

LANDSLIDE DETECTION AND SUSCEPTIBILITY MAPPING USING INNOVATIVE REMOTE SENSING DATA SOURCES

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ABSTRACT

Landslide susceptibility analysis using univariate statistical models is a complex and sensitive task. The resulting quality of the functional models is directly dependant on the quality of the input data with respect to spatial resolution, classification accuracy and completeness. In this paper, the application of innovative Remote Sensing data sources is evaluated. The classification of Very High Resolution (VHR) Satellite data proved to deliver accurate land cover classes. Results show that congruent quality from QuickBird data compared to aerial photographs can be obtained. As QuickBird images have a larger coverage and a better radiometric stability, the development of automatic tools is favoured. Interpretations based on Earth Observation data seem to be the only possibility to obtain landslide inventories that cover large areas and are widely complete. Only VHR imagery allows the detection of small landslides. Digital Terrain Models based on airborne Laserscanner data facilitate a precise derivation of geomorphometric parameters. The analysis of the susceptibility modelling results shows the high significance of geological and land cover parameters.

Keywords: Remote Sensing, Landslides, Susceptibility Modelling

INTRODUCTION

High mountainous regions are challenging to human society in many senses. For centuries, people living in these areas had to contend with the unfavourable climatic conditions, the difficulties of settling on steep slopes and cultivating sparse agricultural land or the force of transporting goods on endangered paths or roads. Moreover, these unfavourable conditions have also strongly influenced the means of collecting information for scientific investigations in such an extreme environment. Cumbersome field work taking much of manpower and therefore generating high costs was the usual method for data collection. The identification and mapping of landslide risk zones is an example of such a very labour-intensive work, if solely based on fieldwork. To overcome this drawback, which is specifically severe in inaccessible areas, nowadays remote sensing data can be used.

Generally, the spatial probability of mass movements is influenced by a number of environmental quasi-static factors. Quasi-static means, that these factors are normally stable over a period of time. Most of these factors can be assigned to one of the following main categories: (a) geology; (b) geomorphology and topography; (c) land use and land cover. The triggering factors (dynamic factors) for an actual landslide event are temporal ones such as

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abundant rainfall, rapid spring snow melt or earthquakes. For the generation of basic zoning maps of mass movement susceptibility, the triggering factors are not taken into account. However, indicators for the quasi-static factors should be extracted as automatic as possible. Currently existing very high resolution (VHR) satellite remote sensing systems offer an opportunity to extract land surface information that until recently could only be derived from aerial photographs or by extensive field work.

This work was performed within the scope of the EU funded project ASSIST (Alpine Safety, Security & Informational Services and Technologies). One of the main tasks was the design of a geo-service framework based on innovative Earth Observation (EO) data to support mitigation and emergency measures. This included the combination of remote sensing results with other spatial information such as geological maps or digital elevation models. To address the needs of risk management three types of basic products were generated: base information layers (maps of quasi-static parameters, e.g. land cover), dynamic information layers (maps of dynamic parameters, e.g. snow cover) and products processed from the information layers using modelling approaches (e.g. landslide susceptibility maps). Some results of the latter are described in the following contribution.

OBJECTIVES

The focus in this investigation was the identification of parameters and/or indicators for natural hazards with special emphasis on landslides and the derivation of susceptibility maps. Focal points are the usage of new remote sensing tools and the development of (semi-) automatised procedures for the derivation of environmental factors that might affect landslide occurrence. In order to obtain land cover and land use parameters with adequate accuracy, VHR (very high resolution) satellite imagery were used. Based on these data, supervised classification and visual interpretation were applied and investigated with special emphasis on the development of automatic classification tools. As the test area covers a height difference of more than 2300 m, it is evident that there are manifold surface types. Thus, the applied methodology had to be elaborated in a flexible way involving different approaches for the derivation of the needed parameters. The work did not include the development of new landslide hazard zonation techniques, of which many have been developed over the last decades (e.g. Hansen 1984, Varnes 1984, Soeters and Van Westen 1996, Leroi 1996, Aleotti and Chowdury 1999, Gorsevski et al. 2003, Van Westen et al. 2003, Zhou et al. 2003).

GEOGRAPHICAL AND GEOLOGICAL SETTING OF THE TEST AREA

The test region in the western part of Tyrol/Austria covers an area of approximately 228 km² and an altitude difference of more than 2300 m. The highest summit of the Verwall Mountain Group reaches 3168 m above sea level, whereas the Sanna Valley near Landeck is at a height of approx. 820 m. The test area includes two main geological units: (1) the Verwall Mountain Group is part of the Silvretta crystalline complex and is dominated by metamorphic rocks (mainly phyllites, mica schists, gneiss and some amphibolites) whereas (2) the Lechtal Alps are part of the Northern Calcareous Alps, dominated by carbonatic and clastic sedimentary rocks (limestones, dolomites, marls, sandstones and shales). Both geological units incorporate lithologies which are highly susceptible to different types of mass movement processes. The tectonic environment is dominated by the overthrusting of the nappe systems of the Northern Calcareous Alps on the crystalline units.

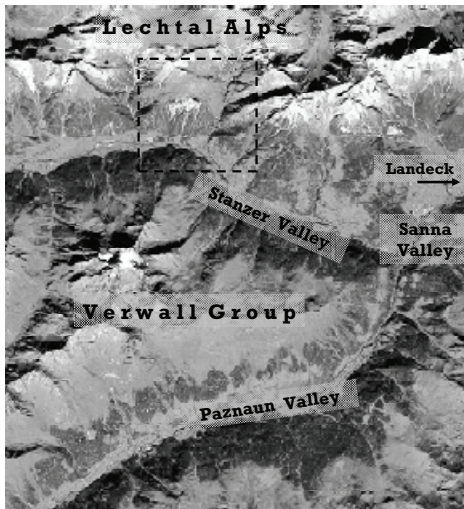


Fig. 1: Location of the test area in the western part of Tyrol (--- border of subset presented in Fig. 3)

The landscape was shaped strongly by the pleistocene glaciation periods. Furthermore, the pleistocene glaciation has left widespread morainic deposits. Today only some minor glaciers in the highest parts of the mountains have persisted. Karst phenomena are typical for the carbonatic units of the Lechtal Alps. The main valleys, the Stanzer- and the Paznaun Valley, are densely populated and extensively used for transport and touristic purposes. Therefore, the area is highly vulnerable to natural hazards and consequences of events are typically more severe than in other, less developed regions. For instance, flooding caused heavy damage on the infrastructure and settlements in August 2005 disrupting the important Arlberg railway route for more than three months.

DATA SOURCES

With the emerging of commercial satellite systems providing VHR data with a ground resolution of 1 m per pixel and below (IKONOS, QuickBird) the potential for space borne applications in many fields has broadened. Based on its detailed spatial information VHR satellite imagery is one possibility to derive the required land cover as well as partly the geomorphological information. Thus QuickBird data with a spatial resolution of 60 cm in the panchromatic mode and an additional four multi-spectral band range with 2.4 m resolution have been chosen as optical remote sensing data source. The acquisition date of the QuickBird scene was the 5th of September 2005 (12 days after the flood event). Typically, the use of stereo images would increase the information content, as three dimensional information about the vegetation (vegetation height) could be obtained. However, in the present case, no stereo data was available.

Aside from the Quickbird data, also Digital Elevation Models (DEMs) played an important part in the analysis. In this investigation two different DEMs were used, i.e. a 25 m grid from the Austrian national land survey 'BEV' and a high resolution 3 m DEM based on LiDAR (Light Detection And Ranging) data. The use of a DEM in high mountainous regions is a prerequisite in the overall processing of the EO Data; e.g. the geocoding and topographic normalization. Furthermore the DEM is the most crucial input data set for the derivation of geomorphometric parameters as, for instance, slope, aspect (orientation of slope), curvature, roughness (variability in slope and aspect in local patches of the DEM) and drainage network. The standard DEM shows a varying accuracy depending on the complexity of the terrain. The accuracy is stated to be about $\pm 2 - 5$ m in non-forested and flat areas and $\pm 10 - 25$ m in mountainous terrain or beneath forest (according to BEV 2007). The lower accuracy values

are more reasonable for most of the present test area. The second available DEM was derived from LiDAR data. The general accuracy of LiDAR DEMs depends on the used point density and on the vegetation cover. LiDAR systems offer good terrain information also beneath forest. The LiDAR data used in the current study have a point density of 1.1 point per m². Therefore, the spatial resolution was set to 3 m for the area-wide LiDAR DEM. LiDAR data with point densities of 4-6 dots per m² were available only for a small section of the test area. These data were used to evaluate the effects of different LiDAR DEMs.

Geological information could be deduced from a digital geological map at a scale of 1:50.000 from the Austrian Geological Survey (GBA 2004). Within the scope of this study additional fieldwork in selected areas was done mainly for verification and specification purposes.

METHODS

The spatial probability of landslides can be obtained through analysing the relation between the locations of past landslide events and a set of environmental factors in order to predict areas of landslide initiation that have similar combinations of factors using statistical methods. The resulting hazard maps are of qualitative nature, concentrating on determining the susceptibility which can be seen as a relative indication of the spatial probability (Van Westen et al. 2006). This chapter is subdivided into four sections according to the corresponding aims. In the first section, the derivation of land cover data from the VHR satellite imagery is explained. The second section deals with the derivation of geomorphometric parameters from the generated DEMs, the third one gives attention to the geological classification and the generation of the landslide inventory. Finally, the fourth section describes the two univariate statistical models used for susceptibility assessment.

Land Cover Classification

Land cover information was derived from orthorectified, topographically normalized and pansharpned QuickBird imagery. The first classification step was focused on the derivation of a coarse land cover layer by applying a pixelwise supervised classification. Some 50 reference areas have been extracted from the pansharpned image by visual interpretation. Subsequently, a spatial merging algorithm was applied on the classification result to obtain a more homogeneous appearance of the individual classes, i. e. to remove the “salt and pepper effect”. This algorithm is used to merge adjacent regions according to their spatial properties. Regions which are smaller than the specified size or regions with a shape index higher than a given threshold are merged. The similarity to neighbouring classes, with which the object could be merged, is calculated based on its neighbourhood properties. Finally, the following landcover classes have been derived successfully: water, snow, ice, broadleaf forest, coniferous forest, four types of meadows, non-vegetated areas and shadow. However, there are still some uncertainties and some difficult areas, where this first classification is too coarse or too inaccurate. One example is the exact delineation of the upper forest border, another example is the further differentiation of the class “non-vegetated areas”. This was performed in the next phase of the classification.

The pixelwise classification based on the spectral values only had shown its limitations for deriving more detailed classes. To accomplish the requirement of a more detailed separation within e. g. the class “non-vegetation”, the textured information of the panchromatic image was used. This is performed using a texture algorithm, which calculates certain statistical

values based on mean or variance within the sectors surrounding a pixel. The radius and the number of sectors (or wedges) can be specified by the user. This texture layer can be used to improve the classification accuracy and detail. Additionally, the results from the texture calculation were supporting the determination of the upper forest border, which is essential to quantify the forest area, especially in the higher elevated regions. Furthermore, the upper forest border line is helpful to differentiate between “non-vegetation” areas within the image. For instance, non-vegetation areas could be settlements and streets in the valley, whereas the same spectral response from above the forest border line shows talus deposits, bare rock and eroded surfaces. Minor errors have to be corrected by visual interpretation, but the effort for this correction is low, because most of the border lines could be correctly derived by the automatic procedure.

Due to their different capability of infiltration and potential for providing material for landslides it was important to separate coarse talus deposits from fine talus deposits. The separation was performed again based on the texture information, which is inherent in the panchromatic image.

Not all of the required indicators can be derived by automatic processing, e.g. rock glaciers, elongated ponds or wet areas. For this purpose visual interpretation is still an adequate procedure. More details on the classification procedure can be found in Granica et al. 2007.

Tab. 1: Categories of Land Cover Classification based on QuickBird Data

Sub-Category	Parameters	Method	
Vegetation	Broadleaf Forest	auto	
	Coniferous Forest	auto	
	Mixed Forest	auto	
	Clear cuts / afforestation	auto	
	Green Alder	auto/vis	
	Dwarf Mountain Pine	auto/vis	
	Rhododendron, Shrubs	auto	
	Meadows	auto	
	Alpine Pastures	auto	
	Sparsely vegetated areas	auto	
	Non-Vegetation	Snow	auto
		Ice	auto
		Water	auto
Buildings		vis	
Roads, Sealed Areas		auto/vis	
Talus Deposits fine		auto	
Talus Deposits coarse		auto	
Bare Rock		auto/vis	
Elongated Ponds		vis	
Wet Areas		vis	
Rock Glaciers	vis		

auto: automatic approach vis: visual interpretation

Land Cover Categories derived from QuickBird Data are shown in Table 1. Some of these parameters can be obtained by automatic approaches, while others still need fully or partly

visual interpretation. Land Cover parameters were merged to a final nine classes for the susceptibility modelling.

Derivation of Geomorphometric Parameters

The topographical and geomorphological situation is one of the most relevant factors for landslides. Geomorphological features mainly have to be mapped by fieldwork and visual interpretation of remote sensing data. Nevertheless important characteristics can be derived from a DEM using standard software tools. This is true for most geomorphometric parameters, such as elevation, aspect, slope, vertical as well as tangential curvature and drainage network. In addition, more sophisticated parameters indicating landslide activity like roughness parameters were calculated. Eigenvectors (according to McKean & Roering 2004) measure the variability of slope and aspect in local patches of the DEM. On this basis, different statistical measures were applied to evaluate the local terrain roughness. As the spatial resolution of the DEM is most crucial for geomorphometric analyses, the 25 m grid from the Austrian national land survey 'BEV' and the high resolution 3 m LiDAR grid were compared.

Geological Classification and Generation of the Landslide Inventory

Geological information was deduced from a digital geological map at a scale of 1:50.000 from the Austrian Geological Survey (GBA 2004). Based on expert knowledge, a simplification of the map information was performed by merging lithological units with similar geotechnical and hydrogeological properties. This step resulted in a significant reduction of map units from an original 116 to a final 16, standing for distinct properties with respect to landslide occurrence. Within the scope of this study additional fieldwork could be focussed on the verification and specification of data and results. Normally much more work has to be spent for collecting detailed information about the geological situation as modern digital geological maps are not available for most of Austria.

GIS-based landslide inventories are the key component of any statistical landslide modelling as they act as training and verification data. The compilation of the present landslide inventory was performed mainly by on-screen interpretation of a simulated QuickBird 'pseudo-stereo' image which has been generated from the monoscopic image and the respective Digital Elevation Model. The simulation of the pseudo-stereo partner was possible with RSG (Remote Sensing Software Package Graz), the in-house software of the Institute of Digital Image Processing. Using ERDAS StereoAnalyst, the 3D views with different colour composites greatly facilitated in the visual identification and classification of landslides. The inventory is restricted to recently active mass movements, which are represented in the field by open scars and sliding surfaces without significant vegetation. As pointed out by Van Westen et al. 2006, the specific combination of environmental factors is quite different for different types of landslides. Therefore, different training data sets are necessary for different types of landslides and separate statistical models have to be developed. Since shallow translational and rotational slides are predominant in the study area, the current investigation is restricted to these types. As was shown by comparative analyses of aerial photos taken in 1999 and additional fieldwork, many of the mapped slides occurred after this date. Most of them probably were triggered or reactivated by the August 2005 precipitation event. Although, the stereo impression greatly improves the determination of specific landslide features, they can still be confused with other processes active in high mountain environments, which create similar patterns (e.g. erosion and transport of loose material by

avalanches, wind erosion). As well the differentiation of bare rock in high mountain environments remains unsolved in many cases.

Landslide Susceptibility Assessment

The results from the described data sources were integrated as input data to derive landslide susceptibility maps on a single pixel basis.

The susceptibility is obtained through analysing the relation between the locations of past landslide events and a set of environmental factors, in order to predict areas of landslide initiation that have similar combinations of factors, using statistical methods. These indirect methods calculate the importance of the combinations of parameters occurring in landslide locations and extrapolate the results to landslide-free areas (Van Westen 1993, Van Westen et al. 2006). As the triggering of different types of landslides depends on different parameter combinations, the current investigation is solely restricted to shallow translational and rotational slides.

Two basic univariate statistical methods were used to model the landslide susceptibility, namely the so-called “Susceptibility method” implemented according to the description of Van Westen 1993 and the “Weights of Evidence (WoE) method” according to Bonham-Carter et al. 1989 and Van Westen 1993. The models were implemented and executed within an ArcGIS environment.

The selection of input parameters is very sensitive to dependencies and redundancies of parameters, because the main assumption for univariate statistical methods is that the environmental factors should be conditionally independent. The use of conditionally dependent variable maps will result in very high probability values for those combinations which have high weight values in different variable maps. This effect therefore will adulterate the results significantly (Van Westen 1993). Two examples from our case study will be given:

(1) The parameter “slope aspect” turned out to be closely connected to the geology. This can be explained by the geological setting of the test area. The area is characterised by the Lechtal Alps to the North (= mainly south-facing slopes) and the Verwall Group to the south (= north- and south-facing slopes). These both units are separated by a tectonic lineament running from west to east. Since landslides are much more frequent in the Lechtal Alps due to their lithology, a high relevance is given to the parameter “slope aspect”, although the determinant factor of the landslide distribution is the specific geologic situation.

(2) The parameter “elevation” is closely connected to the land cover (forest and non-forest areas, non-vegetated areas) which is easily to be understood by the climatic conditions and their effects on the vegetation of high altitude regions.

Therefore after several tests both parameters (“slope aspect” as well as “elevation”) were dismissed completely.

In order to transfer the resulting continuous values into classes and to produce zoning maps, the values were classified into five classes. The classification scheme is based on deciles. Deciles 1 – 3 are assigned to the lowest susceptibility class (D1-3 → 1), the next three classes consist of 2 deciles each (D4+5 → 2; D6+7 → 3; D8+9 → 4). The 10th decile is equivalent to the highest susceptibility class (D10 → 5).

RESULTS AND DISCUSSION

The results of this work showed that, with respect to the derivation of surface parameters, congruent quality from QuickBird data compared to that of aerial photographs with equal spatial resolution can be obtained. Furthermore the QuickBird images have a larger coverage and a better radiometric stability, which has proved to be of high benefit for the development of automatic tools. The quality of the land cover classification based on QuickBird imagery was assessed by using an independent test area set of 5 - 6 test areas for each class. The overall average accuracy is 89.67 %. This accuracy is sufficient for the envisaged purpose.

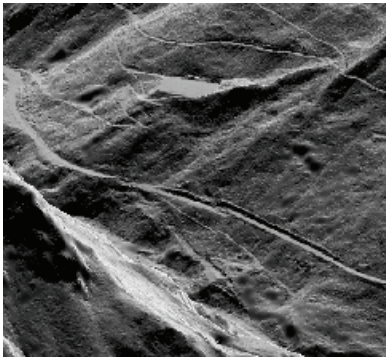


Fig. 2: Shaded relief of LiDAR DEM displaying Zintwald landslide near Landeck.

Regarding the usability of different DEMs for susceptibility modelling the high resolution DEM shows much more details and accuracy enabling a more precise analysis of the surface. The shaded relief of the LiDAR data (4-6 points/m²) represents well all forest roads, ravines, small ridges and undercutting of slopes even in forested areas (Fig. 2), while the 25 m DEM only shows large-scale geomorphic features.

Also a quantitative comparison of the DEMs (25 m resolution vs. 1 m resolution) regarding slope calculations was performed. Table 2 shows the area statistics for this data set. Basically, the differences are not as obvious as they are in the maps, because the statistics over a larger area equalize some of the differences. However, the more accurate differentiation in the slope classes is reflected: the flat as well as the very steep areas are well represented in the LiDAR model but largely omitted in the coarse DEM.

Tab. 2: Comparison of slope calculations from 25 m and 1 m DEM

Slope Class (°)	DTM 1 m (%)	DTM 25 m (%)
0-10	9,55	4,97
10-20	9,93	10,11
20-30	19,86	22,50
30-40	33,26	37,49
40-50	18,69	20,63
50-60	6,70	4,18
60-70	1,79	0,11
70-80	0,21	0,00
80-90	0,00	0,00

The compilation of the landslide inventory resulted in the detection of approx. 1060 landslides. Interpretations based on EO data seem to be the only possibility to obtain landslide inventory maps that cover large areas and are widely complete. Only the use of aerial photographs or VHR satellite imagery such as QuickBird allows the detection of small landslides.

Altogether 44 input classes were used for the susceptibility modelling, of which more than a third consisted of geological classes. The analysis of the calculated weights based on the WoE method showed the highest values for geological and land cover parameters. The highest value was assigned to the geological unit “Cretaceous shales” followed by the land cover units “bare rock” and “sparsely vegetated areas”.

In order to evaluate the quality and transferability of the results of the WoE model (including the parameters), the test area was subdivided into a western and an eastern part. The western area served as model-development area where the weights were calculated. These weights were then applied to the eastern part. The results were evaluated by using the landslide inventory of the eastern part. In the model-development area (west), the percentage in the highest risk class is almost 70%. On the contrary, in the model-evaluation area (east), only about 30% of the landslides were assigned to the highest class. However, the two highest ranked classes share, in both the model-development and the evaluation area, more than 75% of the landslide areas (Tab. 3).

Tab. 3: Results of the evaluation of the WoE modelling

Susceptibility Class	1 (low)	2	3	4	5 (high)
West (%)	1,5	1,9	6,4	20,8	69,4
East (%)	3,1	5,6	14,4	46,1	30,8

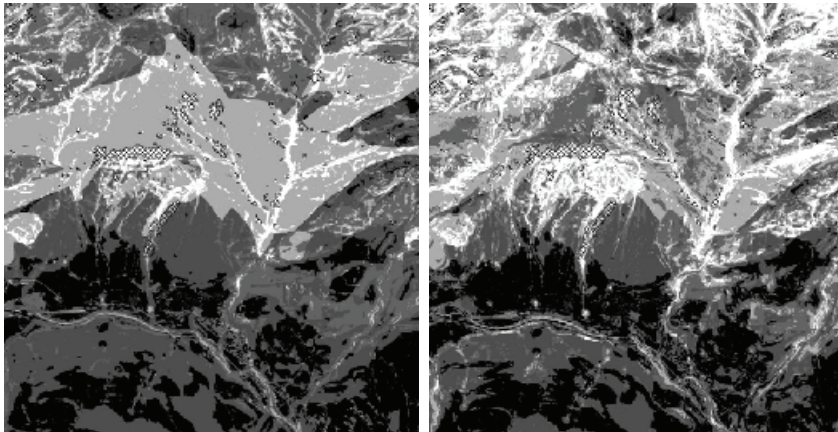


Fig. 3: Subset (~4000 m x 4000 m) of the results of the susceptibility (left) and the weights of evidence method (right) of the study area. Level of brightness indicates susceptibility class (black: lowest, white: highest) and hatched areas show the training landslides.

Comparisons between the Susceptibility method and the WoE method were accomplished and differences of the resulting maps were analysed. The example shown in Fig. 3 focuses on a subset in the southern part of the Lechtal Alps and the valley bottom of the Stanzer Valley. The result of the susceptibility method (left image) shows that the geological formation “cretaceous shales” has an unbalanced strong influence on the calculation. The homogeneous

grey patch in the northern part of the left image clearly demonstrates this effect. The WoE method generally shows similar tendencies, but the areas are more structured, which gives a more realistic impression of the landslide prone areas (right image of Fig. 3). Additional tests showed clearly, that the grouping of geological units may have a major impact on the result.

CONCLUSIONS

Landslide susceptibility analysis using univariate statistical models is a complex and sensitive task. The selection of appropriate input parameters and representative training data sets are crucial for the success of any model. The classification of QuickBird data proved to deliver statistically accurate land cover classes, which have been used as variables in the susceptibility analysis. As the resulting quality of the applied functional models is directly dependant on the quality of the inputs (e.g. spatial resolution and classification accuracy) and quantity of data, this is an important argument for using VHR remote sensing data sources. Additionally, a 'pseudo-stereo' image was generated from the QuickBird satellite image and has shown to be very useful for the visual interpretation of landslides in a time- and cost-saving manner. The different qualities of the used DEMs are clearly discernable in the final susceptibility maps. It is recommended to use a DEM with the finest resolution available, in order to pinpoint the hazardous spots in detail.

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