# Mapping vegetated landslides using LiDAR derivatives and object-oriented analysis

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## Introduction

Rapid mapping of fresh landslides is a necessity for efficient post-disaster response and updating of landslide inventories and susceptibility and hazard maps, and the increasing availability of very high resolution (VHR) remote sensing data has been facilitating such efforts. Fresh landslide scars are predominantly detected based on their strong spectral contrast to their surroundings, in particular the absence of vegetation (Martha et al. in press; Martha et al. 2010). Many currently inactive or reactivated landslides also pose a significant hazard (Van Den Eeckhaut et al. 2007), and thus need to be inventoried/identified/mapped and monitored (Kääb 2002; Metternicht et al. 2005). Such slide features, however, are usually either revegetated or at least still contain partial vegetation cover. Passive optical image data quickly lose their utility in such cases. Light Detection and Ranging (LiDAR) and its wide range of derivatives has become a powerful tool in landslide research, particularly for landslide morphology analysis (Glenn et al. 2006) and landslide identification and inventory mapping (Razak et al. 2011). Such data have been mainly used in expert-based visual analysis, while recently also a number of pixel-based computer-aided detection methods have been proposed (e.g. McKean and Roering 2004). Given the recent success of object-oriented analysis (OOA) approaches in landslide mapping and monitoring with optical data (e.g. Lu et al. 2011; Martha et al. 2010; Stumpf and Kerle 2011), we here test to what extent (semi-)automatic detection and monitoring of (partly) vegetated landslides with LiDAR data are also possible. Many recent OOA studies on landslide recognition have included elevation information, yet only for the classification stage (e.g. Martha et al. 2010). In our work we exclusively rely on the LiDAR data, which form the basis for both segmentation and classification. Features that have been identified as critical in previous studies, such as NDVI to detect absence of vegetation, or grey level co-occurrence matrix (GLCM)-based texture measures, were thus not considered.

## Data and methods

The research initially focused on a test area in the Flemish Ardennes (Belgium) that is characterized by recent and shallow, and old, deep-seated landslides (Van Den Eeckhaut et al. 2007). Due to their hummocky topography the latter are generally under forest. However, since the 1950s increased expansion of settlements and human interference on these forested hillslopes have contributed to reactivation of several old landslides, causing damage to public and private property. We used a 2 m resolution LiDAR digital terrain model (DTM, i.e. with vegetation and other above-ground features removed), from which we derived slope gradient, curvature and difference in elevation. Using these features we developed an OOA procedure based on expert knowledge and statistical analysis, which focused on identification of the principal morphological elements of these slides, i.e. main scarps and flanks, as well as hummocky landslide-affected areas. The procedure was then applied without further modification to a validation area in the same region.

Digital elevation models (DEMs) and their derivatives have become increasingly valuable tools in geomorphological data processing, including with OOA methods. In particular classification attempts based on morphometric parameters, such as local variance at multiple scales (Dragut et al. 2011) or topographic openness (Anders et al. in press), have allowed identification and characterization of complex and morphologically highly variable features such as landslides. However, also the difficulty of using multi-pulse LiDAR data has been demonstrated. Razak et al. (2011) showed that ground surfaces (DTMs) derived from LiDAR vary strongly depending on the processing type, which in turn has a direct effect on the detectability of landslides.

## Results

OOA is a knowledge-based approach that attempts to replicate human cognition, i.e. it tries to formalize rules that are based on an analysis of visual image interpretation. This means that what is typically spontaneous recognition of a feature (such as the very clear landslide signature in Figure 1A) needs to be deconstructed into tangible morphometric parameters. This can be a challenge since the human brain is particularly suited to interpolate and fill in existing gaps, which is more difficult in processing that tends to begin at a certain starting point (such as the relatively easily identified main scarp) and then progressively grows outwards. Two basic rules in OOA state that (i) if a feature of interest is visually detectable in a given dataset (such as shown in Figure 1) it can be detected with OOA, but also (ii) that the accuracy of the automatic processing can typically not be higher than for the visual processing. Figure 1B shows that there clearly exists some ambiguity concerning the slide outline, leading to potential alternative solutions. Barring availability of additional information (extra derivatives, optical data layers, etc.) such uncertainty can also not be solved in OOA.

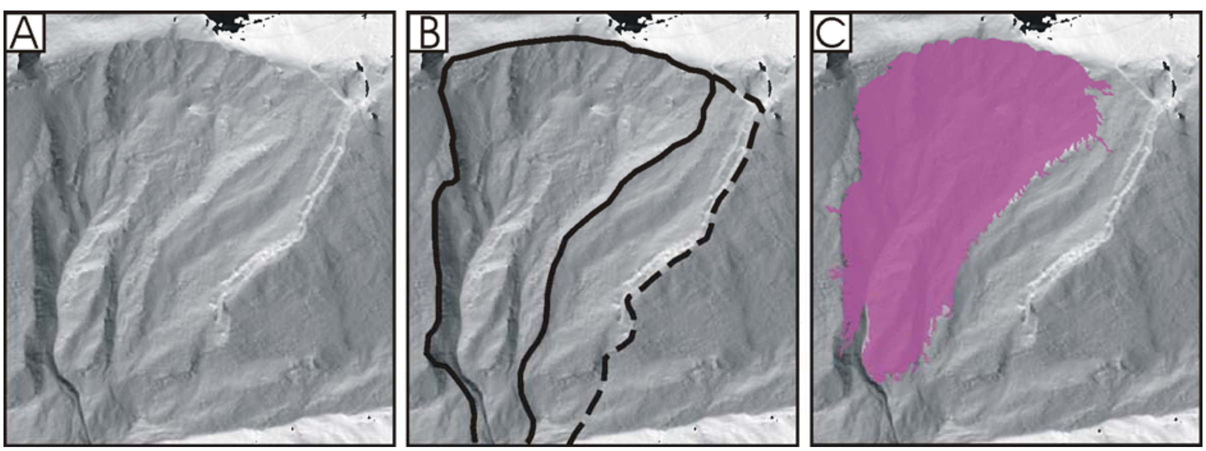


Figure 1. Shaded relief map of a deep-seated landslide in Vorarlberg (Austria; A), and visually delineated landslide outline (B; solid line). However, depending on the feature complexity and data type/quality ambiguities exit, leading to potential alternative outlines (hatched line). Such uncertainty also poses a challenge in OOA. The landslide body extracted with eCognition is shown in C (LiDAR data @VOGIS).

The first result of this work was a comprehensive conceptualization of all morphological elements of the landslide types found in the study area, i.e. main scarp, flanks and interior. OOA-based landslide detection typically begins with landslide candidate identification followed by successive removal of false positives (e.g. Martha et al. 2010). Thus our characterization included features such as fields and field boundaries that show similarity to landslide features and need to be removed. All morphological elements and their identification were then translated into OOA-detection rules, using multiple segmentation levels, derivatives such as surface roughness, plan curvature, slope gradient, or edge layers.

Based on this characterization first landslide-free agricultural fields were extracted. Subsequently the landslide scarp candidates were identified based primarily on slope angle information, from which in turn main scarps were detected based on their concave planform. A similar strategy was followed to detect flanks, though those were found to be much less well expressed. Therefore, also information for segments bordering the sides of the landslides was used. Finally, starting from the main scarps, the landslide affected area was grown in the downslope direction. The result is shown in Figure 1C.

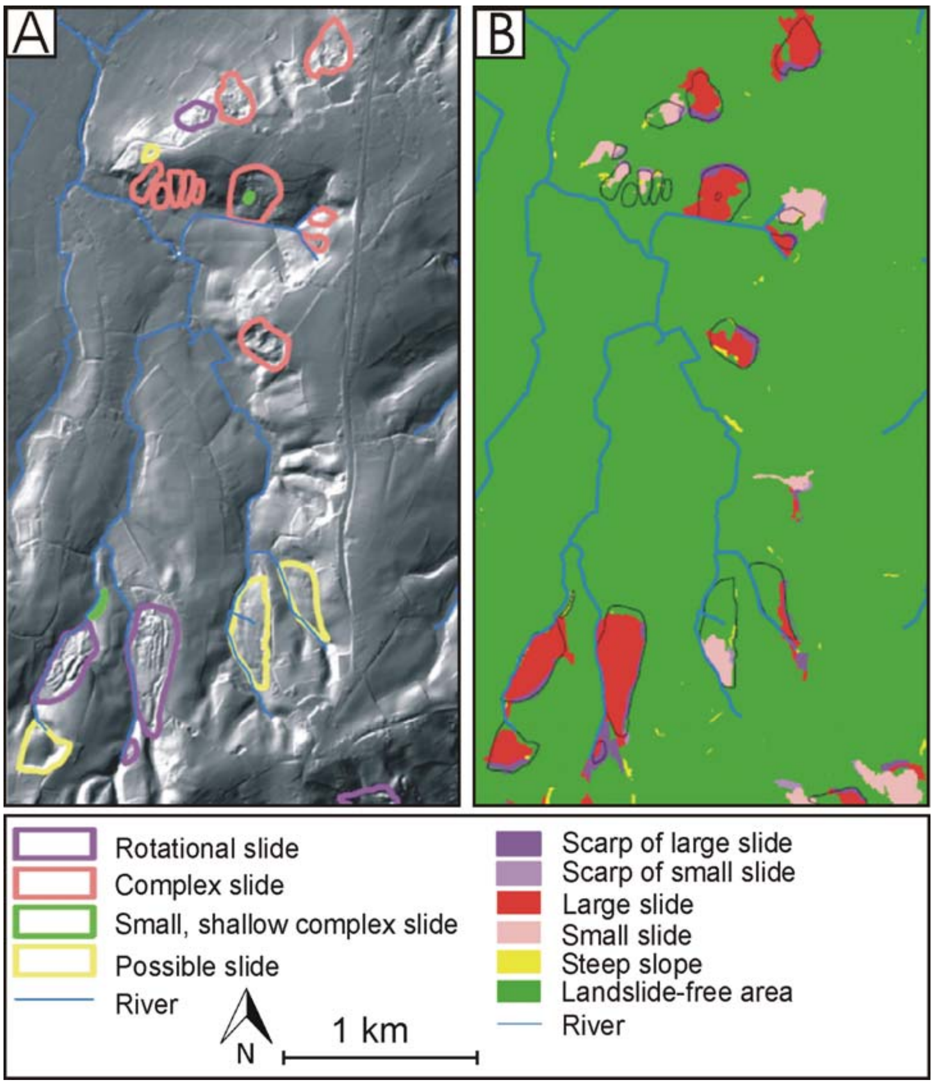


Figure 2. Study area in the Flemish Ardennes: (A) The LiDAR-based shaded relief map (© AGIV) with an expert-based landslide inventory overlaid (Van Den Eeckhaut et al. 2007); (B) Preliminary landslide inventory obtained with OOA.

Figure 2 shows the area in the Flemish Ardennes for which the OOA ruleset was developed, with A depicting the LiDAR data and an expert-based landslide inventory (Van Den Eeckhaut et al. 2007). B shows the landslides identified with OOA. The ruleset was also applied (without further modification) to a larger area (not shown here) to test its applicability on independent data. For both areas the extent of about 70% of the landslides was correctly identified, with only small differences between the accuracy obtained for complex and rotational slides, results that are comparable to those achieved by Martha et al. (2010).

The results show that OOA using LiDAR derivatives allows recognition and characterization of principal morphologic properties of deep-seated landslides. Given the high morphological variability and different levels of anthropogenic alteration, the type of morphometric detection carried out here has to be flexible yet also robust and reliable. This means after identification of the most prominent feature, the main scarp, landslides can in principle be delineated by "growing" them in the down-slope direction along side scarps.

## Further work

Since landslide features such as main and flanks are frequently unconnected or partly obscured by erosion or anthropogenic activity, a more conceptual basis is needed. We thus continue to explore additional morphology-based features, such as topographic profiles, or topographic guidance to deduce likely orientation of the landslide body, to identify landslides based on a complex set of individual evidence considered in their spatial context. We are further continuing our work on the LiDAR data of more mountainous terrain in the Vorarlberg region (Austria; Figure 1), which is characterized by bedrock outcrops and deeper landslides. Here the creation of a transferable OOA routine is more difficult. Nevertheless, our results to date show that an approach combining LiDAR and OOA is suitable to map or monitor mass movements that involve some degree of vegetation cover, and where thus traditional methods based on passive optical data fail.

## References


Anders, N.S., Seijmonsbergen, A.C., & Bouten, W. (in press). Segmentation optimization and stratified object-based analysis for semi-automated geomorphological mapping. *Remote Sensing of Environment, In Press, Corrected Proof*

Dragut, L., Eisank, C., & Strasser, T. (2011). Local variance for multi-scale analysis in geomorphometry. *Geomorphology, 130*, 162-172

Glenn, N.F., Streutker, D.R., Chadwick, D.J., Thackray, G.D., & Dorsch, S.J. (2006). Analysis of LiDAR-derived topographic information for characterizing and differentiating landslide morphology and activity. *Geomorphology, 73*, 131-148

Kääb, A. (2002). Monitoring high-mountain terrain deformation from repeated air- and spaceborne optical data: examples using digital aerial imagery and ASTER data. *ISPRS Journal of Photogrammetry and Remote Sensing, 57*, 39-52

Lu, P., Stumpf, A., Kerle, N., & Casagli, N. (2011). Object-oriented change detection for landslide rapid mapping. *IEEE Geoscience and Remote Sensing Letters, 8*, 701-705

Martha, T., Kerle, N., van Westen, C.J., Jetten, V., & Vinod Kumar, K. (in press). Segment optimisation and data-driven thresholding for knowledge-based landslide detection by object-based image analysis. *IEEE Transactions on Geoscience and Remote Sensing*

Martha, T.R., Kerle, N., Jetten, V., van Westen, C.J., & Vinod Kumar, K. (2010). Characterising spectral, spatial and morphometric properties of landslides for semi-automatic detection using object-oriented methods. *Geomorphology, 116*, 24-36

McKean, J., & Roering, J. (2004). Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. *Geomorphology, 57*, 331-351

Metternicht, G., Hurni, L., & Gogu, R. (2005). Remote sensing of landslides: An analysis of the potential contribution to geo-spatial systems for hazard assessment in mountainous environments. *Remote Sensing of Environment, 98*, 284-303

Razak, K.A., Straatsma, M.W., van Westen, C.J., Malet, J.P., & de Jong, S.M. (2011). Airborne laser scanning of forested landslides characterization: Terrain model quality and visualization. *Geomorphology, 126*, 186-200

Stumpf, A., & Kerle, N. (2011). Object-oriented mapping of landslides using Random Forests. *Remote Sensing of Environment, 115*, 2564-2577

Van Den Eeckhaut, M., Poesen, J., Dewitte, O., Demoulin, A., De Bo, H., & Vanmaercke-Gottigny, M.C. (2007). Reactivation of old landslides: lessons learned from a case-study in the Flemish Ardennes (Belgium). *Soil Use and Management, 23*, 200-211