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Relation between landform and vegetation in alpine regions of Wallis, Switzerland. A multiscale remote sensing and GIS approach

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Abstract

The analysis of habitat factors for the distribution of vegetation based on the analysis of landform characteristics is an important aspect in the process of understanding high mountain ecology. Therefore in the present study a GIS and remote sensing based approach is followed to produce different scale vegetation maps for a study area in the Western Alps (Switzerland). As spatial information on site factors is commonly lacking in mountain areas, the use of a Digital Elevation Model (DEM) is a potential substitute for use in vegetation analyses, as it highly correlates with temperature, moisture, geomorphological processes and disturbance factors. Thus it is crucial to analyse the capabilities of a DEM for indicating habitat conditions in a landscape characterised by high topodiversity and a patchwork of microclimatic habitats. Appropriate landform parameters have been derived, indicating temperature and moisture distribution, exposure towards wind, snow etc. Using contingency tables and principal components analysis the overall influence of topography and landform on vegetation distribution was analysed. Nevertheless, the lack of information on the human dimension leads to some uncertainties in the interpretation of spatial patterns of vegetation. Additionally landform classification schemes decomposing the landscape into basic landform-elements only proved useful for characterising azonal, non-altitudinal vegetation classes. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Vegetation distribution; DEM; Landform analysis; Geomorphometry; Alps; Remote Sensing; GIS

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1. Introduction

Vegetation distribution in alpine cultural landscapes is characterised by spatially inhomogeneous environmental conditions concerning climate, soils, geology as well as frequency and intensity of disturbance. The physical environment is often regarded as one of the most important factors controlling the spatial heterogeneity of the landscape in mountain areas (Bolstad, Swank, & Vose, 1998; Fischer, 1990; Tappeiner, Tasser, & Tappeiner, 1998; Zimmermann, & Eggenberg, 1990). The ecological space of a vegetation type corresponds to its fundamental niche; in contrast to the fundamental the realised niche is defined through interaction with other vegetation types; finally the geographic space of vegetation types or species is equal to its spatial distribution, caused by natural factors and human impact.

Analysing the habitat of a vegetation type means relating its geographic space to those environmental site factors that best represent the realised niche (Guisan, Theurillat, & Kienast, 1998, p. 65). These analyses are often performed using statistical methods and static distribution models (Franklin, 1998; Moore, Lees, & Davey, 1991; Moore, Grayson, & Ladson, 1991; Roberts, Houston, Zimmermann, Flann, & Wight, 2000; Yee & Mitchell, 1991). Since the realised niche and geographic space of a vegetation type in a high mountain environment is closely related to topographic relief (Allen, Hewitt, & Partridge, 1995), it is likely that landform parameters like elevation, slope or aspect are important input parameters for spatial analysis and modelling of vegetation distribution in mountain landscapes. In a complex system of site factors topography is the major (indirect) factor for vegetation distribution (Barrio, Alvera, Puigdefabregas, & Diez, 1997; Gottfried, Pauli, & Grabherr, 1999). Thus, topography creates a patchwork-like pattern of small scale habitats and realised niches within the ecological space.

Besides natural environmental factors, the history of human impact in terms of agricultural land use and animal husbandry (Messerli, 1989), but also former and recent natural disturbance (avalanches, rockfall, mudslides, partly related to human impact, thus being only semi-natural disturbance factors) play a major role for the distribution of vegetation types (Tappeiner et al., 1998). However, in most cases, spatially referenced data on historic (and sometimes even recent) land use practice and disturbance frequency is lacking, corresponding information is difficult to achieve and data handling is often time consuming.

Thus, the actual vegetation distribution is a result of the complex interaction of historic and recent environmental, human and disturbance factors. Nevertheless, even in a landscape which is marked by human impact the overall influence of topography on the distribution of vegetation types is indisputable, even if the latter are quasi-natural or replacement vegetation types.

Digital vegetation information as well as landform and topography-dependent microclimatic conditions of small relief patches are commonly assessed and represented using Geographic Information Systems (GIS). There are three main approaches of performing habitat analyses in current research literature:

1. Analysing the relation between vegetation and direct influence factors which means
   (a) A reliable spatial database based on measurement/mapping of climate and edaphic data, geomorphological processes and human influence factors has to be available.
   (b) Reliable point data are being inter-/extrapolated by the use of digital elevation data using e.g. regression procedures.
   This approach is often subject to incalculable error due to insufficient data quantity and also quality. Additionally, reliable spatial data on climatic variables covering whole areas of research are not likely to be gained in the near future.
2. Analysing the relation between vegetation and the entire set of site factors including direct and also indirect (i.e. topographic) environmental variables. Using statistical techniques often requires non-redundant data; considering the entire set of site factors in statistical analyses can therefore cause extremely unstable results. Furthermore, computing time is increased considerably and results are often hardly interpretable because of interacting variables.
3. The third approach of analysing vegetation habitats was chosen for the present study. It assumes that any direct influence factor can be indicated or parameterised by landform parameters: the spatially heterogeneous pattern of landform derivatives such as slope, aspect, curvature exert strong influence on the spatial distribution of irradiation, precipitation, air and soil temperature, soil water and nutrients, snow accumulation and winds, but also controls geomorphic processes and human interference. Microclimatic conditions have to be indicated by the analysis of topodiversity which is one of the key factors increasing the habitat diversity of high mountain landscapes. The major advantage of this approach is that spatially referenced data on topography are available for large areas at different spatial resolutions, thus offering a much more reliable predictor database compared with direct climatic or edaphic site factors.

Therefore, in this study the analysis of the correlation between vegetation types, distribution patterns and landform characteristics in an alpine environment is stressed. Profound knowledge of such correlation is vital to a complex understanding of alpine vegetation types and its environment. In the view of a changing climate, causing shifts in ecotones and growing-conditions, exact knowledge of system interdependencies is indispensable for designing and operating vegetation models (Bolliger, Kienast, & Bugmann, 2000; Brzeziecki, Kienast, & Wildi, 1995). This is especially important for a highly sensitive area such as high mountains and its vulnerable ecosystems. Hence, if it is demonstrated that spatial patterns of alpine cultural landscapes are linked to topography, it will be possible to model its ecosystems' response to long-term changes in mountain environments (Gottfried, Pauli, & Grabherr, 1998).

For the integration of diversely scaled data of inhomogeneous sources a GIS-based approach seems most appropriate (Blaszczynski, 1997; Brabyn, 1999; Braun, unpublished), offering the possibility to handle and homogenise spatial data on vegetation, landform and natural environment in terms of orthorectification, georeferencing and spatially analysing common structures and patterns.

Remotely sensed data have been widely used for assisting in vegetation mapping in the last few years and have proved an effective tool. They offer the possibility of extrapolating mapping results, especially in large and hardly accessible remote areas (Kalliola, & Surjänen, 1991, S. 55). For further details on the use and and restrictions of remotely sensed data for vegetation mapping see Ahmad, Jupp, and Nunez, (1992), Braun (1996), Chica-Olmo and Abarca-Hernandez (2000), Etten (1998), Kalliola and Syrjänen, (1991), Kühnen and Meurer, (1993), Wyatt (2000) S.3.

The methodologic significance of this work is to develop a remote sensing and GIS-based approach in conformance with geobotanic requirements, bridging the scale gap and thus integrating information from the scale of a set of single plants and aerial photographs of 1-m spatial resolution up to vegetation formations and the scale of satellite sensors of 25 m spatial resolution. Furthermore, statistical analyses for a high-dimensional dataset are applied in order to analyse topographic characteristics of vegetation habitat structures.

Hence, the major aims of this study are to

1. Develop a concise hierarchical mapping and classification system integrating remote sensing capacities and geobotanic requirements.
2. Derive a set of topographic/geomorphometric parameters and aggregate landform objects (by delineation of homogeneous patches in the sense of a landscape mosaic), being capable of indicating all relevant habitat/site factors.
3. Create vegetation maps at two spatial scales using field and remotely sensed data and compare capabilities of satellite sensor data to those of aerial photographs for differentiating taxonomically defined vegetation types.
4. Analyse the relation between those vegetation types and landform parameters qualitatively using descriptive statistics and GIS tools.
5. Analyse the correlation between vegetation pattern and landform characteristics quantitatively by appropriate statistical means

2. Area of research and characteristics for vegetation distribution

The area of research (Fig. 1) is situated in the Wallis/Swiss Alps, the transect from Lötschental across the Rhône Valley into Turtmanntal amounts to about 400 km^2. The area is characterised by high gradients concerning topography, climate and human impact. The area was chosen because it had been subject to many other projects before (Ellenberg & Klötzli, 1972; Leibundgut, 1938; Mosimann, 1985) and many data had been gathered in diploma and thesis projects of the working group.

Elevation ranges from 600 m (Rhône Valley) up to nearly 4000 m in the Lötschental (Bietschhorn 3934 m) and over 4500 m (Weisshorn 4505 m) in the Turtmanntal on a horizontal distance of only a few kilometres. As major valley directions are northeast–southwest (Lötschental), east–west for the Rhône Valley and north–south for the Turtmanntal, an interesting diversity in vegetation types

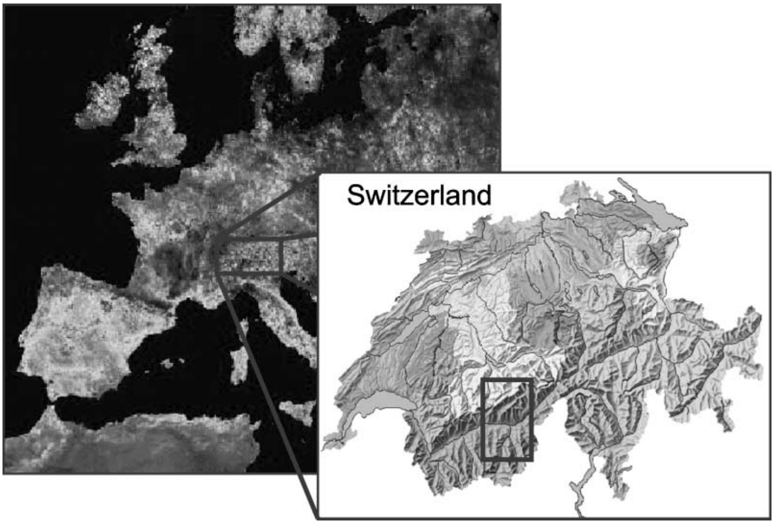

Fig. 1. Area of research. Copyright "Atlas of Switzerland" kindly made available by the Institute of Cartography, ETH, Zurich.

and habitat conditions occurs due to aspect, special local climatic characteristics, irradiation, moisture and local wind systems.

Another differentiating factor for the vegetation is the growing continentality (high daily and annual temperature amplitudes, dry summers) towards the south. While the Lötschental is partly influenced by westerly wind drift and maritime weather (average yearly precipitation of 1100 mm), the Turtmanntal is a significantly dryer central-alpine valley ("inneralpines Trockental") with precipitation rates far below 1000 mm. The increasing continentality is responsible for an upslope shift of ecotones, especially visible in the case of a rise in the mean upper tree-line from 2200 m in the north of the transect to 2450 m in the south, not considering aspect differences.

Human influence is highest in the Rhône Valley with intensive irrigation agriculture. In the Lötschental, changing economic conditions of mountain farming lead to the abandoning of steep slopes and unfavourably situated areas. The complex irrigation system is decaying and animal husbandry is vanishing, resulting in a range of fallow vegetation types. Over the past decades agricultural activities in the Turtmanntal have rarely been intensive, the valley is only inhabited in summer and few montane pastures are used for dairy farming merely during summer months.

3. Data and GIS-integration

3.1. Vegetation data

Various remote sensing and topographic data were used in the present study. Besides a Landsat TM scene and a set of IRS-1C data (multitemporal LISS and monotemporal PAN)[1] 46 panchromatic aerial photographs and seven CIR photographs at scales of 1:20 000–1:35 000 were used. Aerial photographs were orthorectified using ERDAS Orthobase^{TM} software, resulting in a spatial resolution of 1 m for the panchromatic and 2.5 m for the CIR photographs. Root mean square error (RMSE) was accepted with 3 m near-nadir and 7–8 m off-nadir. Multitemporal Landsat-TM and IRS-1C-LISS-Data as well as IRS-1C PAN data (for data fusion purposes) were orthorectified based on the digital topographic map, a Digital Elevation Model (25 m spatial resolution = DEM25) and the orthophotos.

For the integration into the GIS two spatial resolution levels (5 m for the high spatial resolution data and 25 m for the low spatial resolution satellite and DEM data) were chosen.

Field data collected during six field campaigns from 1998 to 2000 made use of CIR orthophotos and pre-stratified sensor data. The hierarchical classification scheme used bases on a habitat typology recently published by leading federal authorities in Switzerland (Delarze, Gonseth, & Galland, 1999). *Vegetation alliances* are the basic unit of this system following the principles of (Braun-Blanquet, 1964). A subset of the forest hierarchical classification system is shown in Table 1.

On the first hierarchy level broad classes in the sense of formations are used; the second level being sub-formations; on the third level these are further subdivided into specific types of deciduous, coniferous and mixed forest, respectively. The fourth (i.e. the basic) level of classification is formed by taxonomically defined *vegetation alliances* like the Larch (*Larix decidua*) and Arolla Pine (*Pinus cembra*) Forest *Larici-Pinetum cembrae*.

Data for about 500 training sites were collected for use in supervised classification and validation. On the one hand training samples were defined for the low spatial resolution analysis; besides that high spatial resolution vegetation units were mapped onto the CIR orthophotos on the basis of vegetation alliances. Representative

Table 1
Forest subset of the hierarchical classification scheme

Deciduous Forest	Floodplain Forest	*Alnion incanae*
	Beech Forest	–
	Other Deciduous Forest	*Quercion pubescenti-petraeae*
	Peatland Forest	–
Coniferous Forest	Scotch Pine Forest	*Ononido Pinion*
	Subalpine Coniferous Forest	*Abieti-Piceion*
		Vaccinio-Piceion
		Larici-Pinetum cembrae
		Junipero-Laricetum
Mixed Forest	Subalpine Coniferous Forest mixed with various broad-leafed trees	–

[1] Data were kindly made available by Euromap Satellitendaten-Vertriebsgesellschaft mbH, Neustrelitz.

plant lists were attached for every class and integrated into an *Access* database, containing site information and indicator values according to (Lauber & Wagner, 1996) as well as per cent coverages for each plant. Using the *ArcView* ODBC-interlink, specific database queries were performed, for example, to find out about ecoogical site characteristics, select sites containing specific plants or plant combinations, which serves as a powerful tool in analysing habitat conditions.

3.2. DEM data

3.2.1. Derivation of landform variables from the DEM

The GIS approach provided the basis for the derivation of different geomorphometric parameters from the DEM25. As hardly any spatial information on the distribution of temperature, moisture, wind or snow is available for the study area apart from point measurements, landform derivatives are to be used as substitutes [compare (Brändli, 1997; Conrad 1998; Jenson, & Dominigue, 1988; Moore, Lees et al., 1991; Moore, Grayson et al., 1991)]. The landform parameters derived and their indication potential for other site factors are given in Table 2.

In the first place, 25 landform variables were created: besides primary parameters like elevation and its first and second derivatives slope (angle and aspect) and curvature (profile and plan), respectively, secondary parameters were created by combining primary ones. For the transformation of the circular variable of slope aspect cosine and sine-transformations were calculated, stressing the north–south- and the east–west-contrast of slope aspect.

Apart from commonly used moisture index created by (Zevenbergen & Thorne, 1987) a new algorithm was implemented and its performance was evaluated compared with that offered by the ArcInfo software package. As surface roughness is one of the major influence factors for vegetation types especially above the alpine treeline, several parameters were created, also integrating different levels of scale, such as the DEM standard deviation in kernels ranging in size from 3×3 to 20×20 pixels.

Combining slope angle and contributing catchment area the so called activity Index was developed as an indicator of high process intensity or frequency.

As radiation and moisture supply can impose major restrictions for vegetation growth, a combined parameter was developed. In analogy with die calculation of the Normalised Difference Vegetation Index (NDVI) the normalised difference of radiation and moisture was calculated.

Technically, for the derivation of landform parameters different software packages (Erdas Imagine, Grass, ArcInfo) were used: results partly show great deviations in the derived parameters, thus being a great source of uncertainty in any topographic analysis. After mutual visual comparison, it was finally decided to use ArcInfo tools as algorithms are well documented and visual inspection showed no obvious errors in contrast to those derived using some Grass tools.

3.2.2. Landform classification

As vegetation units are often linked to geomorphometric or topographic units, the pixel-wise geomorphometric approach was extended to a spatial-unit-based

Table 2
Landform parameters and their indication potential for sites factors

Landform parameter	Variable	Indication of
Elevation	dem	Radiation, Temperature, Wind, Snow, rel. Humidity; Vertical Ecoclimatic Zones, Land Use
Elevation classes (at 100 m intervall)	dem100m	Dto.
Elevation classes (colline - nival)	dem7	Dto.
Slope	slope	Soil Moisture, Wind, Snow, Process Intensity and Frequency, Radiation,Temperature, Land Use
Slope classes	slope8	Dto.
Aspect	asp	Radiation, Temperature, Snow, Moisture, Land Use
Aspect classes	asp9	Dto.
Cosine-transformed aspect	cosasp	North-South-Contrast: Radiation, Temperature, Snow
Sine-transformed aspect	sinasp	East-West-Contrast: Radiation, Precipitation, Snow
Profile curvature	prcurv	(Soil) Moisture, Process Intensity and Frequency
Plan curvature	plcurv	Snow Accumulation, Exposure towards Wind, Soil Moisture, Radiation
Flow accumulation	floac	Soil Moisture, Process Intensity and Frequency
Water distribution model (WDM)	wdm	Soil Moisture, Process Intensity and Frequency
Inverse WDM	wdminv	Distance from Depression/Stream lines, Groundwater
Moisture index (Floac)	mind-flo	Soil Moisture
Moisture index (WDM)	mind-wdm	Soil Moisture
Roughness 1 (3×3 kernel DEM standard deviation)	dem3sd	Exposure towards Wind, Snow, Water supply (locally)
Roughness 2 (10×10 kernel DEM standard deviation)	dem10sd	Exposure towards Wind, Snow, Water supply (on small slope)
Roughness 3 (20×20 kernel DEM standard deviation)	dem20sd	Exposure towards Wind, Snow, Water supply (on large slopes)
Roughness 4 (hierachical approach by N. Zimmermann)	topo	Exposure towards Wind, Snow, Water supply (locally to slope-wide)
Activity index	act	Process Intensity and Frequency, Snow
Radiation	rad	Radiation, Temperature
Radiation classes (at 1000 W)	rad1000	Dto.
Radiation–Moisture index	ndradi	Radiation, Temperature, Soil Moisture

approach of smallest homogeneous landscape units and ecological toposequences. Two different landform classification schemes were applied: an hydrologically based method of surface discontinuities along slope profiles and the second being an apporach of aggregating pixels to form homogeneous landunits.

The first approach is based on the System for Automatic Relief Analysis SARA (System for Automatic Relief Analysis) by Köthe and Lehmeier, (1993), Köthe, Gehrt, and Böhner (1996), Böhner, Köthe, and Trachinow (1997). Using surface characteristics such as curvature discontinuities along slope profiles, the algorithm decomposes the continuous landscape into patches or elements of hydrological meaning. Combining plan and profile curvature three basic landform types are derived as spatial units of equal hydrological or geomorphological characteristics: these are depressions, intermediate areas and vertices. For further information on algorithms and implemented tools, see references mentioned earlier.

The second landform classification schemes is based on an approach developed by Dikau (1988): plan and profile curvature are combined to form a set of basic landform elements. For this purpose, thresholds of curvature radii are defined, delineating concave, straight and convex areas in both directions of profile or plan curvature. Combining the two-dimensional landform element matrix results in $3\times3=9$ basic form elements. For further reference, see Dikau (1988), Dikau, Braab, Mark, and Pike, (1995), Dikau and Schmidt, (1999).

Using these procedures the landscape is classified into three and nine landform objects, respectively, to be compared with spatial patterns of vegetation classes.

4. Methods

4.1. Remote sensing data, vegetation data and derived maps

Signatures were extracted for supervised classification using the maximum likelihood algorithm with subsequent fuzzy convolution of Landsat and LISS data. The fuzzy convolution operation creates a single classification layer by calculating the total weighted inverse distance of all the classes in a window of pixels and assigning the centre pixel the class with the largest total inverse distance summed over the entire set of fuzzy classification layers. This has the effect of creating a context-based classification to reduce the speckle effects in the classification. Classes with a very small distance values, computed during maximum likelihood classification remain unchanged while classes with higher distance values may change to a neighbouring value if there is a sufficient number of neighbouring pixels with class values and small corresponding distance values.

Special problems during the classification arose from illumination effects and topographic shading in the sensor data due to high mountain topography. Using an irradiation model based on an approach by Parlow (1986), including anisotropy and further developed by Schmidt (2001), bandwise topographic normalisation was performed. This model made use of the DEM25, deriving additional layers (slope, aspect, horizon, sky view factor) for the calculation of a topographic correction matrix. Accuracy of training samples and classification results were increased by topographic correction.

Bands used in the classification were partly original bands, vegetation indices (NDVI, NDGI, Tasselled Cap Greenness Index), multitemporal differences of indices, but also texture bands including variance and semi-variogram analysis [a method developed by Chica-Olmo and Abarca-Hernandez (2000) for classification of Landsat TM data].

4.2. Analysis of correlation between vegetation and landform

The analysis of correlation between vegetation types and landform characteristics was performed using GIS summarising and filtering tools as well as Principal Components Analysis implemented in Erdas Imagine for basic applications and additionally the Professional Statistics Software (SPLUS) for further analysis. Three major steps were performed within statistical analysis.

4.2.1. Qualitative analysis

First, a visual interpretation of feature space characteristics, comparing scatter-plots vegetation-alliance-wise, was performed to get an idea of typical ranges of ecological and topographic variables. Additionally, for the landform classification elements, area-balancing diagrams were produced showing percentages of vegetation alliances within each landform element.

Qualitative analysis was performed by overlay and summary tools. For each 5-m pixel the relevant landform variable pixels of 25 m spatial resolution were extracted using moving window with a search radius of 5×5 pixels.

Analyses were performed for every landform variable with all vegetation classes: firstly the relations between single landform variables and vegetation classes were investigated, secondly more-dimensional relationships were focused.

4.2.2. Contingency tables

Then, the correlations were analysed statistically, using contingency tables, relating vegetation alliances to landform parameters and with aggregated landform elements. For the calculation of statistical correlations between vegetation and landform parameters the predictor and response variables have to be uniformly scaled. As the vegetation data are on the nominal scale (i.e. group names), the only appropriate method to analyse correlations is the contingency table for non-metric *factor* data. Thus the landform parameters had to be transferred into nominal data, therefore classes were used instead of raw values. Contingency tables are used to compare actual distributions with theoretical, i.e. normal distributions by means of χ^2-tests. The further apart these distributions are, i.e. the more some vegetation classes tend to cluster within certain landform variable categories, the higher the statistical correlation. The normalised contingency coefficient C is a measure of correlation between the two nominal-scaled variables. For further reference see Bahrenberg, Giese, and Nipper (1990), pp. 210, Franklin (1995), Lobo, Moloney, Chic, and Chiariello, (1998), Pinder, Kroh, White, and May, (1997), for mathematical background.

4.2.3. PCA

A further step conducted in the project were vegetation-alliance-wise Principal Components Analyses. The Principal Components Analysis (PCA) is commonly used to analyse redundancy within a set of variables, creating a set of substitute principal components by rotation and translation of the coordinate system. These principal components have related *eigenvalues* (representing the axis length, i.e. their importance within the new coordinate system). The eigenvalue represents the amount of variation within the original dataset that is explained by this component. The *eigenmatrix* shows correlations between the original variables and the principal components. PCA is often used as a method of data compression. It allows redundant data to be compacted into fewer bands; that is, the dimensionality of the data is reduced. The bands of PCA data are non-correlated and independent, and are often more interpretable than the source data. Landform variables showing high correlation with the first principal components are likely to be most important for the relevant vegetation class.

5. Results and discussion

5.1. Remote sensing data, vegetation data and derived maps

Classification of satellite sensor data resulted in the distinction of 20 vegetation alliances and/or vegetation formations on the basis of sensor data (see Table 3 for classes) with an overall kappa coefficient of 0.86, indicating accurate classification results compared to the kappa ranking schemes given by Landis and Koch (1977), Monsured and Leemans (1992).

Average classification accuracy based on 200 validation points amounts to 77% with 11% standard deviation, the confusion matrix in Table 4 showing class accuracies.

Best classification results are obtained for spectrally distinct classes like snow or rock with 96 and 83%, respectively. Highest inaccuracies were caused by steppe grassland, alder bushes, deciduous forest and debris; for example, only 63% of steppe grassland are correctly classified, the remaining 37% are classified either as montane oak forest or as alpine grassland, resulting from the low spatial resolution of the sensor data, causing many pixels with mixed spectral characteristics in areas with overlapping classes.

Interpreting the confusion matrix one has to keep in mind that percentages express the amount to which vegetation types have been classified correctly (true positive). Commission errors, meaning a pixel has been classified as being class A although not being class A, are not expressed here. Comparing satellite based dwarf shrub areas to the aerial photograph-based map, for example, shows that

Table 3
Classes specifiable by the satellite based classification

1	Water	11	Mixed Deciduous forest
2	Ice, Snow	12	Subalpine coniferous forest, *Vaccinio-Piceion/Larici Pinetum cembrae*
3	Debris, *Androsacion vandelii*	13	Scattered coniferous forest
4	Rocks, *Androsacion alpinae*	14	Montane coniferous forest, *Abieti-Piceion*
5	Steppe, *Stipo-Poion*	15	Montane oak forest, *Quercion pubescenti-petraeae*
6	Subalpine meadow, *Polygono-Trisetion*	16	Montane scotch pine forest, *Ononido-Pinion*
7	(Sub)alpine pasture, *Nardion strictae*	17	Forest clearing
8	Alpine Grassland, *Caricion curvulae*	18	(Alder) bushes, *Alnenion viridis*
9	Dry Dwarf shrub, *Juniperion nanae*	19	Arable land, Viniculture
10	Moist Dwarf shrub, *Rhododendro-Vaccinion*	20	Infrastructure, urban area

Table 4
Confusion matrix of satellite classification versus validation points

Classification	Validation points															
	Snow	Water	Steppe	Montane oak forest	Sub-alpine meadow	(Alder) bushes	Deciduous forest	Mixed forest	Sub-alpine Coniferous forest dense	Sub-alpine Coniferous forest	Dwarf shrubs	Alpine pasture	Alpine grass-land	Pioneer-species on debris	Debris	Rock
Snow	*96*	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water	1	*77*	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Steppe	0	0	*63*	11	0	0	0	0	0	0	0	2	0	0	0	0
Montane oak forest	0	0	18	*89*	0	0	0	1	0	2	0	0	0	0	0	0
Sub-alpine pasture	0	0	0	0	*82*	0	0	0	0	0	0	0	0	0	0	0
(Alder) bushes	0	0	0	0	3	*56*	2	1	0	1	0	0	0	0	0	0
Deciduous forest	0	0	0	0	2	29	*67*	4	1	7	0	0	0	0	0	0
Mixed forest	0	0	0	0	2	0	12	*79*	7	1	0	0	0	0	0	0
Sub-alpine Coniferous forest (dense)	0	0	0	0	0	0	1	11	*81*	8	0	0	0	0	0	0
Sub-alpine Coniferous forest	0	0	0	0	0	7	13	3	8	*69*	1	0	0	0	0	0
Dwarf shrubs	0	0	0	0	2	8	5	1	3	12	*94*	9	9	3	0	0
Alpine pasture	0	0	7	0	9	0	0	0	0	0	5	*77*	8	0	3	0
Alpine grassland	0	4	12	0	0	0	0	0	0	0	0	12	*81*	9	28	13
Pioneer-species on debris	0	3	0	0	0	0	0	0	0	0	0	0	1	*76*	3	1
Debris	0	11	0	0	0	0	0	0	0	0	0	0	1	12	*61*	3
Rock	3	2	0	0	0	0	0	0	0	0	0	0	0	0	5	*83*
SUM	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*	*100*

dwarf shrubs are overestimated extremely by the satellite classification routine. According to the confusion matrix, areas covered with dwarf shrubs are classified correctly by 94%; nevertheless this class is in spectral confusion with (sub)alpine pasture, alder bushes, mixed and deciduous forest as well as scattered coniferous forest as can be derived from the matrix. Comparison of real spatial extent with classification results show that dwarf shrubs are being overestimated by 200%, causing high commission errors and being responsible for much of the overall classification inaccuracy. Similar tendencies towards overestimation caused by spectral interference with debris and rocks can be shown for alpine grassland *Caricion curvulae*.

Besides montane oak forests being classified correctly by 89%, sub-alpine coniferous forests and sub-alpine pastures are classified rather well (89% and 82%, respectively) and comparison of real and classified areas supports these findings.

Although satellite classification results are rather good, the use of validation points for accuracy assessment is not uncritical, because errors tend to cluster and thus are not equally distributed throughout the area (compare (Campbell, 1981; Congalton, 1988; Goodchild, 1994, S. 621)). Nevertheless satellite classification is capable of differentiating classes on the basis of second level sub-formations and third-level vegetation types. It can also be shown that vegetation alliances are distinguishable using low spatial resolution sensor data; however, that only applies for alliances covering large areas like montane oak forests. Alliances that are characterised by a high degree of habitat fragmentation can not be distinguished using sensor data and related techniques.

For the high spatial resolution analysis different approaches were made integrating aerial photographs and field data. In addition to automatic classification procedures for the extraction of meadows, arable land, debris and rock area and several alpine alliances based on their spectral characteristics in the CIR-orthophotos, different texture analysis tools were used. A pattern recognition approach developed at the German Remote Sensing Data Centre was implemented for forest and tree extraction. The kernel-based differentiating and texture-comparison algorithm can be used to extract high accuracy tree positions using a local maximum filter comparing the texture of a defined sample with pixels along each aerial photograph, assigning tree positions where differences between kernel and underlying pixels are lower than specified threshold values (see also (Wulder, Niemann, & Goodenough, 2000) for a similar approach). An example of a tree mask is shown in Fig. 2: large trees can be extracted rather well, whereas smaller trees and bushes (like on the lower left margin of the aerial photograph to the left) are not captured by the kernel used; therefore iterative computation is needed using differently sized kernels. This algorithm is extremely useful for monitoring the partial decline and the abandonment of agricultural sites on unfavourably situated areas such as steep slopes due to changing socio-economic conditions based on agricultural policy trends. The area and size of bushes and trees on formerly intensively meadowed areas can be taken as an indicator for the degree and time scale of abandonment in change detection studies.

Using high spatial resolution aerial photographs makes it even possible to distinguish between different tree species. Thus, for the high spatial resolution

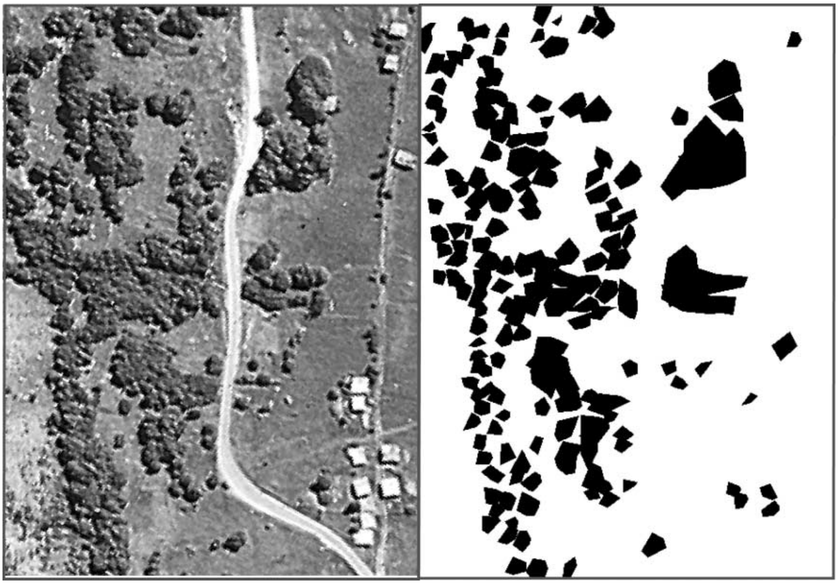

Fig. 2. Pattern recognition for tree extraction: aerial photograph (left) and resulting tree mask (right).

vegetation map, supported by field data, five forest alliances at two density levels were extracted.

Mapping the dwarf shrub areas was done using different approaches, one being a segmentation approach, followed by an object-based classification. Advantages of the object-based technique arose especially for indication of single dwarf shrub plants and agglomerations of species such as *Juniperus communis* ssp. *nana* at their upper elevation limit. The extraction of nearly circular patches of dwarf shrubs is simplified in the object-based approach by the integration of object shape, compactness, texture and context/topology besides their raw spectral characteristics of traditional per-pixel classification. Analogue to tree extraction in the sub-alpine zone, the distinction of dwarf shrubs in the alpine zone can be used to indicate the decline of grazing intensities and livestock numbers.

The two vegetation maps resulting from classification of low and high spatial resolution remotely sensed data had 25 m spatial resolution, discriminating 20 vegetation classes and 5 m spatial resolution using a majority filtering technique with 52 vegetation classes, respectively.

Vegetation data were analysed quantitatively and statistically using the DEM25 and derived data. For reasons of clarity and in order to avoid redundancy, only the analysis using the high spatial resolution (5 m) vegetation map will be discussed later. A further reason for choosing the high spatial resolution map for statistical analysis is that because of higher thematic resolution it is possible to derive much more ecological information than from the satellite-based approach. Results from the correlation analysis between satellite-based classes and the DEM25 and related scale issues will therefore not be discussed in this paper.

5.2. Analysis of correlation between vegetation and landform

An example of each step within the statistical analysis will be shown later and where applicable, mainly concentrating on the forest classes of the *Larici-Pinetum cembrae* (Larch-Arolla Pine forest) and on montane oak forest (*Quercion pubescenti-petraeae*).

5.2.1. Qualitative analysis I—vegetation alliances and landform parameters

First of all elevation and aerial extent of vegetation types will be discussed. The distribution of 12 vegetation classes (partly grouped with similar ecological classes) can be seen in Fig. 3.

On the one hand there are distinct changes in class areas from left to right, meaning with increasing elevation. On the other hand and even more interesting there are great differences in vertical direction, comparing the three valleys. These differences between the valleys tend to balance with increasing elevation, thus causing minor distinctions from the upper sub-alpine level upward. Remaining differences are due to effects of rising continentality and mass effects towards the south (Turtmanntal).

It can be derived from major differences within the lower elevation that human impact is highly variable among the valleys, being highest in the northern Lötschental. Another indicator for less natural vegetation classes and strong human interference is the high number of classes in the Lötschental compared with the Turtmanntal on the montane and lower sub-alpine level: whereas vegetation types are rather near to climax vegetation types within large areas of the Turtmanntal

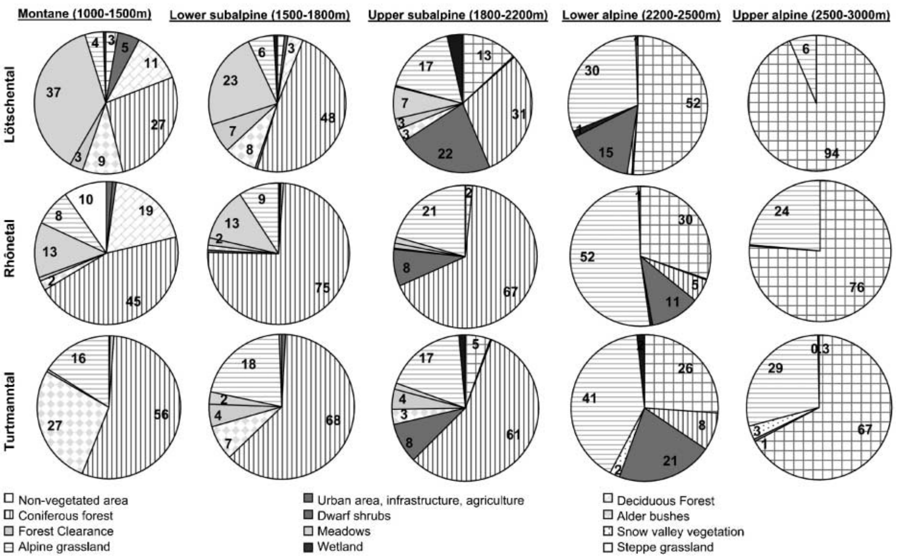

Fig. 3. Elevation distribution of vegetation classes.

even at lower elevations, vegetation classes in the Lötschental are replacement vegetation types far away from natural up to the upper sub-alpine level.

Montane meadows make up for 37% of the Lötschental montane elevation level, together with forest area it makes up for 65% of the area and even on the elevation level between 1500 and 1800 m it covers 23% in contrast to 13% and 2% within the other valleys. In contrast to that, 64% of the Rhônetal montane elevation zone and 56% within the Turtmanntal are covered with forest. Maximum forest coverage is reached here in the sub-alpine zone, reaching values of 61–75% forest coverage, whereas equivalents for the Lötschental only reach 48%. Apart from areas with high geomorphological process activity where avalanche forests still remain, all other forest areas have been cut in the Lötschental during the last centuries.

In addition to analyses concerning merely elevation zones, it is common in vegetation ecology to characterise habitat conditions for vegetation types using elevation-aspect diagrams, the so-called ecograms (Brzeziecki, Kienast, & Wildi, 1993; Ott, Frehner, Frey, & Lüscher, 1997; Wohlgemuth, Schutz, Keller, & Wildi, 1999). Ecograms were computed for all vegetation types, an example of montane oak forest is given in Fig. 4. It shows that montane oaks (*Quercus pubescens*) grow at elevations between 600 and 1400 m, being restricted mainly to southerly aspects. From that we can derive that *Quercion pubescenti-petraeae* needs high irradiation zones, which can only be found in the lower parts of the Rhônetal at southerly directions. Some data points are also found at southeasterly and southwesterly directions, but at lower elevations and with much lower frequency. Thus with a data cluster at southern to south westerly aspects the Quercion-habitat is well defined and distinguishable from other vegetation types.

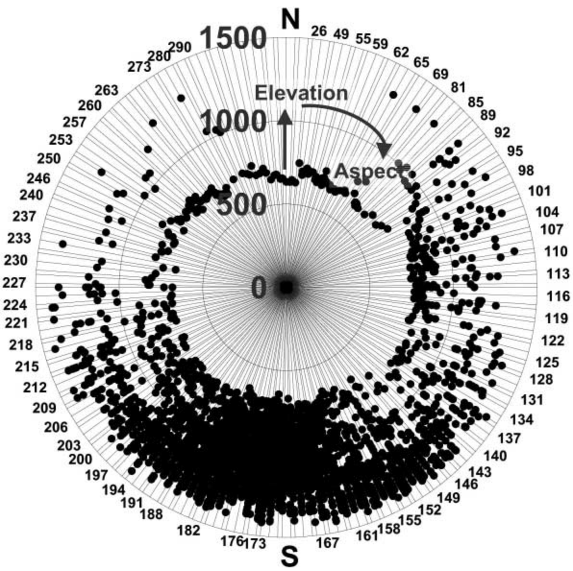

Fig. 4. Ecogram of montane oak forest.

Another example from three different forest classes can be seen in Fig. 5, showing that *Larici-Pinetum cembrae* (upper zone rectangles) occurs at altitudes above 1800 m and below 2400 m, thus forming the upper tree-line in the area of research. Within this narrow band, aspect seems to be of some importance, as this forest type occurs on all aspects apart from southerly directions. This effect could be due to ecological restrictions on south-facing slopes. But the lack of *Pinus cembra* at south facing slopes is not caused naturally, it has to be explained taking into consideration the anthropogenic impact factor. The south facing slope in the Lötschental has been used most intensively for mountain pasture in the past. The tree-line was brought down and *Pinus cembra* was used for firewood or building purposes. Thus, despite the actual situation, the south facing slopes are potential habitats for *Larici-Pinetum cembrae*. This shows one problem present in the analyses. As the human factor is hard to assess and to quantify, it can cause false conclusions. But these conclusions have to keep in mind general habitat rules for the vegetation alliances and the human factor was kept in mind during the analysis. As it is not the aim of this project to accurately model each pixel of occurrence but to analyse capabilities of DEMs for explanation of vegetation habitats, the lack of information on recent and historic human activities can be considered as a minor problem to it.

The rhombus signature cluster in the lower middle again shows habitats of *Quercion pubescentis-petraeae* for comparison. The third forest type (triangle signature spread through the ecogram space) does not seem to correlate with either elevation or aspect. This can be explained by the ecological requirements of *Alnus incana*, which is restricted to areas with high groundwater levels.

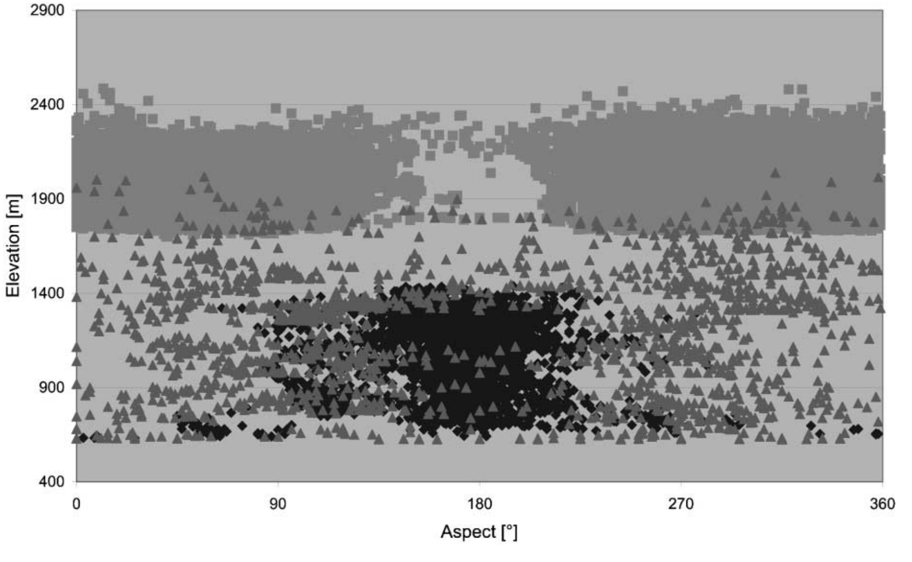

Fig. 5. Two-dimensional habitat analysis of three forest types (rectangles = Larch-Arolla Pine Forest; rhombs = Oak Forest; triangles = Floodplain Forest).

From a multidimensional scatterogram matrix, where every landform parameter is plotted against each of the other parameters, it appears that for *Larici-Pinetum cembrae* elevation and radiation are major influence factors, as all other variables do not show distinct habitat conditions but large amplitudes.

5.2.2. Qualitative analysis II—vegetation alliances and landform elements

The distribution of vegetation alliances and landform elements have been analysed using cross tabulations. Results derived for the three elements-scheme by SARA are shown in Fig. 6.

It appears that seven classes highly correlate with depression zones. Classes 12 (*Abieti-Piceion*, coniferous forest), 18 (*Alnenion viridis*, green alder bushes), 20 (*Alnion incanae*, black alder trees), 28 (*Caricion fuscae/Filipendulion*, wetlands), 31 (*Agrostion*, grass present in gullies), 33 (*Salicion herbaceae*, snow valley vegetation on siliceous rocks), 35 (*Adenostylion alliariae*, tall forbs near water lines) and 49 (*Arabidion caerulae*, snow valley vegetation on calcareous rocks) show coverages between 50% and 75% within the depression category of SARA. Class 18 are dense green alder bushes, which grow along the water lines and on debris/areas of mudslide material. These bushes grow where the soil moisture is very high, but the most important reason for them to grow within this category is that it does not only represent areas of high soil moisture but also areas of high geomorphological activity. Rockfall, mudslides and avalanches keep terminating succession processes, so that only alder bushes can grow there, as they are indifferent towards these processes.

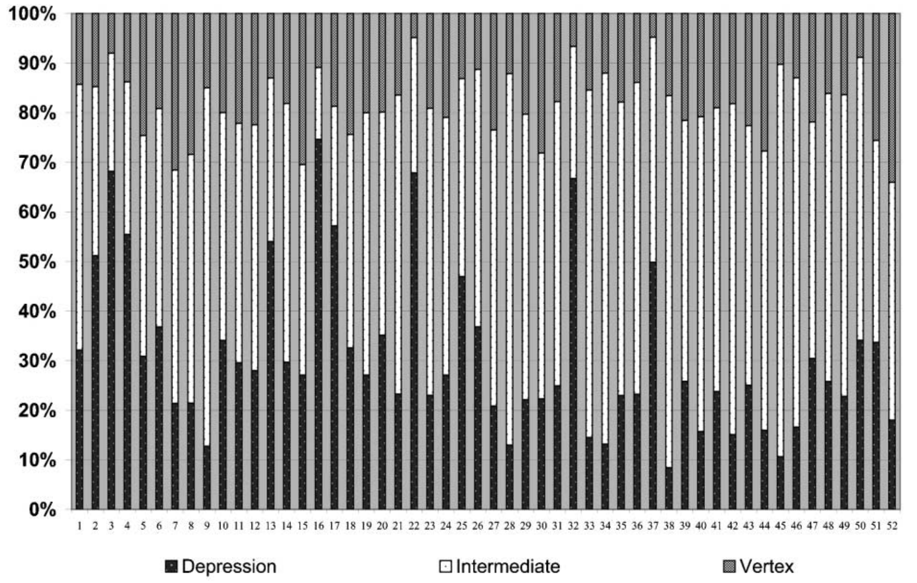

Fig. 6. Percentage of vegetation alliances within the three basic landform elements derived by SARA. (Numbers on the x-axis are numbers of vegetation alliances).

The same applies to class 31, which is a certain type of grass occurring in depression zones of high landslide potential, not necessarily requiring a lot of water.

Classes 20, 28 and 35 only grow where the amount of groundwater is high, so for them SARA-category "depression" is an indicator of good moisture supply. Classes 33 and 49 are counterparts for siliceous and calcareous rocks and occur in high-alpine depression zones, where the snow-free period is below 3 months. During these 3 months, the soil is mostly very wet.

Summarising the results reported earlier it seems that potential habitats for these seven classes can be derived well from the DEM using the SARA 3-categories algorithm. Errors and uncertainties that can occur for these classes and which probably also apply for other classes are caused by scale issues. It occurs in the diagram that all classes are present in all three categories. This is due to two reasons. First of all not every habitat structure and its spatial pattern respond to hydrological features, so that they occur in all three categories. The second reason is that there is a scale gap between the vegetation data and the DEM spatial resolution. The vegetation data have been mapped and classified on the basis of 1–2.5 m spatial resolution aerial photographs and have been rearranged to 5 m spatial resolution. Field campaigns also used that level of detail. The DEM with 25 m spatial resolution is probably not capable of indicating minor depression areas which occur at scales lower than 50 m in diameter. For this reason not all depression zones of the landscape are represented in the structure of the DEM.

Results from the second landform classification scheme were similar to those mentioned earlier, the additional six classes to not yield any additional information: on the contrary nine landform classes made the interpretation even more difficult. Basically the amount of intermediate areas was very high for all vegetation classes, reaching an average of 56%. On the one hand this could be due to choosing the wrong curvature radii thresholds for landform classification. But on the other hand, and more probable, this again shows therefore poor indication potential caused by low spatial resolution of the DEM25. Like in the SARA approach, vegetation alliances responding to high soil moisture can be extracted.

Summarising results shows that recent landform classification schemes are of little use for habitat indication of most vegetation classes. Nevertheless it can be used to pre-stratify research areas for potential habitats of vegetation types requiring high soil moisture. Inquiring effects of higher spatial resolution DEMs will surely lead to better results.

5.3. Contingency tables

Results for the correlation of the whole vegetation dataset and for the *Larici-Pinetum cembrae* subset with six landform parameters can be seen in Table 5. These parameters are (1) elevation-classes at 100 m intervals; (2) elevation-classes at seven major elevation intervals which have been created according to the commonly used vegetation altitudinal zones colline to nival; (3) slope; (4) eight major slope classes; (5) eight major aspect classes plus flat areas; (6) radiation classes at 1000 W intervals.

Table 5
Contingency coefficients (C) for the whole dataset and for the *Larci-Pinetum cembrae* and the *Quercion pubescenti-petraeae*

	Contingency	Whole	*Larici-Pinetum cembrae*	*Quercion pubescenti-petraeae*
1	Dem100	0.88	0.53	0.58
2	Dem7	0.89	0.51	0.57
3	Slope	0.67	0.19	0.23
4	Slope8	0.66	0.16	0.21
5	Asp9	0.68	0.23	0.59
6	Rad1000	0.67	0.45	0.53

Results for the complete dataset show that nearly all of the landform parameters are highly correlated with the vegetation data, C values ranging from 0.67 to 0.89. Elevation seems to have the strongest influence on the dataset as a whole, as the 100 m classes and also the seven classes reach values of 0.88 and 0.89, respectively. Slope, aspect and radiation, either categorised (slope8class, aspect9class, rad) or raw data used as classes (slope) show moderate to high correlations with values between 0.66 and 0.68.

For the *Larici-Pinetum cembrae* C values are much lower, generally only the two elevation variables show values greater than 0.50. Radiation seems to be of some importance, too. The overall low values could be due to the dichotomous dimensionality of the vegetation data. For statistical reasons, all other vegetation units had to be set to zero and only *Larici-Pinetum cembrae* was set to one so that the vegetation variable is only dichotomous. This lower dimensionality together with the fact that the *Larici-Pinetum cembrae* sample is much smaller than the rest of the population (i.e. the zero values) might lead to lower significance and coefficients.

For the *Quercion pubescenti-petraeae* C values clearly show dependencies from elevation, aspect and radiation, but are similarly low for the coniferous forest. Thus, the contingency tabulation might not be the optimal statistical process. Therefore the PCA was performed in addition.

5.4. PCA

Results of the PCA for the complete dataset are shown in Table 6. The eigenvalues, i.e. the cumulative variance explained by the components is equally distributed over several principal components, which shows that there is not much redundancy in the landform dataset as it is of high dimensionality and has to be represented by many principal components. About eight principal components are necessary for an explanatory amount of 80%. The correlations on the right side of the table also support these findings. There is no landform parameter showing very high correlation with one of the components. Thus, we can conclude that nearly all landform variables are equally important for the vegetation dataset as a whole; maybe only the DEM being of some more importance, reaching correlation coefficients of 0.42 for the first component and 0.61 for pca5.

Table 6
Cumualtive eigenvaules (left) and "Eigenmatrix" (right) for the overall Principal Component Analysis (PCA)

PCA	Cumulative variance explanation	Parameter	pca1	pca2	pca3	pca4	pca5
pca1	20.71	dem	**0.42**	0.03	−0.19	−0.02	**0.61**
pca2	34.83	slope	0.04	**0.47**	−0.16	0.13	0.29
pca3	46.51	aspvalcos	0.01	0.24	**0.51**	−0.03	−0.36
pca4	54.96	aspvalsin	−0.03	−0.16	−0.36	0.06	**−0.46**
pca5	61.40	plancurv	**0.37**	−0.09	0.07	0.33	0.00
pca6	67.78	procurv	0.28	−0.10	0.06	**0.47**	−0.01
pca7	73.94	floacc	−0.09	−0.20	0.20	−0.04	0.30
pca8	79.83	wdm	−0.39	−0.10	−0.03	0.27	−0.03
pca9	84.95	wdminv	0.31	−0.04	0.10	0.14	0.10
pca10	89.29	Mind-floac	−0.17	**−0.40**	0.31	−0.01	0.25
pca11	92.71	Mind-wdm	−0.18	**−0.45**	0.27	0.03	0.09
pca12	95.39	demsd	0.03	0.08	−0.01	−0.40	0.14
pca13	97.47	act-ind	**−0.37**	0.26	−0.11	0.38	0.14
pca14	99.04	topo5	**0.35**	−0.10	0.05	0.34	0.02
pca15	100.00	rad	−0.01	−0.41	**−0.55**	−0.02	−0.04

While principal components generally reduce the dimension of the spatial dataset they represent, it is not quite clear in the present case what the components represents ecologically. The first component relates to elevation and to plan curvature, but also to the activity and roughness indices. The second component seems to represent some sort of moisture, being influenced by two moisture indices and slope which is directly related to soil moisture. The third component is clearly related to aspect, while the fourth represents topographic curvature. The fifth component combines elevation and east–west aspect contrasts.

For the *Larici-Pinetum cembrae* (Table 7) about four principal components explain over 80% of the landform data subset. High correlations occur within the first principal component for elevation, the sine-transformed aspect-value and for the radiation variable with values between 0.54 and 0.58. This partly supports the results of the scatterogram and the contingency table (Table 5), which showed correlations between this vegetation type, elevation and radiation. In addition to the contingency table aspect seems to have quite some influence on this type of coniferous forest with correlations in the eigenmatrix (Table 7) between 0.55 and 0.59. Also the profile curvature is of some importance for the 4th and 5th principal component. Therefore it can be concluded that for the Arolla Pine-Larch forest a certain range of elevation on distinct aspects are important. Keeping in mind results from Fig. 5 it seems that human clearcuts of southerly exposed *Larici-Pinetum cembrae* leads to a high importance of aspect variables and radiation. Again, there is no natural cause for that as ecologically this forest type is independent from aspect angles.

In contrast to the examples shown earlier there are high relations between montane oak forest *Quercion pubescenti-petraeae* (see table 8) and elevation (0.73), aspect

Table 7
Cumulative eigenvaules (left) and "Eigenmatrix" (right) for the *Larici-Pinetum cembra*-based Principal Component Analysis (PCA)

PCA	Cumulative variance explanation	Parameter	pca1	pca2	pca3	pca4	pca5
pca1	25.75	dem	**0.58**	0.22	−0.01	−0.29	0.05
pca2	49.27	slope	−0.29	−0.10	−0.02	0.31	−0.52
pca3	71.00	aspvalcos	−0.17	**−0.46**	**0.51**	−0.34	0.16
pca4	79.58	aspvalsin	**0.55**	−0.30	**0.59**	0.24	−0.20
pca5	85.93	plancurv	−0.21	0.30	0.32	0.33	0.16
pca6	91.35	procurv	−0.11	0.18	0.19	**0.46**	**0.47**
pca7	94.43	floacc	0.03	0.01	−0.01	−0.02	0.02
pca8	97.04	wdm	0.20	−0.19	−0.20	0.06	0.38
pca9	98.33	wdminv	−0.19	0.23	0.23	−0.23	0.23
pca10	99.37	mind-floac	0.09	0.01	−0.03	−0.07	0.09
pca11	99.62	mind-wdm	0.16	0.05	−0.02	−0.13	0.16
pca12	99.82	demsd	0.02	0.02	0.00	−0.01	−0.03
pca13	99.93	act-ind	−0.13	−0.31	−0.17	0.34	−0.06
pca14	99.97	topo5	−0.17	0.23	0.23	0.12	0.03
pca15	100.00	rad	**0.54**	0.26	−0.08	0.28	−0.01

(0.42) and radiation (0.83). The first component is a combination of elevation and radiation, thus relating somehow to a certain temperature range, whereas the second and also the third represent a soil moisture component. The last two components again stress the meaning of aspect for the oak forest.

Comparison of results show that PCA seems to be a useful tool for analysing the relation between landform variables and vegetation classes. Although it has been used for similar analyses (Butler & Walsh, 1994), interpretation of the sometimes rather abstract components ecologically is not an easy task. Nevertheless it provides some insight into habitat conditions for different forest types that can easily be transfered into ecological modelling (Table 8).

6. Conclusions

Within the project it was possible to develop a hierarchical mapping scheme for vegetation mapping in an alpine landscape that could commonly be used for the satellite, aerial photographs and field data based approaches. It rests upon syntaxonomic vegetation alliances and thus integrates geobotanic requirements.

On the basis of this hierarchical classification scheme two vegetation maps were developed. The 25 m spatial resolution satellite based map differentiates 20 classes, even reaching down to the lowest classification level of vegetation alliances. The second map results from different classification and segmentation algorithms applied to aerial photographs and field data; 52 vegetation alliances are distinguishable on a scale of 5 m.

Table 8
Cumulative eigenvaules (left) and "Eigenmatrix" (right) for the *Quercion pubescenti-petraeae*-based Prinicipal Component Analysis (PCA)

PCA	Cumulative variance explanation	Parameter	pca1	pca2	pca3	pca4	pca5
pca1	68.91	dem	**0.73**	−0.11	−0.04	−0.06	0.03
pca2	82.25	slope	−0.13	0.03	**0.66**	**−0.62**	−0.35
pca3	87.15	aspvalcos	**−0.42**	−0.07	−0.01	**−0.40**	0.39
pca4	91.02	aspvalsin	−0.30	−0.01	0.06	−0.30	**0.77**
pca5	93.20	plancurv	0.01	**0.41**	−0.31	−0.13	0.08
pca6	95.01	procurv	−0.01	0.32	**−0.72**	−0.20	−0.11
pca7	96.72	floacc	0.02	−0.02	−0.03	0.02	0.01
pca8	98.03	wdm	−0.07	**−0.47**	**−0.45**	0.22	0.10
pca9	99.12	wdminv	0.01	0.26	−0.01	0.29	0.25
pca10	99.66	mind-floac	0.04	−0.07	−0.05	0.05	0.01
pca11	99.83	mind-wdm	0.08	−0.05	−0.07	0.14	0.09
pca12	99.93	demsd	0.02	0.00	0.01	−0.05	−0.03
pca13	99.96	act-ind	−0.19	−0.26	−0.08	−0.37	−0.15
pca14	99.99	topo5	−0.03	0.36	−0.14	0.06	0.01
pca15	100.00	rad	**0.83**	0.05	0.06	0.08	0.06

For the landform analysis, 15 different landform parameters (amounting to 23 variables including similar and aggregated variables) were derived from the 25 m spatial resolution DEM, including slope, aspect, moisture parameters, process related parameters, radiation, etc. The set of landform parameters tries to represent as many facets of the natural habitat as possible, related to climate, wind, snow, moisture and disturbance. Additionally three landform classification schemes were applied, subdividing the continuous landscape into smallest homogeneous landscape units.

All remotely sensed data, DEM data, field measurements and maps were integrated into a GIS with spatial resolutions of 5 and 25 m, respectively.

The statistical analysis made use of different GIS technologies such as cross tabulations, but also statistical procedures (correlations, PCA) besides visual interpretation of ecograms.

The spatial pattern of vegetation alliances in high mountain areas can be explained to a great extent through the use of landform parameters. For some vegetation classes, mainly for the azonal, not altitudinally dependent classes, landform classification schemes apply well and vegetation classes can be assigned distinctly to one or two characteristic landform elements (e.g. *Adenostylion alliariae, Alnenion viridis*, etc.). Especially the SARA classification algorithm proved to be useful for indication of moist habitats.

For the whole vegetation dataset nearly all of the landform parameters (elevation, slope, aspect, radiation, curvature, etc.) show high correlation with contingency coefficients ranging from 0.64 to 0.89. The PCA results show that in order to explain all of the variation within the original landform dataset there have to be about 8–9 principal components, so there is not much redundancy in the data, the data are high-dimensional. Thus, every landform parameter adds some more information to the explanation of vegetation alliances in the study area. Nevertheless, there is still some unexplained variation within the vegetation data, some spatial patterns cannot be explained to the full extent through the use of landform parameters, especially for the zonal, altitudinal vegetation classes. Other influence factors have to be kept in mind, especially the human factor, causing distinct spatial patterns that are somehow different from a natural pattern mainly for the montane and sub-alpine vegetation alliances. Even as there is no spatially explicit information on the human dimension, landform characteristics derived from a DEM are capable of explaining a great amount of the spatial variability of vegetation alliances within the study area.

From a methodological point of view, the PCA results generally show good agreement with the contingency tables, adding some more interesting information to the nominal-scale analysis of the first. For further validation purposes the use of spatial modes like classification and regression tree models (CART) or Generalized Linear Models (GLM) would be of great value.

Finally, scale was found to be an important factor for the analysis of vegetation habitats. As the vegetation map was produced based on high spatial resolution field and remotely sensed data, the DEM could not explain all of the variance within the dataset. This might partly be due to the fact that there is a scale gap between the map and the DEM. Only large topographic structures can be derived from the 25 m spatial resolution DEM, often not representing the fine scale variations in curvature and thus soil moisture or exposure towards wind and weather impacts.

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