Abstract

High mountain regions represent difficult terrain for detecting rock and sediment storage areas. By means of a satellite scene by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and a digital elevation model, the geomorphological setting of the Reintal subcatchment (17 km²) east of the Zugspitze is analysed. Characteristic landforms are classified in an object-oriented approach comprising four spatial levels of differentiation. The complex, object-based decision tree hierarchy largely founds on fuzzy membership functions and to a lesser extent on a minimum distance classifier. The final landform classification scores high in the accuracy assessments. The results show that an identification of the present-day pattern of geomorphological process units is possible by remote sensing. Besides, the approach provides a first insight into the otherwise inaccessible upper regions of the study area which could not be included in any previous survey.

KEY WORDS: geomorphological landform detection, image segmentation, fuzzy logic, object-oriented classification, Reintal, Northern Calcareous Alps
1. Introduction

High mountain regions display a “geomorphic environment of considerable diversity. This variability in both time and space is perhaps the single most significant geomorphic characteristic of the alpine zone” (Caine 1974). Therefore these fragile environments react very quickly and sensitively to global change (Kääb 2002). However, scientific knowledge about their geomorphologic process structure remains sketchy and incomplete, especially quantitatively. Similarly, the question of potentially mobilisable sediments in the upper regions of high mountain catchments still calls for an answer (Schrott et al. 2003). Within a set of projects called “Sediment Cascades in Alpine Geosystems” (SEDAG), the universities of Eichstätt, Erlangen, Halle and Bonn/Salzburg have developed a model to describe landform evolution in high mountain regions.

This study forms part of the SEDAG research and represents the third of a series of papers: geomorphic systems theory and object-oriented remote sensing have been linked in Schneevoigt and Schrott (2006) in order to convey the theoretical and conceptual background of the analysis. Schneevoigt et al. (2008) accentuates its geomorphological side, particularly stressing the nature of the alpine landforms examined. In contrast, this paper at hand describes the remote sensing methods employed in further depth.

It aims at a semi-automatic classification scheme for geomorphological landforms, which can supply otherwise inaccessible information besides assisting landscape monitoring and mapping. As upper areas mostly cannot be observed from the ground, remote sensing applications represent a means of closing this gap which hampers a full understanding of the alpine sediment cascade. Many studies on high mountain geomorphology use GIS coupled with remote sensing data, whereas only few employ genuine remote sensing techniques (for details see Schneevoigt et al. 2008, Schneevoigt and Schrott 2006). Object-oriented image segmentation prior to classification constitutes a novel and promising approach (Blaschke et al. 2002, Benz et al. 2004). This relatively new trend has also found its way into high mountain applications, e.g. with Giles and Franklin (1998) classifying geomorphological slope units.

2. Geographical setting

The Reintal valley is situated 7 km south of the town of Garmisch-Partenkirchen in the Bavarian Alps (Fig. 1). It extends over 8 km in predominantly dolomitised limestone or Wettersteinkalk. As the Zugspitplatt is not linked to the valley in terms of sediment transfer, it has been excluded from the study area amounting to 17 km². No glaciers persist today, but Pleistocene glaciations have typically shaped cirques and hanging valleys in the upper regions, over steepened rockwalls and a broadened valley bottom. The relative relief within the study area amounts to 1690 m reaching a maximum of 2744 m asl at Hochwanner peak, a fact which amongst others confirms the high mountainous nature of the Reintal.

Today, 79% of the sediment stores on the valley floor are relict or inactive and completely decoupled from the sediment cascade system. Avalanche and debris flow tracks, alluvial fans and floodplains represent the most active storage types. In general, process activity rises with valley altitude. Very low clastic sediment output turns the Reintal into an effective serial sediment trap. As most active landforms receive input only, sediment stores build up quickly (Schrott et al. 2003).

3. Data basis

In this study, ASTER scenes were assessed because of their spatial resolution, pricing and near global coverage (Klug 2002, Kääb 2002, with more information). Ten bands of an ASTER scene from 29th May 2001 (Fig. 1) were selected for classification, i.e. all the visible/near-infrared (VNIR) and short wave infrared (SWIR) bands together with thermal infrared (TIR) band 11. The bands were stacked, geometrically rectified to fixed landmarks in a monochrome orthophoto of 1996 and simultaneously resampled by cubic convolution to a resolution of 5 m to match DEM resolution. As in other monotemporal investigations, atmospheric and topographic corrections were rejected, since they can introduce additional errors into the data set (relevant reference in Schneevoigt et al. 2008). Several ratios were used in this work; the Normalised Difference Vegetation Index (NDVI) forms important thresholds in the classification hierarchy (Fig. 3).

A digital elevation model (DEM) of 5 m ground resolution (Fig. 2 top) was generated and hydrologically stream corrected by SEDAG partners using photogrammetric data by the Bavarian Geodetic Survey. It served for the generation of five DEM derivatives. These geomorphometric grids of horizontal, vertical and total curvature, slope and aspect were incorporated in the classification process in addition to the DEM (Fig. 2).

The landforms considered in this study are summarized in Tab. 1 (additional information can be found in Schneevoigt et al. 2008). They result from interacting and partially equifinal processes. Thus strict delimitations of landforms do not always exist in landscape: many forms show no clear boundaries (Figs. 1, 2). As partially interfingered deposits are frequent, form characteristics deviate from the ideals. This “fuzzy nature of most high-mountain terrain features” (Kääb 2002) makes it necessary to consider context for sound classifications. Keeping the interval of
time in mind, the orthophoto of 1996 served as ground truth for crest and rockwall regions as well as for the sediment stores on the valley floor. Digital photos taken, as far as accessible, from opposed slopes and peaks, were used for the same purpose. A geomorphological map drawn up by Schrott et al. (2003) served as reference when dealing with the Reintal valley bottom.

<table>
<thead>
<tr>
<th>upper regions</th>
<th>rockwalls</th>
<th>valley bottom</th>
<th>ubiquity</th>
</tr>
</thead>
<tbody>
<tr>
<td>snow and ice</td>
<td>grass covered slopes</td>
<td>shrub covered talus</td>
<td>bare rock (&lt;50°)</td>
</tr>
<tr>
<td>eastern cirque wall (&lt;50°)</td>
<td>shrub covered slopes</td>
<td>tree covered talus</td>
<td>bare rock (&gt;50°)</td>
</tr>
<tr>
<td>eastern cirque wall (&gt;50°)</td>
<td>tree covered slopes</td>
<td>alluvial fan</td>
<td>fine sediments</td>
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<td>western cirque wall (&lt;50°)</td>
<td>floodplain</td>
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<td>coarse sediments</td>
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<td>western cirque wall (&gt;50°)</td>
<td>rockfall deposits</td>
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<td>channel</td>
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Table 1: Target classes in the classification process, sorted according to their predominant location in the study area.
4. Image segmentation into objects

The object-oriented approach (not to be confused with the homonymous programming mode) consists of two separate steps. First, the data employed is segmented into homogeneous image objects through generalisation and average determination, smoothing out irregular pixel-dominated patterns and creating more realistic forms. Secondly, these entire objects are classified, not individual pixels. Object-oriented image analysis hence unites the spectral analyses of remote sensing and the geometric tools of GIS into one desktop environment.

The segmentation algorithm by Baatz and Schäpe (2000) segments an image in a knowledge-free way via region-growing, an automatized heuristic optimization method: the potential increase of spectral heterogeneity is assessed in a merge weighed by the size of two pixels or segments considered. Next to this colour criterion based on spec-

![Diagram of data base and workflow in object-oriented classification]

Figure 2: Top: Data basis employed in this study. Bottom: Segmentations of the four levels of the main project for landform detection.
tral information alone, shape parameters can be used to correct highly textured data which otherwise would produce frayed and distorted segments. This constitutes an advantage especially in high mountain data. Yet it must be applied carefully, as it implies an arbitrary divergence from the given spectral information based on pure arithmetics (Baatz and Schäpe 2000). Not only spectral data, but also DEMs and all kinds of derivatives from image and elevation information can be integrated in the segmentation process. The available sources or parameters can be weighed by factors to differentiate their respective influence on the creation of a layer. These assets compensate for the extra time-consumption of finding adequate segmentation parameters. To address features at different scales, individual layers must be segmented for each scale. The multiresolution segmentation algorithm (Baatz and Schäpe, 2000) permits a simultaneous depiction of several image levels segmented at various spatial resolutions (Benz et al. 2004). Yet the integration of additional levels only makes sense if this implies a gain of information which cannot be retrieved from the existing levels.

Initially, a strata mask distinguishing three altitudinal storeys was generated in an ancillary project with three levels. In this set of preclassifications, crest regions and valley bottom both carry an error of commission to guarantee inclusion of all relevant image objects. The resulting layer was imported as L4 into the main project (Fig. 2). Here, segmentation on four levels was necessary in order to create the boundaries for all target classes. A small scale parameter conveys the spectral ground information of the Reintal (L1, Fig. 2). Conversely, the imported mask of three altitudinal subsystems (L4) requires a very high scale parameter, and the cirques and hanging valleys (L3) a relatively high one. An intermediate level serves for the final classification (L2), so that smaller landforms can be displayed while preserving a certain degree of generalization.

The segmentation of level L2 comprises the scales and parameters necessary to optimally depict the different landforms. For example, decreasing the colour criterion improves the representation of water bodies, but worsens the taluses at the same time. VNIR bands and DEM derivatives were brought into an equilibrium of 4:3, so that spectral information dominates. Scale 13 guaranteed the existence of necessary boundaries; decisive further ameliorations only set in below scale 10. However, this would have increased the project and processing times on the one hand, while leading to a lesser degree of abstraction due to small image objects on the other. Hence parameterisation resulted in level L2 illustrated in Fig. 2.

Figure 3: Extract of the classification hierarchy of the main project. The figures around the membership function icon to the right indicate the bounds of the fuzzy areas.
5. Classification of the image objects

Each image object can be addressed by mean value, standard deviation and ratio of the incorporated pixels next to its individual geometric features and its neighbourhood. When working on several image levels, relationships, sub- and superordinations, morphometric and class-related features can also be used for class descriptions (Benz et al. 2004, Blaschke et al. 2002). This accommodates three-dimensional alpine applications, provided that segmentation leads to objects which describe natural features geometrically well (Schneevoigt et al. 2008).

The four segmented levels were classified individually after developing the corresponding classification hierarchy (Fig. 3). This knowledge base is edited from class descriptions, which divide into contained features immanent in a class itself and inherited ones passed on by parent classes in the class hierarchy. A combination of hard (L1) and soft (L2, L3, L4) classifiers enables this approach generally resting on fuzzy logic. Hereby, floating thresholds provide a margin for the attribution of an object to a class (Fig. 3, right). Soft membership classifiers return fuzzy values between 0 (no assignment at all) and 1 (full assignment) for each feature and image object considered. Besides, fuzzy logic operators, which produce for instance sums, subsets and means, link different feature terms (Baatz and Schäpe 2000).

6. Results

The classification of level L1 renders ground land cover, level L4 the strata mask, level L3 eastern and western walls of cirques and hanging valleys (see Schneevoigt and Schrott 2006). This leads to a sound L2 landform classification (Fig. 4). The majority of classes such as cirques, rockwalls, floodplains and sediments are identified well. Detection limits are reached with moraine and rockfall deposits, because they have been overprinted by more recent processes for centuries or millennia and therefore leave no characteristic marks on the land surface. Then again, some target classes are further differentiated than previously expected. For instance, the vegetation cover of slopes and taluses was subdivided into high, medium and low natural cover, leading to 20 thematic landform classes (Tab. 1) in Fig. 4.
The final landform classification scores high in the assessments of both overall accuracy (92%), kappa coefficient (0.915), user’s and producer’s accuracy (Tab. 2). Only a few misclassifications occur, but they concern high amounts of pixels, as level L2 consists of image objects of ten to hundreds of pixels. Fuzzy classification stability, i.e., the degree of distinctness between most and second most probable class affiliation, is lower (Fig. 5), but best membership-ship assignments score generally high, too. Alluvial fans tend to intermingle with floodplains, while talus sheets and cones could not be differentiated from one another. This owes to the fact that in situ, these landforms tend to mostly coalesce, so that their exact assignment relies on interpretation by the observer. Overall, the vegetation covers of talus show the highest confusion.

7. Discussion

Image segmentation represents an additional, time consuming step in the classification routine. Finding an optimal segmentation for L2 constituted a veritable challenge, because the often very faint signals from avalanche and debris flow tracks should still be captured without ending at too small a resolution. VNIR bands have to be given considerable weight, as they trace landforms best. Yet the object-oriented approach makes the difficult high mountain terrain manageable (Schneevoigt et al. 2006) and leads to sound results. It remains to be investigated to which extent a purely pixel-based classification scheme may handle this data.

The good results partially owe to the fact that two distinct data sources were combined for analysis: some target classes appear spectrally distinct (e.g., sediments, rocks vs. vegetation covered features), whereas other landforms could be separated by topographic information. Giles and Franklin (1998) investigating geomorphological slope units reach an overall accuracy of 88.5% in their supervised classification based on prior image segmentation and classification from training areas. However, the values in the confusion matrix (Tab. 2) have to be taken with care: on the one hand, object-oriented accuracy assessments tend to overestimate as they are based on averaged image objects and not on individual pixels. On the other, test areas were selected randomly, but without following a regular spatial pattern. Hence further accuracy assessment with different, pixel-based software is required. Besides, the classification quality of older rockfall and moraine deposits could not be assessed, as they form no classes in the hierarchy.

Varying illumination constitutes a problem in high mountain areas. It can partially be mended by band ratio for-
Figure 5: Fuzzy classification stability of level L2. Red = close proximity of best and second best membership assignment; green = distal, stable assignments. The north-easternmost part of the valley shows the most unstable memberships.

Modification, i.e. the division of adjacent satellite image bands: discrepancies between them are reinforced, while similar structures are simultaneously eliminated. Hence while useful features like outlines of vegetation or ice/snow appear more clearly, atmosphere and relief induced variations in illumination disappear, as they are highly correlated in neighbouring bands (Paul 2000). Several ratios were used in this work; the Normalised Difference Vegetation Index (NDVI) forms important thresholds in the classification hierarchy (Fig. 3).

8. Conclusion and outlook

To further evaluate the results, the exact influences of image and DEM data respectively should be assessed by analysing them individually. Moreover, the transferability both of the segmentation parameterisation and the classification hierarchy still has to be investigated. One can assume that the application of such a two-step routine poses double problems. Conversely, Blaschke et al. (2002) argue that object-oriented classification rules should be easier transferable than pixel-based ones, as the former depend less on reflection values and atmospheric conditions. When transferring the methodology developed in this study both to other datasets and regions, the appropriateness of NDVI application should also be compared to soil-adjusted vegetation indices (for details see Schneevoigt et al. 2008).

Many open questions remain to be answered in this interdisciplinary work linking geomorphology and remote sensing. Albertz (2001) stresses that the appropriate analysis of remotely sensed imagery can become highly difficult when operating between disciplines, as remote sensing methods are not delivered with problem-adapted assessment factors. Then again, a broadened knowledge on sediment storage features represents the prerequisite for further insights into processual behaviour and landform development in the fragile mountain environment (Schrott et al. 2003). Considering the good match of the final landform classification and ground truth, the object-oriented approach constitutes a valuable tool for the Alpine sediment cascade, especially in inaccessible regions.

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