images from airborne sensors may require preprocessing to minimize geometric and radiometric distortions before applying photogrammetry to generate 3D data.

2.1.3. Terrestrial Sensors

At various costs, cameras can be installed on terrestrial platforms, including vehicles, tripods, and handheld devices such as mobile phones [28,42,44,76,82–84]. Terrestrial platforms allow capturing images in real-time at close range, thus gaining a clear and detailed view of a landslide area [28,44]. They are ideal for determining the mechanism of landslides, i.e., movement direction and type, with high accuracy and precision. However, they may require a longer time to collect data due to their small area coverage. Thus, it is only suitable for investigation at sampled locations or persistent monitoring (i.e., stationary cameras). The choice and setup of terrestrial sensors require strategic planning to reduce errors and uncertainties in deformation detection [15,82]. For instance, the number and location of cameras are determined based on the size of the region or object of interest, expected displacement size, and occlusions on site to provide comprehensive coverage with a clear line of sight [82]. Moreover, stationary sensors are likely to develop geometric and radiometric distortions caused by inevitable sensor motion (e.g., due to wind) and variations in illumination [15]. Consequently, these distortions can impact the detection of the precise location and shape of the surface deformation and the geometric properties of the object being monitored/tracked (e.g., fracture). Mitigating these distortions requires post-configuration and processing of the images to radiometrically normalize and geometrically align them according to the positioning systems, such as the global positioning system (GPS) and ground control points (GCPs) installed on site.

2.2. 3D Data from Lidar

Over the last few decades, lidar systems, such as aerial laser scanning or terrestrial laser scanning devices, have become powerful and reliable tools for collecting high-resolution three-dimensional structural data [29,31,42,84–90]. Many studies use lidar data as a ground truth reference for elevations because of their high accuracy [38,56,91]. Lidar data have been used to detect and analyze natural disasters like landslides [77,87,92]. In comparison to the photogrammetry-based method, it features several advantages described as follows:

- Direct measurement of the 3D data: Lidar is an active sensor emitting and receiving laser pulses from objects and surfaces, thus directly computing 3D information by evaluating the time of flight. For landslide studies, the point clouds can be used directly or rasterized 2D elevation maps (e.g., DEMs, DSMs, or DTMs) [29,87]. In contrast, the accuracy of photogrammetry point cloud may be scene-dependent and vary spatially.
- High-resolution 3D data: Elevation maps derived from lidar can have high spatial resolution [85,87,89,93], which is important for extracting small-scale 3D geometric features to map landslides and provide detailed and accurate terrain representation and detection of the fine surface and sub-surface deformations [24,27,29,85,94].
- Vegetation penetration: Many landslides occur in densely vegetated or forested areas; unfortunately, these cannot be inspected well using classic optical sensors. Lidar, on the other hand, can penetrate these difficult regions to provide information about vegetation conditions (e.g., type, height, structure, volume, and texture) and changes in bare-ground elevations, which are critical factors of landslide [26,31,55,88].
- Improved accuracy and precision of 3D data: Lidar collects 3D data using laser pulses, which are robust to varying acquisition conditions such as season, weather, and low-light conditions like night-time [87]. Therefore, they can provide more accurate 3D data, often used for validation as ground truth data for landslide-related research [37,94–98] or for 3D modeling and reconstruction of terrains [24,27].
- Numerous types and costs of lidar sensors exist, lidar ranging from basic to professional sensors. Nevertheless, their performance may vary based on the landslide application, region, and selected platform. Therefore, as in the previous section, we compare lidar's 3D data for landslide studies based on the most used platforms, i.e., airborne and terrestrial.

2.2.1. Airborne Sensors

Airborne lidar collects data using UAVs and aircraft, which are available by demand and are mostly efficient for rapid assessment of post-landslide events [26,29–31,77,85,88,89,94]. It provides smaller area coverage than spaceborne sensors due to flying at lower altitudes, and thus, it is suitable for mapping landslides on local and regional scales. The flight's parameters, such as route, altitude, and the sensor's viewing angle, can be controlled based on the characteristics of the examined terrain. Therefore, airborne lidar can map unreachable, hazardous, remote areas such as valleys, volcanoes, and mountains. Nevertheless, mapping using airborne sensors requires rigorous georeferencing and positioning of every point cloud collected, which can be achieved by integrating lidar with GPS. One of the critical issues impacting the overall accuracy of 3D data is the platform's motion, which can be compensated using an inertial measurement unit (IMU) to provide information about the movement and orientation of the sensor. Integrating lidar with GPS and IMU can provide highly accurate 3D data at the sub-meter level. Precise positioning allows accurate calculation of the landslide's geometric features such as slope, volume, and horizontal and vertical displacements. However, airborne lidar requires a clear line of sight to avoid occlusions, missing data, and erroneous measurements, which can be beneficial for accurate separation between bare-ground and off-ground objects.

2.2.2. Terrestrial Sensors

Compared to the previously discussed methods, terrestrial lidar can provide the most accurate 3D data (at the sub-meter level) with a high level of precision because of data collection at a closer range. The highly accurate data allows the identification of fine details and small geomorphological changes on topographic slopes [42,44,83,84]. For example, landslides in coastal regions can occur due to waves crafting underneath cliffs leading to sea notches, which cannot be detected using airborne lidar because of the vertical viewing angle.

Terrestrial lidar moving along the shore can capture these geomorphological features and signs of a landslide [45]. However, the closer range limits the field of view and coverage to small areas, leading to slower data acquisition time. They are often preferred as stationary ground-based monitoring sensors on site. Moreover, terrestrial lidar can freely choose their installment position and orientation to provide a clear line of sight with minimum occlusions. The flexible set up provides more accurate information and quantification of the horizontal and vertical displacements [45,87]. Similar to airborne lidar, terrestrial lidar requires GPS and IMU to provide accurate georeferencing and motion information of the platform and sensor, which can enhance 3D data positioning and accurate comparison to detect changes over time. In some cases, GCPs must also be installed on-site for better spatial linkage and georeferencing of 3D data concerning known reference points.

Using 3D data for landslide studies depends on the project's characteristics and the sensor type [93]. The project's characteristics determine the extent of the area under the study, the project's cost and time, the terrain's complexity, the type of application, etc. On the other hand, the sensor type determines the spatial and temporal resolution that controls the level of detail and data availability over time. The resolution plays a major role in the accuracy of the 3D data, where the higher the resolution, the more accuracy and information we can gain about a terrain. Critical obtained information may include landslide parameters like slope, fine-level features and signs (e.g., cracks), and internal characteristics such as topographical, geological, and hydrological conditions. Therefore, high-resolution 3D data are better for mapping small-scale landslide areas, whereas low-resolution 3D data are sufficient to capture changes on large scales [93,99]. Georeferencing is also crucial because most landslide studies compare data over time; thus, 3D data must be geometrically and spatially well-aligned. Combining lidar with data from optical sensors has been shown to boost performance and provide better accuracy for mapping landslides based on color, texture, changes in slope, etc. [43,54,100]. Other studies have noted that combining data from both platforms, i.e., airborne and terrestrial, can provide a broader perspective and better analysis of the landslide-prone area [45], thus providing a complete terrain profile with information about the vertical and horizontal deformations.

3. 3D Geometric Analysis for Landslide Studies

Investigating landslides is complex due to their numerous natural variations (i.e., triggering factors, processes, and implications). As mentioned in Section 1, 3D geometric analysis can effectively assess landslides through geometry, deformations, and kinematics [35]. The 3D geometric features are more robust and consistent over time than spectral features [22,23,52,53]. Today, more research focuses on 3D geometric analysis to detect, monitor, and predict landslides (e.g., 3D change detection to compute volume or slope changes). In this section, we will describe the most common strategies to investigate landslides using 3D geometric analysis, including the conventional methods [3,18,43,80], fusion-based methods [24,46–49], and artificial intelligence (AI)-based methods [17,65,80,96,97,101–106]. Conventional methods are based on field surveys, manual calculation, visual interpretation of 3D data, and statistical and mathematical calculations of 3D data [3,18,43,80]. Fusion-based methods, on the other hand, integrate information from multiple sensors, platforms, viewing angles, and data types to provide comprehensive and more accurate information about the surface subject to landslide hazards [24,46–49]. Meanwhile, AI-based methods are based on automatically analyzing geometric features extracted directly from 3D data. AI-based methods, including machine learning (ML) and deep learning (DL), dominate today's research and are heavily investigated. They often apply 3D geometric analysis through classification, object-based image analysis (OBIA) [47,51,107,108], and time series analysis [79,82,106]. Their methods are mostly based on feature-level operations to extract and analyze 3D geometric features over time.

3.1. Conventional 3D Geometric Analysis Methods

Field surveys are the oldest means to investigate landslides [3,18,43,80,109]. They include in situ measurements of elevations and slopes using traditional surveying tools (e.g., total station) [87,109]. Moreover, surveyors inspect terrain conditions to find signs of surface and sub-surface deformations and displacements for manual calculation [87,109]. Field surveys provide direct access to concealed areas such as densely vegetated forests, which allows real-time monitoring and accurate inspection of small-scale features [109]. Nevertheless, fieldwork has many limitations, such as being expensive in terms of time and cost, may be subject to human mistakes or errors from instrumental, and can provide very limited data over time. On the other hand, remote sensing technology facilitated visual inspection and analysis of 3D data for small and large-scale mapping of landslide areas. The visual inspection identifies signs of terrain deformations (e.g., fracture, crack, and displacement) using elevation maps, slopes, aspect, surface roughness, topographic wetness index, etc. (Figure 4). However, visual inspection can be impacted by the low spatial resolution of the 3D data (e.g., DEM and DSM) to show small details. Topographic and geomorphological analysis is performed to calculate critical 3D geometric features of landslides, such as slopes, hill shade, curvature, etc., which can be directly computed from the elevation data. These geometric features can be used directly in the visual inspection or further processed to provide more details on the terrain's past and present conditions. Their analysis can include arithmetic calculations, statical and probabilistic analysis, or numerical modeling. Arithmetic calculations involve simple calculations such as differencing of elevation or slope maps; thus, they can be used to calculate volume and changes in elevation and slopes. Statistical and probabilistic methods are used for detection, prediction, and correlating triggering factors. They include Bayesian, Dempster–Shafer methods, fuzzy logic, bivariate, and multivariate analysis [110,111]. Numerical methods are used to reduce the uncertainty in the data, model, and parameters for landslide studies, where they use methods such as linear regression, least squares, optimization, etc.

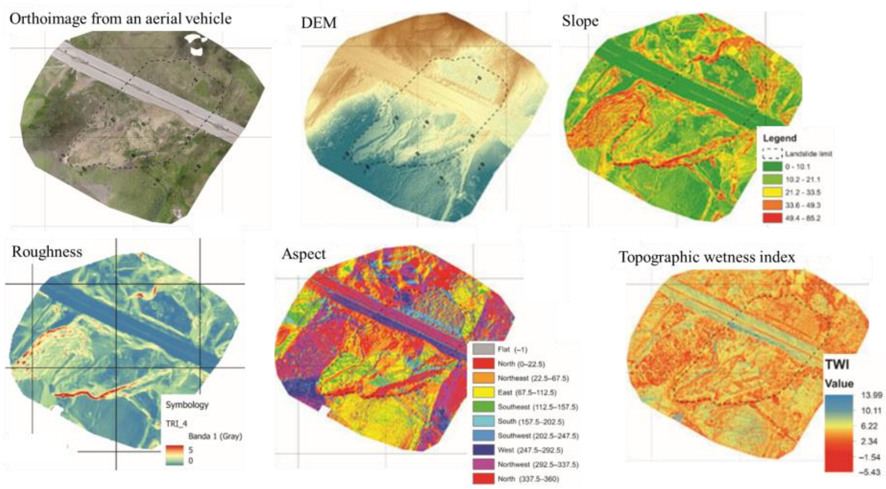


Figure 4. Examples of 3D geometric features used to delineate the landslide area outlined by the black dashed line [112].

3.2. Fusion-Based Methods

Data fusion is one of the most common approaches applied in RS and landslide studies, where auxiliary information is used to improve interpretation and analysis. For 3D geometric assessment of landslides, data fusion has been applied to combine 3D data from multiple sources, dates, angles, and different modalities (e.g., spectral images) [24,46–49,113,114]. Data fusion can support low-accuracy data due to complex terrains (e.g., hilly regions) and low-cost sensors, thus providing a comprehensive and more accurate 3D representation of landslide regions and their geometric information [24,46–49,113,114]. For example, the sensor's viewing and sun illumination angles have been proven to impact the quality and accuracy of the generated DSMs using photogrammetric methods [38,75]. Multiview images contributing to DSM generation can provide more details and information on landslide-prone areas by viewing the scene from different perspectives [45], whereas integrating point clouds from airborne and terrestrial lidar in complex regions such as hilly regions can improve topographic mapping [45]. Multiview 3D data fusion provides an opportunity to cover occluded and shadowed regions between objects and sensors, improving 3D data collection and quality. On the other hand, multisource 3D data fusion can enhance the accuracy and precision of 3D input data by addressing the limitations of individual sensors [24]. For instance, combining a pair of DSMs derived from photogrammetry and airborne lidar, with the latter providing a high-resolution elevation map, can improve the details and identify small-fine features related to landslides. Nevertheless, combining multisource 3D data can be problematic due to the varying uncertainties from different sensors, their calibration procedures, and preprocessing algorithms [45,113]. These uncertainties must be considered during the fusion process to reduce the effect of these sensor differences [45,113,115]. Some researchers have emphasized the importance of spectral image-guided data fusion with 3D geometric data to enhance landslide detection and recognition. The 3D data provides information on the terrain's geometry, such as the steepness of slope and depth of fractures. In contrast, spectral images encapsulate information about surface properties such as color, texture, LULC, vegetation indices, moisture indices, etc. [48,107]. Integrating multimodality data, i.e., elevation and color information, requires feature-level fusion, where features from different data types are extracted and transformed to be equivalent and compatible to perform data fusion. The color information is extremely useful in completing and enriching 3D terrain models and profiles. It can describe important features of the surrounding landslide environment, including existing vegetation, soil type, sediments, etc.

Although data fusion can enhance the accuracy and precision of topographic mapping of landslides, it still faces some challenges and limitations that can impact its performance. One significant challenge of data fusion is the timing in which data are acquired or generated. On many occasions, spatiotemporal inconsistencies are likely to occur due to natural or human actions on the surface over time. Spatiotemporal inconsistency may impact multitemporal data comparison and change analysis of 3D data to assess landslides over time, providing inaccurate information. Additionally, fusion-based methods are sensitive to geometric distortions in the data. Thus, they must apply rigorous georeferencing and data registration before fusion to ensure data overlap precisely in space.

3.3. Artificial Intelligence (AI)-Based Methods

The growing demand for automated and accurate landslide mapping led to the development of AI-based methods, including ML and DL methods. These methods are considered data-driven approaches to learning data association and patterns through complex models. They have been intensively used in landslide studies for their remarkable performance [37,65,94,98,103,116]. They can process 3D data and extract relevant 3D geometric features to provide information about the terrain characteristics (i.e., topography) and surface conditions (e.g., precipitation patterns and land cover changes) [37,94,96]. Popular ML methods include support vector machine (SVM), random forest, decision trees, clustering, etc. [37,94,96]. In contrast, DL methods use convolutional neural networks (CNN), generative adversarial networks (GANs), recurrent neural networks (RNN), long short-term memory (LSTM), attention, and transformers [65,95,104,116–118]. Studies comparing the performance of ML and DL models for landslide detection have found that ML approaches have limited capabilities in handling complex spatial, spectral, and geometric features and can only achieve moderate accuracies [65,95]. On the contrary, DL approaches are more sophisticated because of their network structures, which allow them to extract more complex features and provide high accuracy and precision on the location and existence of landslides [65,95]. DL methods have generally outperformed ML methods in landslide investigation [65,80,105]. In general, the performance of AI approaches varies by their ability to extract complex features, process large-scale datasets, explore spatiotemporal patterns, and generalize across different datasets and landslide areas [80,95]. After reviewing the works of 3D geometric analysis of landslides, AI approaches can efficiently perform object-based image analysis (OBIA) and time series analysis to detect and compare critical features of landslides, which will be discussed in the following:

- OBIA methods group data into unique segments based on their spatial, spectral, temporal, and geometric characteristics [47,51,108]. For 3D geometric analysis of landslides, the classic pipeline of OBIA involves three-step segmentation [119,120], 3D geometric feature extraction [47], and classification to predefined categories (e.g., type of landslide) [108]. Postprocessing (e.g., filtering) can also be used to enhance segments. OBIA allows efficient decision-making capabilities, such as change detection (e.g., slope or volume changes) [107] or identification of critical signs of landslides (e.g., steep slopes or deposited materials) and their properties (e.g., area and shape). OBIA can improve landslide detection and evaluation. Nevertheless, a significant challenge is to provide a precise and accurate separation of distinct classes to avoid over or under-definition of the landslide areas. The performance of OBIA depends on data quality, surface complexity, and the choice segmentation and classification algorithms and their input parameters. 3D data will likely have noise and errors due to sensor limitations, acquisition conditions, and pre-processing algorithms, which can directly impact OBIA and produce misclassifications. The spatial resolution can impact the quality by allowing more detailed analysis of fine features and, most importantly, can reduce inter- and intra-class variability [32,107,119]. These distortions are usually impossible to avoid and will likely influence the accuracy and precision of landslide mapping [108,121]. Furthermore, the performances of OBIA can vary based on surface or terrain complexity. For example, terrestrial lidar can be limited in urban areas due to occlusions from high buildings, trees, and shadows, which may result in low-quality 3D data in these areas [19]. Finally, there are many algorithms for classification and segmentation. Still, the choice of algorithm and input parameters may vary based on data and may require trial and error to determine the best parameters. For example, scale plays a major role in segmentation and may require several scales to determine the best representation of the landslide area.
- Time series analysis is highly important for 3D geometric analysis of landslides as it allows continuous and real-time monitoring of the event. DL methods perform exceptionally when processing time series data and finding spatiotemporal patterns. Methods such as LSTM and RNN show a remarkable ability to capture time dependencies between data and, thus, are suitable for analyzing the change in the multitemporal and time series 3D data [104,106,122,123]. For instance, the authors in [110] have proposed a modified version of LSTMs called cascade-parallel LSTM-CRF to predict landslides by modeling the relationship between environmental factors such as topography, land cover, hydrology, and geology. Attention and transformer mechanisms have recently shown superior performance in many RS environmental applications, including landslide studies [50,104]. For example, the work in [50] uses an attention mechanism in the network to detect landslides in forested areas, where they integrate multimodal data such as optical images, DEMs, and hill-shade images. They compared two aspects: (1) the inclusion of 3D geometric features like elevation data and hill-shade images with color information versus only color information, and (2) the performance of the attention network compared to other networks (e.g., HRNet, SegNet, and ResUNet). They found that 3D geometric features can enhance the accuracy and precision of landslide detection in forested areas for all networks. They have also shown that their proposed attention network can achieve the best detection accuracy. Unfortunately, only a few studies have explored the use of attention and transformers in RS-based landslide investigations, and they are good candidates for future research.

Whereas AI methods offer great potential for landslide studies, two main challenges arise from using these approaches, which can be summarized as follows:

- Data quantity, quality, and distribution:

  AI methods are data-hungry approaches; they require large amounts of training data with high quality. Training data must be well-distributed to equally cover all sorts of variations and compositions of landslides, including the triggering factors (e.g., soil moisture and rainfalls), signs (e.g., steep slopes, shallow or deep landslides, roughness, vegetation covers), geometric properties (e.g., shape and size), etc. Compared to the total global land surface area, landslide events are relatively rare, resulting in imbalanced data where landslide occurrences are significantly outnumbered by non-landslide instances [124,125]. This data imbalance is a common issue when dealing with classification problems, especially on DL models. The imbalanced data can limit the model's ability to generalize and accurately predict landslide occurrences. There are several ways to mitigate the effects of data imbalance, the most common of which is [124]. Furthermore, landslide inventories and ground truth information are necessary to train and validate ML and DL models. However, obtaining high-quality data for training is very challenging due to uncertainties arising from processing algorithms, surface cover (e.g., dense vegetation), acquisition conditions like weather, or inaccessible regions like high mountains where GCPs cannot be set up.

- Feature representation and model generalization:

  Because landslides can be influenced by a single factor or even multiple factors leading to different types of land deformation, selecting the most representative features (variables) for either ML or DL models can be very challenging. These features include terrain attributes, land cover, rainfall patterns, and geological data. Selecting proper features, determining which features contribute the most to landslide occurrence, and incorporating them effectively into the model's architecture are critical steps that usually require domain knowledge [94,95]. Transfer learning (by transferring knowledge from past experiences to new scenarios) is one of the most challenging tasks in model generalization using ML or DL models on landslide studies [114]. However, models trained on data from a specific area may not generalize well to other areas with different geological and environmental conditions [97,98,126]. Thus, developing a model that can transfer landslide knowledge across different geographical areas is a significant challenge. A few solutions exist to improve the results, albeit with limited success, such as increasing the number of training data, controlling patch size based on the detail level required, data augmentation, regularization, transfer learning, etc. [60,97].

4. Landslides Applications Using 3D Data from Remote Sensing Techniques

Most RS and landslide reviews focus on three main applications: detection, monitoring, and prediction, which have been discussed under the context of 2D image analysis [2,3,18,127]. On the other hand, we have not yet discussed the role of 3D geometric analysis in improving landslide applications. This section will discuss examples that benefit from 3D geometric analysis for landslide studies. A summary of these applications is shown in Table 3.

1. **Landslide inventory mapping** refers to systematic data collection and continuous recording of information about landslides in specific regions. Research centers and local authorities often perform this to create a complete profile on the area's history of or upcoming landslide disasters. 3D geometric analysis facilitates and enhances several applications in this context, including detection and recognition [62,80,108,127], monitoring and tracking [6,28,32,64,70,79,82,90,128–130], and classification of landslides [1,130]. Detection and recognition collect information about landslides' status, causing factors, and signs [62,80,108,127] (Table 3). In contrast, monitoring and tracking the evolution of landslides is essential for decision-making and control of the disaster [6,28,32,64,70,79,82,90,128–130]. On the other hand, the classification is often performed to determine the type of movement associated with these disasters and their direction [1,130]. 3D geometric analysis has generally enhanced feature extraction of more stable and meaningful 3D features strongly correlated to landslides. Besides, the

recent development of platforms, sensors, and algorithms provides various means to collect 3D data to monitor landslides in real-time or on-site and identify changes over time. An additional benefit of 3D data is that varying acquisition conditions influence them less than 2D data collected from optical sensors.

Table 3. Landslide applications in the remote sensing field.

Applications	Examples	Highlights
Landslide inventory mapping	Detection and recognition: • Status: past or active • Influencing factors: rainfalls, earthquakes, soil moisture content, lithology, etc. • Signs: scarps, cracks, vegetation removal, volume changes, etc. Monitoring and tracking the progress Classification: • Type of movement: flow, fall, slide, etc. • Depth: shallow or deep • Direction of movement: rotational, translational, or both	• Enhanced feature extraction of more stable features related to landslides, e.g., steep slopes, height variations, and land cover changes • 3D data is more robust to acquisition conditions compared to optical data. • Current advances in platforms, sensors, and algorithms provide various means to collect 3D data. • Real-time and on-site monitoring • Time series analysis for change detection
3D modeling and reconstruction	3D Reconstruction of damaged areas • Infrastructure • Cities • Roads • Heritage areas 3D Visualization • Surface changes • Sub-surface deformations • Terrain profile	• Accurate and precise representation of the terrain. • Understand the terrain's topographical and morphological changes. • Estimating changes in the volume • Allow 3D time-series analysis
Disaster prediction, assessment, and management	Pre- and post-disaster evaluation and simulation • Disaster evaluation • Depth • Volume estimation • Calculation of speed of fall • Failure direction Environmental management and conservation	• Early detection and warning of landslides • Effective danger level determination • Evaluate losses and renovation plans. • Direct calculation of the deposited or depleted material • Ecosystem and biodiversity preservation • Rapid disaster response due to airborne and terrestrial platforms

2. **3D modeling and reconstruction** are prime endeavors for landslide studies in RS [24,27]. It can provide a fairly realistic 3D visualization of the terrain and its topographic characteristics [24,26,27,67]. The 3D model and visualization of landslides enable the identification of surface changes (e.g., deposited or eroded materials), sub-surface deformations (e.g., 3D displacements), and the terrain profile. 3D time series analysis enables quantifying losses, visualizing 3D deformations, and creating a detailed terrain profile. It is possible to evaluate the extent of a hazard and its implications on urban and natural areas through accurate volume computation. Nevertheless, documenting the details of urban areas using 3D data can be beneficial to reconstruct cities, infrastructures, and heritage locations after a devastating disaster.
3. **Disaster prediction, assessment, and management** are the main reasons for landslide investigation in the RS field [2,33,59,70,114,127,131]. The prediction of landslides is the pre-disaster measurement, essential to prevent and minimize losses in lives and the economy. It facilitates the preparation and, if possible, mitigation of the landslide disaster in advance. On the other hand, the assessment is a step taken during and

after the landslide disaster to monitor its progress, speed of fall (happening in the short or long term), failure direction, and extent of the disaster. All these measures can be achieved effectively through 3D geometric analysis to accurately measure horizontal and vertical displacements, evaluate the rate/speed of deformation, and identify pre-failure signs (e.g., cracks, scarp, and changes in slopes). Airborne and terrestrial platforms have facilitated rapid responses to disasters because they can be operated at any time and place, facilitating close and timely event monitoring.

Overall, 3D geometric analysis is crucial in landslide studies, providing comprehensive and accurate information on topography, disaster severity, impacts, etc. Analyzing 3D data in RS contributes to more efficient responses and evaluations of landslides to provide safer and more resilient communities in regions susceptible to landslides.

5. Summary and Future Directions

Remote sensing technologies are effective tools for investigating disastrous landslide events. The 3D data from lidar or photogrammetry methods have significantly improved research on understanding and responding to landslide hazards. It helps applications contribute to landslide inventory mapping, 3D modeling and reconstruction, disaster prediction, assessment, and management. The 3D data are a valuable source of information to understand the various causes and dynamics of terrain failures. The 3D geometric analysis of landslides primarily relies on geometric features extracted from 3D data such as elevations, slope, aspect, hill-shade, etc. These features are more robust and consistent over time than conventional spectral features. The 3D geometric analysis allows effective assessment of landslide signs and hazard levels. This can be achieved by evaluating changes in surface cover, geometry, and kinematics. In contrast, the danger level is assessed by estimating changes in volume, horizontal and vertical displacements, and speed and direction of the terrain failure. Although 3D data can provide higher accuracy and precision for landslide applications, their quality may be impacted by several factors, including the type of sensor and platform, scene complexity, acquisition conditions, and temporal and spatial resolutions. The 3D geometric analysis methods are designed to consider these variations in 3D data concerning landslide regions.

Improving the efficiency of 3D geometric assessment of landslides requires being familiar with (1) 3D data properties and generation methods, (2) landslide causes, mechanisms, and implications, and (3) the 3D geometric analysis methods and their intended applications. In the following, we summarize some of the main benefits, challenges, and opportunities for future works related to 3D geometric analysis of landslides:

- **Selecting the type of 3D data** is a critical decision due to the diversity of sensors, platforms, and landslides occurring in nature. The choice of sensor and platform are often based on the budget, data availability in time, landslide area characteristics (e.g., scale, extent, surface content, obstructions, size, etc.), and application (i.e., detection, monitoring, or prediction). For example, real-time and continuous monitoring of landslides often requires stationary sensors on terrestrial platforms to record and collect 3D data continuously. In contrast, it is recommended to use 3D data from spaceborne sensors that can provide large area coverage for mapping large-scale areas for landslides. However, this may compromise the spatial resolution of the elevation maps, thus reducing the level of detail and precision of the geometric features extracted from the data. Therefore, it is important to understand and consider the limitations of each sensor and platform and the type of 3D data they generate in complex landslide regions. This understanding enables encapsulating their unique uncertainties to improve the accuracy and precision of the landslide application, for example, multisource data fusion to enrich the detail level.
- **The selection of the 3D geometric analysis method** is a key factor for an effective landslide investigation. As mentioned in Section 3, there are three groups of methods: conventional, fusion-based, and AI-based. Each method operates differently to explore 3D data and geometric information with unique benefits and limitations that control

the precision and accuracy of landslide applications. Conventional methods (e.g., field surveys, visual inspection, and topographical calculations) provide rapid, direct, and simple 3D geometric analysis of landslides. However, they may include model uncertainties, human errors, and high processing costs and times. Fusion-based methods are considered powerful approaches to combine multitemporal, multisource, multiview, and multimodal data to enrich the 3D geometric analysis. They can leverage limitations and advantages from individual sensors and provide a valuable and complete terrain profile for landslide 3D geometric assessment. However, they can be sensitive to geometric distortions and unique sensor uncertainties, which require special considerations. AI-based methods can perform better in 3D geometric analysis of landslides due to the automatic processing of large-scale areas and amounts of data with high accuracy. However, they may be challenging in terms of the effective exploitation of spatiotemporal patterns and generalization.

- **Automated detection, monitoring, and prediction of landslides** can be achieved effectively using AI-based methods. ML and DL methods offer the following advantages: First, their models can capture spatiotemporal patterns from 3D data, thus relating data in space and time. Second, they are trained on real instances and events of landslide data and, thus, can provide high accuracy when detecting and predicting landslides due to learning from previous knowledge. Third, 3D geometric features can be automatically extracted from 3D data such as slope, hill shade, curvature, roughness, etc. These features can be used for landslide applications such as classification based on type, size, hazard level, etc., and quantify important 3D parameters of landslides, including 3D displacements and changes in volume. AI-based methods, specifically DL methods, are becoming increasingly available and constantly improving performance. However, some challenges still exist, limiting the performance of AI-based methods for landslide studies. For example, there is a lack of training and ground truth data to capture all variations and extents of landslides as they exist in nature. This also causes the issue of an unbalanced distribution of the training data and biased models toward the learned instances and features. Moreover, this limits the generalization and transfer learning across different landslide sites. Finally, state-of-the-art methods such as attention and transformers deserve more recognition in the field of 3D geometric assessment for landslide studies. Attention and transformers have shown superior performance and ability to capture long-term time dependencies using complex features.
- **3D geometric analysis considerations** can enhance the landslide application. For example, preprocessing of 3D data such as geometric registration and filtering. The registration is intended for the geometric alignment of 3D data in space and time, crucial for accurate data comparison over time. On the other hand, data filtering can reduce noise and errors in 3D data before applying the 3D geometric analysis method, reducing inherited errors and enhancing data quality. Another factor that can be considered is the spatial resolution for optical images used in photogrammetry or image-derived elevation maps. Spatial resolution is highly correlated with the accuracy and precision of geospatial data, where high resolution can better represent the terrain, its features, and the level of detail extracted from 3D data. As a result, the high resolution can enhance the overall 3D geometric analysis of landslides.

In summary, landslides occur primarily due to changes in the internal structure of terrain layers. Analyzing the geometry of 3D data can significantly improve landslide applications. The 3D data introduces many 3D geometric features (e.g., elevations, slopes, aspects, etc.) that can be analyzed and integrated to boost the performance of landslide detection, monitoring, and prediction. Nonetheless, investigating landslides entails a comprehensive understanding of the cause-and-effect relationships in nature. The ongoing development in RS technologies provides countless means to acquire 3D data; however, choosing the appropriate data source can be challenging, as it involves determining the level of detail and uncertainties introduced in each type of 3D data. Similarly, 3D geometric analysis methods are vast and are developing rapidly; some methods, such as those incorporating attention and transformer mechanisms, appear promising and deserve further notice in landslide detection, monitoring, and prediction. Knowing the opportunities and challenges in these areas can provide insights for the RS community to improve landslide applications and risk assessment and management, thus providing better decision-making capabilities to mitigate the disaster.

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