INTEGRATION OF SPECTRAL AND SPATIAL CLASSIFICATION METHODS FOR BUILDING A LAND-USE MODEL OF AUSTRIA

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ABSTRACT:

The first part of this paper deals with methodological aspects of land-cover and land-use classification. Due to the high resolution of today's remote sensors, the single pixel represents land-cover rather than land-use. The outcome of per-pixel classifications will therefore not meet the requirements of a land-use map if the spatial composition of cover types is not considered as well. This can be achieved by applying a spatial postclassification method. We present an algorithm, which analyses the spatial composition of land-cover types in the local neighbourhood of each pixel. The assignment of land-use classes is based on the comparison of the actual composition of land-cover types with a predefined rule-set. In the second part the application of the method for building an Austrian-wide land-use model is discussed. To asses the quality of both the method and the derived land-use model, the results are compared to parts of the CORINE land-cover map of Austria.

1. INTRODUCTION

Information on spatial distribution of land-use represents an essential input to environmental modelling. For analyses on a national scale no appropriate land-use model of Austria has been available up to today. Existing land-use maps do not meet the requirements for an Austrian-wide representation, because they either are not up-to-date or cover only selected regions of Austria. Most of these maps result from photogrammetric or terrestrial observations, which are both cost intensive and time consuming. Satellite remote sensing represents a valuable alternative to the traditional methods, by offering up-to-date information of large areas for reasonable costs.

The first attempt to use remote sensing data on a national scale in Austria was the development of the CORINE land-cover data-base, a European-wide project initiated by the European Commission (EUR, 1993). This model is derived from visual interpretation of analogue satellite images and ancillary data such as aerial photographs or topographic maps. Due to the high expenditure of time needed for visual interpretation the Austrian land-cover map will not be finished before 1997. Nevertheless there exists an urgent need for such a data-set today. This paper presents a method which allows a semi-automated mapping of Level II land-use classes from high resolution satellite imagery. The method is then applied for the derivation of an Austrian-wide land-use model.

2. LAND-COVER VERSUS LAND-USE

Per pixel classification of image data acquired by sensors such as Landsat TM or SPOT HRV is not always adequate for mapping land-use on a regional scale. This is due to the high geometric resolution of the single pixel, which rather represents a single land-cover type than certain land-use classes composed of different cover types. For mapping heterogeneous land-use types the context between a single pixel and its neighbours seems to be the crucial point. This becomes apparent when looking at different land-use types of built-up environments, e.g. low density urban areas. Per pixel analysis of these areas will result in a composition of different cover types such as roofs, pavement, vegetation, bare soil, etc. thus producing a 'salt and pepper' pattern rather than the desired land-use class. Therefore the spectral classification is not sufficient unless the spatial composition of the cover types is considered as well. To solve this problem various attempts have been made to include spatial variation in the classification process.

Textural characteristics can be used to describe the spatial variation of radiance within an image. Haralick (1973) proposed various methods to derive textural measures from digital images. When incorporated in multispectral data sets these texture bands can significantly improve the accuracy of land-use classification (Franklin and Peddle 1990, Sali and Wolfson 1992, Webster and Bracken 1992). Another approach applies a two step process. First, a per pixel classification is performed resulting in a land-cover layer. Second, a postclassification algorithm analyses the spatial composition of the land-cover types and assigns the land-use classes in question. The context between land-cover and land-use classes can either be established by training areas and statistical measures (Zhang et al., 1988, Guo and Moore, 1991, Barnsley and Barr, 1992, Gong and Howard, 1992) or be defined by rules (Steinnocher et al. 1993, Fung and Chan 1994).

The method presented in this study follows the second approach. A spatial postclassification algorithm, applied to the result of a per-pixel land-cover classification, assigns the requested land-use classes using a set of pre-defined rules. For a better understanding, classes resulting from the spectral classification will be called primary classes, the final land-use classes will be called secondary classes.

The algorithm works within a local neighborhood which is defined by a moving window. Within this window a standardized histogram of primary classes is calculated, representing the spatial composition, i.e. the frequency of primary classes found in the local neighborhood. The histogram is then compared to a set of rules which represent the expected frequency of primary classes for each secondary class. As soon as a rule is found to be true, the corresponding secondary class is assigned to the center pixel of the window.

Each rule defines the minimum frequency of one or more primary classes for one secondary class. When compared to the corresponding elements in the histogram the frequency values represent thresholds. If all thresholds are exceeded within a rule, it is recognized as true and the corresponding secondary class will be assigned. Though experiments with this approach produced useful results (Steinnocher et al. 1993), only simple patterns of primary classes could be recognized. Therefore the design of the rule-set was modified to allow for a combination of sub-rules within one major rule. Each sub-rule defines a threshold for one or more primary classes and all sub-rules have to be true to accept the major rule (Figure 1). Processing of the rule-set is performed step by step, starting at the top of the set. As soon as a rule is accepted and therefore applied, the rest of the rule-set will not be considered any more. If no rule is found to be true, a rejection class is assigned.

Apart from the design of the rule-set, the size of the analyzed neighborhood represents a crucial parameter in the postclassification process. Choosing a small window size will lead to a 'noisy' result since only high frequency structures will be recognized. If the window is too large the smoothing effect will become very strong, thus leading to a loss of detail. At this point it has to be noted that the presented postclassification is a generalization process and will always suppress some details. On the other hand, this effect might as well be desired, e.g. for the generation of thematic maps (Wilkinson, 1993). Since generalization usually comes with an increase of scale - i.e. an increase of the pixel size in the raster domain - the algorithm includes the option of resampling, i.e. the size of the resulting pixels can be defined as a multiple of the original pixel size. Since the rule-set and the window sizes are defined by the user, the right choice of these parameters depends highly on the user's experience and on the objective of the application.

3. GENERATION OF THE LAND-USE MODEL

3.1 Data description

The data used in this application comprises 12 cloudfree Landsat-TM scenes, covering the entire area of Austria. All images were acquired between August 7 and October 5, 1991, except one quarter scene, which was taken in August 1992. Due to stable weather conditions within the period of data acquisition, this data-set has a homogenous reflectance characteristic and therefore represents an optimum basis for further processing. In addition to the image data, a digital elevation model of Austria with a resolution of 50 m was available.

For training and testing of the classification process reliable reference information is indispensable. To guarantee a consistent quality of the results, only data available for the entire area of Austria were used. The Austrian topographic map 1:50.000 (ÖK 50) consisting of 213 map sheets provided information on major land-cover/use types such as man-made structures, water bodies, forest, bare rock and glaciers. Though the majority of the maps were updated in the late 1980's, a visual comparison with the image data was performed for training- and test-areas to ensure that no change had occured between the update and the acquisition of the image data. Since the maps do not distinguish between the different uses of open land such as arable land, pastures, natural grassland etc., a second source of information was needed. It was found in a series of analogue satellite photographs, covering about 80% of the Austrian territory. They were taken by a KFA-1000 camera mounted on the Russian space-platform MIR in 1991. The images offer two channels in the red and the near infrared spectrum with a ground resolution of approximately 7 m. Interpretation of these images proved to be extremly valuable for generating reliable reference information.

3.2 Geocoding

To allow for a correct geometrical relationship between remotely sensed imagery and other spatial information layers such as maps, it is necessary to geometrically transform the images to a map projection system. This transformation is commonly called rectification or geocoding. In flat terrain it is sufficient to apply a polynomial transformation based on ground control points. This approach will not be adequate in rugged terrain, since pixel displacements resulting from local differences in elevation are not considered. As most parts of Austria are extremely mountainous a high level geocoding method has to be applied to ensure a geometrically correct result. Based on linear ground control features, the orientation parameters of each image scan are computed by bundle block adjustment. Next the image-scans are geocoded with respect to a Digital Terrain Model. The final result is an Austrian wide ortho-image mosaic with a ground resolution of 25 m. As this part of the processing chain was not performed by the author, no further discussion will be given on this topic. Details on the theoretical background of high level geocoding and on the generation of the Austrian image mosaic can be found in Ecker et al. (1991) and Ecker et al. (1995).

3.3 Spectral classification

As the amount of data to be processed comes up to more than 2 Gigabytes, the ortho images are stratified with respect to the different Austrian landforms. The average size of the resulting sub-scenes is about 5000x5000 pixels, including overlap areas between the scenes.

IF F_{pc} [+F_{pc} ...] > thr [**AND** F_{pc}[+F_{pc} ...] > thr ...] **THEN** SC
  ELSE IF F_{pc}[+F_{pc} ...] > thr [**AND** F_{pc}[+F_{pc} ...] > thr ...] **THEN** SC
    ELSE IF ...
    •
    •
    •
    ELSE IF F_{pc}[+F_{pc} ...] > thr [**AND** F_{pc}[+F_{pc} ...] > thr ...] **THEN** SC
      ELSE rejection class

with F_{pc}: relative frequency of primary class; SC: secondary class; thr: threshold

Figure 1: syntax of the rule-set

The stratified scenes are subject to unsupervised classification, leading to 50 significant spectral classes per scene. The result is compared to reference data, and land-cover types are assigned (Table 1). Unsupervised classification is given preference over the supervised technique, because the assignment of classes a posteriori is generally less time-consuming than the selection of training areas - especially when working on large data-sets. This advantage is diminished by the fact that the signatures generated by clustering will not always meet the expectations of the analyst, i.e. one class can be represented by several signatures, and two or more classes might fall into one generated signature. In the first case aggregation of classes will solve the problem. The second case cannot be solved without additional information from the image data. Applying supervised training for the 'missing' classes helps to overcome the problem, thus leading to a hybrid classification with a few signatures defined over training areas, whereas the majority of signatures results from the clustering process. Experience gained during the project work has shown that the cover types 'mixed built-up' and 'vineyards' cannot be detected reliably by clustering. Therefore, these land-cover types are trained applying the supervised method. The hybrid classification results in a land-cover layer representing all classes except the alpine ones (Table 1, 14-15).

A different approach was used for the analysis of areas above the timberline. In these areas the spectral response of land-cover is influenced by the different illumination angles resulting from variation of the terrain. This so called terrain effect can be significantly reduced by employing ratio images. Despite the loss of information caused by image rationing, the use of the NDVI proved to be sufficient for identification of the cover types in question. To distinguish between 'alpine' and 'non alpine' cover types the digital terrain model is intersected with the classified image. All cover types except forest and water are defined as alpine areas if located above a certain altitude. For these areas the NDVI is calculated and thresholded with respect to reference data, thus allowing for the seperation of *alpine vegetation* and *non vegetated alpine* areas.

1	water	9	grass (high)
2	pure built-up	10	grass (low)
3	mixed built-up	11	wetlands
4	pavement	12	shrub
5	gravel	13	forest
6	bare soil	14	alpine vegetation
7	crops	15	non vegetated alpine areas
8	vineyards	16	glaciers

Table 1: example for land-cover classes

3.4 Spatial Classification

The definition of the final land-use types is adapted from the CORINE land-cover nomenclature (EUR, 1993) and comprises 5 Level I and 15 Level II classes (Table 2). *High* and *low density urban* represent different densities of built-up areas, *green urban areas* refers to artificially vegetated areas within an urban environment, such as parks or cemeteries. *Industrial/commercial/traffic areas* include industrial structures and shopping malls as well as large train stations and airports. *Mineral extraction sites* comprises all kinds of surface mines. These five land-use classes are aggregated under *artificial surfaces*. The second Level I class, *agricultural areas*, is separated into *arable land*, *vineyards* and *pastures*. Agricultural areas, where none of the three land-use types dominates, are defined as *heterogeneous agricultural areas*. *Forest* and *natural areas* comprises *forest*, *natural vegetation*, *no vegetation* and *glaciers*. *Natural vegetation* represents all areas with vegetation cover except forest, which do not result from human activities, e.g. natural grassland and shrubs. *No vegetation* stands for opened spaces with little or no vegetation such as bare soil or rock. *Water* comprises water courses as well as water bodies, *wetlands* represents non-forested waterlogged areas.

Level I	Level II	
I artificial surfaces	I.1	high density urban
	I.2	low density urban
	I.3	green urban
	I.4	industrial/commercial/traffic
	I.5	mineral extraction sites
II agricultural areas	II.1	arable land
	II.2	vineyards
	II.3	pastures
	II.4	heterogeneous agricultural areas
III natural areas	III.1	forest
	III.2	natural vegetation
	III.3	no vegetation
	III.4	glacier
IV wetlands	IV.1	wetlands
V water	V.1	water

Table 2: land-use nomenclature (adapted from CORINE, 1993)

To derive the land-use classes the spatial postclassification algorithm is applied to the land-cover layer. As discussed above, the result of this algorithm strongly depends on the size of the window which determines the degree of generalisation. The size of the output pixel is defined by 4x4 input pixels, thus leading to a cell-size of 100x100m in the final land-use layer. Based on the experience gained from former studies on spatial classification (Steinnocher et al. 1993, Ecker et al. 1995) two different window sizes are defined as local neighbourhood, depending on the land-use classes. In the first run, *artificial surface* classes, *forest*, *glacier*, *water* and *wetlands* are post-classified applying a 8x8 pixel window. This size corresponds to 200x200m, which is suitable for recognising urban structures without causing too much generalisation. Homogenous classes such as *forest* (III.1), *glacier* (III.4), *water* (V.1) and *wetlands* (IV.1) can be found by examining the portion of the corresponding cover-type within the window (Table 3: rule 1-3). To detect heterogeneous land-use types, a composition of primary classes has to be analysed (rule 4-7), e.g. *high density urban* (I.1) is expected to consist more than 70% of *pure built-up* (2) and *pavement* (4), with *pure-built up* covering at least 40% (rule 5). All areas which do not meet any condition in the rule-set are assigned to the rejection class.

rule	condition	land-use class
1	$f(13) > 50\ \%$	:III.1
2	$f(17) > 50\ \%$	:III.4
3	$f(1)\ \ > 50\ \%$	:V.1
4	$f(9)\ \ > 50\ \%$	:IV.1
5	$\{f(2) + f(4)\} > 70\ \%$ AND $f(2) > 40\ \%$	:I.1
6	$\{f(2) + f(4)\} > 70\ \%$ AND $f(4) > 40\ \%$	:I.4
7	$\{f(4) + f(5)\} > 70\ \%$ AND $f(5) > 40\ \%$	:I.5
8	$\{f(3) + f(4)\} > 50\ \%$ AND $f(3) > 30\ \%$	:I.2
	ELSE	:0 (rejected)

with f(n): frequency of land-cover type n (class numbers refer to tables 1 and 2)

Table 3: example of rule-set I

The rejected areas are used as a mask for the primary classification layer, thus leaving only non-postclassified areas for the second processing step. The remaining land-use classes, *agricultural* and *natural areas*, are postclassified with a window size of 16x16 pixels, which equals 400x400m on the ground. The higher degree of generalisation corresponds with the definition of these classes, as they are to represent dominant forms of land-use. This is considered in rule-set II (Table 4) which first examines the dominant occurrence of agriculture (rule 1-3) and natural vegetation (rule 4). If no dominant cover-type is found, a composition of cover-types is considered (rule 5), i.e. any combination of different agricultural cover types or of agriculture with natural vegetation covering more than 80 % will be classified as *heterogeneous agricultural areas* (II.4). Rule 6 and 7 test for the dominant occurrence of vegetation within alpine areas.

rule	condition	land-use class
1	{f(6) + f(7)} > 70 %	:II.1
2	f(8) > 70%	:II.2
3	{f(10) + f(11)} > 70 %	:II.3
4	{f(12) + f(13)} > 70 %	:III.2
5	{f(6) + f(7) + f(8) + f(10) + f(11) + f(12) + f(13)} > 80 %	:II.4
6	{(13 + 14)} > 50 %	:III.2
7	{(15 + 16)} > 50 %	:III.3
	ELSE	:0 (rejected)

with f(n): frequency of land-cover type n (class numbers refer to tables 1 and 2)

Table 4: example of rule-set II

The two resulting layers are then intersected, giving priority to the less generalised structures of the first postclassification. Assuming an optimum design of the rule-sets, all pixels are assigned a land-use class at this stage. Experience has shown, though, that up to 5% of the pixels will fall into the final rejection class, i.e. they are rejected by both rule-sets. The majority of these pixels occur as single pixels within a classified neighbourhood, e.g. on the border between two land-cover types, where neither reaches the majority within the local neighbourhood, though both cover types are close to it. These pixels can easily be classified by assigning the relative majority of a 3x3 neighbourhood.

In addition to these 'border cases', larger rejected areas might occur, resulting from particular combinations of cover types not considered in the rule-sets. For classification of these areas we propose interactive post-editing rather than setting up additional rules, as the consideration of all possible combinations of cover types seems unrealistic. Post-editing might also be necessary for some of the *artificial surface* classes, where the definition of the class is based on the spatial context rather than on the local pattern of cover types, e.g. *green urban areas* are defined as vegetation within an urban environment. Similar problems might occur in the separation of industrial areas from particular mineral extraction sites such as gravel-pits. Being aware of these problems the post-editing process can be concentrated on the doubtful areas, thus reducing the time needed for interactive work to a negligible amount within the entire project.

4. RESULTS AND DISCUSSION

To assess the quality of the land-use model it was imported to a GIS and compared to the CORINE land-cover data-base. Six map sheets were chosen from available parts of the CORINE data-base, each covering about 500 km^2. Therefore, the total number of pixels evaluated comes up to about 300.000, which equals 3.5 % of the entire area investigated. When selecting the map sheets, attention was paid to consider different forms of the Austrian landscape. The test sites contain all classes except *glacier* as no layer containing *glacier* is available yet.

For comparison the CORINE vector layers are converted to a raster representation, using the raster of the land-use model as geometric reference. In addition, the 44 CORINE classes are aggregated according to the 15 land-use classes. CORINE defines the smallest mapping unit with 25 hectares, therefore all areas smaller than 25 hectares are eliminated in the land-use model and redefined applying an iterative majority filter.

Intersection of the two models at all test sites allows for the derivation of confusion matrices. Table 5 shows the overall confusion matrix for Level-I and Level-II land-use classes, including totals and percentages of identical results. The rows of the matrix represent the CORINE land-cover, the columns are the result of the automated classification. With a sample of less than 100 pixels, *Mineral extraction sites* (I.4) is underrepresented and therefore not considered in the matrix. The following discussion is based on comparison of conflicting areas to reference data. It concentrates on the examination of systematic errors of both the automated and the visual classification.

When analysing the confusion values of Level-I classes a high correspondence between the two data sets can be observed (>90 %). Some deviations are found between *artificial surfaces* (I) and *agricultural areas* (II), resulting largely from differences in *low density urban* (I.2), and between *agricultural areas* (II) and *natural areas* (III), which is due to a different classification of forest.

Within agricultural areas there is a significant confusion between *heterogeneous agricultural areas* (II.2) and *arable land* (II.1) as well as *pastures* (II.3). The reason for this disagreement becomes obvious when comparing maps of both models (Figure 3). Whereas the automated classification reacts rather sensibly to local variations of land-use, visual interpretors have a tendency to integrate larger areas within one class (compare patchy pattern in the left upper part of the left map with same area in the right map in Figure 2).

The most critical confusions are found within *natural areas* (III). *Forest* (III.1) was slightly overestimated in the automated approach, which results in differences of totals for this class (compare sum of column III.1 with sum of row III.1 in Table 4). Comparison with reference data has shown that long and narrow valleys which are surrounded by forest, get lost during the postclassification process, although they are larger than 25 hectares and therefore classified in the visual interpretation. These patterns are typical for the alpine landscape and cause the majority of confusion between forest and agricultural areas.

Natural vegetation (III.2), which occurs predominantly in the high alpine regions, is strongly confused with *forest* (III.1) and *no vegetation* (III.3). Detailed analysis has shown that areas clearly recognised as *forest* in the reference data were actually classified as *natural vegetation* in the CORINE data-base. This may be partially explained by the fact that dwarf-pines, classified as *forest* in the automated process, were interpreted as *natural vegetation* in the CORINE land-cover maps. Though dwarf-pines cover large areas in the Alps, it is doubtful that they are the only explanation for this confusion. We assume that the different illumination angles are the essential reason for

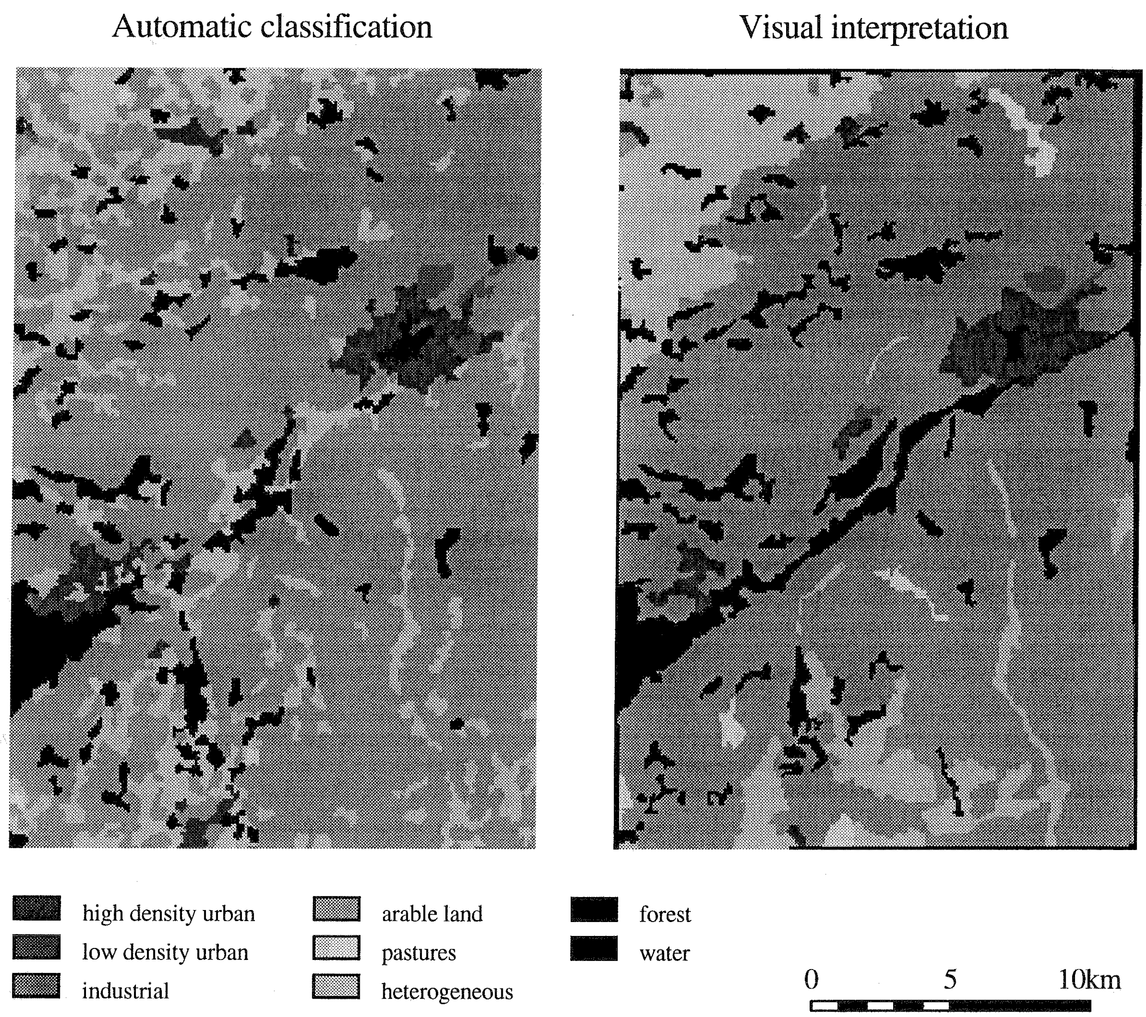

Figure 2: Result of automatical classification compared to CORINE land-cover map (ÖK 50-49 Wels)

CORINE		**Land-use model**																
L I		**I. artificial surfaces**				**II. agricultural areas**				**III. natural areas**			**IV**	**V**			Σ	%
	L II	I.1	I.2	I.3	I.4	II.1	II.2	II.3	II.4	III.1	III.2	III.3	IV.1	V.1	Σ	%		
I	I.1	**26**	6	0	0	0	0	0	0	0	0	0	0	0	33	79.8	252	81.5
	I.2	7	**116**	1	8	17	4	0	9	2	0	0	0	4	170	68.6		
	I.3	0	3	**4**	2	0	0	0	0	2	0	0	0	2	13	27.6		
	I.4	1	7	0	**23**	2	0	0	2	0	0	0	0	1	36	62.7		
II	II.1	0	18	0	6	**715**	4	2	65	16	2	0	0	1	829	86.2	1531	89.1
	II.2	0	1	0	0	8	**81**	0	5	2	3	0	1	1	102	79.2		
	II.3	0	5	0	0	13	1	**81**	60	32	4	0	3	2	201	40.3		
	II.4	0	11	0	0	76	3	40	**211**	52	2	0	1	2	398	53.0		
III	III.1	0	3	0	1	20	1	13	29	**818**	21	2	0	2	910	89.8	1067	93.1
	III.2	0	0	0	0	0	0	3	0	48	**33**	1	0	0	84	39.0		
	III.3	0	0	0	0	0	0	0	0	15	30	**26**	0	0	73	41.6		
IV	IV.1	0	0	0	0	1	2	0	1	0	3	0	**76**	3	86	88.4	86	88.4
V	V.1	0	1	0	0	0	0	0	1	3	0	0	2	**154**	161	95.2	161	95.2
	Σ	35	172	5	40	853	96	139	382	991	98	29	83	173	**3097**			
	%	76.0	67.7	65.6	56.6	83.8	84.2	58.3	55.2	82.6	33.5	91.5	91.3	88.8		**76.3**		
Σ		253				1471				1118			83	173			**3097**	
%		81.3				92.8				88.9			91.3	88.8				**90.2**

Table 5: Confusion matrix for Level I and Level II land-use classes (elements = absolute numbers / 100)

the contradiction between the models. By including index images in the classification process, the topographic effect could be significantly reduced, whereas for the visual interpretation only the original images were available. The same consideration is valid for the confusion between *natural vegetation* and *no vegetation*, though areas without vegetation cover were slightly underestimated in the automated approach.

Summing up, the confusion between the two data-models can be explained by three major causes - the different methods applied, the different representation of the data, and in a few cases a different interpretation of the nomenclature. The last aspect refers above all to the definition of *natural areas* and is subject to ongoing discussion. A certain amount of confusion is due to the limited accuracy of linear features in raster representation.

The major differences, though, result from the different methods applied. Whereas the automated approach has a tendency of smoothing complex shapes, it is rather sensitive to local variations of land-cover. The visual interpretation, on the contrary, is very accurate in the demarcation of single objects but is less sensitive to changing patterns within a larger heterogeneous environment. These effects are obviously caused by the different approaches towards generalisation. Visual interpretation usually defines the dominant class in an image as "background" and "cuts out" the remaining classes. The post-classification algorithm is always limited to the window size and therefore does not consider dominant classes in a larger environment, but reacts to any change within this local neighbourhood. This effect can best be observed when analysing *heterogeneous agricultural areas*. This class is strongly confused with *arable land*, *pastures* and *forest*, which are all thematic neighbours of this class and typical candidates for "background classes". The total of this confusion comes up to 11% of the entire test area and therefore represents the major disagreement between the two models.

5. SUMMARY AND CONCLUSIONS

The presented paper gives a contribution to the discussion of land-use versus land-cover classification. A method is presented that examines the spatial composition of land-cover types in a local neighbourhood and assigns land-use classes based on a predefined set of rules. Though postclassification of this kind will always have a generalising effect and therefore leads to a loss of details, it is powerful in detecting heterogeneous land-use classes composed of a particular composition of land-cover types.

The application of the method is not limited to a single test region but is performed for the entire area of Austria. Comparison of the resulting land-use model with parts of the CORINE land-cover map of Austria confirms the usefulness of the chosen procedure for mapping land-use on a regional scale. Nevertheless, there exist obvious differences in the two models, which are due to the different approaches towards generalisation. For the postclassification process, the size of the local neighbourhood seems to be the crucial parameter. Though two different window sizes were used in the application this might not be sufficient for a reliable recognition of all land-use objects. Furthermore, the postclassification algorithm could be improved by not only considering the frequency of land-cover types, but also their spatial arrangement.

Unexpected contradictions between the models were found in the alpine areas. Besides the different thematic interpretations of a few land-cover types, the essential reason for the confusion of classes seems to lie in the different illumination angles in rugged terrain. Whereas in the manual approach no correction was performed at all to overcome this problem, index images were used in the automatic classification process, thus reducing the topographic effect to a certain extent. Although image rationing does improve classification accuracy in alpine areas, it might be valuable to perform topographic normalisation by applying a Digital Terrain Model.

Although the presented approach needs further research, it represents a valuable alternative to visual interpretation of satellite imagery, as it is definitely less time-consuming and therefore significantly reduces the costs of land-use mapping on regional or national scale.

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