THE POTENTIAL OF OBJECT-BASED AND COGNITIVE METHODS FOR RAPID DETECTION AND CHARACTERISATION OF LANDSLIDES

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ABSTRACT:

Geoinformatics tools have proved to be of great value in disaster risk management, such as through remote sensing allowing accurate and timely acquisition of information on hazard processes, elements at risk or consequences of a hazardous event, which can be analysed or integrated with auxiliary information in GIS programmes or models. Landslides are one of those phenomena where geoinformatics developments have opened up new ways to monitor potential or ongoing slides, but also to build inventories of previous mass movements as the basis for hazard and thus risk assessment. This constitutes a valuable tool for a hazard type that led to more than 400 fatal disasters worldwide in 2008 that in total killed over 32,000 people, and often is the only method that allows rapid and timely landslide mapping in mountainous areas.

In the past such mapping was primarily done by visual analysis of aerial photos or, increasingly, satellite imagery, and a number of automatic methods have been developed. However, until recently only pixel-based methods, primarily employing different classification or change detection techniques, were developed. Those are beginning to be replaced with approaches based on objects or segments. Object-oriented analysis (OOA) is inherently more suitable, as it can address the phenomena studied, landslides in this case, as what they are – objects, not pixels – that have spectral, spatial and contextual characteristics. They thus allow limitations of pixel-based methods, which are largely restricted to using spectral and texture information, to be overcome. Past landslide characterisations have identified a number of different landslide types and defined them, for example in terms of source material type, run-out length, failure plane curvature or crown shape. Potentially any of these characteristics can be employed in OOA, provided suitable data needed to calculate those parameters are available.

In this paper we show how multispectral 5.8 m IRS P6 LISS-IV imagery of parts of the High Himalayas in India, together with elevation information extracted from 2.5 m stereo-Cartosat1 data, can be used for automatic mapping and discrimination of debris slides and flows, as well as translational or rotational rockslides. The approach developed is able to eliminate false positives that have proved difficult in previously reported research, such as clear-cuts, roads or riverbeds, and allows an effective integration of process knowledge, for example the spatial relation of landslides with causative factors such as slope or road construction. Landslides mapped in an independent watershed of 53 km^2, using a process developed for a smaller area, were detected and correctly classified with accuracies of 76.4% and 69.1%, respectively, the smallest one measuring less than 800 m^2. This suggests that object-based automatic methods can well be used to substitute visual interpretation or field mapping, particularly when large areas need to be covered.

Using OOA efficiently also raises several problems. The actual analysis is reliant on proper image segmentation, the subjectivity and trial-and-error nature of which has been the subject of years of research. Hence we also address how image information itself, rather than visual fine-tuning, can be used for an objective segmentation. Finally, we also discuss how the OOA approach presented here can be extended to include also the mapping of other parameters needed in risk assessment, such as elements at risk.

1. INTRODUCTION

Landslides are one of the most destructive natural hazards, causing damage to lives and property in all mountainous areas of the world. The actual number of annual landslides is not known, in part due to different databases employing different minimum size or damage thresholds, but also because individual events frequently go unrecorded. The uncertainty is true for global inventories as much as for individual mass-slide occurrences, such as following earthquakes or tropical storms. For example, the 2008 Wenchuan/Sichuan earthquake alone triggered thousands of slides, many of which were joined into slide clusters, and the actual number has not yet been determined. Such incomplete inventories, however, create problems, as accurate and comprehensive information on past slides is the basis for landslide hazard, and thus risk, assessment. With landslides typically compounding the already difficult access to slide-prone areas, field-based mapping is not practical and often outright impossible, and nature typically obliterates traces of all but the largest slides within a few months or years. Remote sensing data thus appear ideal for rapid synoptic mapping. Aerial photos, with their high spatial resolution and tonal richness used to be the main tool for slide mapping (e.g. Norman et al., 1975), with the multitude of visual assessment clues and stereo viewing supporting a knowledge- and experience-driven cognitive landslide detection and type discrimination approach (Colwell, 1960; Mantovani et al., 1996). However, the frequent absence of timely post-slide imagery, comparatively small spatial coverage and high cost, and principal utility for photogrammetry and visual assessment undermine their value for rapid post-slide mapping, especially in multi-slide situations covering large areas. Aerial photos have been gradually replaced by satellite data, first used for slides large enough to be detectable with medium resolution sensors such as Landsat, either directly (Francis and Wells, 1988) or indirectly (McKean et al., 1991). More recently launched satellites, with improvements in spatial resolution, pointability and, frequently, stereo capability, have been increasing the suitability of spaceborne data. However, it has also been shown that traditional automatic image processing methods, such as image classification or change detection, have limited suitability (for a review see Borghuis et al., 2007). This is because typically landslides are interspersed with a range of spectrally similar landscape features, such as rock outcrops, clear-cuts, roads or riverbeds, which conventional pixel-based methods can not distinguish from landslides. While integration of different data, including elevation information, has been shown to help (McDermid and Franklin, 1994), it generally fails to eliminate such false positives (Nichol and Wong, 2005).

1.1 Landslide detection with object-based methods

The failure of pixel-based methods is not surprising as they do not address landslides as what they are – spatial objects embedded in a specific environmental context. A number of studies have already investigated the potential of object- or segmentation-based processing methods. In this alternative approach images are broken down into spectrally homogenous segments, possibly at different spatial scales, that have a range of spatial, spectral, textural and contextual characteristics (Baatz and Schäpe, 2000; Dragut and Blaschke, 2006) and that serve as the basis to incorporate feature and process knowledge into the analysis. As all created objects are part of a horizontal and vertical topological structure, i.e. having a spatial relationships with neighboring segments in the same segmentation level, but also with super- or sub-objects in higher or lower levels, respectively, segments adhering to given characteristics can be considered in relation to features with other accurately describable attributes. Barlow et al. (2003) explored the utility of image segmentation for landslide mapping, already making use of DEM derivatives and NDVI measures, but finding the Landsat ETM+ data used to be insufficient for the discrimination of similar features such as logging roads. In a follow-up paper (Barlow et al., 2006) the authors used higher resolution SPOT data and discriminated debris slides, debris flows, and rock slides. Moine et al. (2009) also made use of spectral, shape, texture and adjacency rule in an OOA-context.

1.2 Objectives

As in the work by Barlow et al., Moine et al. did not consider the failure mechanism, which is critical to distinguish major landslide types. A principal objective of this work is to extend the classic landslide characterization by Varnes (1978) based on types of material and movement, creating a generic landslide type characterization based on currently available geodata parameters, that also integrate geomorphometric indicators. We distinguish the following landslide types: (i) translational rock slide, (ii) rotational rock slide, (iii) debris slide, (iv) debris flow, and (v) shallow translational rock slide (for detailed type descriptions, as well as block diagram illustrations of those types, see Martha et al., 2009). We test our approach in a landslide-prone area in the High Indian Himalayas, as described in the following section.

2. DATA AND METHODOLOGY

2.1 Study area

The Himalayas are considered a global landslide hotspot, with continuous uplift, seismic activity, and widespread road construction leading to frequent slope failures that challenge the economic developments of regions typically already underdeveloped. We thus argue that comprehensive and accurate landslide inventories are a basic requirement for risk assessment to support better planning and mitigation measures. For our work we considered an 81 km^2 area in the state of Uttarakhand in India (Figure 1). It comprises the Madhyamaheshwar sub-catchment (28 km^2), where we developed the method, and the Mandakini catchment (53 km^2) we used for independent validation of the method.

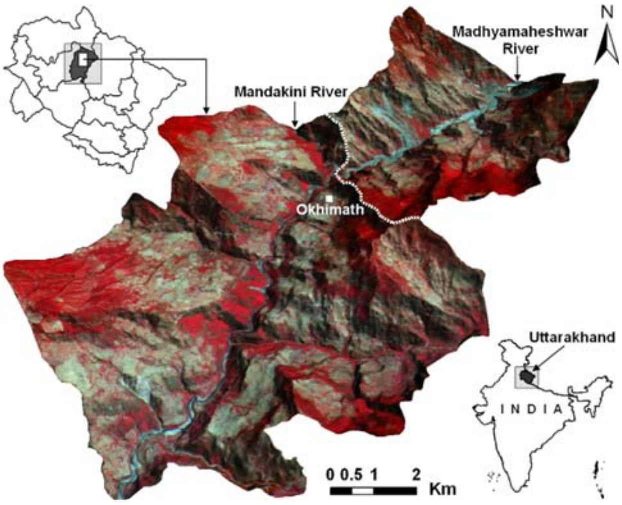

Figure 1. Overview map of the study area around the city of Okhimath in Northern India, comprising Madhyamaheshwar sub-catchment and the Mandakini catchment.

2.2 Spatial data used

A vast image archive of most parts of the world has been built up by the Linear Imaging Self-scanning System IV (LISS-IV) sensor onboard the Indian Remote Sensing Satellite (IRS) P6, also known as Resourcesat-1. With 5.8 m ground resolution and wide coverage it is ideally suited for repeat observations of vast areas. We used a 3-band scene (G, R, NIR) obtained on 16 April 2004, which we orthorectified using a 10 m DSM created from 2.5 m resolution stereoscopic data from Cartosat-1 acquired on 6 April 2006. The sensor carries aft- and forward looking cameras and data are provided with rational polynomial coefficients (RPCs) that allow block triangulation and DSM generation with as little as one ground control point (GCP). The quality of the derived DSMs, also relative quality when no GCPs are used and in difficult mountainous terrain, has previously been shown (Martha et al., in press). This is of critical importance as not only timely optical imagery is needed for landslide detection; in an approach based on morphometry, including curvature, also accurate post-event DSMs are needed, and both ideally without requiring field data.

2.3 Image segmentation and OOA procedure

Multiresolution segmentation, a process controlled by scale, shape, colour, compactness and smoothness parameters (Baatz and Schäpe, 2000), was performed using the LISS-IV data. Segmentation with a small scale factor (10) was chosen in this case as most of landslides are of small size. A three step OOA procedure was developed to detect and classify landslides. In the first step, using a normalised vegetation difference index (NDVI) threshold value, vegetated areas were separated from non-vegetated area. In the second step, landslide false positives (river sand, barren land, shadow, built-up area, and roads) were eliminated sequentially using generic DEM-derived parameters. For example, road was separated from landslide using orthogonal relationship between the main axis of road and general flow direction derived from the DEM. Similarly, a drainage network automatically derived from the DEM was used to classify the objects as water bodies that could not be identified unambiguously using low reflectance values in the NIR band (Figure 2). In the third step, all detected landslides were classified based on the type of material and movement Varnes (1978).

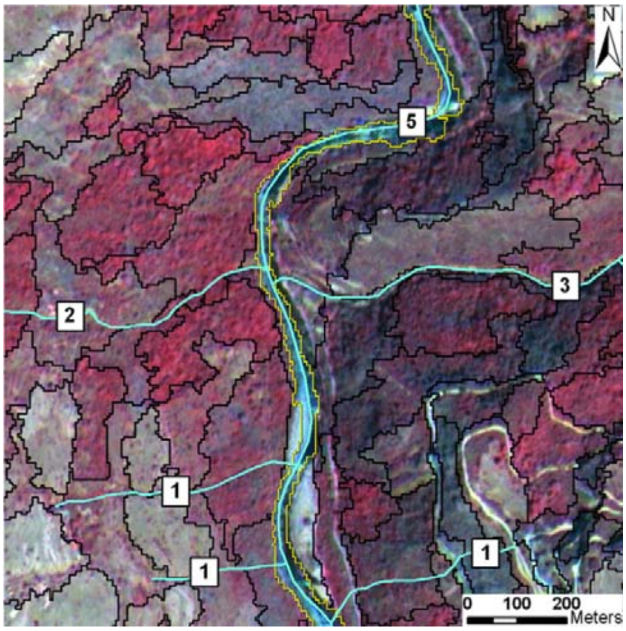

Figure 2. High order drainage (order 5 in this case) was used to classify objects as water body.

3. RESULTS

3.1 Extraction of landslide candidates

Fresh rock and soil are exposed after the occurrence of a landslide. This characteristic of a landslide is best quantified from remote sensing data by NDVI, which is very sensitive to low level of vegetation change. Therefore, landslide candidates are extracted by applying an NDVI threshold value of 0.18.

3.2 Landslide recognition and identification

Since NDVI was used as a cut-off criterion, all objects with lower NDVI values were considered as landslide candidates. From those all landslide false positives were sequentially eliminated using generic first and second order DEM derivatives, such as slope, flow direction, terrain curvature and hill shade.

Recognised landslides were classified based on its material and type of movement. Adjacency to barren rock and agricultural land was used to classify a landslide as rock slide and debris slide, respectively. For classification based on failure mechanism, the remaining landslide objects were resegmented using terrain curvature, based on their straight slope and concavity nature, and were classified into translational and rotational landslides, respectively. Using this method, a total of five types of landslide was detected (Figure 3).

3.3 Accuracy assessment

Accuracy assessment was carried out by comparing those against a manually prepared landslide inventory map. Stereoscopic visual interpretation of satellite data was carried out to prepare a landslide inventory map. This area was previously mapped by Naithani (2002) and Rawat and Rawat (1998) for the preparation of landslide inventory map, which was consulted during stereoscopic interpretation.

76.4% of the landslides were correctly detected and 69.1% corrected classified using the method developed. In terms of areal extent, 69.9% of the landslide areas were correctly recognised and 69.5% correctly classified (Figure 3).

4. SUITABLILITY OF OOA FOR LANDSLIDE RISK ASSESSMENT

The results shown in this paper suggest that OOA is more suitable to detect and identify landslides in remote sensing imagery than traditional pixel-based methods, hence promises to facilitate hazard assessment. A comprehensive mitigation plan, however, requires risk information, thus we require a comparable understanding of elements at risk (EaR) and their vulnerabilities. As those risk components are equally spatio-temporal in nature, object-based methods may also be suitable. Previous work has shown how physical infrastructure (buildings, road networks, etc.) can be effectively mapped with OOA (e.g. Akcay and Aksoy, 2008; Walker and Blaschke, 2008). More difficult would be to establish the physical vulnerability of individual infrastructure elements, especially since damage is highly dependent on the physics of an impact, that is kinetic energy and actual infrastructure surface area hit. In India landsides affect mostly roads, with 3 possible forms of effect: (i) roads get covered with landslide debris that can be cleared, (ii) roads suffer some damage in the process, or (iii) road sections get completely removed with the sliding flank. As roads can be effectively identified with OOA (in this study they were explicitly removed as a form of false positives), their spatial relationship with respect to slide-affected slopes can be established, and thus some knowledge gained on the likely damage form a road may suffer. Where buildings are involved a minimum likely slide volume can be used, beyond which total damage can be expected. For selected areas flanks identified in the hazard assessment can also be modelled, and results integrated with EaR identified in the OOA.

Comprehensive risk analysis should also include social, environmental and economic vulnerability, though such studies are scarce, especially in the OOA context. Ebert et al. (2009) showed how social vulnerability (SV) can be mapped in urban areas affected by flooding and slope instability, using segmentation-based analysis based on physical proxies. This is likely less applicable in dispersed mountain communities that, furthermore, are facing a hazard with limited impact range. This means that the social standing of a person, or their education level or influence in a community, are less relevant than in highly differentiated urban setting where hazard exposure

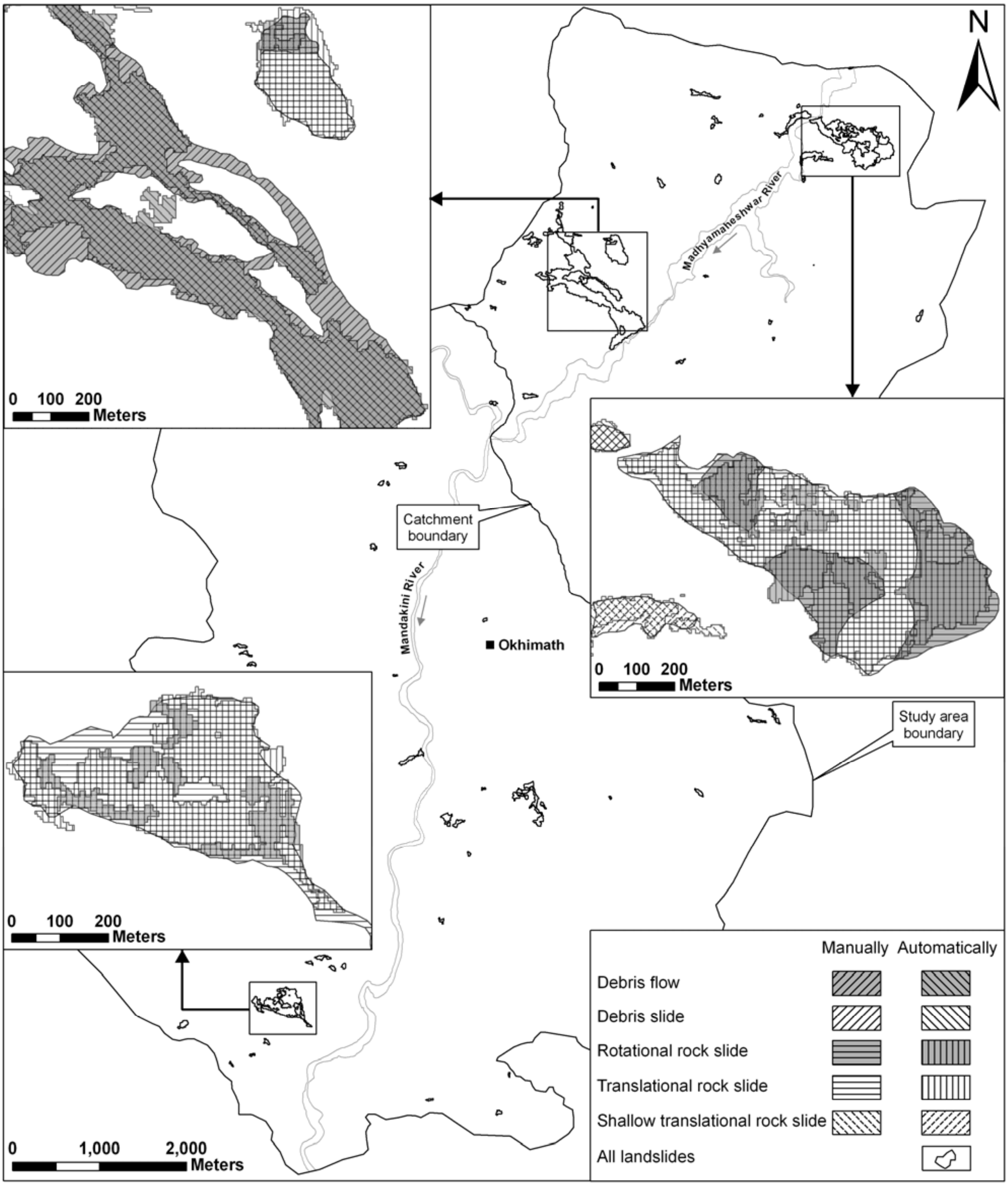

Figure 3. All five types of landslides and their agreement with the reference landslide inventory map.

intersects more gradually with SV distribution (Cutter et al., 2003; Ebert et al., 2009). Environmental and economic vulnerability are rarely included in risk studies, largely because sound methodologies are lacking and the important secondary consequences slides can lead to. For example, the consequences of interruptions in economic production, or subsequent loss of income of affected people, are poorly understood, as are quantifiable potential losses of specific ecosystems that may get affected. In the case of landslides, GIS tools are best suited to study road networks with respect to location of importance centers to assess the specific economic value of roads. Such network analysis can then also reveal the cost of traffic having to be diverted via alternative roads. Such comprehensive landslide risk assessment procedures in remote mountainous areas remain to be developed.

5. CONCLUSIONS AND DISCUSSION

OOA was used in this study to detect and classify landslides in high resolution satellite data and with support of DEM information. The parameters considered for analysis in this study, such as slope, flow direction, terrain curvature, are of generic nature and hence this model, in principle, can be employed in any area to map landslides rapidly, thereby reducing the time and effort needed for such inventorisation and the amount of landslides traces lost, which is paramount for any disaster management programme. The accuracy of landslide detection and type identification is good and we are continuously working on this model to improve it further. However, the threshold values considered for the detection and classification purpose likely have to be adjusted when the model is applied to other areas.

Apart from this short term goal, worldwide landslide disaster management programmes also have a long term objective, i.e. landslide hazard and risk management. OOA has also been shown to be useful in the preparation of elements at risk maps, which is crucial for landslide risk assessment. Once landslide vulnerability for elements of risk is known, it can be integrated in GIS to prepare landslide risk map. The algorithm developed in this project is available on our website (http://www.itc.nl/OOA-group), and we welcome testing of the approach with other data types and in other areas.

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