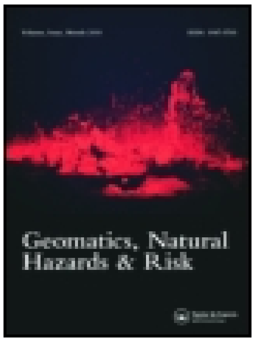

Geomatics, Natural Hazards and Risk

ISSN: 1947-5705 (Print) 1947-5713 (Online) Journal homepage: http://www.tandfonline.com/loi/tgnh20

Landslides investigations from geoinformatics perspective: quality, challenges, and recommendations

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GEOMATICS, NATURAL HAZARDS AND RISK, 2016
http://dx.doi.org/10.1080/19475705.2016.1238850

Landslides investigations from geoinformatics perspective: quality, challenges, and recommendations

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ABSTRACT

Understanding and assessing the landslides is immensely important to scientists and policy-makers alike. Remote sensing conventional methods and modelling approaches in geographical information system (GIS) tend to be limited to authentic quality and spatial coverage. This study aims to identify challenges and quality of landslides assessment based on remotely sensed data by the mean of existing works of the literature and practices we attempted in the Zagros and Alborz Mountains in Iran and the red rock shield Lake, China. Remote sensing data for landslides investigations require a high-resolution digital elevation model (DEM) from either aerial photography, satellite images, airborne laser scanning (ALS) or terrestrial Light Detection and Ranging (LiDAR) derived in order to enable a reliable and valid output performance. This paper presents weaknesses and strengths of the existing remote sensing techniques in the last decades and further provides recommendations for a reliable approach to the future landslide studies. Also, this study estimates the operational use of state-of-the-art technologies (i.e. unmanned airborne vehicle (UAV)) for landslides assessment in the near future that is a realistic ambition if we can continue to build on recent achievements. However, this paper does not deliver a detailed methodology of a DEM generation from the remote sensing approach for landslides assessment.

ARTICLE HISTORY
Received 25 June 2015
Accepted 16 September 2016

KEYWORDS
Landslide; remote sensing and GIS; DEM; ALS; LiDAR; UAV

1. Introduction

Disasters triggered by natural hazards are an unparalleled threat to sustainable development. Disaster risk managers and decision-makers depend greatly on the detailed and reliable assessment of risks to prevent or lessen the adverse effects of disasters. Landslides are the movement of a mass of rock, debris (Mohamed et al. 2016) or earth down a slope (Highland et al. 2008; Farrokhnia et al. 2011). Definition of the landslide is diverse and reflects the complex nature of various disciplines, such as geology, geomorphology and soil engineering (Highland et al. 2008; Jebur et al. 2014). We consider landslides as a general term, and it uses to describe the downslope movement of soil and rock under the effects of gravity (Cruden 1991).

Remote sensing technologies such as Light Detection and Ranging (LiDAR) provide advanced products and tools that support these efforts. A visualization-like digital elevation model (DEM)-derived remote sensing techniques is a basic tool for the hazards loss reduction, land-use planning, particularly in mountain areas. Landslide investigations involve several qualitative or quantitative approaches and are discussed in many scholarly research papers (Wu & Sidle 1995; Pack et al. 1998;

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Lee et al. 2002; Zhou et al. 2003; Schulz 2004;Watts 2004; Pradhan et al. 2006; Yilmaz & Yildrim 2006; Schulz 2007; Ercanoglu et al. 2008; Yalkin 2008; Pradhan & Buchroithner 2010; Pradhan & Pirasteh 2010; Yilmaz 2010; Goetz et al. 2011;Choi et al. 2012; Solaimani et al. 2013; Zarea et al. 2013; Jebur et al. 2014; Lee et al. 2014; Su et al. 2015). Moreover, the amount and the quality of available data such as DEM, appropriate methodology of analysis, and modelling are significant to the landslide susceptibility mapping (Carrera et al. 1991; Montgomery and Dietrich 1994; Pack 1995; Dai & Lee 2002; Pack & Tarboton 2004; Huabin et al. 2005; Evans et al. 2009; Mehrdad et al. 2010; Guzzetti et al. 2012; Konstantinos et al. 2016).

Researchers implemented the diagnosis of landslides process by means of geographical distribution of landslides, developing algorithms and codes (Pirasteh et al. 2015), and generating susceptibility maps, and models. Also, some of the researchers attempted the semi-automated approach (Siyahghalat et al. 2016), identifying landslide-contributing factors, accuracy performance, geological and engineering perspective, utilizing remote sensing technologies, and early warning systems (Wu & Sidle 1995; Zhou et al. 2003; Watts 2004; Jebur et al. 2014; Lee et al. 2014; Su et al. 2015). Nevertheless, very few researchers have discussed on challenges and qualities of the output with a reliable recommendation as well as developing an algorithm for landslides detection from the LiDAR point clouds data. However, this paper is not interested in emphasizing on the detailed methodology of the DEM generated from remote sensing and influencing factors for landslides. We aim at presenting the qualities and challenges of the DEM derived from remote sensing approaches and an empirical perspective for landslide studies. Furthermore, it inspires and motivates researchers to progress future directions of landslides assessment and susceptibility mapping.

2. Remote sensing approaches, strengths, and weaknesses

There are three major remote sensing techniques in landslides investigation. They are (1) aerial photography that has been considered as an early technique (Su & Stohr 2000), (2) interferometric synthetic aperture radar (InSAR) (Travelletti et al. 2008; Jaboyedoff et al. 2012; Bianchini et al. 2016) and (3) LiDAR (Su & Bork 2006). InSAR techniques are considered to be as the ground-based or satellite-based techniques. All of these techniques have advantages and disadvantages with limitations. The purpose of using InSAR techniques is mainly to detect landslides, and it is quantification of small displacements over large areas. Remote sensing techniques and imageries interpretation aim to distinguish geological and geomorphic features that enhance identification and assessment of landslides within a landscape. Recently, LiDAR (or terrestrial laser scanning (TLS)) use to provide high-resolution point clouds of the topography to generate a DEM and further to understand landslides phenomena. In addition, it has several applications such as mapping (Ardizzone et al. 2007; Jaboyedoff et al. 2012), monitoring deformation, and particularly landslides or rockfall displacements (Teza et al. 2007; Oppikofer et al. 2009; Abellan et al. 2010). Table 1 provides examples of remote sensing of landslide studies in the summary.

Remote sensing techniques have been widely used in extracting landslide and stability influencing factors (Table 2) in the form of a grid; for example, detection of an object expression has begun since

Table 1. Landslide remote sensing investigations.

Passive remote sensing techniques				Active remote sensing techniques
Subaerial				Subaqueous
Air photos	Satellite imagery	Radar imagery	LiDAR imagery	Multibeam imagery
Ali et al. (2003a, 2003b); Farrokhnia et al. (2011); Pirasteh et al. (2009); Zarea et al. (2013); Guzzetti et al. (2012)	Chen and Medioni (1992); Ali et al. 2003b; Ali and Pirasteh (2004); Highland et al. (2008); Jebur et al. (2014)	Stow (1996); Carnec et al. (1996); Tarchi et al. (2003); Rizvi and Pirasteh (2007); Roering et al. (2009); Pirasteh et al. (2011); Rizvi et al. (2012)	Schulz (2004); Schulz (2007); Roering et al. (2009); Jaboyedoff et al. (2012)	Piper et al. (2003); Mosher et al. (2004); Li et al. (2015a, 2015b)

Table 2. Data layer of landslide studies and source of the data.

Data layers	Remote sensing/source	GIS data type
Landslide data	Collected from field and GPS, geospatial distribution collected from database	Pointcoverage
Slope	DEM derivative derived from ALS, SRTM, aerial photographs	GRID
Aspect	DEM derivative derived from ALS, SRTM, aerial photographs	GRID
Curvature	DEM derivative derived from ALS, SRTM, aerial photographs	GRID
Distance from drainage	DEM derivative derived from ALS, SRTM, aerial photographs Developed in GIS environment, buffer	GRID
Geology (litho types)	Extracted from satellite images based on digital and visual interpretation and digital image processing, collected from field and GPS, geospatial distribution collected from database	GRID
Distance from lineaments	Extracted from satellite images based on digital and visual interpretation and digital image processing, collected from field and GPS, geospatial distribution collected from database, developed in GIS environment, buffer	GRID
Soil types	Extracted from satellite images based on digital and visual interpretation and digital image processing, collected from field and GPS, geospatial distribution collected from database, developed in GIS environment	GRID
Land cover	Extracted from satellite images based on digital and visual interpretation and digital image processing, collected from field and GPS, geospatial distribution collected from database, developed in GIS environment	GRID
Vegetation index (NDVI)	Extracted from satellite images based on digital image processing, geospatial distribution collected from database, developed in ENVI environment	GRID
Rainfall data	Non-spatial data collected from stations	GRID

the introduction of Landsat MSS in 1980. Remote sensing imageries (Table 1) used in landslide hazard assessment studies are Landsat, IRS, LISS, advanced spaceborne thermal emission and reflection radiometer (ASTER) (Figure 1), Spot, and aerial photo.

As an experimental study to identify challenges, we have used (1) ASTER data from Damavand Alborz Mountains Iran, (2) airborne laser scanning (ALS) data from the Alborz Mountains Iran, (3)

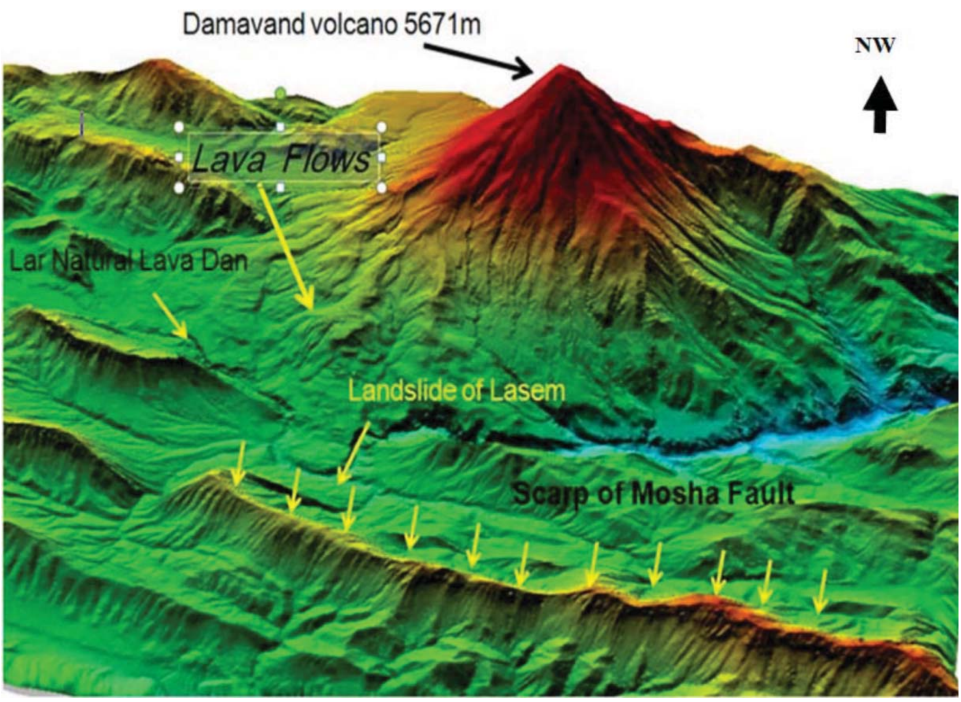

Figure 1. Colour hill shaded 3D surface view over Damavand Volcano in the Central Alborz region, Iran (processed from ASTER DEM 15 m).

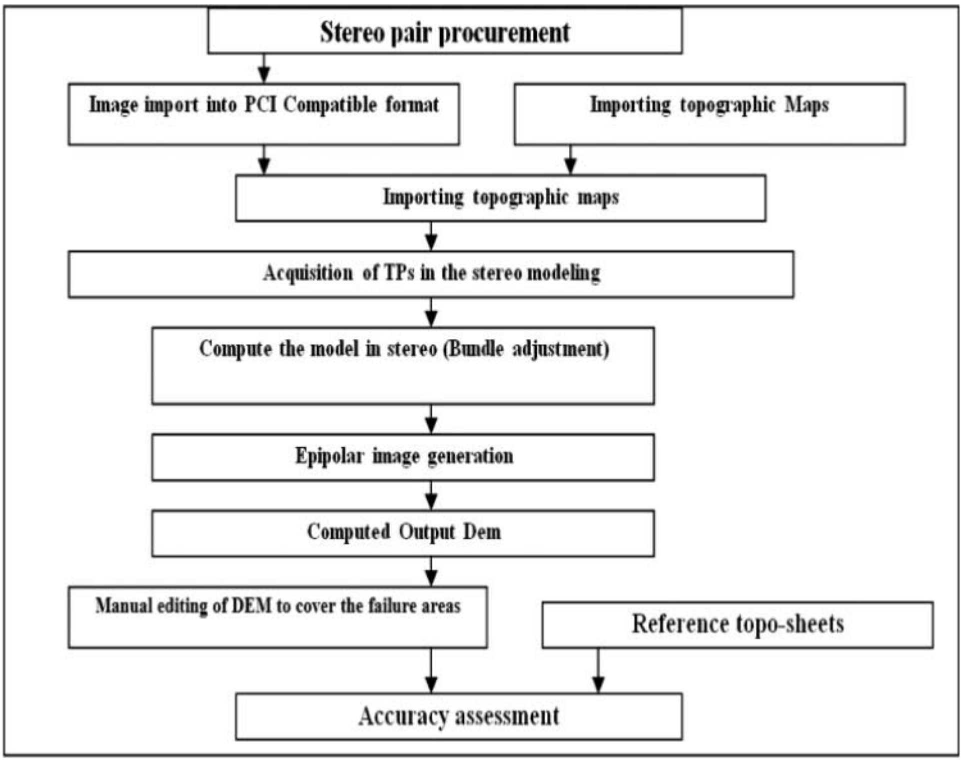

Figure 2. Diagram of generating a DEM from ASTER data.

aerial photographs and digital topography maps from the Zagros Mountains in Iran, and (4) terrestrial LiDAR data from China. The data have been processed to generate a DEM in the GIS environment with 15 m for ASTER, 2.5 m for ALS, 10 m for aerial photographs, and 0.5 m for terrestrial LiDAR, respectively, in resolution to determine the weakness and strengths of a DEM on landslide investigations.

We experienced that SRTM data quality characteristics including its vertical accuracy, the influence of vegetative cover the presence of data voids, and the effect of speckle noise are limitations in this study. ASTER data lie in its large coverage at a consistent quality, providing unprecedented opportunities for regional applications. We improved the quality of the ASTER data by substantial editing, the development of void filling procedures.

In addition, the refinement of techniques to extract the detailed information from the DEM has been implemented (Figure 2). The spatial resolution of the ASTER data is another limitation in small-scale studies. However, 15-m pixel resolution of the DEM could enlighten detection of topographic, geologic, and geomorphic features that involve landslides. The ASTER 15 m in resolutions represent serious limitations for fine-scale landslide analysis in the study area.

Vertical accuracy of the ASTER data is also a weakness to support a fine-scale landslide studies. Also, ASTER data limitation lies in the fact 'first-return' elevation data. It is resulting in substantial overestimates of elevation in the Damavand volcano where vegetation covers it. However, we identified that for an extraction of detailed information in the Damavand volcano, we require high-resolution data such as LiDAR.

The Triangular Irregular Network (TIN) derived from ALS data from Alborz Mountains (Figure 3) with 2.5 m in pixel resolution has allowed us to detect more informative landslide features than the DEM derived from aerial photography, topographical maps, and SRTM satellite data.

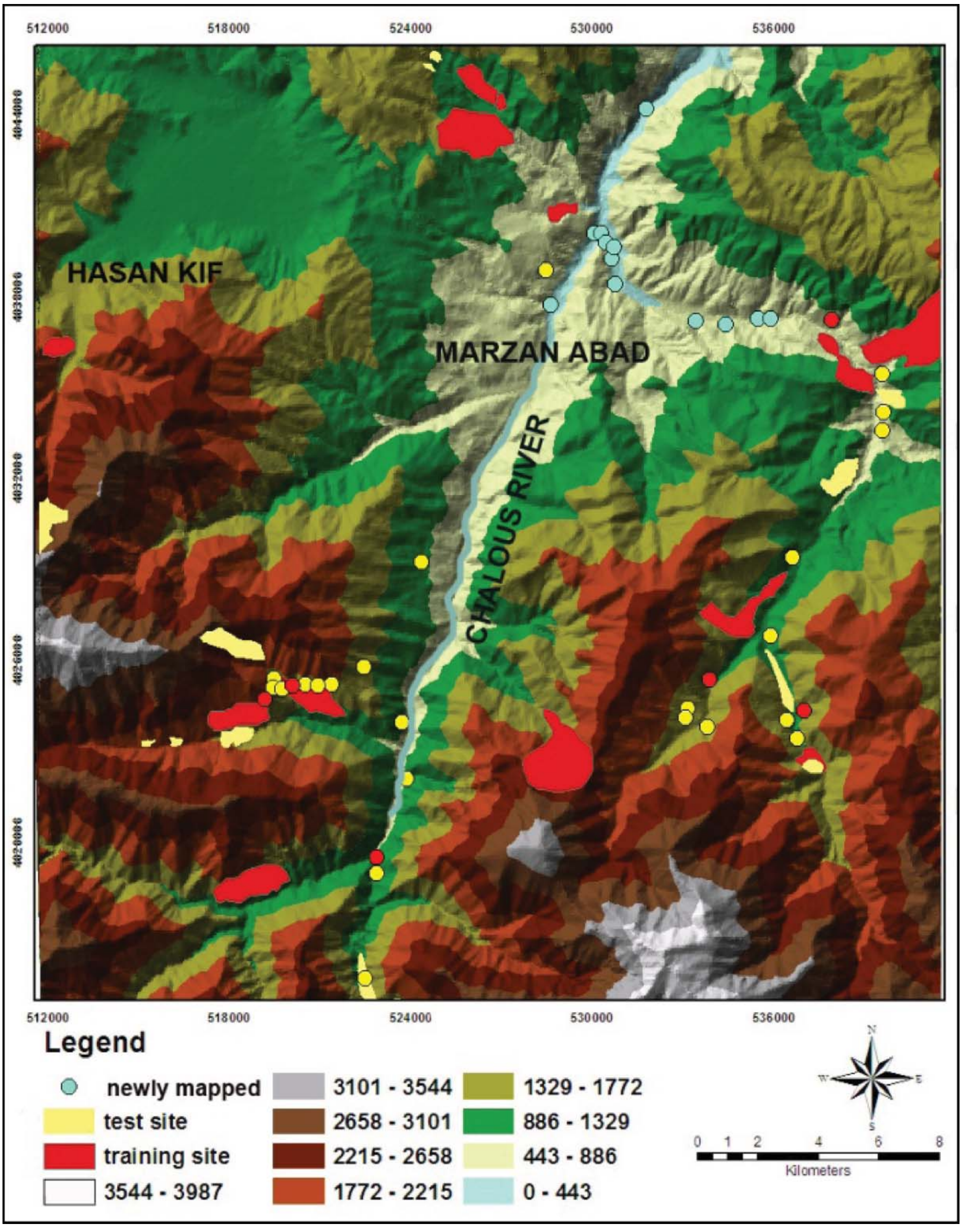

Figure 3. TIN derived from ALS showing landslide locations in the Alborz Mountains, Iran.

We also selected Zagros Mountains to generate a DEM (Figure 4) from two different datasets and perspective. Topographical maps in vector form with a contour interval of 10 m allow us to produce a DEM with the spatial resolution of 10 m from a large area in the Zagros Mountains. The photogrammetry technique that primarily focuses on the monitoring of a small set of specific points (e.g. under a geodetic control network) with the time series of coordinates has been considered. However, the challenge is that to get a flight permission from Iranian authorities and it cannot be a good idea to use aerial photos and topographical maps for studying landslides and monitoring natural hazards. Thus, it is not possible to study landslides before and after the occurrence or expect to practice an early warning system as we think of the future direction of landslide investigations in Iran. In

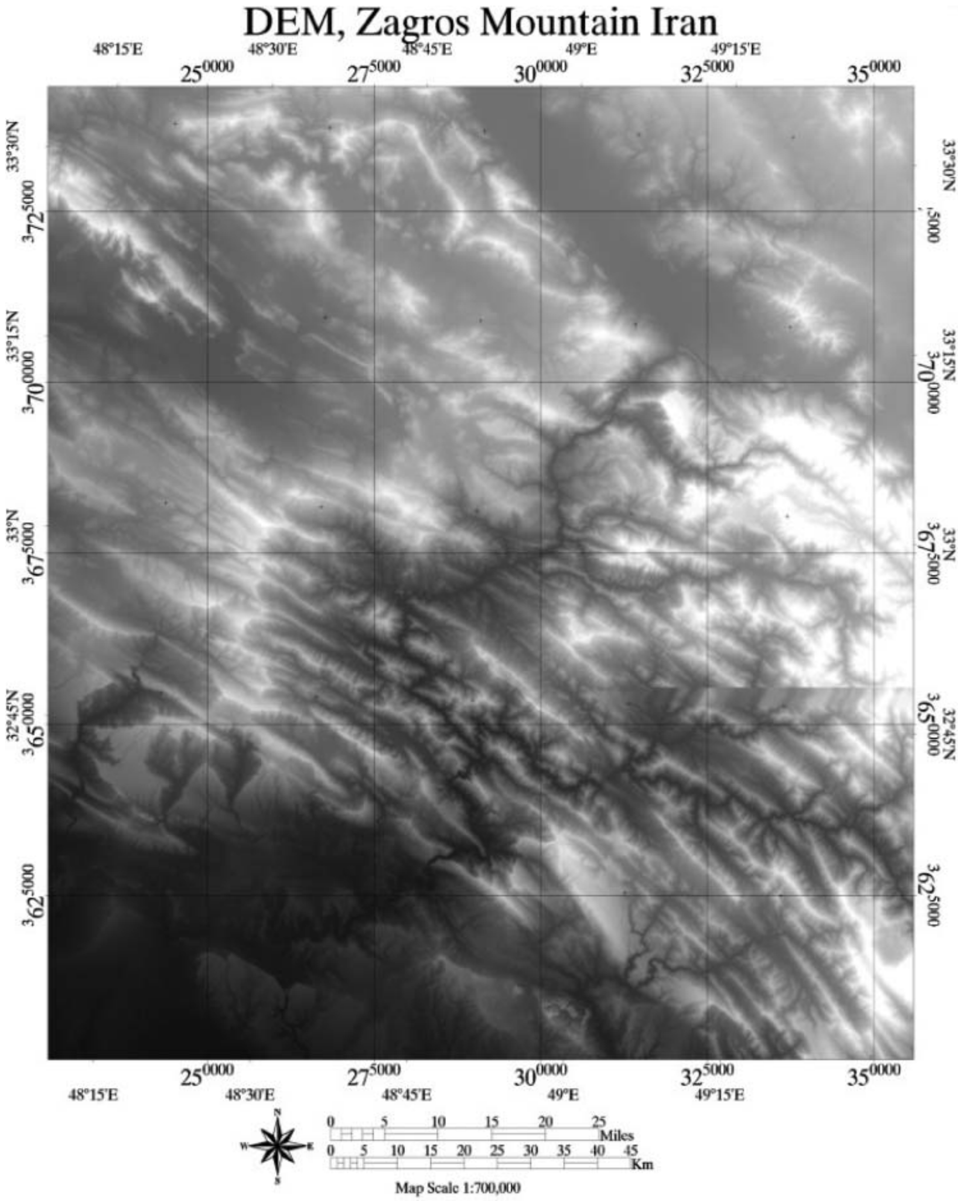

Figure 4. DEM representation derived from the aerial photography and topographical maps with 10 m in pixel resolution.

addition, the cost and limitation of sensors and cameras are the weakness of using this method. Moreover, the weakness is that the points collected from theodolites, photogrammetry, levels and Global Navigation Satellite System (GNSS) perform quite low in density. For example, the low-density DEM determines the potential to differentiate morphologically (McKean & Roering 2003; Roering et al. 2009) components within a landslide and how to provide insight into the material type and activity of the slide. Thus, these surveying techniques and aerial photography with low-density measurements still cannot provide a good accuracy and quality to visualize the objects to extract an informative description of the changes for the unstable areas and landslides under monitoring.

Therefore, a high-density sampling technique such as terrestrial or airborne LiDAR opens a new potential to research scholars to reach more informative deformation of the monitored landslides

Figure 5. Field observation with ground control points, Red Rock Shield Lake, China.

before and after the event and to determine the loss of destructions accompanying with ground control points (Figures 5 and 6). LiDAR data can process to remove vegetation, buildings, and other above-ground features, thus creating a bare-earth DEM. This study results in a high accuracy of landslide determination, identifying morphologic features (Ali et al. 2003a, 2003b; Pirasteh et al. 2009, 2011).

The dense vegetation area may obscure the morphology of landslides both in the field and in remotely sensed data such as satellite images or aerial photos. LiDAR data can be processed to reveal the topography beneath vegetation and have proven useful in identifying tectonic fault scarps (Haugerud & Harding 2001; Haugerud et al. 2003; Sherrod et al. 2004), previously unmapped landslides, and other geomorphic landforms.

The TLS data from red rock shield Lake, China, has been collected, and we tried to compare the two sets of LiDAR data before and after the event that can indicate the changes (Figure 6).

The strength of using TLS as compared to the other techniques is to generate a high-resolution DEM (0.5 m) as well as an easy accessibility with a low cost of the LiDAR system in China. However, this becomes a challenge when we try to collect TLS data in a rugged topography or inaccessible area in Iran. Also, removal of the noise and errors from LiDAR data for detection of landslides has required an algorithm and remained an interest of researchers. If we collect the LiDAR data desirably, we can extract

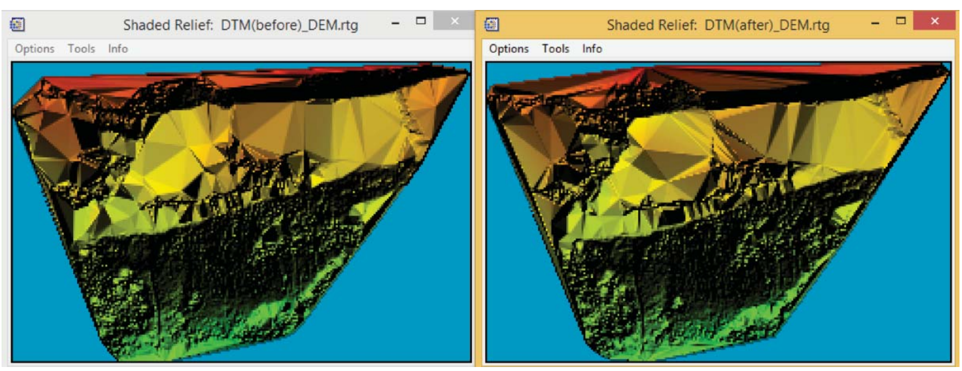

Figure 6. TLS data for the landslide in Red Rock Shield Lake, China, after and before the event.

Table 3. Different kinds of DEMs.

DEM types	Resolution (m)	Resource
Aerial photos	2–10	Airborne
TLS	0.5	Laser scan
ALS	2.5–5	Airborne
ASTER	DEM 15	ASTER L1A
IRS P5	3	IRS P5
SRTM	90	EDC
GTOPO30	1000	EDC HYDRO
DLOBE30″	1000	NOAA

a high quality of geomorphometric parameters, such as slope, curvature, roughness, and topographic wetness index by using stencils of landslide polygons overlaid on respective thematic maps derived from the DEM. However, further refinement of the accuracy of LiDAR systems may be required to map fine-scale vegetations and terrain applications in rangeland environments. Also, vegetation and slope have statistically significant effects on the accuracy of a LiDAR-derived bare-earth DEM. High-resolution DEMs for morphologic analysis of the surface can have a considerable impact on quality of the result. The accuracy of the DEM derived from remote sensing (Table 3) directly related to the resolution of the image and the contour interval in a topographical map.

2.2. LiDAR

LiDAR is a relatively new and revolutionary surveying technology. As an advanced technique, LiDAR can provide a good set of three-dimensional data with *X*, *Y* and *Z* axes to generate a DEM, as well as other information such as intensity, colour, geologic and geomorphic using DEM's derivatives to assess and monitor landslides. These techniques can provide millions of data measurements, in a few minutes that are commonly denoted as '3D Point Clouds.' Compared to traditional surveying techniques, LiDAR technology shows a great potential for landslides (Jaboyedoff et al. 2012). These methods have been emerging as a hot and attractive research topic. It is because LiDAR can capture the data very fast with high data density, 3D object representation, as well as user-friendly operation. Particularly, the high-density 3D points captured by LiDAR can provide a chance to identify the detailed and distinctive landslide characteristics in partial areas (Derron & Jaboyedoff 2010). In addition, a significant amount of such 3D data induces new research challenges, such as huge data management, extraction of useful information, and 3D landslide reconstruction.

ALS systems have been reviewed and discussed in Wehr and Lohr (1999) and Baltsavias (1999). A clear reference to an updated discussion is commented in Shan and Toth (2008). During 2005–2015, literature on TLS has rapidly grown up and applications of LiDAR have been identified from time to time. Petrie and Toth (2008) expressed the basic principle of TLS, and this can be a useful reference for understanding the mechanism of LiDAR. Finally, a brief review of LiDAR (and other remote sensing techniques) utilized in landslide studies is found in Prokop and Panholzer (2009) and SafeLand Deliverable 4.1 (2010).

3. LiDAR advantages and challenges

Digital elevation data developed from any remote sensing methods, including LiDAR, are not perfect. There is no doubt satellite imageries accompanying with a survey have an excellent advantage for landslides investigations. As LiDAR compared with conventional photogrammetric techniques (Wait 2001), the advantage is that photogrammetric techniques require two different lines of sight to see the same points on the ground from two different perspectives, but LiDAR only required a single laser pulse to penetrate through the trees or vegetations to measure the ground beneath (Liu et al. 2012). In other words, LiDAR has far fewer areas where the terrain is obscured by trees that block the lines of sight.

Landslide LiDAR and satellite remote sensing have faced, and continues to face, several challenges not only in terms of engineering geology and natural hazard sciences underpinning the landslide assessment and susceptibility mapping, but it has also suffered from the lack of funding, time, upgrading policy of governments with the growth of technologies (i.e. especially for the developing countries), infrastructure and the flight permission needed to coordinate research efforts across what has been historically and scientifically a rather fragmented community.

In general, LiDAR has proven to be more accepted in the last decade in comparing to a DEM derived from the satellite images or aerial photographs. This article emphasizes that still there is a limitation because LiDAR cannot accurately delineate stream channels, drainage networks, or ridgelines visible on the satellite images or photographic images. For example, contours derived automatically from LiDAR data may depict stream channels differently than manual photogrammetric techniques. In addition, the unedited LiDAR-derived contours may be acceptable for many applications such as applications where contours along a stream must depict continuous downhill flow.

A rapid acquisition of data over widespread areas, an ability to access rugged topography data from the inaccessible area, high-resolution DEMs generated from LiDAR, time, and accuracy with a cheaper production of DEMs in a long term are the advantages compared with traditional photogrammetric techniques. Moreover, the primary advantage of LiDAR-derived DEMs for landslide recognition is the landscape visualization flexibility, because it uses multiple combinations of hillshading. It also associates with the second-derivative datasets. It is also a challenging issue in very steep terrain and cliffs, due to lack of clear shots. Limiting threshold of a DEM resolution is a disadvantage of LiDAR too.

As for the vegetated area, low-to-height vegetation can present unique challenges (Hopkinson et al. 2004) for generation of DEMs. When the canopy is high, it is difficult for LiDAR pulses to penetrate, because sparse vegetation cover can lead to confusion between ground and vegetation returns (Streutker & Glenn 2006; Riaňo et al. 2007). Thus, this makes identification of ground returns for DEM generation difficult. Also, if a topography is complex, then spatially variable slope, aspect, and elevation will influence the vertical accuracy of LiDAR data, because of horizontal displacement (Hodgson & Bresnahan 2004; Su & Bork 2006).

One of the advantages of the LiDAR is that there is open source software available to process LiDAR datasets. We should use proprietary GIS software as it, although expensive to purchase, has the advantage of ready integration with other core GIS activities. In terms of LiDAR-derived DEMs, the data layers are readily integrated into standard GIS applications, and it makes the capture of new features very easy and time-efficient. Comparisons over the past few years indicated that landslide recognition using LiDAR-derived DEMs (Liu et al. 2012) is up to 5–10 times quicker than traditional photogrammetric techniques in the same landscape. However, the main disadvantage of LiDAR technology lies with the limiting threshold the DEM resolution places on the size to identify the objects. Also, geological features, such as bedding and layering, can sometimes be mistaken for instability as compared to field verification; it is always an essential component of the process.

4. Mapping challenges: past and present

Landslide mapping and modelling have been developed in many parts of the world, but most cases consist of prototypic approaches. Numerous methods (see Appendix) have focused on generating landslide investigations. Nevertheless, previous studies have discovered that a number of shortcomings need to be overcome. Thus, this paper has identified problems as follows:

(1) Perhaps, it is not surprising that a complex interrelationship causes landslides, and that agreement about how to influence variable factors involved in landslide hazard assessment is not uniform among the researchers. Clearly, no general agreement has been reached on the scope, techniques, and methodologies for landslide hazard investigations.

Figure 7. Two samples of newly mapped landslide locations in the field study, Alborz and Zagros Mountains, Iran.

(2) Previous studies (Ali & Pirasteh 2004) have discovered that structural features and geomorphologic analysis (George et al. 2012) play an important role in landslide assessment. However, no study has identified the interface of thrust fault, nappe, klippe, fenster, scarp, strike-slip fault, fold, hogback, lineament density, drainage density, elevation drop, water gap, net erosion, channel slope, sinuosity, straight-line length and stream gradient index in a rugged topography in order to assess landslides utilizing LiDAR.

(3) As for LiDAR, it permits to improve geological mapping as well as the landslide inventory mapping. It happens when we increase the resolution of the landslide contours, and this leads us to identify geomorphologic features such as scarps and displaced material. Nevertheless, these conceptual methods are usually employed to detect landslides (Keaton & DeGraff 1996; Soeters & VanWesten 1996) in different climates and environments such as tropical and mountainous regions. Some of the morphological features of the landslides are easy to extract and unlikely some are not possible to be delineated from DEMs or hillshades produced alone by photogrammetry techniques, satellite images (i.e. RADAR and InSAR), and LiDAR. Limitations vary from technique to technique, and it depends on the resolution of the images, topography, climate, and environmental conditions. However, one of the main issues in laser scanning is the vegetation removal either by automatic methods or manually. Nevertheless, any remote sensing approach does not replace field investigations (Figure 7). However, it changes the fieldwork methods and can be considered as a part of the validation processes of a landslide inventory produced by high-resolution DEMs.

5. Results and discussion

Although this study has not explored and discussed the detailed landslide methodologies, it shows that perhaps, photogrammetric techniques and aerial photographs promise to be more efficient than LiDAR for discerning boundaries of recently active landslides within landslide complexes particularly for an active tectonic region such as Zagros and Alborz Mountains in Iran. One of the challenges of resolution of LiDAR is that it cannot resolve many landslide boundaries (Wait 2001) within landslide complexes in the study area. In addition, LiDAR on board unmanned airborne vehicle (UAV) may be the future direction of delivering a suitable remote sensing approach to generate a high-resolution DEM, if geomatecians can reach an agreement with decision and policy-makers to update the regulations of the country, because we imagine that UAV has a promising potential to provide the invaluable complementary source of data with a high-resolution pixel size at local to global scales and it is undergoing rapid developments.

This study shows that the high-resolution DEM is increasingly being used in various applications of natural hazards such as landslides. We predict that in the next few years, LiDAR sensors and UAV technologies will probably be a standard tool for many applications including landslide studies in the next decade. This study estimates that the current trend, full coverage by ALS-DEM and UAV technology in most of the developed countries will be reached within the next few years. Thus, we expect that this technique is progressing more often among researchers and soon will be in the industry sectors because it has more accurate and precise ALS and TLS devices and UAV that allow us to generate more accurate DEMs. Nevertheless, UAV and LiDAR are a relatively new and revolutionary surveying technologies developed in recent decades, and there is a lack of developing algorithms and software in error removal of the LiDAR data (Liu et al. 2012; Juber et al. 2014; Su et al. 2015).

We suggest that remote sensing techniques and image analyses are a quick and valuable technique for identifying landslides and map them in the GIS environment by using various techniques of GIS analysis. Because we can produce a 3D view of the terrain and DEM. Also, the availability of LiDAR point cloud makes image reconnaissance (Spaete et al. 2011) very versatile, although cost-prohibitive in some cases.

This study emphasizes that a rapid acquisition of data over widespread areas, an ability to access rugged topography data from the inaccessible area, high-resolution DEMs generated from LiDAR, time, and accuracy with a cheaper production of DEMs in a long term are the advantages compared to traditional photogrammetric techniques.

Moreover, this study aimed to encourage of using the second derivatives of high-resolution DEMs such as stream-gradient indices to investigate signatures of landslides in the active tectonic region for the future studies. This review literature indicates that the primary advantage of LiDAR-derived DEMs for landslide recognition is the landscape visualization flexibility because it uses multiple combinations of hill-shading. It also associates with the second-derivative datasets. However, it is a challenging issue in very steep terrain and cliffs, due to lack of clear shots. This study experienced that the disadvantage of LiDAR technology lies with the limiting threshold the DEM resolution places on the size to identify the objects. We also identified that geological features such as bedding and layering could sometimes be mistaken for instability as compared to the field verification, as it is always an essential component of the process.

6. Quality and performance assessment

One of the fundamental steps in the landslide assessment process and landslide determination for susceptibility prediction is validation (Davis & Goodrich 1990; Paolo et al. 2010). Sometimes for the performance assessment and validation, existing landslides verification in the field (Eeckhaut 2007) is significant to confirm our delineations or characterizations of landslides from remotely sensed data such as LiDAR point cloud. In particular, when there is no evidence of the extent of the landslide on LiDAR data or any photographic record of its existence, it is highly recommended to identify the indicators of slope failures such as obvious scarp, bent trees, and cracks in brittle materials.

This paper indicates that the performance assessment of active landslides such as in the Zagros and Alborz Mountains in Iran can be determined by multi-temporal airborne and terrestrial laser scanning. We can create a 3D motion using the range flow algorithm (Ghuffar et al. 2013) to determine the movement of landslides. This 3D with high-resolution of the LiDAR data with centimetre in pixel size and detailed information can perform a better quality of generating DEM derivatives and further landslide susceptibility maps.

7. Conclusion and recommendations

This study concludes that: (1) landslides assessment is a very important issue in deformation of the environment and the earth's surface within the environmental science and engineering, and such assessment is useful for reducing/preventing damages. Perhaps, to study the tectonic geomorphology of the Zagros Mountains for landslide investigations would be a significant contribution to determine the quality of the high-resolution DEM; (2) classical surveying techniques can only provide data measurements with a very low sampling, and may not provide detailed information for deformation description in the Zagros and Alborz Mountains, particularly for a large monitored object; (3) satellite images are not desirably a good choice in terms of high quality to generate high-resolution pixel size of DEM to study the deformation like landslide; however, they can be used for geological and geomorphological interpretation to identify influencing parameters, such as vegetations, faults, folds and drainage networks, and extract information for landslides assessment; (4) LiDAR or LiDAR sensor onboard UAV have alternative advantages in capturing high-density 3D point cloud data that opens substantial potential for the applications of natural hazards assessment like landslides. Moreover, the huge data of point cloud still has remained a problem among people because computers will need to be more powerful with increasing data acquisition. Thus, computer engineers and related researchers will need to keep into consideration for a fast LiDAR point cloud data analysis of more than 200 kHz. In addition, people in private industries, government agencies, and public/private stakeholder consortiums are planning or may have the recent intention to work with large-scale acquisitions data of LiDAR. However, LiDAR data acquisition and digital processing have remained a challenge and of interest to the researchers that may have unlimited defined applications such as landslides monitoring and assessment.

Finally, this paper remains with few questions such as (1) Could we combine accurate DEM generated from LiDAR and develop an algorithm to detect landslides and deformation patterns from the point clouds? (2) Could we integrate surface measurements with early warning systems? and (3) Could we generate more precise second derivatives of a DEM than the existing DEMs to investigate tectonic geomorphology and landslides change detection (i.e. before and after)? To explore high-resolution DEMs is not limited to landslide studies but also we need to think of the future direction for subsurface and its extrapolation with surface DEMs. Therefore, the motivation of this paper is to encourage researchers to find how the huge amount of 3D point cloud datasets from LiDAR or/and LiDAR onboard UAV can be analyzed and further to compute landslides for assessment and susceptibility mapping. Thus, this paper motivates to build a novel and advanced deformation assessment method via '3D point clouds' that enables us to generate an informative deformation description for landslides assessment and a large monitored object. This method may allow to identify automatically landslides from point clouds.

Acknowledgments

We identified challenges and quality of landslides assessment in the study areas. Remote sensing data are useful for landslides investigations, particularly when we acquire a high-resolution digital elevation model (DEM). Authors estimate the operational use of the UAV for landslides studies more often shortly. However, it is a realistic ambition if we can continue to build on recent achievements by using the state-of-the-art technologies. This article is a part of the Ph.D. thesis that delivers review literature, challenges, and quality of landslides in the study areas using three different spatial resolutions of DEMs.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

No	Author and year	Research focus	Description	Strength and weakness
1	Goetz et al. (2011) Ren et al. (2014); Mohamed et al. (2015)	Integrating physical and empirical landslide susceptibility models using generalized additive models. Wavelet analysis and support vector machine (SVM).	Investigated the possibility to enhance landslide susceptibility modelling by integrating two physically-based landslide models, the factor of safety (FS) and the shallow stability model (SHALSTAB). They used digital elevation model and land-use characteristics related to forest harvesting in Vancouver Island, British Columbia, Canada. Variables representing physically-based models do not significantly improve the empirical models, but they may allow for a better physical interpretation of empirical models. They found slope, land-use data, safety factor and profile curvature are the most important predictor variables. They used wavelet and SVM to predict displacement of landslides in the Three Gorges in China. Seven years of monitoring landslides recorded since 2003 that landslides have become reactivated.	Establishing a significance relationship between terrain attributes and land use. The resolution of DEM was 25 m. But, they have not mentioned whether a high spatial resolution of DEM can increase the quality of model or not. However, a particular variable increase or decrease the probability of an outcome or does it have no effect on outcome?
2	Su et al. (2015); Lee et al. (2002); Lee et al. (2014); Pradhan and Pirasteh (2010); Yilmaz and Yildrim (2006); Choi et al. (2012), Solaimani et al. (2013) Wu and Sidle (1995); Pack et al (1998)	Logistic regression (LR) for landslides. The SINMAP approach to terrain stability mapping.	LR – the advantage of this model over a simple multiple regression is from the addition of an appropriate link function to the usual linear regression model. The variables may be either continuous or categorical, or a combination of both types. They attempted modelling of the spatial distribution of shallow debris slides combining a mechanistic infinite slope stability model with a steady-state hydrology model. This model allows to derive wetness index and stability index maps.	They consider the advantage of LR; however, they have not tried to compare the quality of the model they have developed. In addition, lack of the contributing factors makes it unclear whether if we add other factors to the model, to what extent there will be an increase in the accuracy? The advantage of this model is a good correlation between wetness and stability. They only relay on DEM.
3	Mehrdad et al. (2010); Watts (2004); Yalkin (2008), Renée (2012); Jebur et al. (2014)	GIS-based landslide susceptibility mapping using analytical hierarchy process (AHP).	AHP is a multi-objective, multi-criteria decision-making approach, which enables the user to arrive at a scale of preference drawn from a set of alternatives.	They used AHP to study the pair-wised parameters. However, they have not indicated the number of conditioning factors that increases the quality. They have not considered the DEM resolution into consideration.
4	Lee et al. (2002, 2014); Zhou et al. (2003); Gomez and Kavzoglu (2005); Pradhan	GIS-based landslide susceptibility mapping using artificial neural networks (ANN).	ANNs are generic nonlinear function approximation algorithms that have been	In none of the studies they use high-resolution DEM derived by LiDAR or UAV technologies.

(*continued*)

No	Author and year	Research focus	Description	Strength and weakness
	et al. (2006); Yilmaz (2006); Yilmaz (2010); Pradhan and Buchroithner (2010); Pradhan and Pirasteh (2010); Choi et al. (2012); Zarea et al. (2013); Jebur et al. (2014); Ercanoglu et al. (2008)		extensively used for problems such as pattern recognition and classification. The categorization of a terrain into ordinal zones of landslide susceptibility may also be regarded as a classification problem.	They only considered few parameters to landslide recognition. They have not talked about quality of the model and the map.
5	McKean and Roering (2003); McKean and Roering (2004); Su and Bork (2006); Spaete et al. (2011); Glenn et al. (2006); Streutker and Glenn (2006)	Landslide detection and surface morphology mapping using high-resolution airborne LiDAR; Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity.	Utilized high-resolution DEMs from airborne laser altimetry (LIDAR) data to characterize a large landslide complex and surrounding terrain near Christchurch, New Zealand. Statistical analysis used to map the local topographic roughness in the DEMs over a spatial scale of 1.5–10 m.	They consider structural features and stress on LiDAR technology to present how it is useful for measurement of roughness topography. Vegetation and slope effects on accuracy of a LiDAR studied. But, there is no accuracy performance and determination of the validation. However, the disadvantage of this approach is lack of validity and influencing factors. They indicated that high-resolution topographic data have the potential to differentiate morphological components within a landslide and provide insight into the material type and activity of the slide. Visualization is the strength to present with high accuracy. Nevertheless, no validity, quality and accuracy discussed.
6	Rau et al. (2011); Niethammer et al. (2012)	Landslide mapping using imagery-UAV.	Hong Kong is the study area. Compared satellite and airplane, and found that the UAV is a portable and dynamic platform for data acquisition. Emphasizes on colour ortho-image and a DEM	Stressed on the UAV mechanism and usefulness. They considered rain, slope and earthquake as triggering factors but never discussed other factors. New landslides detected from UAV.
7	Guzzetti et al. (2012)	Mapping landslides.	He studied common methods of providing landslide, geomorphologic, event, seasonal and multi-temporal maps. They also discussed providing landslide maps using old and modern technologies	He considered high-resolution DEM derived from aerial photo, but not LiDAR. The advantage of this work is development of multi-temporal maps. There are only few contribution factors to landslide.