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DATA AND KNOWLEDGE INTEGRATION FOR OBJECT-BASED LANDSLIDE MAPPING – CHALLENGES, OPPORTUNITIES AND APPLICATIONS

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Abstract: Accurate mapping of landslides and the reliable identification of affected areas are essential for advancing the understanding of landslide erosion processes and for providing valuable information for disaster risk reduction. Remote sensing provides remarkable opportunities for landslide detection, mapping and monitoring, particularly in remote and difficult to access areas. While the variety of remote sensing data and advanced image analysis methods open up great possibilities, a certain understanding of the landslide processes and environmental characteristics is beneficial for deriving useful and valuable information and tackling the complexity of landslides. Object-based image analysis (OBIA) is well-suited for mapping complex natural phenomena such as landslides since it mimics human perception and allows the integration of optical, radar, and topographic remote sensing data as well as expert knowledge for feature extraction. This overview article aims to discuss and highlight the potential and challenges of OBIA for semi-automated landslide investigation.

Keywords: Landslide, object-based image analysis (OBIA), remote sensing, semi-automated mapping, data integration, knowledge integration, change detection

DATEN- UND WISSENSINTEGRATION FÜR DIE OBJEKTBASIERTE KARTIERUNG VON GRAVITATIVEN MASSENBEWEGUNGEN – HERAUSFORDERUNGEN, CHANCEN UND ANWENDUNGEN

Zusammenfassung: Die genaue Kartierung von gravitativen Massenbewegungen und die zuverlässige Identifikation von betroffenen Gebieten sind unerlässlich, um das Verständnis von Massenbewegungsprozessen zu verbessern und wertvolle Informationen für die Reduzierung des Katastrophenrisikos bereitzustellen. Die Fernerkundung bietet bemerkenswerte Möglichkeiten für die Erkennung, Kartierung und Überwachung von Massenbewegungen, insbesondere in abgelegenen und schwer zugänglichen Gebieten. Während die Vielfalt der Fernerkundungsdaten und -methoden neue Möglichkeiten eröffnet, ist auch ein gewisses Verständnis der Massenbewegungsprozesse und der naturräumlichen Gegebenheiten von Vorteil, um nützliche und wertvolle Informationen abzuleiten. Die objektbasierte Bildanalyse (OBIA) eignet sich gut zur Kartierung komplexer Naturphänomene wie Massenbewegungen, da sie die menschliche Wahrnehmung nachahmt und die Integration von optischen Bildern, Radardaten und topographischen Daten sowie Expertenwissen für die Informationsextraktion erlaubt. Dieser Beitrag zielt darauf ab, das Potenzial und die Herausforderungen von OBIA für die Kartierung von Massenbewegungen darzulegen und zu diskutieren.

Schlüsselwörter: Gravitative Massenbewegung, objektbasierte Bildanalyse (OBIA), Fernerkundung, teilautomatisierte Kartierung, Datenintegration, Wissensintegration, Veränderungsanalyse

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1 INTRODUCTION

1.1 LANDSLIDES AND THEIR IMPACT

Landslides are a major natural hazard in almost all mountainous regions. Every year landslides cause numerous fatalities, significant damages to infrastructure and disturbances to livelihoods in many parts of the world (Salvati et al. 2010, Petley 2012, Haque et al. 2016, Froude & Petley 2018, Herrera et al. 2018, Pollock & Wartman 2020). While the complete and timely documentation of landslide events is still lacking, the impact of landslides on societies and the number of landslide-related disasters are increasing worldwide (Hernández-Moreno & Alcántara-Ayala 2017). The on- and off-site economic, environmental and social impacts of landslides can be very significant, and include, for example, reductions in agricultural and forest productivity, reduced real estate values, damage to the road and railroad infrastructure, contamination of freshwater habitats by increasing sediment loads in rivers, changes in surface morphology, effects on the wildlife and habitats, and social upheaval and displacement (Crozier 2005, Kjekstad & Highland 2009, Alimohammadlou et al. 2013, Zumpano et al. 2018).

A landslide is the movement of a mass of rock, earth or debris down a slope due to gravity (Cruden & Varnes 1996). According to the type of movement, Cruden & Varnes (1996) differentiate between five kinematically distinct types: falls, topples, slides, spreads, and flows. By considering the type of material and the type of movement as the main parameters, Varnes (1978) further distinguished between 29 different landslide types. Hungr et al. (2014) revised the Varnes (1978) classification primarily based on a more detailed characterisation of the material involved and came up with an updated version that includes 32 landslide types. Landslides can significantly vary in size, ranging from individual falling rocks to whole mountain slopes that collapse (Davies 2015). They can be triggered by various natural factors, for example, heavy rainfall events, increased snowmelt, permafrost thawing, earthquakes, volcanic eruptions, slope undercutting due to erosion, but also by human activities such as road construction, excavation work and loading, and mining. Landslides occur over a wide range of scales, from single local events to regional events with thousands of landslides.

While landslides are already a significant problem under present-day climate regimes, climate change will likely result in an increase in the frequency and magnitude of landslide triggering events, such as heavy rainfall events. For example, climate models predict more frequent dry spells, followed by intense rainfall events, which are the primary trigger of landslides in Central Europe (Tichavský et al. 2019). Scoccimarro et al. (2016) state that by the end of the 21 st century the intensity of such heavy precipitation events is forecast to increase across the Euro-Mediterranean region. Chiang & Chang (2011) analysed the potential impact of climate change on typhoon-triggered landslides in Taiwan. They concluded that with an increased annual maximum rainfall due to the intensification of typhoons, the area potentially affected by landslides would also increase. An increase in landslide activity as a response to climate change is also expected in high-latitude and high-elevation regions (Patton et al. 2019). Consequently, rainfall-induced landslide risk increases (Haque et al. 2019), potentially affecting a larger proportion of the population (Gariano & Guzzetti 2016). Furthermore, landslide response to climate change invokes precautionary management decisions (Crozier 2010).

"History is the best guide to the future. Geologists say that any effort to reduce the risks from landslides must start with an inventory, a detailed map showing where landslides have happened". This quote from a National Broadcasting Company (NBC) News article written by Pulitzer Prize-winning journalist Bill Dedman (Dedman 2014) after the disastrous Oso landslide in Washington, United States of America, in March 2014, showcases the importance of investigating landslides and improving our knowledge about this natural hazard.

With these considerations in mind, the importance of efficient methods, such as remote sensing, for landslide investigation becomes evident. The complexity of landslides requires advanced and innovative image analysis methods for adequate landslide inventory mapping (Guzzetti et al. 2012), rapid landslide detection after triggering events and monitoring and documenting the evolution and reactivation of single large landslides.

1.2 REMOTE SENSING FOR LANDSLIDE INVESTIGATION

Remote sensing provides an excellent opportunity for investigating landslides and related changes on the Earth's surface. The increasing availability of Earth observation (EO) data from a range of high resolution (HR) and very high resolution (VHR) optical and synthetic aperture radar (SAR) sensors as well as digital elevation models (DEMs) over the past two decades has opened up remarkable opportunities for landslide investigation, particularly for analysing remote and difficult to access areas. Optical satellite images and aerial photographs are valuable and cost-effective resources. They have mainly been employed for mapping event-triggered landslides in combination with morphological properties derived from DEMs. SAR data are capable of measuring and monitoring millimetre-scale surface displacements of slow-moving landslides with interferometric SAR (InSAR) techniques (e. g. Crosetto et al. 2016, Solari et al. 2020), such as Persistent Scatterer Interferometry (PSI) (Ferretti et al. 2000, 2001) or Small BASeline Subset (SBAS) (Berardino et al. 2002, Lanari et al. 2004). In general, remote sensing applications for landslide investigation include landslide recognition, landslide monitoring, and landslide hazard assessment (Scaioni et al. 2014), whereby the selection of an appropriate technique depends on the purpose, spatial coverage, available investigation time period, and available resources (Guzzetti 2000, van Westen et al. 2006, Guzzetti et al. 2012, Chang et al. 2014).

Traditional approaches for landslide assessment include resource-intensive ground surveys and visual image interpretation using VHR data (van Westen et al. 2008), whereby experts manually delineate and classify landslides by qualitatively analysing a series of characteristics that can be recognised in the images. These characteristics comprise concepts such as shape, size, colour, texture, and setting (Guzzetti et al. 2012). Although manual visual mapping is still a common procedure, it is a time-consuming and subjective task. Thus, there has been a trend towards semi-automated landslide mapping approaches based on different remote sensing data.

Moreover, as the amount of (freely) available satellite data has grown, so has the power of the data analysis methodologies. Image classification methods can basically be divided into pixel-based and object-based approaches (van Westen et al. 2008, Moosavi et al. 2014, Scaioni et al. 2014).

For several reasons, pixel-based image analysis methods are only suitable for landslide mapping to a limited extent. Pixel-based approaches do not allow us to appropriately tackle the complexity, varying sizes, and characteristics of landslides because of their inability to consider spatial characteristics or context information. Thus, the differentiation of landslide pixels from other land cover types with similar spectral signatures, such as bare land or construction sites, or the distinction between landslide types is almost impossible. Pixel-based landslide mapping methods tend to be sensitive to errors (Martha et al. 2010), frequently resulting in salt-and-pepper classifications.

In contrast to pixel-based methods, object-based image analysis (OBIA) or geographic object-based image analysis (GEOBIA) methods allow for seamless work with existing multi-scale geospatial data by combining image processing and geographic information system (GIS) functionalities in an interlinked framework (Blaschke 2010, Blaschke et al. 2014). OBIA relies on image segmentation and classification and uses spectral, spatial, textural, contextual, morphological, and hierarchical properties for land cover mapping and feature extraction. Individual (geomorphological) features are treated as aggregates of pixels and can be grouped into homogeneous objects, providing additional information on topological relationships of neighbourhood, embeddedness or shape (Drăguţ & Blaschke 2006). This approach mimics how human perception works (Lang 2008) as human interpreters also make use of a range of characteristics for image interpretation. Thus, OBIA is well-suited for semi-automatically identifying and classifying complex natural phenomena with diverse characteristics and appearances, such as landslides. Moreover, OBIA allows detailed (change) information to be captured in a reproducible and systematic manner (Chen et al. 2012). The applicability of OBIA for landslide investigation has also been demonstrated by the fact that object-based landslide mapping approaches generally produce higher accuracies than pixel-based approaches (Martha et al. 2010, 2012, Moosavi et al. 2014, Keyport et al. 2018).

Based on existing literature and by referring to examples from the author's own research (cf. Hölbling 2021), this overview paper aims to discuss and highlight the potential and challenges of OBIA for semi-automated landslide investigation based on various remote sensing data. In the course of this, a focus is placed on data and expert knowledge integration for object-based landslide mapping and monitoring purposes and demonstrating the application potential for creating added value from the semi-automated mapping results.

2 OBJECT-BASED IMAGE ANALYSIS FOR LANDSLIDE MAPPING: SUCCESS AND REMAINING CHALLENGES

2.1 STATUS AND RESEARCH GAPS

Guzzetti et al. (2012) stated that a joint analysis of different types of remote sensing data with emerging techniques represents an open field of research, with potential new applications for the detection and mapping of event landslides. Similarly, Napieralski et al. (2013) argued that comprehensive approaches combining multiple data sets are essential for mapping complex landscapes and identifying geomorphological features, while concurrent technological developments force us to integrate different theoretical perspectives on space, time, processes, and systems. However, given the large number of sensors and processing techniques, it is challenging to determine suitable data and the best approach for mapping and monitoring (Joyce et al. 2014). Technical progress allows us to develop advanced image analysis methods. Moreover, reliable and efficient analysis frameworks are required to tackle the complexity of landslides and their varying characteristics. OBIA provides such a framework to address these challenges while existing semi-automated approaches can still be optimised.

Considerable progress has been made in the use of object-based approaches for landslide investigation in the past decade. This has been demonstrated in several studies that employed different semi-automated approaches that rely on image analysis and machine learning methods combined with a varying degree of expert knowledge. Most existing studies have utilised optical satellite images and DEM data. For example, Stumpf & Kerle (2011) tested the random forest (RF) machine learning technique on different VHR optical images with the aim of reducing the need for manually selecting thresholds and features. A support vector machine (SVM) supervised learning algorithm within OBIA was used by Heleno et al. (2016). Open-source tools and machine learning algorithms for object-based landslide mapping were applied by Amatya et al. (2021), who developed a semi-automated landslide detection system based on various open-source Python packages and modules, and by Knevels et al. (2019), who used SVM for landslide detection with Light Detection and Ranging (LiDAR) data. Other studies employed fuzzy classification schemes within a knowledge-based approach (Feizizadeh et al. 2017), applied multi-scale approaches that rely on different segmentation levels (Lahousse et al. 2011), aimed at segmentation optimisation for knowledge-based landslide detection (Martha et al. 2011), or combined deep learning and transfer learning with OBIA methods (Lu et al. 2020).

Despite recent efforts, further research is needed to work towards a more comprehensive data integration of various remote sensing data from different sensors into OBIA landslide mapping approaches. Optical data have mainly been used to map event-triggered shallow landslides, whereas SAR data have primarily been useful for detecting slow-moving deep-seated landslides. Casagli et al. (2016) emphasised that the integrated analysis of optical and SAR data should be intensively followed to fully exploit the potential of different EO data for landslide mapping. However, OBIA approaches that compare or integrate both optical and SAR data for landslide mapping are still rare.

The analysis of multi-temporal images allows the detection of changes that can be attributed to new and/or reactivated landslides (Borghuis et al. 2007, Mondini et al. 2011). Bontemps et al. (2008) pointed out that further research is needed to create analytical frameworks to deal with the changes related to natural variability more efficiently. However, little emphasis has been placed on the development of efficient semi-automated object-based classification approaches for landslide change detection and time series analysis.

Furthermore, the ability of object-based approaches to consider spatial and morphological properties enables them to differentiate between different landslide processes (Barlow et al. 2006). So far, only a few studies have made use of the potential of the joint analysis of optical and DEM data for the semi-automated detection and differentiation of different landslide types or sub-parts (e. g. Barlow et al. 2006, Hölbling et al. 2012, 2015, Heleno et al. 2016, Karantanellis et al. 2021). Especially the mapping of different landslide types significantly benefits from the integration of expert knowledge. However, a major challenge remains in transferring (common) expert knowledge into computer-based classification rules, particularly when dealing with complex geomorphological features such as landslides that exhibit high variability in their appearance and characteristics. Although several studies have employed expert knowledge for object-based landslide mapping, further research is needed to increase the efficiency, transferability, automation, and objectivity of such approaches, while at the same time aiming to create added value information products from semi-automated mapping results.

2.2 DATA AND KNOWLEDGE INTEGRATION

Most of the criteria an interpreter would employ in visual image analysis can be modelled in OBIA by using GIS and remote sensing techniques to get closer to the interpreter's capacity (Lang 2008). Each potential landslide object can be defined by a range of different properties that can be derived from various remote sensing data. This includes, for example, spectral properties such as the mean and standard deviation values of spectral bands, or spectral indices such as the Normalised Difference Vegetation Index (NDVI), spatial properties such as the size, the length/with ratio or the object compactness, textural properties such as tonal differences and patterns caused by disturbance of the surface, morphological properties such as the mean slope or curvature, contextual properties such as the shared border with neighbouring objects from a different class or the relative location on a slope, or hierarchical properties that allow establishing connections between different segmentation levels. All these properties can be used to define expert-driven, knowledge-based classification rules. In this course, human knowledge, i. e. the cognitive procedure of recognising landslides, can be transferred into reproducible and transparent computer-based classification rules (Lang 2008, Osberger 2010, Lu et al. 2011).

By making use of various HR and VHR optical, SAR, and topographic remote sensing data, landslides can be examined more efficiently than when relying on single data sets alone because the most appropriate characteristics of each data layer can be addressed (Hölbling et al. 2012). To create appropriate mapping workflows, knowledge about the suitability of different data and their properties that are well-suited for semi-automated landslide mapping is important. Optical aerial and satellite imagery usually serves as the main source for landslide mapping but has often been used in combination with DEM data and derived products, such as slope and curvature, to improve the classification results. Depending on the aims of the study, the study area and the landslide characteristics (especially the size of the landslides), optical images with different spatial resolutions from different sensors can be used for landslide mapping, from aerial photography with a sub-metre resolution to Landsat images. DEM data and the derived morphological information can be very helpful in the analysis workflow. However, its usability depends on its quality, resolution and the acquisition time. DEM data are rarely available from the same or a similar time as optical data (i. e. often only a pre-event DEM is available), and thus, the available DEMs do not necessarily reflect the actual topography after landslide events. Despite these limitations, DEMs and derived products can serve as auxiliary data to increase the accuracy of object-based mapping (Joyce et al. 2014). While optical satellite images are particularly useful for mapping event-triggered landslides, it is challenging to directly assign distinct backscatter signatures of SAR data to landslides. However, in combination with other data, textural features of SAR data can be useful for the detection and classification of single large landslides (Guzzetti et al. 2012, Hölbling et al. 2018a). Moreover, due to its almost complete all-weather capability, SAR data are more likely to be available after landslide triggering events, such as heavy rainfall, as compared to optical data, thus potentially allowing a rapid response. Within an OBIA approach, optical and SAR data can be exploited in one interlinked workflow (Dabiri et al. 2020), whereby the changes in backscatter information between pre- and post-event data can be beneficial for mapping purposes. While the potential of OBIA becomes especially evident when integrating multiple data, the complexity of OBIA mapping workflows and rulesets often simultaneously increases. Even if it is challenging to define the most appropriate data types (Joyce et al. 2014), relying on different optical, SAR and topographic remote sensing data allows for a more comprehensive analysis of landslides.

Finding universal classification rules and thresholds for semi-automated or fully automated mapping is hardly possible due to the complexity of landslides and because landslide characteristics can differ even within small areas. Thus, the integration of expert knowledge into mapping processes seems valuable. This means that knowledge-based classification rulesets can be created, whereby the selection of classification features, parameters and thresholds is done in an expert-driven manner. This process significantly benefits from a certain understanding of landslide processes and the study areas, if possible also gathered in the field and during discussions with local experts. This can be very helpful for considering aspects for semi-automated landslide mapping that are not directly discernible from the visual assessment of the data used. The integrated use of various remote sensing data sources coupled with expert knowledge can also help to remove false positives with similar spectral signatures, e. g. harvested agricultural fields, cleared forests, construction sites, and quarries, and can facilitate the differentiation of landslide types. Such existing expert knowledge also reduces the time required to set up classification rulesets and select appropriate features, parameters, and thresholds. Thus, gaining information and knowledge about the environmental settings, landslide events, triggers and

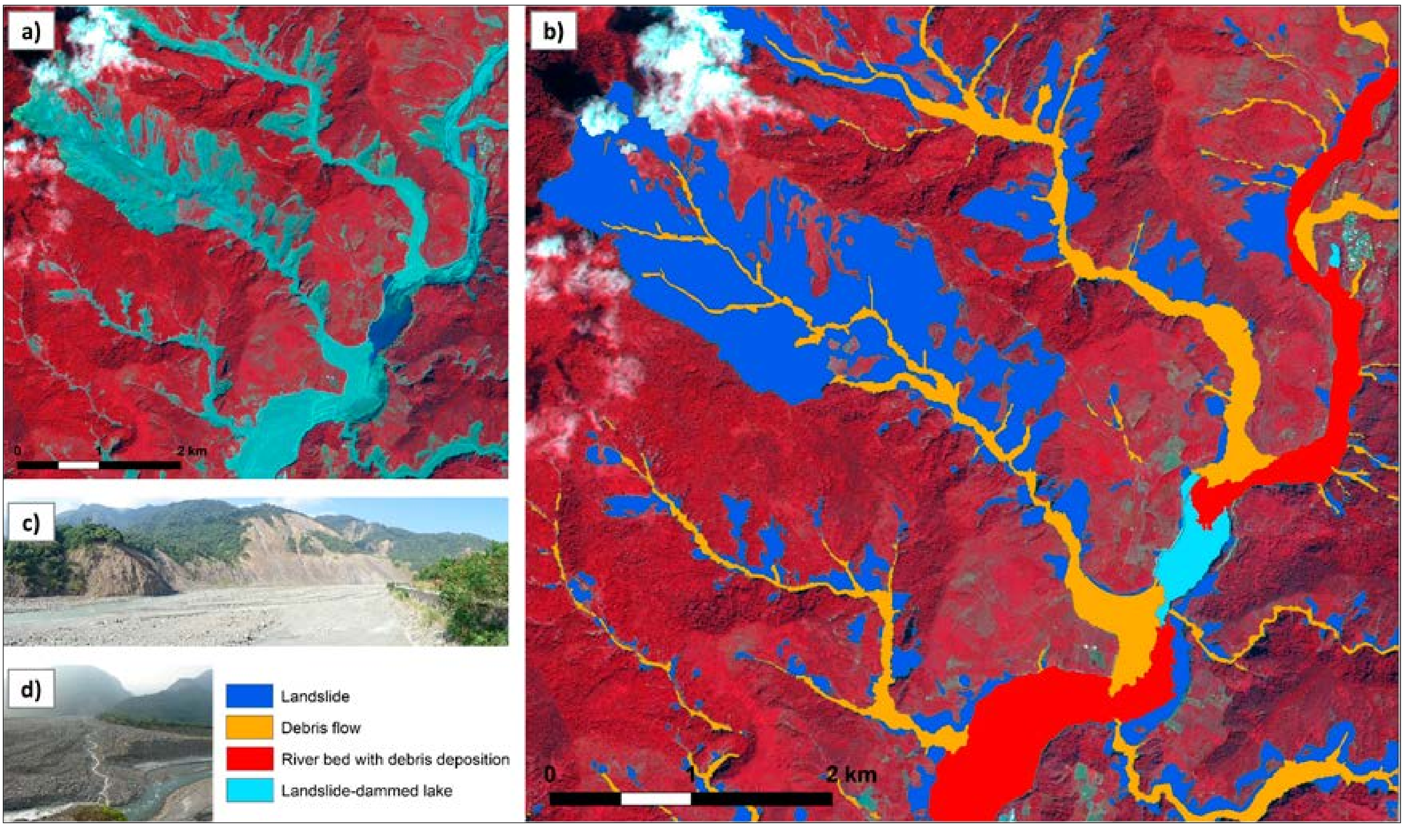

Figure 1: Object-based landslide mapping for a study area in south-central Taiwan. a) SPOT 5 satellite image showing landslides caused by heavy rainfall during typhoon events. b) OBIA landslide mapping results (based on the SPOT 5 image and topographic data) with differentiation into types, i. e. landslides (material source area), debris flows (transport area), the main river bed with the debris deposition, and landslide-dammed lakes. c) and d) Impressions from the study area showing landslides, debris flows and deposition areas (photographs: © D. Hölbling).

impacts prior to any analysis is beneficial. Figure 1 shows an example of landslide mapping in Taiwan. The classification scheme, which resulted in the differentiation of different landslide types using optical and DEM data, was established based on discussions with local experts during workshops and field visits. Image objects were created using the multiresolution segmentation algorithm implemented in the eCognition (Trimble) software, whereby the selection of segmentation parameters was supported by a statistical assessment using the estimation of scale parameter (ESP) tool (Drăguț & Eisank 2010). After the identification of landslide candidate objects primarily based on NDVI and brightness information, the landslide types were separated using DEM derivatives such as slope, curvature, and flow accumulation.

However, despite advantages that can be seen in relying on expert knowledge, a certain degree of subjectivity is inherent to an expert-driven approach, even if the classification rules are transparent and reproducible. Hölbling et al. (2015) assessed this with local landslide experts in Taiwan, who were asked to perform a mapping exercise to differentiate and delineate landslide types. The expert interpretations were highly heterogeneous and showed the difficulties in objectively separating landslides from debris flows, even if the manual mapping was only performed for a rather small area. This is in line with the findings of Galli et al. (2008), who compared three landslide inventories that had been created by different people through visual image interpretation and found substantial spatial mismatches among them.

Transferring expert knowledge into computer-based landslide classification rules requires finding a balance between general applicability, which could potentially limit the mapping accuracy, and including too many specific classification parameters that result in classification rulesets that are too complicated and nested, thereby limiting the objectivity, transferability and automation. To overcome these issues, Eisank et al. (2014) proposed a method to optimise the landslide classification process by transferring common expert knowledge into computer-based classification rules. The proposed knowledge models depict the information experts primarily use for landslide mapping with remote sensing data, including the data layers and spectral, spatial and morphological features and thresholds. Such an approach could improve the objectivity, transferability and robustness of a knowledge-based landslide mapping system (Eisank et al. 2014) and can serve as a basis for further developments in this direction.

2.3 CHANGE DETECTION AND TIME SERIES ANALYSIS

Without an understanding of the baseline state of a location, it is hardly possible to determine whether an observed feature is the result of an event (Joyce et al. 2014) and to conclude which triggering event caused a landslide and when it happened. Especially in areas that are frequently affected by landslides, it is important to gain information about new landslides that occur after triggering events, their spatio-temporal patterns and their evolution over time. Optical remote sensing data are effective for surface change mapping, especially in areas where vegetation cover has been removed by landslides (Joyce et al. 2014). Object-based change detection (OBCD) (Hall & Hay 2003, Blaschke 2005, Chen et al. 2012, Hussain et al. 2013) can significantly improve the identification of changes for specific geographic entities found over a given landscape as it offers unique methods for exploiting HR and VHR imagery to extract timely and meaningful geospatial change information (Chen et al. 2012). Semi-automated OBCD approaches can be applied to regularly update landslide maps and inventories after major triggering events (Hölbling et al. 2015).

So far, only a few semi-automated approaches for landslide change detection have been proposed, e. g. by Lu et al. (2011) and Martha et al. (2016), using optical satellite imagery aided by DEMs. Plank et al. (2016) and Dabiri et al. (2020) combined pre- and post-event optical and SAR data for change detection. Hölbling et al. (2015) developed an object-based approach for landslide and debris flow change mapping in northern Taiwan using pre- and post-event SPOT 5 imagery to semi-automatically detect typhoon-triggered changes. Following a joint segmentation of pre- and post-event imagery, they analysed each resulting object in terms of its spectral transformation, i. e. the change in values of calibrated spectral indices (NDVI and Green Normalised Difference Vegetation Index (GNDVI)), and thus could increase the transferability of the approach instead when using absolute spectral thresholds. Such a method is particularly useful when comparing optical images acquired during different seasons (e. g. resulting in different appearances of vegetation, illumination conditions) or images with different radiometric characteristics, in cases where appropriate pre-processing such as atmospheric correction is not possible (e. g. when the original imagery is not available or when already performed pre-processing is not well documented), or when using images from different sensors.

An approach for time series analysis was suggested by Behling et al. (2014), who analysed optical satellite image time series and identified changes based on NDVI trajectories. Hölbling et al. (2020) used Landsat time series from 1984 to 2018 to semi-automatically map the evolution of a major landslide in Taiwan, whereby only minor adaptations in the classification thresholds were required for the different Landsat sensors. The mapping results revealed details regarding the evolution of the landslide. Historical and recent aerial panchromatic and multispectral photography from five points in time (1944 to 2011) were used by Hölbling et al. (2016) to detect shallow landslides in a study area in the south-eastern North Island of New Zealand. Due to the limited spectral information, the brightness (panchromatic) information was used to detect landslides, which usually appeared brighter than their surroundings (e. g. Martha et al. 2012), in combination with morphological characteristics, such as the slope gradient, and spatial properties, such as compactness and length/width ratio. High-quality pre- and post-event DEMs or even DEMs from multiple points in time could improve OBCD and time series analysis. However, such data are rarely available. Nevertheless, the information derived from the DEMs can be used as auxiliary data to remove false positives during the classification process and to facilitate the differentiation of landslide types.

3 VALIDATION AND INTERPRETATION OF OBJECT-BASED LANDSLIDE MAPPING RESULTS

The validation of semi-automated landslide mapping results is essential for determining their accuracy and the reliability of the applied methods and for assessing their suitability for further use. Usually, classification accuracies are assessed by comparing OBIA outcomes to results from visual image interpretation (i. e. manually digitised reference polygons, ideally produced by an independent expert), e. g. in terms of spatial overlap and under- and overestimated areas, or to official landslide inventories or reference maps from governmental (or similar) organisations, using either polygon-based or point-based databases. Object-based landslide mapping accuracies can be assessed using different spatial accuracy metrics (cf. Hölbling et al. 2017), however, accuracy values should be interpreted with care since they depend on the method applied and the reference data and they do not necessarily reflect the validity and applicability of the mapping results.

Accuracy values can vary depending on the data, study area and landslide characteristics. For example, Hölbling et al. (2016) achieved only moderate accuracy values for mapping shallow landslides in New Zealand due to the difficulty in detecting landslide scars using a semi-automated approach. The landslide classification mainly relied on the spectral differences of the landslide objects to the neighbouring areas, but landslide tails – unlike landslide scars – did not show a distinct spectral difference to their surroundings (Figure 2). Moreover, revegetation takes place faster on landslide tails than on landslide scars owing to a lack of remaining soil. This makes the semi-automated detection of tails more difficult, especially when the used imagery is not taken immediately or soon after a landslide event. It turned out that the interpretation of landslide tails requires a highly trained eye and sophisticated interpretation skills and that it is hardly possible to fully transfer such capabilities to computer-based classification rules (Hölbling et al. 2016). The same is true when vegetation cover (partly) remains on landslide bodies (Figure 2) because the primary assumption for classifying landslides with OBIA is the change in the spectral response, often caused by the removal of vegetation after landslide events. In optical images, landslides usually appear brighter than their surroundings due to the exposure of bare ground (Martha et al. 2010, Behling et al. 2014). In such cases, manual interpretation allows the inclusion of vegetated areas as part of a landslide body, while this is challenging with a semi-automated OBIA approach due to a lack of distinct characteristics that can be employed in the classification process (cf. Albrecht et al. 2017, Hölbling et al. 2017).

The best accuracy is usually achieved by manual digitising techniques because they benefit from the interpreter's knowledge (Joyce et al. 2014). Mapping results created by individual experts through visual interpretation are often the only reference available (Hölbling et al. 2016). The advantages of manual mapping include delineating single landslides as single objects, differentiating landslide source and deposition areas and splitting up complex compound landslides into individual landslides (Hölbling et al. 2016, 2017). However, manually prepared reference data rarely constitute a completely true reference since their production depends on various

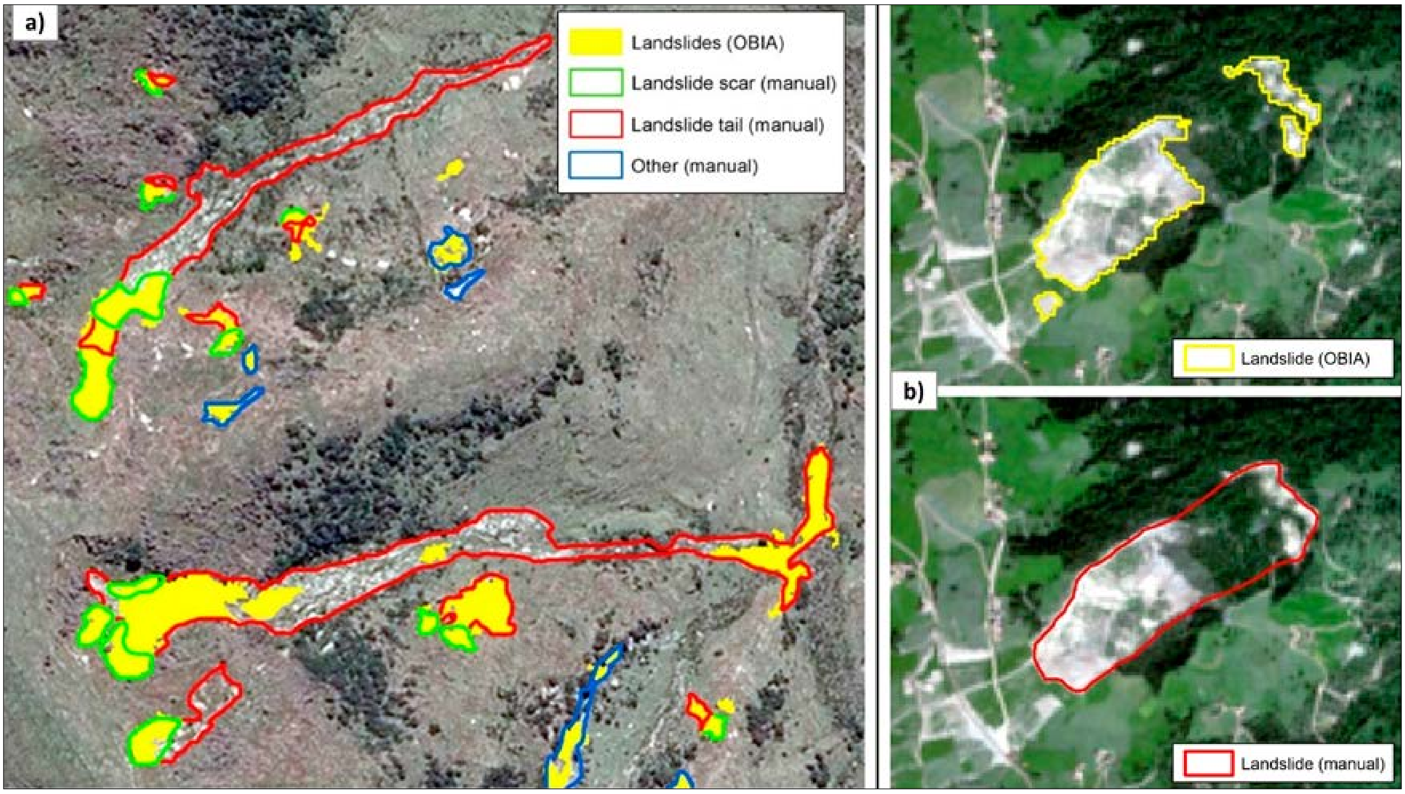

Figure 2: Challenges in object-based landslide mapping. a) Shallow landslide mapping in New Zealand based on aerial photography and topographic data. Due to the missing spectral difference to their surroundings, landslide tails, as identified by manual mapping, could only be partially detected with OBIA (modified after Hölbling et al. 2016). b) Landslide mapping in northern Italy based on Sentinel-2. The part of the landslide that is covered by vegetation was not identified with OBIA due to a lack of distinct characteristics, but the inclusion of this part was logically inferred by expert knowledge during manual mapping (modified after Hölbling et al. 2017).

factors, including the data used, the mapping scale, and the experience, skills, and knowledge of the interpreter, which influence the accuracy, completeness and reliability (Mantovani et al. 1996, Galli et al. 2008, Hölbling et al. 2012, 2015, Scaioni et al. 2014). Aside from the selection of the applied accuracy assessment method, it is thus also important to carefully select reference data and to consider the associated uncertainty inherent to the reference data when interpreting classification accuracies (Hölbling et al. 2017). These facts are often overlooked.

Existing landslide inventories, for example, those produced and maintained by national geological surveys and mainly created through a combination of visual interpretation of aerial photography and field surveys (Guzzetti et al. 2012), constitute another source of reference data, even if their completeness, accuracy and up-to-dateness can vary significantly (Herrera et al. 2018). A comparison of OBIA mapping results with existing landslide inventories from Italy revealed significant differences (Hölbling et al. 2012). On the one hand, many new landslides that were not present in the inventories were identified; on the other hand, several landslides, such as slow-moving landslides covered by vegetation, were missed since they did not show a distinct spectral appearance or contrast to the surroundings. These findings reveal another aspect of the difficulties associated with assessing the mapping accuracy of semi-automatically produced landslide maps.

4 APPLICATION AND ADDED VALUE CREATION

To gain additional knowledge and create added value, the application potential of OBIA and the applicability of OBIA landslide mapping results can be explored in several ways. The OBIA mapping results can be combined with movement rates derived from InSAR analysis to obtain a more complete picture of landslides and their behaviour (e. g. Hölbling et al. 2012). The integration of landslide mapping results based on different data and created using different methods allows for the enrichment and updating of existing landslide inventories. On the one hand, this enables improving landslide delineations while providing additional information about landslide types through the OBIA results. On the other hand, information regarding the movement rates and directions can be attached to the derived landslide polygons. The added value of differentiating landslide types with OBIA is especially given when specific landslide types pose a high risk to society. This is, for example, the case in Taiwan, where the distinction between landslides and debris flows (see Figure 1) is important because debris flows often cause more severe damage to people and infrastructure than the initial landslide event since they can reach wide areas downstream (Lin et al. 2002, Hölbling et al. 2015).

Monitoring land surface changes is necessary to understand mass-transport systems, to detect related environmental variability, and to assess natural hazards (Kääb 2002). Remote sensing data offers ideal opportunities to document the development of landslide-affected areas over time. Moreover, landslide mapping results from multi-temporal analysis can be corre-

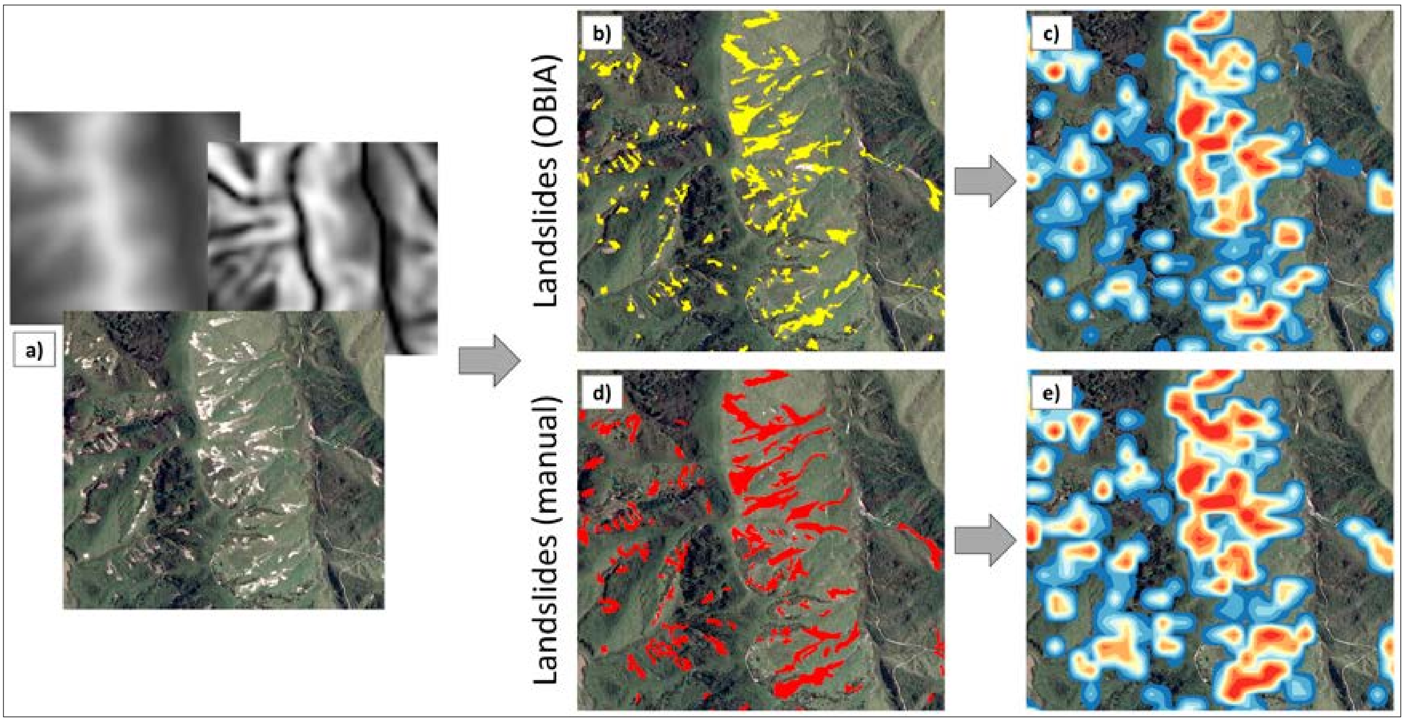

Figure 3: Landslide hotspot maps based on OBIA and manual landslide mapping results (cf. Hölbling et al. 2016). a) Aerial photograph and topographic data of a subset of the study area in New Zealand. b) OBIA mapping results. c) Manual mapping results. d) Landslide hotspots computed based on the OBIA landslide mapping results. e) Landslide hotspots computed based on the manual landslide mapping results.

lated with triggering events such as heavy rainfall. Climate change is expected to increase the intensity and frequency of heavy rainfall events, which are the primary trigger of rapid-moving landslides (Gariano & Guzzetti 2016). Consequently, this might result in a larger portion of the population being exposed to rainfall-induced landslide risk (Gariano & Guzzetti 2016). Thus, it is important to analyse rainfall patterns that can destabilise slopes (Kirschbaum & Stanley 2018). For example, Hölbling et al. (2020) correlated the changes in the mapped landslide area of a large landslide in Taiwan with heavy rainfall during typhoon events to discover potential relationships between landslide evolution and rainfall as the triggering factor. The findings indicate that the duration of the heavy rainfall event was the main parameter that caused the extension of the investigated landslide. Such studies contribute to a better understanding of reactivation intervals and how typhoon events and the associated rainfall influence the evolution of large landslides. Moreover, pre- and post-event data acquired before and after landslide triggering events allow for new insights into spatio-temporal changes in the environment. The OBIA time series analysis also revealed that the repeated sediment delivery from the landslide blocked a river several times in the past, leading to the creation of a temporary landslide-dammed lake, which poses a risk to people and infrastructure downstream (Hölbling et al. 2020). Such cascading effects of landslides often remain unknown in remote areas but can be revealed by remote sensing-based time series analysis. The derived information can lead to a better understanding of landslide behaviour and support early warning, for example, when predicted rainfall amount, duration, and intensity can be related to expected sediment delivery and potential consequences such as the damming of rivers.

Semi-automatically detected landslides can be used as a basis for creating landslide hotspot maps (Hölbling et al. 2016, Figure 3). Such hotspot (or density) maps allow the immediate identification of the most landslide-affected areas. Information on the spatio-temporal evolution of landslide hotspots contributes to the understanding of landscape dynamics and can be useful for stakeholders in the development and planning of site-specific intervention measures. Landslide hotspot maps are also valuable for planning field surveys and in situ campaigns to prioritise disaster response and mitigation measures. Thus, the value of remote sensing-based landslide hotspot maps is manifold. Hölbling et al. (2016) showed that the hotspots calculated based on the OBIA mapping were similar to hotspots computed based on manual mapping results (Figure 3). An important aspect is that the OBIA mapping required significantly less time than the manual mapping, demonstrating the applicability of the semi-automated approach for deriving landslide hotspots.

Object-based landslide mapping workflows can also be integrated into web services to assist targeted natural hazard management. For example, Hölbling et al. (2018b) developed a pre-operational web service for landslide mapping, which enables users and practitioners to perform analysis in a straightforward manner without the need for advanced image analysis skills. First, the proposed workflow allows users to select segmentation-derived image objects as training samples. Second, landslide candidate objects are classified based on machine learning classification algorithms. Third, users can manually modify the results, perform further analysis in the web service such as a comparison with other geospatial data (e. g. OpenStreetMap) and download the landslide mapping results.

5 CONCLUSIONS

Remote sensing allows us to document and monitor landslides by looking back in time for years or even decades, but it can also be used for rapid mapping purposes and fast information provision after landslide triggering events. The increasing amount of remote sensing data coupled with advanced mapping and monitoring methods may lead to new findings and insights in order to better understand and illustrate landslide processes. Efficient image analysis methods such as OBIA can be used, for example, to detect different types of landslides, to create landslide inventories, and to gain an overview of spatio-temporal landslide occurrences and patterns. Consequently, information derived from remote sensing can be of significant value. It can lead to a better understanding of landslide evolution and reactivation in relation to triggering factors, it can be used to assess the impact of landslides on the environment and society and can serve as input for spatial planning, risk zone identification, and disaster response measures. Therefore, improving our capability to map and monitor landslides is not only of scientific value but also has considerable practical implications and socio-economic importance. While landslides are already a significant problem under present-day climate regimes, climate change will likely lead to more frequent and extreme landslide triggering events, such as heavy rainfall events. Consequently, their impact on individuals and communities is increasing. With this in mind, the significance of efficient semi-automated methods for landslide investigation becomes evident. Respective results can support hazard and risk analysis and the implementation of prevention and mitigation measures to reduce the risk for people and infrastructure.

Future research should focus on further developing strategies to fully exploit the vast amount of data and available expert knowledge about landslides for integration in object-based mapping workflows through knowledge models or digital landslide signatures. Such models or digital landslide signatures can specify the optimal combinations of data layers and parameters for image segmentation and the best-suited set of features and thresholds for classification. Ultimately, this could lead to more objective, robust and automated mapping systems that are applicable in different regions, even if this is highly challenging considering the complex nature of landslides. Moreover, recent advances in big EO data analysis and artificial intelligence (AI), such as deep learning, provide great opportunities for landslide mapping by identifying them based on complex recurring patterns and characteristics. However, expert knowledge should remain an important aspect in landslide studies because any mapping task benefits from a certain understanding of landslide processes and the environmental characteristics of the study area. Thus, novel ways of integrating deep learning with OBIA for landslide analysis, particularly for studying complex landslides that are not easily detectable in remote sensing data, seem to be promising and should be further researched in future.

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