The application of civic technologies in a field survey of landslides

František Chudy1 | Martina Slámová2 | Julián Tomaštík1 | Daniel Tunák1 | Miroslav Kardoš1 | Šimon Saloň1

1 Faculty of Forestry, Department of Forest Management and Geodesy, Technical University in Zvolen, T. G. Masaryka 24, 960 53, Zvolen, Slovakia
2 Faculty of Ecology and Environmental Sciences, Department of Landscape Planning and Design, Technical University in Zvolen, T. G. Masaryka 24, 960 53, Zvolen, Slovakia

Abstract
Slope failures are financially devastating natural hazards that contribute to land degradation in many areas throughout the world. The adaptation of civic technologies (Google Tango) in a field survey of landslides was examined. Data acquired from different resources and processed using different technologies were merged into a single model to concurrently demonstrate the interoperability and scalability of these data and the model quality. Reference control points were established using a survey-grade Topcon Hiper SK global navigation satellite system receiver and a Topcon GPT 9003 M total station. An aerial survey was performed in an area of approximately 30,000 m² using airborne laser scanning (9 points/m²) and aerial photogrammetry using a remotely piloted aircraft system (500 points/m²). The models suffered from data gaps in less visible areas, and micro-scale landforms reflecting landslide activity were poorly visible. The missing details were supplied using data obtained from close-range photogrammetry (9,132 m²; 92,300 points/m²) and a Lenovo Phab 2 Pro running Google Tango, which acquired detailed point clouds in near real-time conditions (1,847 m²; 109,000 points/m²). Scans using the phablet provided point clouds with homogeneously dispersed data gaps, but the spatial accuracy was lower. However, the ergonomics of its field use and its low cost made it competitive with other technologies. The results confirmed that models based on point clouds acquired using different technologies allow the identification and measurement of micro-scale landforms that may indicate landslide activity.

KEYWORDS
digital models, image-based technologies, landslides, point clouds

1 | INTRODUCTION
Slope failures are one of the major natural hazards worldwide (Le, Gallipoli, Sanchez, & Wheeler, 2016). Integral use of alternative technologies for the identification and effective assessment of natural hazards might contribute to the prevention of land degradation in many endangered areas (Raouf, Peng, & Shah, 2017). High-end information and communication technologies are becoming more important than ever in land surveys (Olyazadeh, Sudmeier-Rieux, Jaboyedoff, Derron, & Devkota, 2017). Publicly available powerful modern technical equipment facilitates big data operations, and synchronization amongst cloud networks can deliver high-quality data to the general public in a short
amount of time (Marvin et al., 2016). From a different point of view, public interest in open government data contrasts with vague ideas about how data relate to the lives of common people (Schock & Shaffer, 2017).

Google’s Tango project was developed by Google’s Inc. Advanced Technology and Projects team in 2014. It was primarily designed for augmented reality (AR) gaming (Google, 2017). The adoption of Google’s Tango technology in a field survey of landslides might provide a new perspective on the application of cutting-edge “civic technologies in the investigation of land degradation processes. We are aware that the effects of fine-scale land degradation would not be buried in the statistics for larger areas (Warren, 2002). From another perspective, the mapping and measuring of micro-scale landforms using common geodetic techniques often provide sparse or insufficient data to identify subtle landforms, particularly when a site is located in forested or remote terrain (Ortu o et al., 2017). Digital models developed from aerial survey data obtained using image-based technologies often suffer from data gaps in less visible areas (rocky and steep slopes), and micro-scale landforms indicating landslide activity cannot be properly recognized (Kasai, Ikeda, Ashahina, & Fujisawa, 2009; Olyazadeh et al., 2017).

In this context, a survey performing the supplementary mapping of missing data in digital models of slope failures was initiated. For this purpose, we employed the Lenovo Phab 2 Pro using Google Tango technology. The first tests of this technology in forests (Hyppä et al., 2017; Tomašík, Saloň, Tunák, Chudý, & Kardoš, 2017) suggested that the accuracy of its acquired 3D data might be sufficient; however, its application for mapping and measuring slope failures had not been broadly tested for forested land and rugged terrains. The Tango technology provides an integrated package that offers processing capabilities (using a smartphone’s own computational resources), connections (wireless local area network, global system for mobile communications), and other sensors (such as global navigation satellite systems; Hyppä et al., 2017). These attributes make Tango efficient and user-friendly for data acquisition by the general public and not only by experts in geodesy.

We emphasize several characteristics that make Google’s Tango technology an appropriate tool for mapping and measuring the micro-scale landforms of landslides. The Google Tango project applies a methodical ‘Markerless AR’ approach, which means that this technology has no prior references about the captured environment. Therefore, it offers a complete map of the ‘as-built’ scene in near real time, which is very important for AR applications (Kopsida & Brilakis, 2016). The use of AR enables the visualization of construction progress in an image by superimposing a 3D model on the actual construction scene (Jadidi, Ravanshadnia, & Alipour, 2014). During all phases of scene building, the 3D geometric scene of the site is reconstructed, and progress photographs are georegistered in a virtual environment (Golparvar-Fard, Pe a-Mora, & Savarese, 2009).

The process of as-built scene building means that a scene is replenished by the data generated during the capturing phases. In the case of the Google Tango Project, both the pose data and 3D reconstructed point clouds can be used along with iterative optimization methods to refine the alignment between the as-planned and as-built data. This technology uses motion sensors such as inertial measurement units, which can significantly improve the tracking performance when combined with an embedded depth sensor and a point cloud (Kopsida & Brilakis, 2016).

2 | THE AIM

The investigated landslide is located in a deep valley with rugged terrain. The site is covered by a 90-year-old forest stand that mainly comprises beech and hornbeam. Present gaps in the forest canopy are mostly caused by the activity of the studied landslide. Landslide processes pose a unique risk for existing infrastructure—the road from the district town of Zvolen to the village of Železná Breznica.

Because it is difficult to access the inventory site, it is impossible to investigate the entire area of interest on the same scale using only one type of an image-based contactless technology, and using data generated by different aircraft and using different techniques is recommended for achieving a precise digital terrain model (Hsieh, Chan, & Hu, 2016; Le et al., 2016). Two research objectives are addressed in this article based on the precise results from previous studies conducted using smartphone global navigation satellite system (GNSS) positioning in forests (e.g., Tomášík, Tomašík, Saloň, & Piroh, 2017) and the potential applications of civic technologies, specifically the Lenovo Phab 2, for landslide mapping.

2.1 | Examining the Lenovo Phab 2 data quality and interoperability across different scales and amongst digital models

The comparison of different techniques/technologies for landslide mapping has been broadly discussed (Raouf et al., 2017). We assume that the data collected by the Lenovo Phab 2 may supply missing details from less or nonvisible areas. To confirm the scalability of digital models, the dataset accuracy was examined. Data gaps, which are caused by terrain characteristics (e.g., vertical surfaces), interfering objects (e.g., trees), and other factors, are often present in the digital terrain models (DTMs) and digital surface models (DSMs) that are developed from the data obtained by conventional techniques, including airborne laser scanning (ALS) light detection and ranging technology (LiDAR), imagery from remotely piloted aircraft systems (RPAS), and close-range photogrammetry (CRP; up to approximately 300 m). All these technologies were applied in the field survey. The data gaps present in different models of CRP and Tango were visually compared, and their occurrence was explained.

Generally, accuracy assessment of geometric analysis is difficult to perform. A completely perfect landslide inventory map against which to compare the results does not exist, as landslide inventory maps created from LiDAR analysis by different experts result in inventory maps with considerable differences (Eeckhaut et al., 2007). Nevertheless, data need to be sufficiently accurate and precise. For the purposes of geographic information system (GIS) environmental applications, the residual errors and root mean square errors of control points are measured to assess the geometric transformation accuracy. Residual error is a measure of the fit between the true locations and the transformed locations of the control points (Zhu, 2016). The method selected for examining the residual errors of transformations did not yield an actual error assessment in this article. However, the method yielded valuable results regarding the models’ accuracy in the short term without requiring time-consuming and expensive ground control point (GCP) measurements and position accuracy testing. This method is important because it may be easily implemented in field surveys for the purposes of territorial planning.

*Cutting-edge technology for the general public.
2.2 Assessing the applicability of landslide digital models in participatory GIS

The surfaces of active landslides are characterized by scarps, areas of temporary or permanent water ponding, and ridges, which are generally short-lived landforms that can quickly be destroyed (Parise, 2003). Therefore, the adoption of an easy-to-use device for mapping and measuring micro-scale landforms may accelerate the data collection of these ephemeral but very important landforms. The efficiency of the Lenovo Phab 2 Pro for performing landslide inventory was examined (time savings, low cost, and ease-of-use aspects), acknowledging that participatory planning approaches permit updates of national databases on natural hazards by the general public (Figure 1).

Gathering spatial data across different spatial and temporal scales through a user-friendly interface would help planners address the complexity of planning procedures. The current techniques for automating the progress of data collection promise to eliminate the labour-intensive tasks associated with manual data collection (Golparvar-Fard et al., 2009; Matta & Serra, 2016).

3 THE CASE STUDY ON LANDSLIDE INVESTIGATIONS

3.1 Geoinformation system on slope failures in Slovakia

A systematic study of slope failures in Slovakia (over a nearly 50-year-long period) was coordinated by the state administration body of the Division of Geology and Natural Resources of the Ministry of Environment of the Slovak Republic and resulted in the publication of The Atlas of Slope Stability Maps (1:50,000; Šimeková et al., 2006). The State Geological Institute of Dionýz Štúr (ŠGÚDS is the Slovak abbreviation used in Figure 2) provides a geospatial geological database that is available as part of the ‘Geological Information System’ project, which was launched at the end of 2005 (Liščák & Káčer, 2013). Altogether, 21,190 slope failures that cover an area of 2,575.912 km² are registered in The Atlas of Slope Stability Maps (1:50,000; Šimeková et al., 2006) and pose either damage or threat to 5.25% of the area of the Slovak Republic, and landslide areas constitute 77.68% of slope failures (Bednák & Liščák, 2010). The landslide databases of France, Italy, and Slovakia are considered the most complete landslide databases in Europe (Eeckhaut & Hervás, 2012). Despite this fact, many landslides are not included in these official databases. Here, one of these landslides is characterized in a case study from Central Slovakia.

3.2 The landslide localization and its natural settings

The investigated landslide is located on the borders of three cadastral districts (Železňá Breznica, Budička, and Tníe; 3020.73 ha), and it is located in the Kremnické vrchy Mts. These mountains belong to the Neogene volcanic region in Central Slovakia. According to Bakon et al. (2015), landslides may threaten up to 60% of the peripheral areas of neovolcanic regions in Slovakia, where their slope deposits comprise clay, clay-sandy, clay-stony, sandstone-rocky to rock-bearing slope sediments, and debris (Maglay & Pristaš, 2002). Slope deposits
mainly occur in the central area of these cadastral districts, and most slope failures are concentrated here. Potential and stabilized landslides cover 663.83 ha (21.98%) of three cadastral districts, whereas active landslides occupy only 37.43 ha (1.24%) of this area (Figure 2). A map of slope failures was derived from the national database based on the work of Šimeková et al. (2006).

4 | METHODOLOGY

4.1 | Applied technologies in data acquisition

The selection of a mapping method depends on the availability of datasets and the local context (Ahmed & Dewan, 2017). Natural conditions influence the data acquisition process (Hsieh et al., 2016; Pirasteh & Li, 2016). Forests constitute a specific environment for surveying landforms using image-based remote sensing technologies. Although trees indeed represent an obstacle to the visibility of the
terrain from the point of view of the laser station, the presence of low vegetation also masks the actual shape of the ground (Barbarella & Fiani, 2013). All remote sensing technologies used in this survey were applied during the dormant or leaf-off period of vegetation to achieve the best data quality. Trajectories of remote sensing technologies are demonstrated in Figure 3 and in Figure S1.

### 4.1.1 ALS (LiDAR) technology (Spring, 2011)

Although a landslide was observed during the field survey in 2013, older LiDAR data from 2011 were used because later LiDAR scanning was not available from the given site. A RIEGL LMS Q680i airborne scanner was employed for scanning with an average flight height of 700 m above ground level and a scan angle of 60° FOV (field of view), an overlaid average of 40%, and a scanning frequency of 122 Hz. Raw data were classified into base classes: ground, ground and vegetation, and vegetation alone; this classification was previously conducted by the service provider. Consequently, the data were processed using software provided by the company of RIEGEL Laser Measurement System GmbH Terrasolid Ltd. The scanning process and parameters were defined by the ALS service provider without any possibility of further adjustments considering the characteristics of the scanned area. LiDAR scanning was applied during the mapping of the most extensive area (36,531 m²).

### 4.1.2 Aerial photogrammetry performed using a RPAS (Spring, 2017)

Imagery was acquired using the Phantom 3 Professional RPAS with an average flight height of 43 m above ground level. A total of 852 images were obtained with a spatial resolution (ground sampling interval) of 14 mm. The camera had the following parameters: sensor: 1/2.3" CMOS; effective resolution: 12.4 M (total pixels: 12.76 M); lens: field of view 94° 20 mm (35 mm format equivalent) f/2.8 focus at ∞. The imaging material was processed using the Agisoft PhotoScan Professional 1.2.6 software 144 (as described by, e.g., Turner, Lucieer, & Wallace, 2014). The investigated area was 29,617 m². Eleven GCPs were used for georeferencing, which formed approximately three slopewise lines, namely, left (4 points), middle (3 points), and right (4 points). However, the actual positions of the GCPs were dependent on the occurrence of gaps in the forest canopy.

### 4.1.3 CRP (Spring, 2017)

A calibrated SLR EOS 5D Mark II digital camera with EF 16–35 mm f/2.8 L II USM from Canon was employed for CRP. A total of 1,253 images were obtained with geometric resolutions ranging from 0.65 to 1.54 mm. The camera offered a full-frame CMOS sensor (36 mm × 24 mm) with a resolution of 21.1 megapixels. The focal length was set as 35 mm, and the aperture, sensitivity, and shutter speed were adjusted depending on ambient conditions in the forest stand. We used the Gig tube Wireless II viewfinder to optimize the image axis when the camera was placed on a pole. According to the capturing method, the number of frames in the block ranged from 80 to 400. These frames were subsequently connected into a single model. The scanned area was 9,132 m².

The applied photogrammetric survey was based on the principles of the 'Structure-from-Motion' method. This method operates under the same basic tenets as stereoscopic photogrammetry, namely, that 3D structures can be resolved from a series of overlapping, offset images. This approach fundamentally differs from conventional photogrammetry, in which image acquisition involves capturing overlapping photographs of multiple locations (Westoby, Brasington, Glassera, Hambreya, & Reynolds, 2012). Using a preplanned route ensures the best photo collection and avoids data losses that are common in forest
environments (Chudy et al., 2014). Using this method, a complex series of detailed photos was collected from deep cracks, scarpas, and gullies. Continuous imaging running under a remote control in the camera menu was set-up. Thus, the motion and rotation paths around the axis of the camera were secured. The elevated position of the projection centre was stabilized using a telescopic pole, thus ensuring a minimal distance of 3 m to the surveyed objects. The adjustment of the photographing parameters ensured that there was a sufficient depth of sharpness to create high-quality images in the sloping and rugged terrain under vegetation exhibiting irregular shading.

4.1.4 Reality capturing by the Lenovo Phab 2 Pro (Spring, 2017)

For detailed surveying performed on micro-scale landforms in an area of 1,847 m², the Lenovo Phab 2 Pro was employed. This device uses Google Tango technology for reality capturing. An RGB-D camera with a 'Time-of-Flight' infrared sensor, which uses a given principle to determine the distances to objects (currently, it mainly uses infrared radiation), ensures the function of ‘depth perception’; the function of ‘motion tracking’ is enabled by the embedded sensors in the device that allow position and motion tracking; and the function of ‘area learning’ means that the device looks for the same objects within already existing 3D models and real space (Google, 2017). This device was handheld during the field survey, and no stabilization was used.

4.1.5 The point field and GCPs (Spring, 2017)

The point field was established using coded targets as reference control points to assess the accuracy of DTMGs and DSMs. Using identical check points in digital models, point clouds were transformed into the national coordinate system JTSK (position), while elevations were registered in Baltic vertical datum after their adjustment (Bpv). GCPs under open-area conditions were established using a geodetic dual-frequency Topcon Hiper SK GNSS receiver with the Internet-enabled Slovak permanent observation service providing real-time data corrections with accuracies ranging from 0.02 to 0.04 m. Subsequent measurements were conducted under forest conditions using a total station Topcon GPT 9003 M. The point field and GCPs are displayed in Figure S2.

In practice, analytically driven methods typically rely on numerical methods for a complete evaluation (Heuvelink, 1998). The results of previously conducted actual error assessments of Tango technology (Tomáštík, Saloň, et al., 2017; Table 1) were considered to be indicative of the estimated values of acceptable accuracy of the digital models in this article. The characteristics of the forest environment were very similar, and the devices employed by researchers were identical.

The root mean square coordinate errors in Table 1 were calculated as follows:

\[
RMSE_x = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}}
\]

\[
RMSE_y = \sqrt{\frac{\sum_{i=1}^{n} y_i^2}{n}}
\]

\[
RMSE_z = \sqrt{\frac{\sum_{i=1}^{n} z_i^2}{n}}
\]

where \(\Delta x\), \(\Delta y\), and \(\Delta z\) are the differences between the reference coordinates and the coordinates determined from the point cloud, and \(n\) is the number of points in the set. The number of control points was greater than 30 in all the referenced studies. The \(RMSE_x\), \(RMSE_y\), and \(RMSE_z\) errors were used for the calculation of the root mean square horizontal error \(RMSE_{xy}\) as follows:

\[
RMSE_{xy} = \sqrt{RMSE_x^2 + RMSE_y^2}.
\]

This is the direct measurement of accuracy of the studied technologies.

This experiment was not designed to assess accuracy in terms of the measurement of multiple control points. Instead, a residual error diagnostic was used to quantify model accuracy. Model error can be incorporated by assigning errors to model coefficients or by adding a residual error term to the model equations. The mean transformation residuals are generally used to measure the transformation’s overall accuracy. These residuals measure the accumulation of positional errors of all the control points during the transformation (Zhu, 2016); they describe how consistent the transformation is among the different control points (links) and indicate how a model represents reality.

### TABLE 1 Root mean square horizontal and vertical errors and standard deviations of particular measurement methods used in the study (based on previous research; Chudy et al., 2014; Tomáštík, Mokroš, Saloň, Chudý, & Tunák, 2017; Tomáštík, Saloň, et al., 2017)

| Method                                | Horizontal accuracy | Vertical accuracy |
|---------------------------------------|---------------------|-------------------|
|                                       | RMSE\(_x\)          | SD                | RMSE\(_y\)          | SD                |
| Airborne LiDAR\(^a\)                  | 0.04                | –                 | 0.02                | –                 |
| RPAS photogrammetry\(^b\)             | 0.04–0.11           | 0.02–0.05         | 0.06–0.20           | 0.06–0.11         |
| CRP\(^c\)                             | 0.01–0.02           | –                 | 0.01–0.02           | –                 |
| Google Tango\(^d\)                    | 0.15–0.29           | 0.07–0.11         | 0.10–0.22           | 0.08–0.10         |

Note. CRP = close-range photogrammetry; LiDAR = light detection and ranging technology; RMSE = root mean square error; SD = standard deviation; RPAS = remotely piloted aircraft system.

\(^a\)Chudy et al., 2014.

\(^b\)Tomáštík, Mokroš, et al., 2017.

\(^c\)Tomáštík, Saloň, et al., 2017.

\(^d\)unpublished research.
The mean residuals for ALS, RPAS photogrammetry, CRP, and Google Tango are reported in the article. Calculations of digital model quality using transformation residuals are available for practical users, whereas experimental accuracy testing requires specialized technologies and staff.

The overall RMSEs were calculated from the mean errors acquired for individual coordinates in this article; for example, the root mean square spatial error $\text{RMSE}_{XYH}$ was calculated as follows:

$$\text{RMSE}_{XYH} = \sqrt{\text{RMSE}_X^2 + \text{RMSE}_Y^2 + \text{RMSE}_H^2}.$$ 

The positional (horizontal; $\text{RMSE}_X$), vertical ($\text{RMSE}_H$), and spatial ($\text{RMSE}_{XYH}$) accuracies were calculated for individual models. Additionally, the errors associated with the methods applied to acquire the coordinates of GCPs (i.e., GNSS and total station) were also considered here.

Data gaps were visually identified and compared in DSMs obtained from CRP and the Lenovo Phab 2 Pro. The reasons for their occurrence and their characteristics are explained.

### Table 2

| Image-based technologies | Aerial | Remotely piloted aircraft system | Terrestrial | Reality capturing by the Lenovo Phab 2 Pro |
|--------------------------|--------|----------------------------------|-------------|-------------------------------------------|
| Evaluation criteria      |        |                                  |             |                                           |
| Costs                    | HW (EUR) | A licence contract with a company: 20 EUR for localities included within recent projects; 200 EUR/km² for new localities. | Aerial survey: 600 EUR Data processing: 1,200 EUR | 500–2500 | 480 |
| Data acquisition time   | (hr)    |                                  |             |                                           |
| Data processing time    | (hr)    |                                  |             |                                           |
| Model accuracy          | Spatial $m_{XYH}$ (m) | ±0.047                          |             |                                           |
|                         | Positional (horizontal) $m_X$ (m) | ±0.05                           | ±0.02       |                                           |
|                         | Vertical $m_H$ (m) | ±0.03                           | ±0.007      |                                           |
| Relevance for specific ambient conditions | Forest stands–vegetation growth: small (1); medium (2); high (3) 1 depending on vegetation cover | 1 depending on vegetation cover 2 | 2 |
|                         | Rugged terrain: small (1); medium (2); high (3) 3 | 3 | 2 | 2 |
|                         | Method interoperability: difficult (1); applicable (2); very good (3) 2 | 2 | 2 | 2 |
| Mapping of active landslides: yes (1)/no (0) 1/0 mostly influenced by topography and density of canopy trees | 1/0 mostly influenced by topography and density of canopy trees 1 | 1 |

Note. Values given in the table are indicative and depend on characteristics of the study site.

The mean residuals for ALS, RPAS photogrammetry, CRP, and Google Tango are reported in the article. Calculations of digital model quality using transformation residuals are available for practical users, whereas experimental accuracy testing requires specialized technologies and staff.

The overall RMSEs were calculated from the mean errors acquired for individual coordinates in this article; for example, the root mean square spatial error $\text{RMSE}_{XYH}$ was calculated as follows:

$$\text{RMSE}_{XYH} = \sqrt{\text{RMSE}_X^2 + \text{RMSE}_Y^2 + \text{RMSE}_H^2}.$$ 

The positional (horizontal; $\text{RMSE}_X$), vertical ($\text{RMSE}_H$), and spatial ($\text{RMSE}_{XYH}$) accuracies were calculated for individual models. Additionally, the errors associated with the methods applied to acquire the coordinates of GCPs (i.e., GNSS and total station) were also considered here.

Data gaps were visually identified and compared in DSMs obtained from CRP and the Lenovo Phab 2 Pro. The reasons for their occurrence and their characteristics are explained.

### 4.2 The assessment of digital model applicability in participatory GIS

First, the data interoperability between different digital models on several scales was examined.

The DTM and DSMs processed using different technologies were merged into a single model, thus concurrently demonstrating the interoperability and scalability of the data. Differences in the point cloud density of the scaled models enable visualizations of the study site, from a general overview to specific micro-scale landforms indicating activity (e.g., minor scarps), which may be important for landslide activity monitoring. The GNU-licensed CloudCompare software was used for this purpose. This step was possible only after all partial models were transformed into a uniform coordinate system: in this study, the S-JTSK (Datum of Uniform Trigonometric Cadastral Network) coordinate system, which is the obligatory system for surveying in Slovakia. The process resulted in some overlapping (duplicate) parts from differing methods. These parts were not edited in this study;
however, future research could refine this methodology to prioritize the most precise and most complete data during this process. The least accurate dataset must be considered when determining the accuracy of the entire model.

Second, the effectiveness of data acquisition during the mapping process was compared amongst different technologies and evaluated considering the following criteria:

a. costs, acquisition time, and processing time;
b. data quality; and
c. relevance of specific environmental conditions (e.g., forest stands in a phase of vegetation growth, rugged terrain, method interoperability, and the mapping of micro-scale landforms of active landslides).

5 | RESULTS

5.1 | The comparison of digital model quality, emphasizing the Lenovo Phab 2 Pro data

5.1.1 | Comparisons of data accuracy and visibility of landslide details in digital models

Additional adjustment of the scanned parameters was impossible because LiDAR data were obtained from a contracted mapping service (specified in detail in Table 2). The average point cloud density was approximately 9 points/m²; the value of $\text{RMSE}_{\text{XYH}}$ declared by the provider was 0.047 m. The distance of the scanning laser device (700 m) from the mapped object allowed the borders and major landforms of the landslide to be identified (i.e., a head scarp, ridges, major scarps, undulating terrain, and a gully-related landslide system; Figure 4a); however, it was impossible to identify the particular micro-scale landslide landforms being reflected.

The aerial photogrammetry performed using RPAS produced a much denser point cloud (500 points/m²), while the area (29,617 m²) was comparable to that covered by LiDAR; the value of $\text{RMSE}_{\text{XY}}$ was 0.05 m and that of $\text{RMSE}_{\text{H}}$ was 0.03 m. In both cases, data gaps occurred in deeply rugged terrain that is indicative of active landslides (major scarps and steep slopes of ridges; Figure 4b).

CRP produced models with a point cloud density of up to 92,300 points/m². The $\text{RMSE}_{\text{XY}}$ values of individual models (fragments) ranged from 0.001 to 0.032 m (with an average value of 0.02 m), and the values of $\text{RMSE}_{\text{H}}$ ranged from 0.001 to 0.023 m (with an average value of 0.007 m). These results reflect the excellent accuracy of landslide mapping and the acceptable accuracy of the measurements of micro-scale landslide landforms, which indicate slope movement. Relatively fresh and clear minor scarps indicate landslide activity, and wet areas in the gully reveal the presence of water in the landslide (Figure 4c).

The Lenovo Phab 2 Pro was employed for the reality capturing of the smallest area, which had the highest point cloud density of

![FIGURE 4](https://wileyonlinelibrary.com)
109,000 points/m²; this value was comparable to the point cloud density obtained from CRP, which was on the order of hundreds of points per square metre (92,300 points/m²). The transformation residuals (RMSE<sub>XY</sub>) of the Lenovo Phab 2 Pro ranged from 0.10 to 0.15 m, thus resulting in lower accuracy than the CRP accuracy (RMSE<sub>XY</sub> = 0.02 m; RMSE<sub>H</sub> = 0.007 m). The presence of undulating terrain under the minor scarp and uncovered soil substrate in the upper part of the gully reflected recent landslide activity (Figure 4d).

5.1.2 | The visual comparison of data gaps in digital models

Differences in data gaps between different models were evident. The point clouds obtained from CRP showed the accumulation of data gaps in heavy rugged terrain (Figure 5a), whereas the point clouds acquired by the phablet showed data gaps that were more or less homogeneously dispersed in DSMs (Figure 5b).

Generally, occurrences of data gaps in point clouds can develop when applying any mapping method in rugged terrain covered by vegetation. Using a handheld mobile device (not a camera on a telescopic pole) provides more flexible opportunities for planning the capturing trajectory. Thus, avoiding zones with data gaps is under the control of the researcher. Moreover, the Lenovo Phab 2 Pro used the near real-time rendering of point clouds; thus, an operator could immediately see the scanned space, and appropriate corrections were performed during the field survey.

5.2 | The applicability of the involved technologies to landslide mapping and measuring

The different point cloud densities in the DTMs and DSMs allow view scaling from the whole model to its details, as is illustrated by the interactive models in Figure 4. The DTMs and DSMs developed by different procedural steps from point clouds acquired by different technologies may be merged into a single model after undergoing a reliable transformation into a uniform coordinate system. Such an ‘integrated’ model can be further processed in the GIS environment by using its countless applications.

An analysis of the effectiveness of landslide mapping and measurement (Table 2) indicates that ALS is the most suitable technology for the mapping of ‘previously known’ landslides (based on maps or previous studies), primarily due to its optimal relationship between its appropriate data accuracy and costs.

FIGURE 5 Data gaps in digital surface models acquired by (a) close-range photogrammetry and (b) the Lenovo Phab 2 Pro. [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 6 Close-range photogrammetry—digital surface models (DSMs): (a and c) minor scarps—details, (b) a slope exhibiting undulating terrain with tension cracks under the stabilized older landslide, and (d) a gully. The Lenovo Phab 2 Pro—DSMs: (e) a minor scarp with overturned trees and (f) a gully with an uncovered soil substrate in its upper part. Note: An interactive version, with 3D objects, is available online at Research Gate [Colour figure can be viewed at wileyonlinelibrary.com]
The Google Tango technology is suitable for mapping smaller areas and individual objects; these data can be merged with the DTMs and DSMs created from the point clouds acquired using different techniques (Figure S3). Data obtained from CRP are appropriate for rapidly mapping and measuring short-lived micro-scale landforms representative of landslide activity; minor scarps are displayed in 3D interactive models (Figure 6a,c); a slope exhibiting undulating terrain with tension cracks under an older, stabilized landslide is presented in a 3D interactive model (Figure 6b); a gully is displayed in Figure 6d. CRP technology is more time consuming and expensive than the Google Tango technology. The Lenovo Phab 2 Pro is suitable for the fast and low-cost mapping of small-scale landforms in great detail (see 3D interactive model in Figure 6e, documenting a minor scarp). Furthermore, it is suitable for mapping larger but not very extensive landforms; one example is a gully with an uncovered soil substrate in its upper part (Figure 6f).

6 | DISCUSSION

6.1 Advantages and constraints of technologies involved in the landslide survey

Landslide deformation measurements are very important; however, these point-based measurements can be time consuming if the required data density is high (Prokešová, Kardoš, & Medvedová, 2010). At the study site, the adequate recognition of details indicating landslide activity was limited or impossible in digital models developed from point clouds obtained by aerial survey, mainly due to the natural constraints that made some landforms (particularly small-scale landforms) invisible. This limitation was the main reason for the use of terrestrial technologies (CRP and Google Tango) in the landslide survey.

The study primarily focused on the applicability and complementarity of particular technologies. However, as the accuracy of every survey method must be tested before its practical application, the current study agrees with previous research regarding accuracy when the same technologies and equipment were used. For ALS and terrestrial photogrammetry, Chudy et al. (2014) documented that RMSExy is 0.041 m for ALS and 0.014 m for CRP. RMSExy from 0.037 to 0.114 m were reported for RPAS photogrammetry under conditions with differing degrees of forest canopy openness (Tomaštik, Mokroš, et al., 2017). A study on Google Tango accuracy (Tomaštik, Saloň, et al., 2017) reported an overall positional (horizontal) RMSE of 0.200 m for plots with sizes of ~500 m². The transformation residual calculations presented in this article were approximately the same as the residuals reported in the current study. However, other results in the same study indicated that smaller objects can be measured with a significantly higher degree of accuracy; for example, the mean errors of tree diameters were approximately 2 cm. The Tango-measured stem diameters matched those from tape measurement with an RMSE of 0.73 cm, and these diameters had an average bias of 0.3 cm in another study (Hyppä et al., 2017).

Using various integrated technologies in a field survey allows research project scalability (Marvin et al., 2016). Digital models purchased from mapping services (LiDAR scanning or RPAS survey) are usually inexpensive only for large localities and represent an easy-to-use alternative to field surveys. The establishment of scanning parameters is typically determined in the licence contract between a customer and a provider. The investigated area had been recently scanned by this provider for the purposes of another project. Therefore, the price of LiDAR scanning was much lower than it is in new localities. Due to the impossibility of establishing additional parameter settings, this technique was less adaptable for the mapping of landslides characterized by relatively high dynamic rates and the presence of micro-scale landforms with ephemeral characteristics.

Usually, terrestrial surveys are performed by the researchers themselves. The results indicate that the mapping and measuring of landforms using CRP and the Lenovo Phab 2 Pro are not suitable for more extensive areas mainly because they require time-consuming fieldwork. We tested the phablet under relatively unfavourable natural conditions. The transformation residuals of models based on the Lenovo Phab 2 Pro were quite modest, with residuals ranging from 0.10 to 0.15 m per coordinate, which was beyond the accuracy of the other technologies employed in the survey. Data obtained by LiDAR, RPAS, and CRP photogrammetry were of comparable quality, with transformation residuals ranging from 0.02–0.05 m and 0.007–0.03 m, respectively. In the case of the CRP mapping that uses the Structure-from-Motion method, data gaps might have been eliminated by following a precisely planned sequence of steps during the survey, as documented by Chudy et al. (2014).

The Tango uses depth sensors that utilize structured light and measure distortions in a projected pattern to determine depth. Thus, the usage of this device is limited because ambient light overpowers the sensor of the device and the energy diffuses in both directions (Gao & Peh, 2016). Previous results (Roberto, Lima, Araújo, & Teichrieb, 2016) have suggested that the depth estimation error increases linearly with respect to the distance between the device and an object. The drift of the Tango technology, which causes inaccuracies, is a known issue and is related to imperfect solutions in the trajectory of the device (i.e., imperfect loop closures) causing the defective alignment of individual scans (i.e., their frames). Future improvements to fix this issue are expected from Google. When Area Learning is enabled, the Tango device remembers the visual features of areas it has visited, and it uses them to correct errors in its understanding of its position, orientation, and movement. This memory allows the system to perform drift corrections (Google, 2017). Moreover, by providing results in real time, the Google Tango technology allows mapping and measurements to be directly evaluated in the field and thus allows workers to immediately perform additional field research to refine these mapping results. Therefore, the data generated by the Tango technology can be collected in a short time and in great detail using a low-cost and user-friendly technology that is important for the applications of civic technologies to field inventories.

6.1.1 The adaptability of civic technologies for the field survey of landslides

Landslides are a major threat in mountainous and hilly areas across Europe, as they can often have serious impacts on population, property, and infrastructure (Eeckhaut & Hervás, 2012). Quaternary slope
deposits play an important role in the occurrence of landslides in Slovakia. Slope failures (see Figure 2) limit the future urbanization of the territory of the concerned municipalities. Although the studied landslide was documented in field photos in 2013, it has not been added to any database until now, and it has never been officially monitored. Currently, it does not affect the road below its body. Nevertheless, slope movement in its upper parts (a head scarp) was documented in photos taken during the field surveys in 2013 and 2017 (Figure S4).

Involving local authorities is particularly important during the process of anticipating landslides (Spizzichino, Margottini, Triglia, & Iadanza, 2013). Currently, most people wear tracking devices, and available tracking data are increasing (Drummond, Joao, & Billen, 2006). Measurements made using Kinect- or Tango-type systems could also be applied in a crowdsourcing context (Hyypä et al., 2017), allowing non-experts to undertake specialized tasks for certain purposes more quickly and at lower costs (Capineri, 2016). Future landslide hazard studies require the use of multiscale and multitemporal spatially referenced data from a wide variety of sources that are shared through web-based platforms (Hou, Lu, Wu, Xue, & Li, 2017). Computer-aided territorial planning and accessibility to geographic data might support the development of breakthrough ideas in spatial planning and related decision-making processes (Matta & Serra, 2016).

In particular, when there is no evidence of the extent of a landslide observed in the LiDAR data or any photographic record of its existence, the identification of slope failure indicators (scarps, bent trees, and cracks) is highly recommended (Pirasteh & Li, 2016). The measured parameters of these landslide formations (e.g., the height of the tear-off, the depths of cracks or the depth, and width of the erosive gully through which water flows from the landslide), which are hard to capture using common geodetic methods, may be rapidly evaluated using near real-time Tango technology to determine whether the landslide is active or even dangerous. It is only a matter of time before landslide details (with data) are recorded in cloud-computing services that can be downloaded by experts or by the public. Eventually, these data could be used for landslide monitoring or generating a 3D model from associated point clouds.

7 | CONCLUSIONS

In conclusion, Google Tango is one of a number of emerging low-cost 3D scanning technologies that could become a key element in allowing citizens and the community to become engaged in decision-making processes concerning environmental issues (Counsell & Nagy, 2017). Territorial planning is a unique tool for creating well-maintained and well-functioning landscapes. Local people are aware of the driving forces behind land degradation, and the use of GIS proves its added value in the participatory process of integrated land use planning (Hessel et al., 2009). Experts as well as the general public often go into the field and discover uncharted landslides that can be recorded using low-cost technologies, such as CRP or Google Tango. The terrestrial technologies studied here, including CRP and Google Tango, appear to be suitable for the complementary densifying (filling in missing details) and refining (filling in data gaps) of the DTM s and DSMs developed using aerial surveying techniques (LiDAR and RPAS photogrammetry). Tango technology provided relatively accurate measurement results in a large-scale survey. These findings make both technologies competitive. Google Tango point clouds have not yet been directly transformed into global coordinates, and the absolute positions of objects are not directly known; however, these can be determined, for instance, using GNSS devices. Moreover, capturing the study site in great detail without assessing zones of aggregated data gaps is very interesting. The high-density point clouds, flexibility of the scanning trajectory, and near-real-time point cloud processing make Google Tango a powerful tool that is expected to have multifunctional applicability to many other scientific branches.

ACKNOWLEDGMENTS

This work was supported by the Scientific Grant Agency MŠVVaŠ SR and SAV (VEGA) grant no. 1/0804/14 and no. 1/0868/18. We thank the Technical University of Zvolen Faculty of Forestry and Faculty of Ecology and Environmental Sciences for funding the publication of this article. We would like to give special thanks to the American Journal Experts for English language editing.

ORCID

Martina Slámová http://orcid.org/0000-0002-5578-7993

REFERENCES

Ahmed, B., & Dewan, A. (2017). Application of bivariate and multivariate statistical techniques in landslide susceptibility modelling in Chittagong city corporation. Bangladesh. Remote Sensing, 9(4), 304. https://doi.org/10.3390/rs9040304

Bakon, M., Papco, J., Perissin, D., Lazecky, M., Sousa, J. J., Hlavacova, I., ... Real, N. (2015). Monitoring of landslide activity in Slovakia territory using multi-temporal InSAR techniques. In Proceedings of FRINGE’15: Advances in the Science and Applications of SAR Interferometry and Sentinel-1 InSAR Workshop. Frascati, Italy, 23–27 March 2015, Ouweland H (Ed). ESA Publication SP-731; 264–276. DOI: https://doi.org/10.5270/Fringe2015.264.

Barbarella, M., & Fiani, M. (2013). Monitoring of large landslides by terrestrial laser scanning techniques: Field data collection and processing. European Journal of Remote Sensing, 46(1), 126–151. https://doi.org/10.5721/EuJRS20134608

Bednárík, M., & Liščák, P. (2010). Landslide susceptibility assessment in Slovakia. Mineralia Slovaca, 42, 193–204.

Capineri, C. (2016). The nature of volunteered geographic information. In C. Capineri, M. Haklay, H. Huang, V. Antoniou, J. Kettunen, F. Ostermann, & R. Purves (Eds.), European handbook of crowdsourced geographic information (pp. 15–33). London: Ubiquity Press.

Chudy, F., Sadibol, J., Tunak, D., Pasko, M., Belacek, B., & Slamova, M. (2014). Detailed mapping of anthropogenic and natural micro-relief forms in forest stands. GeoConference on informatics, geoinformatics and remote sensing: conference proceedings. Sofia: STEF92 Technology. 3, 137–143. https://doi.org/10.5593/SGEM2014/B23/S10.017

Counsell, J., & Nagy, G. (2017). Participatory sensing for community engagement with HBIM. In Y. Arayici, J. Counsell, & L. Mahdjoubi (Eds.), Heritage building information modelling (pp. 242–256. ISBN). Abingdon UK: Routledge. ISBN: 978-1-138-64568-4.

Cruden, D. M., & Varnes, D. J. (1996). Landslide types and processes. In A. K. Turner, & R. L. Schuster (Eds.), landslides: Investigation and mitigation (pp. 36–75. ISBN). Washington DC: Serial: Transportation Research Board, National Research Council. ISBN: 0-309-06151-2.
Tomaštík, J., Saloň, Š., Tunák, D., Chudý, F., & Kardoš, M. (2017). Tango in forests—An initial experience of the use of the new Google technology in connection with forest inventory tasks. Computers and Electronics in Agriculture, 141, 109–117. https://doi.org/10.1016/j.compag.2017.07.015

Tomaštík, J., Jr., Tomaštík, J., Sr., Saloň, Š., & Piroh, R. (2017). Horizontal accuracy and applicability of smartphone GNSS positioning in forests. Forestry: An International Journal of Forest Research, 90(2), 187–198. https://doi.org/10.1093/forestry/cpw031

Turner, D., Lucieer, A., & Wallace, L. (2014). Direct georeferencing of ultrahigh-resolution UAV imagery. IEEE Transactions on Geoscience and Remote Sensing, 52, 2738–2745. https://doi.org/10.1109/TGRS.2013.2265295

Warren, A. (2002). Land degradation is contextual. Land Degradation and Development, 3, 449–459. https://doi.org/10.1002/ldr.532

Westoby, M. J., Brasington, J., Glassera, N. F., Hambreya, M. J., & Reynolds, J. M. (2012). ‘Structure-from-Motion’ photogrammetry: A low-cost, effective tool for geoscience applications. Geomorphology, 179, 300–314. https://doi.org/10.1016/j.geomorph.2012.08.021

Zhu, X. (2016). GIS for environmental applications: A practical approach. (pp. 110–112). London, New York: Routledge. ISBN: 9780415829076.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

How to cite this article: Chudý F, Slámová M, Tomaštík J, Tunák D, Kardoš M, Saloň Š. The application of civic technologies in a field survey of landslides. Land Degrad Dev. 2018;29:1858–1870. https://doi.org/10.1002/ldr.2957