Modeling alpine geomorphology using laser altimetry data
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A typical landscape in Vorarlberg (Lech) where natural landforms are intertwined with infrastructure and human activity. It is a challenge to find the balance between socio-economic requirements and preservation of the natural landscape.
CHAPTER 1

General introduction


The vast majority of human activity interacts with landforms that make up the Earth’s surface. The scientific investigation of these landforms and the processes that shape them (i.e. geomorphology) can therefore be seen as fundamental to ensure a continuous safe, economic and sustainable development of our environment (Griffiths et al., 2011).

Geomorphology seeks to explain the diversity, origins and dynamics of terrain on the Earth and other planetary bodies (Tucker and Hancock, 2010). Mapping geomorphology is important for understanding the spatial, chronological and genetic relations between land elements (Gustavsson et al., 2006). While morphological mapping aims to describe sets of changes of slope characteristics and their spatial distribution across a land surface, geomorphological mapping tends to identify, interpret and represent the landforms by their form (morphology) and formational processes (Knight et al., 2011). A traditional geomorphological map contains several information layers on the morphography, hydrography, morphogenesis, current processes and the availability of unconsolidated materials. A geomorphological map can be considered a model to visualize a simplified representation of the geomorphological setting according to the interpretation of the geomorphologist. Geomorphological maps often form the basis of landscape evolution studies or landscape reconstructions and may be used for many relevant applications, such as geoconservation and natural hazard assessment or landscape management.

Traditionally geomorphological maps are hand-drawn line and/or symbol maps based on contour lines from topographic maps, air photo interpretation and extensive field work campaigns (e.g. Seijmonsbergen, 1992; Doornkamp et al., 1980), see Knight et al. (2011) for a review on field mapping techniques. Nowadays large field work campaigns just for geomorphological mapping are considered too expensive. Yet, in the last decades technological advances to acquire, store and process large amounts of topographic data has opened up new opportunities in geomorphological mapping and affiliated research, for example by producing geomorphological maps digitally and on the basis of elevation data or derived thematic maps. High-resolution digital elevation data have great potential of improving analysis tools for making (parts of) geomorphological research
more efficient so that larger areas can be analyzed in a smaller amount of time. In the process of mapping, digital elevation data can be used to quantitatively characterize landforms by their morphometrical properties, and use these characteristics as geometrical or geomorphological signatures for automated recognition of geomorphological features. Only few landforms follow theoretical rules in their morphological expression in the landscape. Therefore the automated extraction of specific types of landforms can be very challenging, especially if many complex and compound and/or degraded landforms are present. Also many morphological expressions can be the result of different geomorphological processes (i.e. equifinality). This is why combining expert knowledge with contemporary analysis tools should play a vital role in semi-automated mapping methods. Even when only part of the landforms or landform types can be extracted from digital elevation data, automated analysis tools help us to more efficiently produce or fill in maps with ‘easy-to-identify-landforms’, while detailed attention can be dedicated to more complex landforms, settings, or applications.

A geomorphological map contains a wealth of information on the spatial distribution and genesis of landforms and associated formational processes and materials at a certain moment in time. For some applications however, it may be valuable to investigate the impact of specific scenarios to future landform or landscape evolution. Models that describe the dynamics of geomorphological processes may help to understand their impact on landscape development. A drawback of using landscape evolution modeling in geomorphological studies is the lack of validation methods. On the one hand there is the temporal scale on which processes are modeled for which future predictions cannot be validated with field measurements. On the other hand is the (fine) spatial scale on which processes act. Moreover, modeling with high-resolution data sets is often too computationally demanding so that small areas or coarser data sources are used at the expense of detail and/or accuracy. This can be overcome by introducing new methods to apply high-resolution data sets in dynamic simulation models.

This thesis brings together both field knowledge and high-resolution digital elevation data, and the associated analysis tools, to improve contemporary methods in geomorphological research. This includes a methodological framework on automated geomorphological mapping and dynamic landscape evolution modeling. In order to provide the required background information, the following subsections of this chapter give a short introduction on the data and analysis tools that form the basis of this research. In section 1.1 the concepts of digital terrain analysis and geomorphometry are briefly introduced and explains how geomorphological mapping can benefit from high-res digital elevation data. This section includes some background information on 1) LiDAR data and processing, 2) analysis of Digital Elevation Models (DEMs) and Land Surface Parameters (LSPs), and 3) automated feature extraction of geomorphological features with Object-Based Image Analysis. Following that, section 1.3 elaborates on how digital elevation data is applied in the dynamic modeling of geomorphological processes and briefly motivates why the scientific community should continue improving landscape evolution models. Section 1.4 states the explicit research objectives of this thesis and explains the context of the individual chapters to the overall objective of the thesis. Section 1.5 introduces the study area in which these objectives are tested.

1.1 Digital terrain analysis and geomorphometry

1.1.1 LiDAR data and processing

The potential of digital terrain analysis is highly dependent on the quality and detail of digital elevation models (DEMs). The DEM being a digital representation of the land surface (Pike, 1995; Hengl and Reuter, 2008). DEMs can be specified in 1) Digital Surface Models (DSMs) that describe the elevation of the vegetated surface including infrastructure, and 2) Digital Terrain Models
(DTMs) that contain elevation values of the terrain surface without vegetation and infrastructure. DTMs are often of most interest to geomorphologists. A widely used technology for producing high quality and detailed DEMs (both DSMs and DTMs) is LiDAR (Light Detection And Ranging). LiDAR is the light equivalent of well known RADAR (Radio Detection And Ranging). A LiDAR set up consists of a laser scanner which, in the case of airborne LiDAR data, is attached to the bottom of a small aircraft or helicopter. The laser scanner shoots laser pulses directly to the Earth’s surface and measures the reflection time between the scanner and the measured object. In combination with a GPS the x, y, z location of the target is registered. A laser scanner is able to fire laser pulses at very high frequencies (e.g. at 20 kHz i.e. 20,000 pulses per second) and is therefore able to capture the landscape’s topography in very high detail.

The raw laser scanner data is a mesh of millions of data points which need to be interpolated into a regularly spaced gridded DEM to make it computationally usable. The point cloud represents the location (x, y) and elevation (z) of the terrain and overlying vegetation, infrastructure or other objects in the landscape. A filtering algorithm is required to first classify the data points into ground points and non-ground points. One of such algorithms is described by Kraus and Pfeifer (1998) which iteratively interpolates a surface through the data points, and removes the data points that are located above the interpolated surface. After few iterations the interpolated surface is lowered until it resembles a theoretical terrain surface. Because of the high point density (>2.5 points m\(^{-2}\)) of laser altimetry data, LiDAR DTMs can be very detailed with a spatial resolution of 1 x 1 meter, and a vertical accuracy of 25 cm or better. However, noteworthy is that the horizontal and vertical accuracy is highly dependent on the vegetation cover and the corresponding amount of laser pulses which have penetrated through the vegetation layer. At locations where only few laser pulses reach the ground surface, point densities dramatically decrease. This results in a spatially non-uniform distribution of DTM accuracy. Although DTM accuracy was not quantitatively estimated in this research, this heterogeneous error distribution has been considered when analyzing spatial variability in the data.

1.1.2 DEMs and Land Surface Parameters

The field of ‘geomorphometry’ is often described as the ‘science of digital terrain analysis’ (Hengl and Reuter, 2008). Geomorphometry uses DEMs as a basis for landscape analysis and deals with the quantitative analysis of (a digital version of) the Earth’s surface. Many derivatives or thematic maps can be calculated from elevation data which describe specific terrain properties. Such derivatives are therefore mentioned as ‘terrain attributes’, ‘terrain parameters’, or ‘Land Surface Parameters’ (LSPs). Examples of such LSPs are slope and curvature maps that are direct derivatives of elevation (i.e. slope as the first derivative, and curvature as the second derivative). Also indirect properties exists, such as the relative elevation (i.e. the percentage a center cell is higher located than surrounding cells within a specific moving window or kernel), and openness (which describes the mean angle of a location with respect to its horizon). These LSPs can be calculated over a wide variety of scales. The relative elevation or openness for example, can be measured over only few cells or meters, but can also be calculated over hundreds or thousands of grid cells to visualize the topographic variability at different scales. Fig. 1.1 shows examples of openness and relative elevation measured with a kernel size of 25x25 and 251x251 m, with a 1 m LiDAR DTM as its source.

1.1.3 Automated extraction of geomorphological features

Once a variety of LSPs have been computed we can use them to extract geomorphological features in the same way remote sensing bands are used to extract land cover classes (Lillesand et al., 2007), i.e. based on unsupervised and supervised classifications. Unsupervised classifications create a user
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Figure 1.1: Examples of LSPs that are derived from a 1 m LiDAR DTM (A): with relative elevation at two scales (B-C, with blue colors as relatively low, red as relatively high relative to a moving window), slope angle (D, with green as gentle and red as steep slopes), and topographic openness (E-F, with bright colors as 'open' and dark colors as enclosed areas measured over two window sizes).

defined number of classes and cluster areas into classes based on variation in the LSPs calculated by statistical measures. Two most used algorithms of unsupervised classification are K-means and ISODATA (Iterative Self-Organizing Data Analysis). Unsupervised classifications are often used for extracting elementary forms in different landscapes at a range of scales from regional to global (e.g. MacMillan et al., 2000; Burrough et al., 2000; Iwahashi and Pike, 2007). Such classifications can be fully automated and may use many LSPs to categorize DEM-based grid cells into a number of classes. The classes resulting from unsupervised classifications are often not directly related to landforms or other landscape features of interest, and the meaning of the generated classes are to be determined afterwards. In contrast, supervised classifications are more knowledge-driven and require a training set of grid cells that represent user-specified categories. In other words, with supervised classifications a user trains classification rules by manually identifying features in the data and links them with data values; the remaining grid cells are classified according to criteria derived from these categories and the corresponding set of training grid cell.

1.2 Object-Based Image Analysis

In coarse-resolution data sets a single grid cell value forms an average representation of multiple features of interest. Analyzing such datasets require grid cell or pixel-based analysis techniques, where each grid cell is analyzed separately. In high-resolution data sets a single feature of interest
Object-Based Image Analysis (OBIA) is represented by multiple grid cells. When analyzing such features of interest using high-resolution data, the groups of grid cells are the subject of study, rather than the individual grid cell values themselves. Along with improved data acquisition technology and related increased detail of data products, there has been a shift from pixel-based classification towards object-based classifications.

OBIA clusters image grid cells of one or multiple gridded data sets into objects, and classifies objects using properties related to raster data values, shape characteristics or the mutual relationships between objects. When using geospatial elevation data, the data resemble a landscape. Geospatial objects, as created by the clustering of grid cells, resemble landscape objects or landform elements. OBIA closely resembles the functioning of the human brain to divide a landscape into landscape features and objects, and interpreting those objects by their shape, location in the landscape, terrain properties and their mutual relationships—OBIA is very intuitive to use in geographical applications.

Methods to cluster image grid cells into objects (hereafter mentioned as ‘image segmentation’) are divided into four categories, i.e. point-based, edge-based, region-based, or a combination of these (Schiewe, 2002; Pal and Pal, 1993). The most used method for creating objects from geospatial elevation data is region-growing segmentation (Benz et al., 2004; Dráguň and Blaschke, 2006; Van Asselen and Seijmonsbergen, 2006), which is implemented in the commercially available software eCognition. It takes into account multiple gridded layers with different spatial resolutions during the segmentation process, hence the algorithm is referred to as a multi-resolution segmentation algorithm (Baatz and Schäpe, 2000).

Once the objects are generated they are categorized using classification rules or a nearest neighbor approach with manually depicted samples. In this thesis we chose to use classification rules that are constructed based on criteria formulated from a geomorphological perspective, thus expert-driven. The classification rules are built of membership functions, where each object is subjected to some criteria that calculate the membership value to the specific class. These membership values range from 0–1. Objects may have membership values of e.g. 0.7 to an eroded bedrock feature, but also 0.5 membership to a different class, such as shallow mass movement feature. In this way membership functions create fuzzy classifications (Wang, 1990b,a; MacMillan et al., 2000). From a geomorphological perspective, this would, theoretically, reflect the degree to which a landform is formed by a combination of different fossil or active processes.

Another important feature of OBIA is the ability to take into account criteria on spatial relationships between the objects. This allows to place objects into a (spatial) context. Aside from using morphological characteristics (from LSPs), shape properties and spatial relationships can be considered for the characterization of objects. This potentially allows to also extract morphogenetic information from elevation data, and when LiDAR data is used, also at detailed scales. This would be a significant step forward in (semi-) automated geomorphological mapping, and major advantage over other methods which only extract morphometrical land units (e.g. Iwahashi and Pike, 2007; Bolongaro-Crevenna et al., 2005; Ehsani and Quiel, 2008) or extract only low-level geomorphological features (e.g. Etzelmüller et al., 2007; Yokoyama et al., 2002).

However, a reoccurring drawback of OBIA is the subjectivity that comes with estimating segmentation parameters and classification rules. While different pixel-based classification methods are fully automated, object-based classifications are often concerned with manual heuristics to fine-tune segmentation parameters to obtain the best segmentation results. High quality objects—i.e. objects that closely follow the boundaries of features of interest—are prerequisite for accurate classification results and high quality maps. This subjective parameter optimization leads to the poor transferability of segmentation parameters to different studies, thus decreasing the reproducibility of the work flow—which is often one of the aims of automated mapping. One important objective of this thesis is to overcome this by standardizing and automating the optimization of
segmentation parameters (Chapter 2). This concept was then implemented into a protocol for digital geomorphological mapping (Chapter 3). Two applications of digital and semi-automated geomorphological mapping are illustrated in Chapters 4 and 5 (see also section 1.4)

1.3 Dynamic modeling of geomorphological processes

Dynamic landscape evolution models are recognized means for increasing the understanding of geomorphological processes and their impact on the environment over time. They “allow us to visualize landscape development and provide a powerful tool to sharpening our theories and interpretation of the landscape” (Tucker and Hancock, 2010). Until recently, a landscape evolution model (LEM) was a cartoon-like series of pictures showing the sequential development of a landscape over time. From the 1980’s a LEM had taken a new meaning: “a mathematical theory describing how actions of geomorphic processes drive landscape evolution” (Tucker and Hancock, 2010) (and vice versa). Such models describe the underlying theory and mathematical equations, and are implemented in computer programs or scripts that calculate the approximations of the equations.

Landscape evolution models show the topographic development of a landscape over time, by altering grid cell elevation values according to geomorphic transport functions (GFTs, often formulated as partial differential equations). LEMs often use a digital elevation model as initial landscape topography. Tucker and Hancock (2010) provide an excellent overview of landscape evolution models, their components and widely accepted concepts and equations for a variety of geomorphic processes. They mention that a landscape evolution model is composed of multiple components: 1) a statement on the continuity of mass; 2) geomorphic transport functions that describe the movement of sediments along hillslopes; 3) representation of runoff generation and the routing of flow across the landscape; 4) geomorphic transport functions that describe the erosion by water and water-sediment mixtures; and 5) numerical methods to calculate their solutions in space and iterate forward in time.

Dynamic geomorphological models allow testing hypotheses, and evaluating and visualizing geomorphic impacts of specific environmental scenarios, thus have important environmental applications. However, major issues in landscape evolution modeling are related to the differences of scales on which processes act, the increasing computation time when simulating geomorphic processes in high spatial detail, and the lack of verification and validation methods (Oreskes et al., 1994). It is therefore important to further develop new modeling techniques to increase the detail of such models and finding ways to evaluate model performance.

Chapter 6 of this thesis addresses the issue of modeling at two different scales. Two main geomorphic models in a catchment (river channel incision and adjacent hillslope development) are separated and modeled with two different strategies. The channel incision is modeled by vectorizing the river channels extracted from a 1 m LiDAR DTM. This allows calculating the channel lowering in one dimension. The hillslope development model uses a grid cell-based approach to calculate the mechanical weathering of bedrock and transportation of regolith across the landscape (in two dimensions) using relative coarse grid cells (50 m x 50 m). Both models simulate the dynamics at their appropriate scale level before they are coupled and together affect the landscape’s topography (i.e. digital elevation). Chapter 7 of this thesis combines the work of the earlier chapters and illustrates the integration of OBIA with landscape evolution models by visualizing, and evaluating, model results with automated landform classifications. It allows taking into account spatial relations of landform evolution during simulations. We therefore suggest using landform classifications for model evaluation.
1.4 Research objectives and structure of this thesis

The overall objective of this thesis is to combine expert knowledge and field experience with contemporary digital analysis tools in geomorphological research. Novel methods have been introduced to apply LiDAR data for more efficient geomorphological mapping and dynamic simulation of landscape evolution. The following specific objectives for the individual chapters can be formulated:

1. Improving the objectivity and reproducibility of object-based classifications, by semi-automating the optimization of classification parameters and the extraction of geomorphological features from laser altimetry data (Chapter 2);

2. Integrating field work, LiDAR LSP interpretation, digitizations, and object-based feature classifications into a protocol for digital geomorphological mapping in mountainous areas (Chapter 3);

3. Demonstrating the application of automated feature classifications in two case studies, i.e. geoconservation assessment (Chapter 4) and geomorphological change detection using multi-temporal LiDAR data (Chapter 5);

4. Integrating LiDAR data into a coupled and dynamic landscape evolution model to simulate multiple geomorphological processes, i.e. fluvial incision and knickpoint retreat vs. hillslope development, at their appropriate scale (Chapter 6);

5. Integrating object-based feature classifications in the visualization and evaluation of a landscape evolution model (Chapter 7).

1.5 Study area

The methods described in this thesis are tested in the mountainous area of Vorarlberg, which is the westernmost State of Austria. Vorarlberg is located at the geological boundary of the Western Alps and Eastern Alps, on the Northern side of the European Alps. During the mountain building phase the existing rocks were laterally displaced, thrust and stacked to form the tectonical nappe structures (Friebe, 2007; Oberhauser, 1998) which are, in Vorarlberg, generally southwest-northeast oriented. The major nappes of the Western Alps occurring in Vorarlberg, are the Helveticum and Flysch nappes; the two dominating nappes of the Eastern Alps are the crystalline Silvretta nappe and the sedimentary Northern Calcareous nappe, which together belong to the Upper East-Alpine realm. See Fig. 1.2 for an overview of the location of the various nappes and test areas.

Clastic Tertiary sedimentary rocks (including conglomerates, sands, clays and marls) that were derived as erosional products from the uplifted mountains, now occur as the Molasse at the northern flanks of the Alps. The overthrust Helvetic nappe is mainly composed of limestone formations. The Penninic ‘Vorarlberger’ Flysch includes formations that consist mainly of alternations of sandstones, limestones, breccia, and marls. The Vorarlberger Flysch nappe is overthrust from the south by the calcareous part of the Upper East-Alpine nappe. This Northern Calcareous nappe is locally known as the Lechtal nappe, of which the most important Triassic formations are Muschelkalk Formation, Arlberg Formation, Raibler Formation, Haupt Dolomite Formation and Kössener series (Friebe, 2007). The Haupt Dolomite Formation is widely distributed in the area and forms the highest massives. The test areas of the following chapters are mainly located in this Northern Calcareous nappe (Fig. 1.2).

The Silvretta mountains form the highest part of Southeastern Vorarlberg. The Silvretta nappe is mainly composed of metamorphic rocks such as amphibolites, micaschists, para- and orthogneisses, and granitic rocks. The river Ill has its source here and drains the entire region.
before it flows into the river Rhine and towards Lake Constance (Bodensee). For a more in-depth geological description of the area we refer to Oberhauser (1998) and Friebe (2007).

The current geomorphological setting in Vorarlberg is closely linked to the uplifted mountains, its underlying geological structure and lithological variation, and has witnessed alternating fluvial and glacial activity during the changing climatic conditions of the Pleistocene. Intense and repeated glacial erosion has resulted in typical alpine geomorphology, that includes U-shaped, hanging valleys, cirques, and eroded valley shoulders. Within these major landscape elements, depositional evidence of former glacial and ice-marginal action, such as subglacial till, morainic ridges and ice-marginal deposits may occur. The extensive glacial erosion has triggered a wide spectrum of geomorphological processes during and after glacial retreat, such as (deep reaching) rock slides, rock fall, karst and fluvial erosion, carving deeply into the disintegrated and weathered bedrock.

The detailed geomorphological process and landforms have been documented in the various test areas and will be described in more detail in the individual chapters.