LAND USE CLASSIFICATION IN COMPLEX TERRAIN: THE ROLE OF ANCILLARY KNOWLEDGE

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ABSTRACT

The strong impact of land use on the climatic and hydrological cycle necessitates a detailed knowledge of the land use/land cover for land surface modelling. Within the research project GLOWA-Danube a knowledge-based classification method is applied on optical remote sensing data. Two important facts have to be addressed in the classification procedure: The large size as well as the heterogeneity of the test site.

Seven LANDSAT TM and ETM+ images were acquired covering the entire catchment. Due to the strong influence of topography, all scenes were georeferenced to the DTM and corrected for atmospherical and illumination effects. A multisource and multistage classification procedure was developed, including a GIS knowledge base consisting of elevation and slope data, soil information and the mean annual precipitation distribution. Water, snow and clouds were masked separately using thresholds. Also the separate retrieval of settlements represents a further improvement to the methodology. This class often showed overlapping with open or sparsely vegetated soil, harvested grassland and mature cereals. The best results were obtained using the backscatter of a RADARSAT image, the NDVI and principal components derived from the LANDSAT images. The core algorithm is an enhanced knowledge-based fuzzy logic classifier. It includes, beside the spectral information, a physiogeographical knowledge base to assign a pixel to a class. The finally resulting land use map of the Upper Danube catchment consists of 27 classes. A critical point is the accuracy assessment. Although a comparison with census data on a community base gives a good estimation, pixel-bx-pixel or field-based accuracy assessments have to be conducted as well. But this can only be done for areas where reliable ground truth data are available.

Keywords: Upper Danube catchment, knowledge-based land use classification.

INTRODUCTION

The development of an integrated environmental decision support system is one of the major issues within the HGLOWA-Danube project. It will be able to simulate water-related issues of environmental management under ecological, economical and cultural aspects, such as flood risk and protection, agriculture and water quality and quantity. The coupled modelling of fluxes of water, energy and matter is a decisive part within the integrative model approach. GLOWA-Danube is funded by the German Federal Ministry for Education and Research (BMBF) and is concerned with integrative techniques, scenarios and strategies regarding the global change of the water cycle. It is aiming at the development and validation of the web-based Global Change Decision Support System DANUBIA (T1).

Land use and its small-scale changes have a significant influence on all fluxes, thus highly differentiated and up-to-date land use information is necessary for the modelling approach. Among available land use information, spatially distributed data sets like CORINE are available (2). These data are not based on up-to-date survey and the differentiation of cropland is rather limited, which are major drawbacks for flux modelling. The combination of optical remote sensing data with ancillary data layers and the application of advanced knowledge-based classification methods, provides valuable information for land use classifications. This approach has proven highly effective for classifying land use in heterogeneous areas in several studies (3,4,5,6,7). High resolution remote sensing data like LANDSAT-TM, combined with robust algorithms provide precise parameterisations for hydrological models. Commonly, these classification methods are applied on data of geographically homogeneous areas. Concerning the study area of GLOWA-Danube, two important facts have to be addressed in the classification procedure: The large size as well as the heterogeneity of the test site. Dealing with an area as large as the Upper Danube catchment, it was necessary to develop a time- and cost-efficient classification chain.

STUDY AREA AND DATA

The Upper Danube catchment

The Upper Danube river catchment is defined by the discharge gauge Achleiten near Passau, located downstream the inflow of the river Inn. It covers an area of about 77,000 km². The catchment is characterised by very strong relief intensity (altitudes range from 287 m near Passau to Piz Bernina 4,049 m asl), introducing tremendous physiogeographic and meteorological gradients (precipitation: 650 to >2,000 mm/a, annual mean temperature: -4.8 to +10.5°C). The study site can be divided into three ecologically homogeneous areas. The southern part spans from the Central Alps to the Alpine Foreland at a latitude south of Munich. Land use is conditioned by adverse climatic conditions in terms of high precipitation and low temperature. It is dominated by natural vegetation cover and grassland. Adjacent to the North an agriculturally intensively used upland area follows. The strongly differentiated land cover and land use are mostly determined by human impacts. In general, the intensity of land use follows a climatic and topographic gradient from the Alpine Foreland towards the Danube valley. Loess soils, sufficiently high temperatures and less summer precipitation facilitate the cultivation of crops like sugar beet, maize, rape seed and cereals. The world's largest hop production area is located there. North of the river Danube and east of the river Naab the agricultural favour decreases towards the rough mountainous areas of the Bavarian Forest.

A number of metropolitan areas are spread over the study site, the largest being Munich, Innsbruck, Augsburg, Regensburg and Salzburg. These areas are characterized by high-density urban, industrial, and residential land use. The total population in the study area sums up to more than 10 million inhabitants.

Data Set

The imagery used in this study consists of seven LANDSAT-5 TM and LANDSAT-7 ETM+ images of 1999 and 2000. The satellites totally cover the study site within 3 days (Figure 1). For the paths 194 and 193 excellent data are available from 18th and 19th June 2000. Unfortunately, cloud coverage is too high in all images of path 192 acquired in 2000. The best images available for this path date from 26th June 1999 for the northern, mainly agricultural cultivated area, and from 14th September 1999 for the southern, alpine part. The images acquired in June allow a good separation of most crops. The September image is suitable for classification as well, due to the mainly natural vegetation and the location in the Alps. A multitemporal image set is not available for the year 2000. The ancillary GIS data set consists of a 50 m resolution DEM, a digital soil map derived from the soil type map 1:1 Mio. of the German Federal Institute for Geosciences and Natural Resources and a map of mean annual precipitation distribution, interpolated from meteorological station data. The data were resampled to a 30 m pixel size and projected to UTM.

Pre-processing

The different acquisition dates and the strong relief intensity necessitate an exact radiometric and geometric pre-processing to convert the recorded digital numbers to corresponding reflectance values. In a first step a georeferencing module was applied on the seven scenes to rectify the images to the DTM mentioned above. The procedure developed by Itten & Meyer (8), and a second-order polynomial transformation were used to eliminate the relief displacement. Secondly, the elevation- and terrain-dependent radiometric influence of atmosphere and illumination was corrected. The atmospheric transfer model LOWTRAN 7 was used as input to the illumination correction model for rugged terrain, which calculates the irradiance on an inclined surface (3). The corrected scenes were composed to a final data set covering the entire study area. It contains 12,300 lines and 14,500 columns.

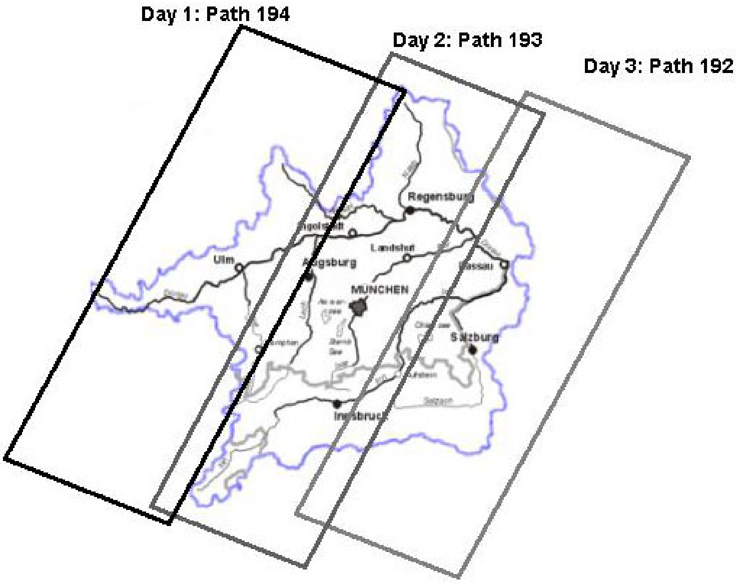

Figure 1: The coverage of LANDSAT 5 and 7 overlaying the boundaries of the Upper Danube catchment.

METHODOLOGY

Conventional multispectral classification methods only use the spectral response of objects. Especially in large and environmentally heterogeneous areas a major problem appears: objects of one and the same land use class exhibit significantly different spectral signatures, which are due to different phenological stages. This causes spectral confusion and thus classification errors.

The commonly used standard maximum-likelihood approach is only adequate for treating information from a normally-distributed single data source. It is ill-equipped to handle ancillary information. Therefore, in this work a multisource classification procedure was applied, utilising the data fusion and knowledge-base approach.

Due to the size and complexity of the area under study, a multistage classification procedure was developed, using several approaches to derive optimised sub-classifications. The results finally were stacked to produce an overall land use map.

Stratification and Training

Combining the GIS data set and the corrected LANDSAT scenes, the problem appeared that the resulting data stack would exceed the 2 GB file size limit of a 32 bit computer. This necessitated a partition of the data into manageable subsets. Furthermore, image analysis and a detailed analysis of the phenological development of different crops showed spectral dissimilarities within one and the same land use class. Therefore, the imagery was stratified into physiogeographically similar zones to avoid confusions between training area signatures across the region and thus improve final classification accuracies (6). Following the constraints “as large as possible” by file size and “as small as necessary” by physiogeographical factors, the area was divided into three regions:

- the Alps and the Alpine Foreland
- the uplands of Bavaria and Baden-Wuerttemberg and Austria including the Danube valley
- the north-eastern part (Bavarian and Oberpfalz Forest and the Naab catchment)

Figure 2 shows the differences in spectral signature of maize fields in the Alpine Foreland and in Loess plains south of the river Danube.

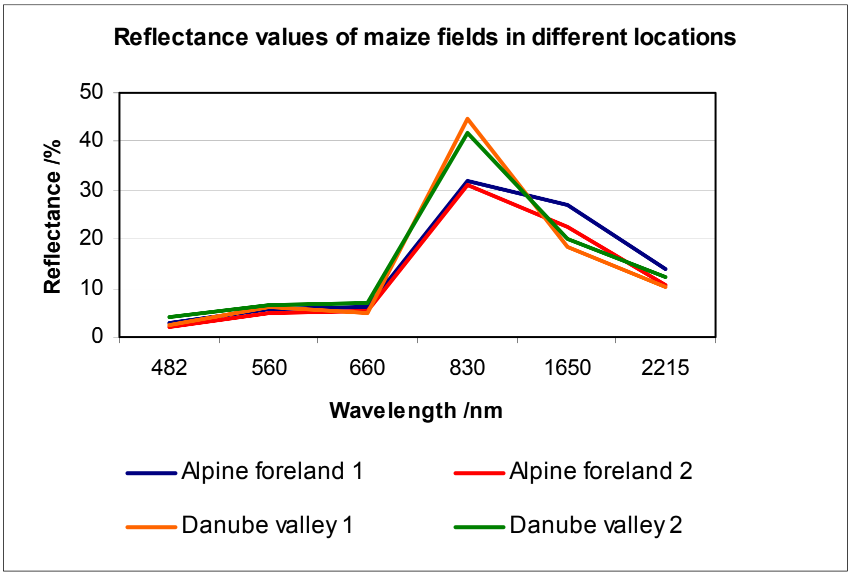

Figure 2: Comparison of the spectral signatures of maize in different areas.

Representative training data sets for most classes were defined separately for each stratum. Only for classes which are independent of phenology (settlement areas, gravel pits, rock etc.), or which show no significant phenological differences within the regions (forests, wetlands, meadows), one and the same spectral signature set could be applied on all subsets. The number of land use classes varies from subset to subset. In the alpine stratum, the highest number of classes has to be differentiated, because in addition to the agricultural classes, alpine vegetation (mountain pasture, dwarf pines, alpine tussock grass etc.) and rock have to be classified.

Masking

Prior to a classification procedure, it is advantageous to mask classes that can be separated easily by applying thresholds, and classes which lead to misclassifications. This reduces the number of training areas and therefore the possibility of misclassifications. The classes *water*, *cloud*, *snow* and *ice/glacier* were masked using threshold values in the LANDSAT bands 4 and 5.

A more complex problem is the classification of settlement areas. Including them into the regular classification procedure did not show satisfying results. In many areas they cannot be spectrally separated from bare soil, set-aside agricultural land, ripe winter barley fields and some of the wetland areas sophistically. Even using ancillary GIS data does not improve separability. To solve the problem, a data fusion approach has been developed to mask settlement areas. A threshold method was applied on a data set consisting of LANDSAT imagery, deduced image data (principal components, *NDVI*), and SAR data. Additionally the physiogeographical information *elevation* and *slope* was included. The key element was the incorporation of the SAR data. A snow-free, radiometrically and geometrically corrected and resampled RADARSAT scene from January 19th 1997 was used, which almost covers the entire study area. Settlement areas are well discriminable in this scene from agricultural land by their higher backscatter values. But to separate forested areas and settlements no definite threshold value could be determined. Thus, only including radar data does not show sufficient results. The best results were achieved by using the combined data set and a hierarchical threshold approach.

First attempts to mask settlement areas using CORINE data did not show satisfying results. Due to the spatial resolution, many of the small settlements do not show up in CORINE. But these areas are of great importance for hydrological modelling and thus for the GLOWA-Danube project. Figure 3 underlines the differences between the settlement areas derived by the threshold approach and the CORINE data. Already a visual comparison shows the underestimation in the CORINE data.

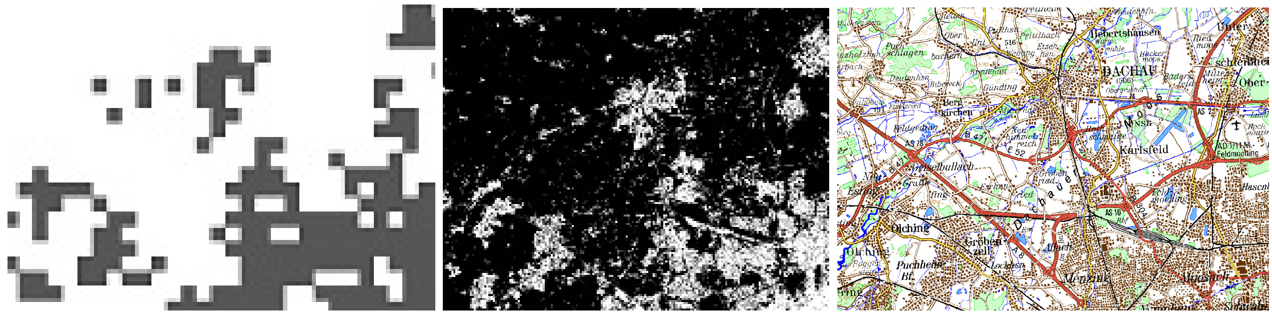

Figure 3: Comparison of the settlement areas in the CORINE data (left), the settlement mask (centre) and the topographical map (right) for an area north of the city of Munich.

The rule-based classifier ENPOC

The core of the multistage classification approach is a rule-based fuzzy logic classifier, combining the spectral information with ancillary data layers and a knowledge base. It is taking into account the probability of occurrence of a land use class in dependency on environmental factors such as slope, altitude, soil and climatic conditions (termed geofactors). The possibility of a specific land cover type varies with the geofactors, which influence their spatial distribution (4,7,9,10,11).

The ENPOC (ENvironmental POssibility Classifier) algorithm is an enhancement of a standard Maximum Likelihood Classifier (3,12). In addition to the classic procedure it is characterized by the possibility of integrating non-spectral data, which have significant impact on the land use distribution. A fuzzy geographical knowledge base is the key to multisource class separation.

The ENPOC-classifier is based on the ecological non-compensatory rule, which indicates that the most unacceptable factor has the strongest impact on the occurrence of a class (Figure 4) (13). From the ancillary GIS data, four geofactors were derived: the annual mean temperature (*el),* substituted by the elevation, the slope gradient (*sl*), the soil quality (*soil)* and the precipitation (*pr*). Using geographical and agricultural expert knowledge, a fuzzy set for each land use class concerning each geofactor is defined, containing membership functions (MF). For each geofactor, a MF expresses a pixel's degree of membership to a class. As an example, the MFs for the geofactor *elevation* are represented in Figure 4. The degree of membership (possibility) to a land use class is described on a scale from 0 (*not possible*) to 1 (*fully possible*).

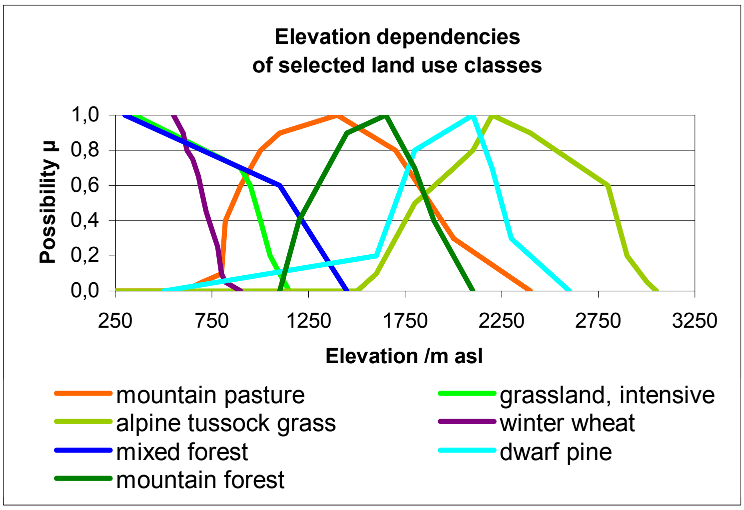

Figure 4: The membership functions elevation *for seven land use types.*

In the first classification step, the spectral possibilities μ_{sp} were derived by applying the Maximum Likelihood classifier to 6 spectral bands of the TM scenes. To obtain the spectral possibilities for each class, the spectral probabilities $p(X \cdot \omega_i)$ are standardised by the maximum probability of the classification of a pixel *x* (3). For each pixel only those classes are considered in the next steps, which show a possibility >0. At this stage, for each pixel an information source consisting of the spectral information, the geofactors, and the appropriate membership functions is available. To define the most possible class a pixel *x* belongs to, the local possibilities μ_{el}, μ_{sl}, μ_{soil} and μ_{pre} derived from the membership functions according to the topical values of each geofactor and the spectral possibilities μ_{sp} are combined by applying the rules of fuzzy logic information fusion.

According to the ecological non-compensatory rule the ENPOC algorithm calculates the overall possibility μ for each class and each pixel by applying the fuzzy intersection (Eq. 1) (13). The possibilities are equally weighted.

$$\mu(x) = \min\left(\mu_{sp}(x); \mu_{el}(x); \mu_{sl}; \mu_{soil}(x); \mu_{pre}(x)\right) \tag{1}$$

where $\mu_{el}(x)$, μ_{sl}, $\mu_{soil}(x)$ and $\mu_{pre}(x)$ are local possibilities of a class at pixel *x* for all sources (geofactors and spectral data), derived from membership functions and the spectral possibility, and μ is the overall possibility.

The fusion equation (Eq. 2) determines the final possibility measure Π_{total} (also called grade of membership *MG)* for a pixel *x* to belong to a class C_k (11). It is calculated by dividing the minimum possibility measure Π_s of a class *k* at a pixel *x* by the highest possibility measure a class achieves at that pixel:

$$MG = \prod_{total}\left(C_k \mid x\right) = \frac{\min\limits_{sources}\left[\prod_s\left(C_k \mid x\right)\right]}{\max\limits_{classes}\left\{\min\limits_{sources}\left[\prod_s\left(C_n \mid x\right)\right]\right\}} \tag{2}$$

where: $\prod_s\left(C_k \mid x\right)$: possibility measure a pixel belongs to a class k computed for a source s

$\prod_{total}\left(C_k \mid x\right)$: final possibility measure (=Grade of Membership *MG*)

Finally, defuzzification is carried out by applying a fuzzy MAXIMUM decision rule. The pixel is assigned to the class showing the highest Π_{total}. A pixel remains unclassified when two or more classes achieve the same value for Π_{total}.

Figure 5 exemplarily shows the procedure for four land use classes. Using only the spectral probability, the pixel would have been addressed as *barley*, because it is showing the highest spectral probability. Taking the geofactors and the membership functions into account and applying the fuzzy MINIMUM rule (Eq. 1), the class *barley* is now showing the lowest and the class *rock* the highest possibility. By applying Eq. 2, the resulting Π_{total} for the four classes are 0 (barley), 0.0625 (mountain forest), 0.25 (mountain pasture) and 1 (rock). According to the defuzzification rule, the pixel is now assigned to the class *rock*.

Multistage classification

Developing and testing the classification procedures, the following processing chain proved to be the most efficient:

- Radiometric and geometric correction
- Stratification of the data set into physiogeographic similar areas
- Registering of GIS with image data
- Separate masking of the classes *snow*, *ice*, *cloud* and *water* using thresholds
- Classifying settlement areas using a multisensoral data fusion method
- Classifying the data by applying the ENPOC-Classifier
- Merging of classification and masked classes
- Filtering the resulting classification map using a neighbourhood approach (3×3 postclassification filter).
- Merging the separately classified segments of the Upper Danube catchment to a final land use map.

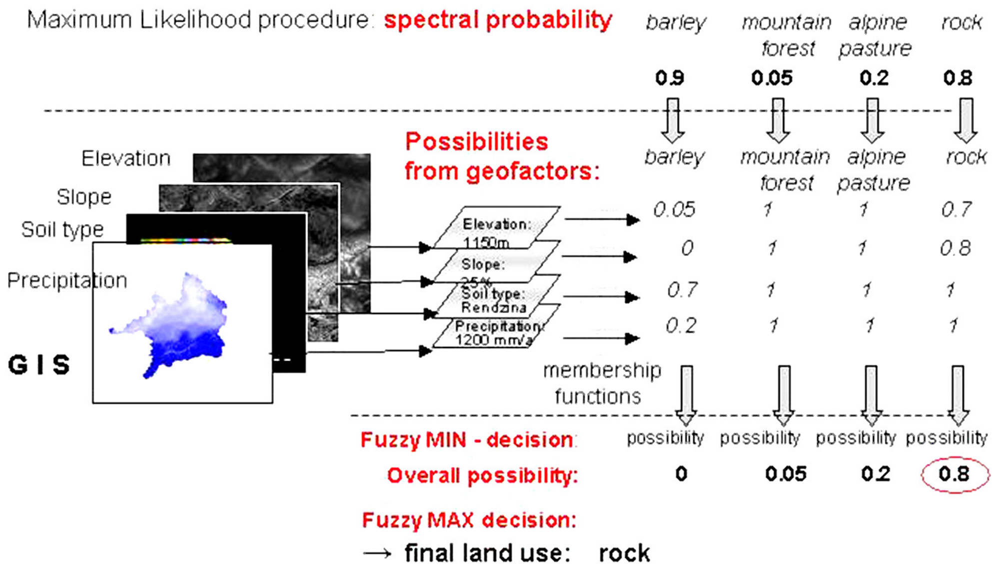

Figure 5: The ENPOC classification approach

RESULTS AND DISCUSSION

The multistage classification chain was applied to each data subset. The high amount of classes which can be detected is due to the favourable acquisition dates. In the study area the spectral signatures of many crops (but not all) and of natural vegetation cover can be differentiated best in a period between middle and end of June. This is of paramount importance for hydrological and energy flux modelling, because the transfer of energy and matter between groundwater, soil, vegetation and atmosphere is determined depending on the plant physiology and the different agricultural practice (i.e. fertilization). A hierarchical land use system was developed. It contains four levels with seven classes in the first, and 27 classes in the fourth level (Table 1). Figure 6 shows two examples of the classification result. The left one is located in the Central Alps displaying mainly natural vegetation classes, the right one shows an agriculturally intensively used area in the Lech valley south of the city of Augsburg. Validation and verification of the classification results are difficult due to the large size of the study area. It is a still ongoing process and is done in two steps:

- quality estimation (validation) by comparing the classification result with census data
- accuracy assessment for selected areas

In the following, two examples of validation are outlined. The quality estimation approach is discussed using an example of the eastern Bavarian upland area, an accuracy assessment is carried out in an area of the Alpine Foreland.

Quality estimation

For the State of Bavaria, which covers half of the study site, statistical data of the agricultural land use on a community basis are available. Although a pixel-by-pixel comparison is not feasible with these data, they provide an excellent basis for validation.

This validation, however, is constrained by the fact that some field data are not available due to data security and in some cases not all fields of a farm are located within the same community. Also, only the agriculturally used area is considered. Nevertheless, the data enable a good estimation of the classification quality. The community boundaries and the classification result were co-registered and the percentage of each land use class was calculated.

Figure 7a shows a comparison of the classification results and the survey data for several communities in the sub-catchment of the river Rott, located in the eastern part of the study area. It is one of the agriculturally most intensively used areas in the study site. The survey data are from the year 2000, the classification is based on 1999 image data. In an intensively used agricultural domain, no significant changes in land use are to be expected within one year.

Table 1: Land Use Classification System

Level 1	Level 2	Level 3	Level 4
Artificial Surface	Settlements/roads	Sealed surfaces	Sealed surfaces
		Gravel pits, mining	Gravel pits, mining
Water	Water	Water	Water
Natural areas	Wetland	Fen	Fen
		Peat cuts	Peat cuts
	Alpine grassland	Alpine grassland	Alpine grassland
	Rocks	Rocks	Rocks
Snow and Ice	Snow	Snow	Snow
	Glaciers	Glaciers	Glaciers
Forest	Deciduous	Deciduous	Deciduous
		Softwood	Softwood
	Evergreen	Coniferous	Coniferous
	Mixed forest	Mixed forest	Mixed forest
Agriculture	Grassland	Meadows	Meadows
		Pasture	Pasture
		Mountain pasture	Mountain pasture
	Cropland	Winter cereals	Winter wheat
			Winter barley
			Rye/Triticale
		Spring cereals	Spring cereals
		Maize	Maize
		Root crops	Sugar beet
			Rape seed
			Potatoes / Legume
		Hop	Hop
		Specialised crops	Specialised crops
	Uncovered soil	Uncovered soil	Uncovered soil

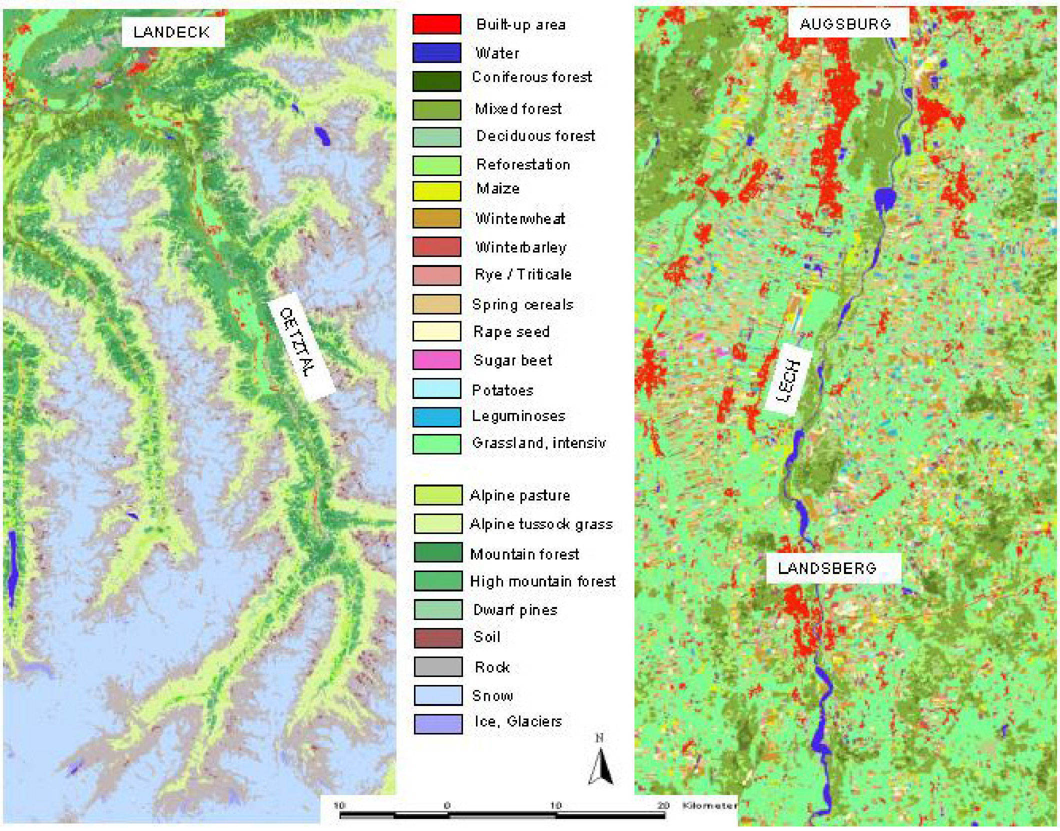

Figure 6: Two sections of the classification result. On the left a part of the Central Alps is shown dominated by natural vegetation, on the right the agriculturally intensively used valley of the river Lech south of Augsburg.

In a first validation approach, all grassland and cropland classes were aggregated and the proportions of survey data and classification were compared. On an average they differ only by about 2%. Significant differences occur only within the neighbouring communities of Eggenfelden and Hebertsfelden. This is due to the census method mentioned above. A detailed validation is shown in Figure 7b. Five different crops are compared. Again, classification result and census data are matching closely. The differences of the neighbouring communities are clearly visible. The mismatching occurs mainly in the class *maize*, which is the dominating land use in this area. The results were also averaged for all communities, which gives a much better impression of the classification accuracy (Figure 7b).

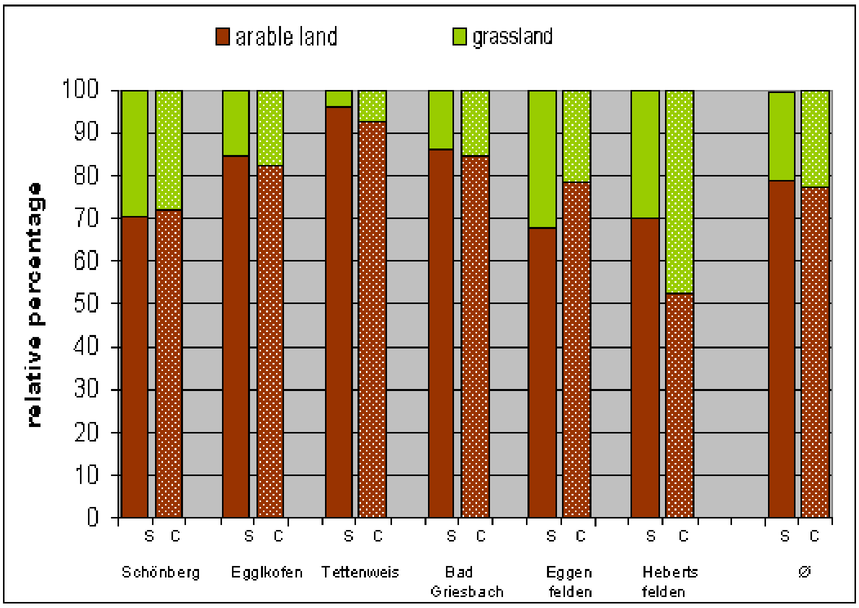

Figure 7a: Comparison of survey data and classification results of aggregated grassland and cropland classes for selected communities. The dotted columns represent the classification result, the bold ones the survey data.

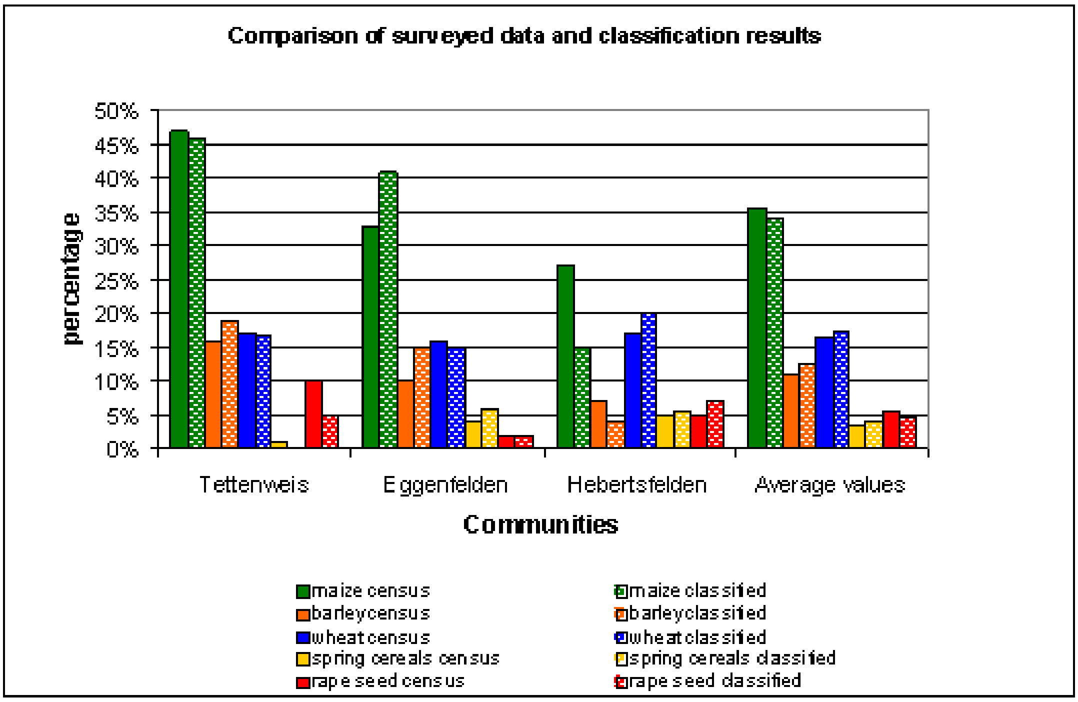

Figure 7b: Comparison of surveyed data and classification results for five different crops.

Accuracy Assessment

The accuracy analysis is done using independent sets of validation sites, which are different from the training data sets. The sites are distributed over the study area and the ground truth data are collected by:

- interviewing farmers
- using available land use maps
- analysing color IR aerial images (alpine areas).

Table 2 shows the pixel-by-pixel accuracy matrix for the *Gilching* test site, located in the Alpine Foreland, southwest of the city of Munich. The resulting classification was compared pixel-by-pixel to an existing land-use map of that area.

Table 2: The pixel-by-pixel accuracy matrix of the testsite Gilching*. The table shows the number of classified pixels, the user's (UA) and producer's accuracy (PA) in % (14).*

	Reference Map												
Classification Result	mixed forest	grass	gravel	maize	rape seed	winter rye	winter wheat	spring cereal	build-up areas		total	UA %	PA %
mixed forest	**6038**	76	1	0	0	0	10	13	8		6146	98,2	93,1
grassland	303	**5451**	93	147	88	70	118	150	143		6263	83,1	89,3
gravel	48	16	**728**	0	0	0	0	0	14		808	90,3	82,3
maize	0	309	29	**710**	1	0	5	8	21		1383	65,6	82,6
rape seed	0	27	0	0	**899**	1	40	17	0		984	91,4	89,2
winter rye	34	33	5	0	8	**448**	91	36	3		658	72,3	79,8
winter wheat	0	20	6	2	9	153	**1844**	207	3		2244	86,6	86,5
spring cereals	0	71	0	1	3	15	25	**1158**	2		1279	90,5	72,9
build-up areas	60	103	19	0	0	0687	0	0	**1257**		1439	87,4	86,6
										18233 ≡ 88%			
total	6483	6106	887	860	1008	687	2133	1589	1451		21204		

UA = user's accuracy
PA = producer's accuracy

The overall accuracy of 88% is a satisfying result (14). But a closer evaluation of the classified categories reveals some problems. Although the acquisition date allows a high number of field crops to be differentiated, the confusion of grassland with several classes is evident. This is partly due to limitations in the ground truth map (i.e. build-up areas are generalised). The especially poor separability between grassland and maize is a result of the similar spectral signatures of these two classes. Comparisons with the results of the quality estimation point out that it seems to be a local phenomenon which is limited to some areas in the Alpine Foreland, where geofactors have no significant influence. But further investigations have to be conducted to estimate the misclassification within the Danube catchment.

CONCLUSIONS

A classification chain was developed to produce up-to-date and high resolution land use maps from LANDSAT-TM data for a mesoscale and complex area, differentiating 27 land use classes.

It was not possible to solve the task with a single classification procedure due to the computer limitations described. Within the processing chain two approaches were combined: a knowledge-based fuzzy logic classification procedure and a data fusion concept. Only the integration of ancillary data and knowledge enabled the task to be solved. The original aim, to use only one training area set and classify the total data set in one single step, failed in the first place due to the size of the data set. It could not be handled in the available 32 bit computer. Secondly, the heterogeneity of the study area caused different spectral signatures and required an adjustment in membership functions from subset to subset. A critical point is the accuracy assessment for such large areas.

Although a comparison with census data on a community base gives a good estimation, pixel-bx-pixel or field-based accuracy assessments have to be conducted as well. The collection of reliable ground truth data appeared to be a challenging task.

The experiences dealing with areas of such size can be summarized as follows:

- To develop a time- and cost-efficient procedure, sufficient geographical knowledge is necessary. Thus, time-consuming misclassifications can be avoided.
- Exact geometric and radiometric pre-processing enables a consistent classification ranging over several TM scenes.
- The more ancillary data and geofactors can be included, the better the result. Especially high quality soil maps reduce misclassifications.
- The separate masking of classes, which can be separated by thresholds, significantely reduces misclassifications.
- Including SAR data for classifying settlement areas improves the result clearly.
- The hardware and software can never be powerful enough for data sets of such size.

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