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LAND COVER MAPPING USING LANDSAT SATELLITE IMAGE CLASSIFICATION IN THE CLASSICAL KARST - KRAS REGION

UGOTAVLJANJE POKROVNOSTI KRASA S KLASIFIKACIJO SATELITSKIH POSNETKOV LANDSAT

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Žiga Kokalj & Krištof Oštir: Land cover mapping using Landsat satellite image classification in the Classical Karst - Kras region

Such a diverse and sensitive eco-region as Karst needs to be managed with special attention and consideration of its natural and cultural resources. Land cover is an important indicator, which enables the analysis of their condition and development monitoring. Advanced satellite images classification represents an accurate and cost-effective alternative to the classical techniques of land cover mapping. The methods used to produce a reliable land cover map are presented in this paper. The complexity of the area requires a combination of various data such as Landsat satellite images, digital elevation model, digital orthophotos as well as existing topographic and thematic maps. The maximum likelihood algorithm was used as the main classifier and the accuracy of results was further improved by fuzzy classification, altitude and inclination filtering and auxiliary data integration.

Key words: remote sensing, land cover, land use, classification, satellite imagery, Classical karst.

Izvleček UDK 528.85:711.14(497.4)

Žiga Kokalj & Krištof Oštir: Ugotavljanje pokrovnosti Krasa s klasifikacijo satelitskih posnetkov Landsat

Kras je ekološko zelo raznolika in občutljiva regija zato potrebuje posebno premišljeno gospodarjenje z naravnimi viri in kulturno dediščino. Pomemben kazalnik, ki omogoča analizo njihovega stanja in spremljanje razvoja, je pokrovnost. Daljinsko zaznavanje oziroma napredna klasifikacija satelitskih posnetkov sta natančna in cenovna ugodna alternativa klasičnim tehnikam kartiranja pokrovnosti. V prispevku so opisane metode za pridobitev zanesljive in uporabne karte pokrovnosti zemeljskega površja. Kompleksnost območja narekuje kombinacijo različnih virov podatkov, kot so satelitski posnetki Landsat, digitalni model višin, ortofoto posnetki in obstoječe topografske in tematske karte. Kot glavni klasifikacijski algoritem je bila uporabljena metoda največje verjetnosti, natančnost pa je bila povečana z uporabo mehke klasifikacije, omejevanjem z višino in nagibom ter dodatnimi sloji podatkov.

Ključne besede: daljinsko zaznavanje, pokrovnost, raba tal, klasifikacija, satelitski posnetki, Kras.

INTRODUCTION

The Karst or classical karst is an extensive limestone plateau, well distinguished from the nearby regions due to its steep rise above the neighbouring predominantly flysch areas. It is a distinct border region, which is evident in several characteristics. It lies in the vicinity of the Adriatic Sea; nevertheless the steep elevation gradient prevents the sea's soothing effects to reach it. Due to the vicinity of the high karst plateaux in the north there are substantial continental influences. The transition between the Mediterranean and continental impact is present in the high winds; Burja, a strong north wind is common during the winter (Perko *et al.* 1999).

Due to its typical water and soil characteristics the Karst landscape is extremely sensitive to pollution and therefore special attention has to be paid to its management. All available means should be employed in the ef-

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fective management and monitoring of natural resources. The interaction between mankind and the environment has to be taken into consideration, since it is the greatest threat to sensitive areas such as the Karst region. Landscape observation methodologies that offer accurate results and enable historical, e.g. annual, comparisons should be employed.

Remote sensing surveys provide a rapid means of data collection that can achieve complete coverage of large areas, with far lower costs than those associated with field survey. Remote sensing can detect features unseen on the surface, map them accurately, and offer interpretations based on their form, distribution, and context. Image interpretation and processing have now become standard tools, and the use of aerial photographs, satellite imagery and other remote sensing techniques have become increasingly sophisticated particularly because digital spatial imagery has become ever more ubiquitous (Kvamme 2005).

Aerial photography is the oldest domain of remote sensing of karst landscapes and sill receives a great focus, especially for its detail, but other sensing devices have been placed in the air in recent decades, including passive multispectral and thermal sensors, and active radar and laser altimeter systems, making aerial remote sensing truly multidimensional (Kvamme 2005). A number of satellite systems have played a significant role in modelling end exploring karst landscapes. Landsat was the first satellite program for collecting repetitive, synoptic, multi-spectral imagery for monitoring and analysing Earth's resources and environment. Early studies focused on environmental zones or land-cover mapping, because spatial resolution was too coarse to detect smaller karst features. However, relatively recent introduction of high (spatial) resolution satellite imagery, with a sell size in the range of 1 m, enabled detection and mapping of individual karst features, especially when combined with lidar technology. Ikonos and QuickBird are the two most often used high resolution commercial satellites, offering multispectral data at 4 m and 2.4 m spatial resolutions, with panchromatic data at 1 m and 0.61 m respectively. Lidar (LIght Detection And Ranging) is the optical equivalent of radar, an active instrument capable of rapidly generating highly accurate digital models of topography as well as the vertical structure of other surfaces (buildings, trees) from the air. Lidar is a technology providing remarkable surface detail, with absolute vertical accuracy up to a few centimetres, even in vegetated areas, and horizontal sampling densities well below a meter. The potential for mapping karst features is immense as lidar can penetrate forest canopy and thus provide information on features that are not identifiable on either topographic maps or aerial photography.

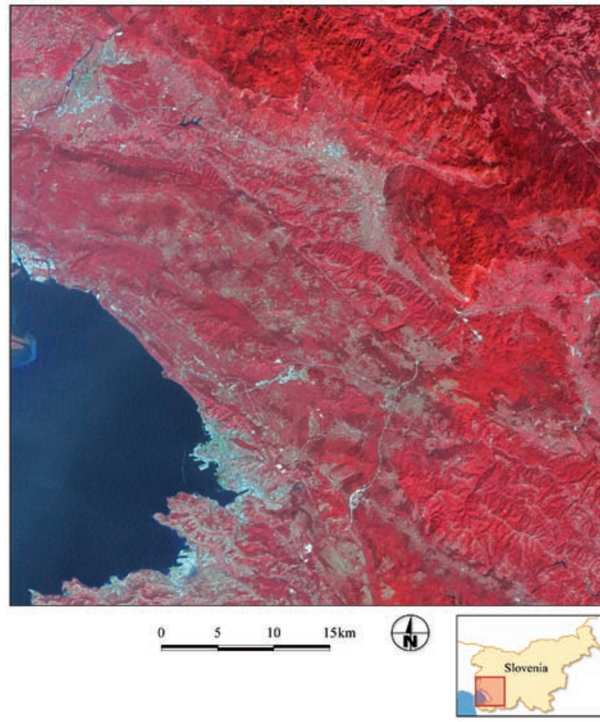

Fig. 1: The Karst plateau and its vicinity as seen on the 1999 Landsat satellite image.

Remote sensing applications for karst environment studies were first focused on geological lineaments extraction (Suzen *et al*. 1998). Sabins (1997) describes techniques for geological and geomorphological surveillance of tropical karst using radar images, while Hung *et al*. (2002) used image fusion of Landsat images and edge detection filtering for fault and lineament extraction, serving for cave development analysis in the tropical karst area of north-western Vietnam. Hung *et al*. (2003) presented an environmental analysis consisting of methods for image transformation, image fusion, lineament extraction, time series, and change detection for studying land cover changes. The groundwater recharge and discharge zones were defined by the technique of image transformation. Further hydrological applications were realised by estimating water recharge potential by determination of lineaments and drainage frequency density, lithologic character, karstic domains and land cover/land use with utilization of Landsat and SPOT imagery and aerial photos (Shaban *et al*. 2006). Kresic (1995) describes Dinaric karst in the Balkans as a favourable area for application of hydrogeological remote sensing techniques, due to the geomorphologic characteristics, in particular the specific surface drainage and karst forms, the varying vegetation that most often reflects the existence of different geologic formations on the surface, and distinct tectonic features. He proposes a method for determination of fractures and faults, as well as ground water flow direction from processing of satellite and aerial imagery. An interesting study was conducted by Peng *et al.* (2000), who employed remote sensing to investigate karst landscape of south-eastern China for the potential of building the world's largest radio telescope. Such investigations of topography can be readily assisted by the Shuttle Radar Topography Mission (SRTM) digital elevation model. The mission, flown on the space shuttle in 2000, created a digital elevation model covering 80 % of the Earth's land surface by radar interferometry. The model with a resolution of 30 m provides an excellent tool for regional topographic analyses.

In the past classification of satellite and aerial imagery has proved to be a good alternative to field observations of large areas for it enables a detailed classification into ten or more land cover classes, as well as rapid execution and temporal comparisons (Shengtian *et al.* 1999). The image classification technology is well known and often used, but has to be applied specifically to every observed environment and phenomena. In classifying the Karst land cover, special attention was paid to all necessary steps, from data selection to accuracy assessment. As basic classification does not provide sufficient accuracy in the presented study we used advanced classification methods, such as post classification modelling.

LAND COVER CLASSIFICATION

The main purpose of satellite and other imagery classification is the recognition of objects on the Earth's surface and their presentation in the form of thematic maps. Land cover is determined by the observation of grey values in the imagery. Classification is one of the most important steps in handling remote sensing imagery and represents important input data for geographic information systems (GIS) (Oštir 2006).

The first step in the classification is the selection of suitable data (images). We had several reasons to use Landsat satellite images in our project. They have an excellent price-quality ratio, good spectral (seven bands from visible to the infrared spectre) and spatial characteristics (30 m resolution). Two multispectral images have been applied, one from Landsat 5 (18/8/1992) and the other from Landsat 7 (15/9/1999, Fig. 1). Both cover the entire study area and are cloudless, which enables simple processing and accurate classification. Images were georeferenced to the Gauss-Krueger co-ordinate system, using multiple control points (86 for Landsat 5 and 102 for Landsat 7) with a higher density in the Karst region. The achieved average positional error is 32 m, which is approximately the pixel size. Both images were merged into a single multilayer data file, omitting the sixth, thermal band because of the lower resolution and its minimal contribution to the quality of the classification.

The classification of satellite and other images is divided into supervised and unsupervised. The main difference between the two is in the way the spectral signatures are created. With supervised classification the operator determines the areas, where a distinct particular type of land cover is present and then the computer computes the spectral signatures. On the other hand, in the unsupervised classification the computer creates the spectral signatures using mathematical data clustering in the multidimensional feature space.

The determination of the used land cover classes was influenced by the previous classification of entire Slovenia (Oštir *et al.* 2000). This enabled the comparison and difference analysis of the final results. Unlike the previous classification the three "urban" classes (urban, densely built-up, and scarcely built-up) were united into built-up areas. The following categories were used:

- coniferous forest,
- deciduous forest,
- mixed forest – forest with approximately the same proportion of coniferous and deciduous trees,
- bushes and overgrowth – bushes, transition from forest to meadow, overgrowing meadow, low (mainly Karst) forest,
- open – meadows and pastures,
- agriculture – fields, vineyards, orchards,
- built-up areas – cities, villages, industrial areas, wider roads and parking places, construction sites,
- water – sea, rivers, lakes, salt-pans.

The first and most important step in supervised classification is the selection of training samples. The operator digitalises the areas with known land cover on the screen. Image processing software then computes the spectral signatures of the land cover types. The process runs interactively, as the quality of the training samples has to be constantly evaluated and usually some have to be improved or even discarded.

The mixed forest class was not used as a sample; it was obtained by unsupervised classification, as described bellow. On the basis of digital orthophotos, unsupervised classification into 20 classes and local area knowledge

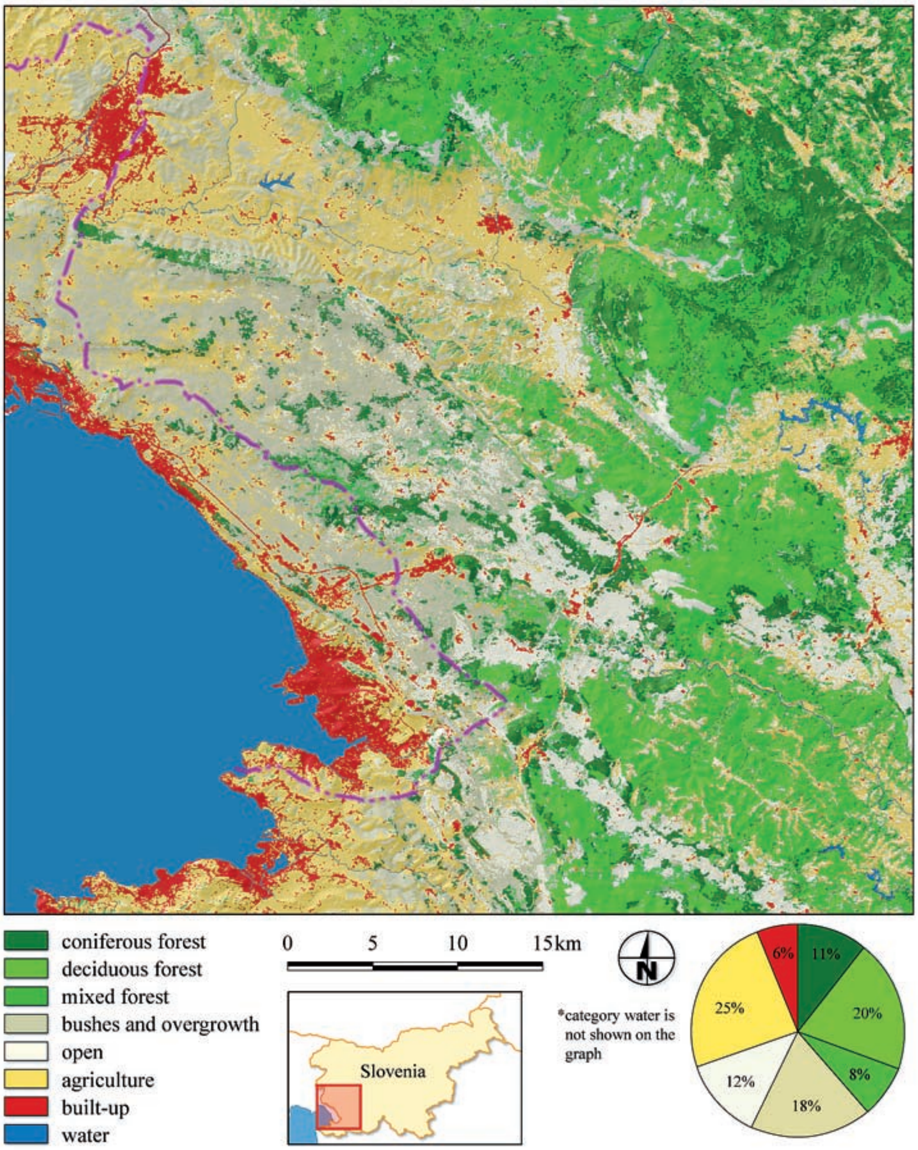

Fig. 2: Land cover map of the Karst region and its vicinity from the combined TM (18/8/1992) and ETM+ (15/9/1999) images.

three to five training samples were determined for each category. Their suitability was checked by the graphic presentation of the spectral response, separability and contingency evaluation, blending in the spectral space and test-classification.

The maximum likelihood method was chosen as the main classification algorithm. Comparing the classification result to the digital orthophotos situation showed that the built-up areas were in places classified as ploughed fields or other open ground areas and vice versa. Eliminating the problem with extra ploughed field training samples did not solve the problem, as at that point a considerable part of the built-up areas was classified as agricultural areas. Using the normalised difference vegetation index (NDVI) also proved to be inappropriate, due to the same problem – too many misinterpreted pixels. We decided to use the fuzzy classification approach. The observed area was classified into two layers. The first layer determined the most probable land cover class, while the second determined the next most probable class. For the built-up areas that were determined as agricultural areas in the second layer of the classification the attribute was changed into agricultural areas. By this action the above mentioned problem was solved in most cases (Fig. 2).

For the classification of forests, training samples of coniferous and deciduous forests were selected, while the mixed forest was initially supposed to be obtained by considering areas with a similar proportion of both. Unfortunately the procedure failed, since the acquired percentage of mixed forests was too small. The influence of the rugged terrain on the surface illumination created an additional problem as the deciduous forest on the shady slopes showed similar spectral values as the coniferous one on the sunny slopes. Topographic normalisation was used without any success. Better results were obtained by the unsupervised classification of forest surfaces only. Once more the masked (by forests) satellite image was classified by the unsupervised classification into 3, 6, and 10 classes. In ideal circumstances the classification into three classes would distinguish coniferous, deciduous and mixed forests. Unfortunately, this was not a straightforward process and the best results were obtained by interpreting the classifications in 6 and 10 forest types. Aerial photography interpretation helped to choose the 10-class classification, as it was the

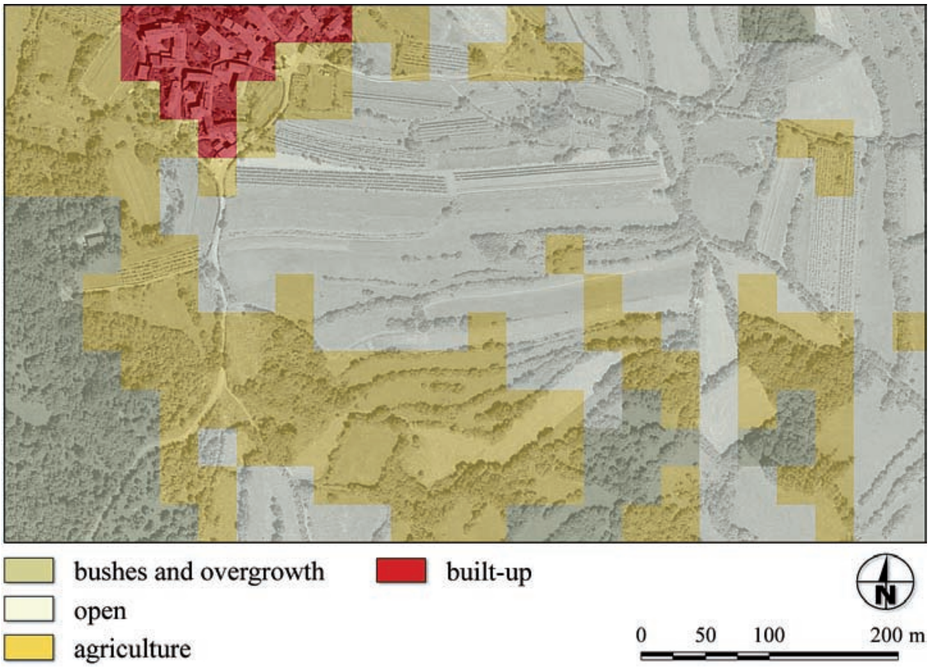

Fig. 3: The problematic category division resulting in the great variability of land use is one of the main characteristics when classifying satellite imagery of the Karst region. In the picture one can see the area south of Volčji Grad village. The land cover layer is partially transparent, the background is a digital orthophoto (Source: DOF, 2002, © GURS).

best for distinguishing between the forest types. Certain classes were then merged into three basic categories and their value was added to the initial classification.

Distinguishing fields, bushes and meadows caused additional problems (Fig. 3). For example, it occurred that the class agricultural area covered bushes or meadows. The problem, which is a result of the fragmented land division, different land use types and rapid overgrowing of the Karst region, is especially evident, because meadows can be detected through thin bushes that create a similar spectral signature in all three categories. One also has to consider the acquired data from the satellite images, as in the late summer a large amount of the fields is already barren, and due to the drier grounds it is harder to distinguish between different kinds of vegetation.

Due to the insufficient spatial resolution of the Landsat satellite imagery only larger rivers are directly detectable. In order to avoid a 'discontinuous' river scheme and to improve the accuracy we used the existing vector hydrology data. The final land cover map was masked by including rivers wider than 5 m, as well as lakes, swamps, salt-pans and the sea.

Further quality improvement of the classification was made by considering (limiting) the altitude and inclination. The interferometric digital elevation model (DEM) with the resolution of 25 m (Oštir *et al.* 2002) was used as the source of the altitude data. The Gams altitude borders study (1960) and the inclination definitions according to the farming suitability of the ground (Kladnik 1999) were also considered. The altitude of 1450 m was selected as the forest border, the altitude of 850 m and a 22° inclination were determined for agriculture, while the altitude of 900 m and a 25° inclination was considered for built-up areas. Everything higher and steeper than the determined limits was reclassified into an open category. Due to the fact that an accurate DEM was not available at the time of the study the area on the Italian side more than 5 km from the state border was excluded in the post-classification.

Further spatial filtering was used to eliminate the noise from the results and achieve partial generalisation. An adapted majority filter (Kokalj and Oštir 2006) of 3 by 3 pixels was used in order to detect the isolated pixels and assign them the prevalent class in their vicinity.

RESULTS

The attribute accuracy of the classification was evaluated by using 120 control points with known land cover, determined from the aerial photography. The final accuracy is very high and exceeds 90 %. Through the analysis of the quality it was established that agricultural areas and open categories were mostly misclassified, for in almost all cases they should have been found in the bushes and overgrowth category. However, taking into account the

Class	*Reference points*	*Classified points*	*Accurately classified*	*Users accuracy*
Coniferous forest	18	18	17	94 %
Deciduous forest	21	22	21	96 %
Mixed forest	14	12	12	100 %
Bushes and overgrowth	23	16	16	100 %
Open	16	19	16	84 %
Agriculture	17	21	17	81 %
Built-up	5	6	5	83 %
Water	6	6	6	100 %
Total	120	120	110	

Table 1: Accuracy assessment of the land cover classification.

	Classification for Mobitel (1999)		*Classification for Aquadapt (2004)*	
	ha	*% of total area*	*ha*	*% of total area*
Urban	1700	0.6		
Densely built-up	6000	2.1		
Scarcely built-up	16,800	5.9		
Built-up total	24,500	8.6	17,200	6.0
Coniferous forest	23,000	8.0	31,100	10.9
Deciduous forest	71,400	25.0	57,300	20.1
Mixed forest	14,500	5.1	22,900	8.0
Forest total	108,800	38.1	111,300	39.0

Table 2: Comparison of built-up areas and forests between the single temporal and multitemporal classification.

rapid overgrowing phenomenon, the amount of young low forests and the very variable land use changing over short distances (extreme fragmentation) this is understandable. Some misinterpretation can also be found in the forests, which suggests that additional attention is necessary for accurate distinguishing.

The comparison with a previous classification (Fig. 4, Tab. 2), created for the planning of the mobile telephone network, shows differences mainly in the built-up and forest categories (table 2). The previous classification distinguished between three classes of built-up areas, i.e. urban centres without vegetation, densely and scarcely built-up areas with vegetation and gardens. In the presented classification these classes were merged and are all presented by built-up areas without dense vegetation. Thus, greater differences appear in the countryside where the newer classification does not consider the small built-up areas in the hills whereas the previous one did. However, the previous classification also considers a number of non built-up areas, mainly agricultural in the Koprska Brda region as well as in the neighbourhoods of big cities.

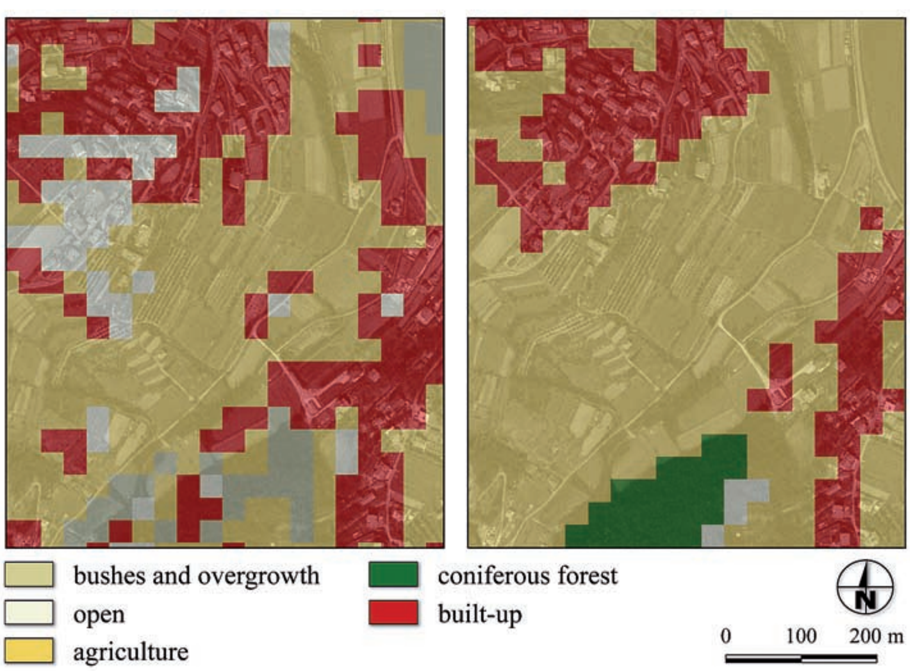

Fig. 4: Multitemporal classification is especially useful for designating built-up areas. Comparison of the old (left) and new (right) classification reveals major improvements. The land cover layer is partially transparent, the background is a digital orthophoto (Source: DOF, 2003, © GURS).

The discrepancy in the percentage of certain forest types occurs due to the differences in obtaining the raw forest data. The previous classification determined the coniferous and deciduous forests through supervised classification, and the mixed forest data was obtained by considering their relative proportions. The new classification determined forests through unsupervised classification and by later merging of the classes. In spite of this the difference in the total share of forests is rather small when the two classifications are compared. Deciding which classification is better suited as regards the available means (area knowledge, digital orthophotos) is a difficult task, however, the forest map, which can be found at the Slovenian Ministry of Forestry, can be used (with some hindrances). We believe extensive fieldwork is necessary in order to verify certain sample areas.

CONCLUSIONS

It has been proven that the classification of satellite images is an efficient tool when determining the land cover in the Karst region. By using such a classification one can perform the mapping of a larger area and observe its temporal development in a relatively short period of time. The Landsat imagery used in this study proved to be appropriate for distinguishing approximately ten to twenty land cover categories with a spatial resolution of 30 m. Due to the uniqueness of the Karst landscape, especially the high fragmentation of land ownership, complex cultivation patterns, variable soil conditions and rapid overgrowing, it is difficult to distinguish some of the classes and more advanced methods need to be applied, e.g. post-classification.

The use of various image data, filtering according to altitudes and inclination, and the combination of supervised and unsupervised classification enable a significant improvement in the quality of the final land cover map. The attribute accuracy of the produced classification – assessed by comparing a larger number of test points with ground data collected from aerial orthophotos – is high and exceeds 90 %. The categories agricultural land and open spaces are most commonly misclassified; however some misclassification also occurs within the forest types. The classification of two (merged) images eases the distinction between the classes; especially the built-up areas can be easily distinguished from the other categories. When comparing the two classifications differences could mainly be noticed in forests and built-up areas. In order to determine the benefits of individual classifications additional fieldwork would be required.

This study confirmed our assumption that a simple land cover classification can not be used if we wish to achieve high accuracy. It has been proven that the land cover determination depends on its location as it is necessary to consider all local characteristics, the natural phenomena and occurrences as well as man made objects. We can clearly claim that land cover classification should be performed for smaller landscape units. The Karst region with its specifics demands a detailed research, supported by terrain limiting training samples selection and detailed result quality checking. One of the most interesting questions when considering future studies is the usefulness of high-resolution (spatial and spectral) satellite and airborne sensors, especially lidar, for detailed research of natural and anthropogenic Karst characteristics.

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