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Spatial indicators for nature conservation from European to local scale

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Abstract

The paper presents an overview of the objectives and exemplary results of the FP 5 project "Spatial Indicators for European Nature Conservation" (SPIN). The SPIN project is focused on the development and testing of advanced classification methods and spatial indicators based on multisensor satellite data and GIS to accomplish monitoring and management tasks in the context of Natura 2000 and nature conservation. A representative selection of eight regional test areas covers a pan-European network and allows comparative investigations to provide accepted recommendations for regional and European nature conservation. The selected results of four case studies are presented and discussed. The range of work covers the production of regional and local habitat maps by object-oriented classification, a case-based reasoning method for change detection as a management support tool for planning and regulating local land use, the selection and application of structural indicators for the monitoring of Natura 2000 habitats and the downscaling and disaggregation of soil information. Results and the further implementation of presented methods are discussed in the conclusions.

Keywords: Baseline geometry; Case-based reasoning; Habitat mapping; Landscape metrics; Land cover change; Object-based classification; Remote sensing; Soil map modelling

1. Introduction

The implementation of the EU directives on the conservation of natural habitats and of wild fauna and flora (92/43/EEC) and on the conservation of wild birds (79/409/EEC) in the Natura 2000 network

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constitutes an important step towards the harmonisation of nature conservation in the European Union, and makes standardised scientific monitoring legally binding for the first time. The requirements of a harmonised and sound monitoring and management of the designated protection areas are a challenging task for local authorities responsible for the individual sites, as well as for authorities on the regional, national and EU level that are in charge of the assessment and channelling of the huge data flow arising with the monitoring activities from the local sites.

The additional tasks arising through the implementation of the directives will lead to the demand for additional financial subsidies for monitoring tasks. Hence, there is a genuine interest in the development of cost-effective monitoring methodologies.

Indicators are expected to be a powerful means to aggregate the data to policy-relevant information and provide a stable basis for reporting (EEA, 2003). It will also bring stability to data flows and thus improve data quality and comparability in the longer run. Indicator systems have been developed by different policy makers, e.g. the OECD, EEA, EUROSTAT, but the common shortcoming of such policy-driven indicator systems is their design primarily for comparative studies across countries, and hence the lack of explicit spatial information and the relation to functional ecological aspects that is needed for decision-making concerning the implementation of the habitat directive and Natura 2000.

The overarching objective of the EU FP 5 project "Spatial Indicators for European Nature Conservation" (SPIN) is to implement a tangible work flow to convert data from different sources (satellite sensors, nature conservation plans and ecological field records down to the species level) into explicit spatial information on the state and quality of key habitats protected within the Natura 2000 network and their adjacent areas.

Thus, the SPIN project aims:

- to develop and apply innovative classification techniques in a multiscale, multitemporal and multisensor approach, in order to generate habitat and vegetation maps from regional to local scale according to a certain mapping key (EUNIS, FFH, user demanded);
- to set up a framework of spatial indicators to assess the conservation status of habitats mostly based on delineated units from the previous classification step. Indicators cover different aspects and are based on different methodological approaches, such as change indicators, pressure indicators, biodiversity indicators, structural indicators and functional indicators;
- to perform comparative case studies; a pan-European transect is covered by eight test areas, in order to gain scientific knowledge about the ecological and practical value of investigated indicators in different biogeographical regions and habitats.

A major challenge for indicator development is to find the right balance between user requirements at different working scales, the general concepts of environmental indicators such as the DPSIR and technical feasibility using remote sensing data.

To find a common denominator for a harmonised solution in all regional test areas, a standardised case study design was developed that comprises: a common basic dataset, the use of EUNIS as a common classification key, the production of two regional habitat maps of EUNIS level 1 for the period of 1990 and 2000, a change map from 1990 to 2000, a local habitat map of EUNIS level 2 or a regional key, as well as a pre-defined set of indicators selected from the methodological categories investigated within the project.

The common datasets and the common selection of indicators support comparative analysis of the test areas on the regional scale. On the local scale, however, SPIN methods can be adapted to the local specifics of each test area to allow more detailed analysis of the conservation status of habitats. Whereas on the regional scale indicators are reduced to a comprehensive set of rather basic indicators of area, structure, change and pressure, on the local scale indicators are much more tailored to the habitats of interest, including more labour intensive indicators of biodiversity and soil-based landscape functional indicators.

In this article, we will show examples from four different test areas illustrating the SPIN concept, as to how to deal with the different requirements of nature conservation management and monitoring at different administrative levels.

For the European countries, there is a range from local site management, regional planning to European policy making which have direct impact on nature conservation. The first case study shows the approaches of a semi-automated mapping of habitats on the regional and local scale in Schleswig-Holstein in Germany by the use of object-oriented classification techniques. The detection of land cover changes by case-based methods are discussed by the analysis of changes in the Otepää Landscape Reserve in Estonia. The selection and applicability of structural indicators for local site management is demonstrated within the case example of the Wenger Moor in Austria. Refinement of soil data, which is indispensable for a comprehensive description of habitats, by disaggregation is demonstrated and discussed in the fourth case example of the Postojna Area in Slovenia. Results and further implementation of the presented methods are discussed in the final conclusions.

2. Multiscale classification for mapping of habitats on the regional and local scale (the case study area of the Eider Treene Sorge Lowland, Germany)

For the regional planning of landscapes, data are needed to support the analysis of the distribution and development of major land use types (settlements, agriculture, forestry, nature conservation), and potential conflicts among these (e.g. agriculture versus nature conservation). Therefore, regional maps of actual land cover data should relate to these land uses. Relating such land cover data of time series to statistical socio-economic data, the main drivers of landscape changes may be distinguished. The potential conflicts of competing policy measures can be investigated, and strategies for their harmonisation, e.g. the harmonisation of nature conservation and agricultural policy measures, can be proposed.

A regional approach, however will level out the particularities of individual areas and hence is often detached from the practical requirements for conservation. Consequently, acceptance by the local end user will be moderate. In order to supply end users with appropriate data, a more flexible approach for the production of habitat maps is desirable, with an opening of the classification key for local class specification at a lower hierarchical level and a definition of a local working scale to suit the demands of local conservation managers.

A hierarchical concept of test areas is defined, and these are linked to specific operational levels. On the regional scale, the investigation area covers the districts Schleswig-Flensburg and Nordfriesland, with an area of approximately 4156 km^2. The predominant land use is agriculture, mainly cereal cropping on the fertile soils of the young quaternary moraines in the east and lime marshes in the west, and mainly grasslands and pastures on the leached, sandy or wet soils in the Geest and marshes in the middle.

On the local scale, the core area of investigation covers about 5.5 km^2 and is located in the Eider Treene Sorge lowland, covering the Natura 2000 bog habitat “Wildes Moor”. After a long period of degeneration caused by drainage, the bog is now mostly under nature conservational management. Nevertheless, due to the intensive land use of pastures and grasslands in the surroundings of core habitats, the site is still affected, and conflicts between agricultural land use and nature conservation exist.

On the regional scale, the land cover classification was based on a dual-date set of Landsat ETM+ scenes from 2001. The acquisition dates of the scenes are spring (2 May 2001) and summer (5 July 2001). Index layers of the normalised difference vegetation index (NDVI) as well as a normalised ratio of bands 4 and 5, were computed for both scenes and combined with original red and infrared bands for the classification.

For a habitat classification on the local scale, high resolution data were provided with high resolution stereo camera (HRSC) scanner data taken in August 2001. This airborne scanner has a spatial resolution comparable to analogue airborne camera data (5–30 cm) in the visible and infrared spectral channels, a better geometric accuracy and an additional digital surface model (DSM). Due to the high processing demands of the eCognition software and in order to provide comparability of the assessed methods to applications on VHR satellite images (characteristic image resolution ranging from 1 to 5 m), the resolution of the HRSC scanner image was resampled from 20 cm to 1 m. A pre-processing of the DSM, which is provided together with the HRSC scanner data, was done to achieve a relative measure of object heights. A 17×17 mean filter was chosen to compute the difference to the original DSM. The difference between a smoothed surface and the original surface of the DSM allows the detection of the steep rise in elevation caused mainly by trees, hedgerows and buildings.

For both scale levels, additional information was included in the classification process by the integration of a soil map at 1:200,000 and topographical data on the built-up area, roads and lanes.

Ground truth data were obtained during two field campaigns in 2002 and 2003. To have strong proof for the accuracy of the classification of the different spectral variations of arable lands and grasslands, ground truth data were spread over all natural zoning areas.

The EUNIS key (EEA, 2003) as a common and not mainly EO-driven classification system was chosen for both regional and local classification. In some cases, it obstructs the direct application of spectral signatures inherent to established classification methods, at the expense of processing time, and increases dependency on ancillary data. These pitfalls are outweighed by creating a common denominator for habitat mapping and further application of indicators. Furthermore, EUNIS habitat maps are widely accepted among users as the classification system enables cross-checking with national or local systems.

Major advantages of the object-oriented classifications for applications in regional planning procedures include the easy integration of additional knowledge and the representation of the landscape through objects rather than pixels. The integration of additional knowledge is a valuable means to distinguish ecologically meaningful land use/cover types that do not necessarily have very distinct spectral features. Furthermore, land cover maps will not be accepted by end users when they show the land cover as having a ‘‘salt and pepper’’ appearance, as is often the case for pixel-based classifications (Blaschke, 2000). Object-oriented classifications show a rather homogenous representation of landscape patterns and are therefore much more suitable to meet the demands of end users.

The software package eCognition enables a multiscale segmentation that allows the adaptation of the segmentation levels to the object size of relevant habitats in the image. The classification can be supported by the use of context regarding neighbourhood and hierarchy, shape- and class-related features (Definiens, 2001).

While on the regional scale the focus is put on a consistent strategy of land cover classification that is transferable to scenes of other years for the production of time series, on the local scale special focus is put on the conceptual design of a hierarchical network for the proper segmentation and classification of habitats, the use of hierarchy- and context-related features which are especially suited for the classification of VHR images and the capability of the HRSC digital surface model to support the classification process. The applicability and performance of object-oriented classification for habitat mapping on the base of VHR images are discussed by Möller et al. (2002), Antunes et al. (2003), Burnett et al. (2003) and Lang and Blaschke (2003), while there are only a few examples of its application on a regional scale, as Esch et al. (2003).

For the *regional classification*, four scale levels were implemented. The principles of the multiple levels are summarised in Table 1. Levels 1 and 4 were both used to provide additional data. On the first level, soil data that had been integrated as a shape file was classified according to the soil type to serve for knowledge-based rules. Level 4 was segmented on a course scale and then classified with an NDVI threshold for the separation of marine and continental environment. Inland water bodies were manually classified as continental. A nearest neighbour classification based on the training samples was performed on level 2. This, together with the additional information of levels 1 and 4, was then used for the classification of EUNIS habitats on level 3. To provide higher spatial accuracy for rather small objects of constructed areas and infrastructure, the classification outcome of level 3 was resampled to 15 m. Infrastructure, i.e. highways, railways, streets, as well as constructed areas, is taken from the official topographical information system. A separation of dense inner city building areas, suburban building areas and sparse building areas, is done by the application of thresholds of NDVI.

For the *local classification*, a multiscale strategy was developed for the detection of the different vegetation or habitat types that are represented in different object and habitat scales in the image, e.g. recognition of trees and buildings, classification of larger habitats of forests, grasslands and arable fields and classification of small habitats as bog vegetation and water holes. Seven scale levels were segmented in

Table 1
Schematic overview of data and methods used for the multiscale segmentation and classification in eCognition

Parameters			Datasets [• used]							Applied method/results	
Level	Process	Scale-param.	ETM NDVI (dual-date)	HRSC		DSM		Soil DB	ATKIS roads	Rules	Classification
				Ch. 1–4	Index	Diff.	Bin.				
Local classification											
1	Classification							•		Attribute table query	Main soil types
	Segmentation							•			
2	Classification				•	•				Spectral fuzzy thresholds, neighbourhood	Vegetation, non-vegetation, shadow, high and low objects
	Segmentation	4		•			•		•		
3	Classification	CB								Hierarchical object queries, neighbourhood	Shadow classes, potential trees and buildings
	Segmentation	12							•		
4	Classification			•	•	•				Standard nearest neighbour, hierarchical object queries	Small-scale habitats: lakes, grassland and bog types
	Segmentation	22		•					•		
5	Classification									Hierarchical object queries, neighbourhood	Tree groups and forest, forest and tree shadow
	Segmentation	33							•		
6	Classification		•	•	•			•		Standard nearest neighbour, area and shape index	Large habitats: agriculture, grasslands, bogs, forest
	Segmentation	190		•					•		
7	Classification	CB								Classification-based aggregation of sub objects	Main land cover types
	Segmentation			•					•		

Level	Process	Scale-param.	ETM-May		ETM-July		Soil DB	ATKIS roads	Rules	Classification
			Ch. 3–5, 7	Index	Ch. 3–5, 7	Index				
Regional classification										
1	Classification						•		Attribute table query	Main soil types
	Segmentation	5	•		•		•	•		
2	Classification		•	•	•	•	•		Spectral fuzzy thresholds, standard nearest neighbour	Spectral classification of land cover primitives
	Segmentation	5	•		•			•		
3	Classification		•	•	•	•	•		Spectral fuzzy thresholds, hierarchical object queries	EUNIS habitats level 1
	Segmentation	5	•		•			•		
4	Classification			•		•			Spectral fuzzy thresholds	Separation of marine and continental environment
	Segmentation	150	•		•					

Comments: level: segmentation level in eCognition, object size increase from 1 to higher numbers; scale-param.: scale parameter used in eCognition for segmentation; CB: classification-based segmentation used; HRSC 1–4: B, G, R, NIR; HRSC index: NIR, NDVI, brightness index; ETM index: NDVI, normalised chan4–chan5; DSM diff.: surface difference original and low pass filtered DSM; DSM bin.: binary mask of applied threshold to DSM diff; soil DB: soil database BÜK 200; ATKIS roads: buffered vector road layer; rules: rules and classification algorithms used; classification: object and habitat types classified.

eCognition and used for classification. Table 1 outlines the basic methods and datasets used on the different scale levels. The first level represents the soil classification as knowledge base, as in the regional classification. On the second level, a very basic spectral delineation of the scene into very small sized objects of vegetation, non-vegetation, shadow and relative high and low objects was applied. Class-related queries of neighbours and subobjects were used to merge the object primitives into more meaningful objects as buildings and trees in level 2. While level 4 mainly served to assist in the extraction of shadow borders from forests, levels 3 and 5 are used for the main classification, either of small (level 3) or large (level 5) habitats. Some spectral confusion between arable land, grassland and semi-natural habitats occurred, but could be solved by the integration of dual-date Landsat ETM+ datasets available for the same year. Level 6 represents the main land cover classes and structures: agricultural land, forests, tree lines and groups, semi-natural land. In cases of application on other areas/data, this level might be replaced by an existing land cover or biotope map.

The classification accuracy of the regional land cover map was assessed by means of an error matrix. The overall accuracy is 86.19%, the overall Kappa Statistics is 0.80. The assessment was based on ground truth data from the field campaign in 2003 that have not been used for training (see Table 2). The points selected were visually checked with the image data of 2001, and in cases of uncertainty excluded from the sample. The producers accuracy of the classes was 36, 80, 75, 76, 91, 68 and 91% for EUNIS classes A, B, C, D, E, G, I and J, respectively. The reason for the rather low accuracy value for marine habitats is the difficulty of the classification of littoral saltmarshes. Their phenology may vary a great deal due to the variability of flooding times, and furthermore their classification is based on a separation of marine and continental environment on level four in the classification process, which is difficult at the coastline, due to the object segmentation algorithm. In general, it can be stated that land cover types with variant object sizes and forms reach lower accuracy values than classes with clearly distinguishable object boundaries, as is the case for agricultural and grassland parcels. The described methodology was already transferred to similar datasets for the production of EUNIS habitat maps of 1995 and 1990.

For local classifications, the accurate delineation of habitats generally improves with the increase of spatial resolution of the input data, leading to more accurate classification with a higher information content. Nevertheless, problems of accurate segmentation and classification arise, which have been identified for different types of vegetation and habitat, e.g. trees, forests, grassland, arable land and bogs. While the segmentation and classification of field and bog habitats is promising, the inner segmentation of forests in particular is not well done by the algorithm of eCognition. Very specific and therefore divergent rules for the classification of different habitat types had to be defined, resulting in examples of suitable solutions for the classification of selected habitat types. The habitat map produced on the local scale reaches a delineation of habitats that is comparable to aerial photography interpretation. Inner habitat delineations, e.g. of different states of phytosociological

Table 2
Accuracy assessment table

EUNIS 1	Class name	Reference totals	Classified totals	Number correct	Producers accuracy (%)	Users accuracy (%)
	Not classified	0	19	0		
A	Marine habitats	11	6	4	36.36	66.67
B	Coastal habitats	10	8	8	80.00	100.00
C	Inland surface water habitats	12	9	9	75.00	100.00
D	Mire, bog and fen habitats	25	21	19	76.00	90.48
E	Grassland and tall forb habitats	211	220	191	90.52	86.82
G	Woodland and forest habitats	57	42	39	68.42	92.86
I	Agricultural habitats	210	208	192	91.43	92.31
J	Constructed habitats	0	3	0		
	Totals	536	536	462		

communities, is much finer with HRSC-based object-oriented classification, and gives a much better spatial representation of objects than common biotope maps based on colour-infrared aerial photography interpretation. Thus, habitat classifications as presented may well serve to update existing biotope and land use maps. On the other hand, the high differentiation of and within objects needs to be generalised to be compatible with existing maps. No overall accuracy assessment can be provided yet, as detailed vegetation data sufficient for training and validation was first available in the final stage of this study, and will presented in a latter publication. The compatibility of the classification outputs to exiting basic geometries on the regional and local scales is supported by the integration of data on infrastructure from ATKIS. Further details of the studies presented are given in the SPIN report D7 (Bock et al., 2003).

3. A case study of land cover changes at Otepää, Estonia

Both socio-economical changes after the re-establishment of the Republic of Estonia, the reorganisation of Otepää Landscape Reserve into Otepää Nature Park and the restriction of logging from 1997 have changed the land use, landscape, and wildlife habitat distribution of Otepää Nature Park. Most of the study area lies within the Otepää Nature Park, which covers 2243 km^2 (22%) of Otepää Upland in Southeast Estonia. The Otepää Upland is an end-moraine accumulative insular height with irregular hilly moraine relief. The altitudes in the study area range from 60 to 217 m above sea level.

The temporal landscape changes should be most visible in the area of ploughed fields and overall forest coverage. Satellite images in combination with different map layers are the best attainable data sources to map and quantitatively estimate the land cover changes. The mapping of land cover changes is essential for the planning and regulation of local land use.

Two Landsat images (Landsat 5 TM from 15.05.1985 and Landsat 7 ETM+ from 16.05.2000) were combined with map and elevation data, 1:10,000 digital base map, soil type and type of soil mineral origin characteristics from a 1:10,000 digital soil map, slope angle and elevation relative to the mean altitude within 100 m neighbourhood from a digital elevation model, that characterise the properties of vegetation site types. All image and topographical data were resampled to the same $10\ \mathrm{m} \times 10\ \mathrm{m}$ grid in the Estonian base map coordinate system.

Most representative training polygons were delimited on images from the years 1985 and 2000 for the separation of fields from other agricultural land and for the separation of wood from open natural land. Training polygons for the land cover interpretation of the year 2000 were confirmed using records from vegetation field mapping in the summers of 2000, 2001 and 2002, covering approximately 1/10 of the study area. Maps from the 1980s and personal memories, in addition to the satellite image, helped to select the training polygons for the year 1985.

Linear discriminant analysis, which is traditional in land cover mapping, assumes continuous variables and a normal distribution of values. Although the distribution of the pixel values of the Landsat images is close to normal, the additional map data are usually categorical variables, or if continuous, then significantly different from normal distribution. Joint application of such different explanatory variables is possible in general and generalised linear statistical models, in hierarchical classifications according to conditions and critical values, using pre or post classification in addition to discriminant analysis, or using case-based (also called: nearest neighbour, similarity-based, exemplar-based) techniques.

Case-based prediction is an empirical, universal and flexible approach of scientific reasoning (Mitchell, 1997; Aha, 1998). The application of case-based reasoning to image interpretation is either pattern recognition or pixel-based image processing. Pixel-based processing is understood here as an inductive methodology during which signatures or generalised rules are not created—where unknown pixels are classified by comparing them to raw pixels of the training data. In case of pattern recognition, various characteristics of the local pattern are compared to the examples. Machine-learning can be applied in both cases to find out the best features and examples, called exemplars, if these are a part of a case-based predicting system. There is no need to use all training data in calculating predictions because some observations duplicate each other, and some are noisy.

A software tool of machine-learning and nearest neighbour's prediction created at the Institute of Geography of the University of Tartu, Estonia, was used to create the maps of the estimated distribution of fields and woods in the study area. A user of the software can select: the method of machine-learning (12 different algorithms), the type of the dependent variable and the respective objective function (mean linear deviation, standard deviation, kappa quotient of classification fit, the share of correctly predicted probability of a binominal variable, the matching share of a multidimensional variable), the maximum number of features to use, the number of dependent variables, the maximum accepted difference in explanatory variables, an initial value for the sum of similarity demanded for decision, the number of training observations, the names of input and output data files. If the number of preferred training pixels in the case of raster data is less than the number of pixels within the training polygons, the training pixels are selected from training polygons at a regular interval.

The output of the machine-learning process gives a fitted value for the sum of similarity demanded for decision, and fitted weights for features and exemplars. The zero-weight of a feature means the feature is not used in predictions, and the zero-weight of a training observation means that this training observation is excluded from the set of exemplars. The overview of the learning process is recorded: time, weights, leave-one-out cross-validation fit, predicted value for every training observation.

The set of features and exemplars selected by the machine-learning module are used as components of the prediction system. The predicting module calculates nearest neighbour predictions using weights of features and exemplars, a set of feature vectors of exemplars, a pre-classification feature and feature vectors of predictable objects. The predicted values and the level of similarity at every decision is output into a binary or ASCII file. The formula of calculations and other details of the methodology are given in Remm (2004).

The machine-learning process selected only a minor part of features, and the relevant features were different in all four cases (Table 3). The differences in features can be attributed to the differences in the properties of images due to different sensors, but also to the less firm decision of training sites of the historical land cover situation. On the other hand, different combinations of features and exemplars can give an approximately equal cross-validation fit in machine-learning. The final combination is partly occasional because of random decisions at some stages in many machine-learning algorithms. The weights of features and training observations and their combinations suggested by machine-learning could be objects of special investigations on indicator values of characteristics of spatial data and combinations of different data layers.

The base map is one of the two predictors separating classes in 2000, because field mapping for the base map took place in the study area in 1997 and 2001, which is closer to the year 2000. Nevertheless, the same base map also has the highest weights for the interpretation of the image from 1985. Soil types also have high weights in 1985. The high value of an explanatory feature does not necessarily mean that the feature itself, without other features, is a

Table 3
Weights of features and the number of exemplar pixels (no.) in estimation of the distribution of fields and wood

Year 1995	Soil1	Soil2	Base map	Slope	Rel. elev.	TM1	TM2	TM3	TM4	TM6	TM7	No.
Wood/open	1.91	0.22	2.03	0.02	0.25	0.00	0.00	1.79	0.00	0.00	0.67	49
Field/meadow	0.3	1.23	1.54	0	0	0.79	0	1.96	1.4	0.47	0.32	106

Year 2000	Soil1	Soil2	Base map	Slope	Rel. elev.	ETM1	ETM2	ETM3	ETM4	ETM5	ETM6.1	ETM6.2	ETM7	ETM8	No.
Wood/open	0	0	0.93	0	0	0	0	1.07	0	0	0	0	0	0	40
Field/meadow	0	0	0.86	0	0	0	0	0	0	0	0	1.14	1	0	46

Soil1: soil type; soil2: type of mineral origin of soil; base map: land cover according to the 1:10,000 base map; slope: slope angle in degrees; rel. elev.: elevation relative to the mean of 100 m neighbourhood; TM1–7: channels of Landsat 5 Thematic Mapper; ETM1–8: channels of Landsat 7 Enhanced Thematic Mapper.

good predictor. The interpretation can also be that other features should be treated separately if the category on the relevant map is different.

In this study, changes in woodland/open land were counted only on relatively natural land, including base map land cover categories: forest, felled forest, scrub, marshland and a class called ‘‘other open land’’. Water bodies, settlements, artificial surfaces and agricultural land were excluded from wood cover estimations. The results reveal that only 61% of natural land was covered by wood according to the image from May 1985 versus 80% wood cover in May 2000. Thus the estimated share of open natural land has diminished from 39 to 20% within 15 years (Fig. 1). This change can be attributed in part to the exclusion of previous natural meadows, especially wet and alluvial meadows, and also fens from agricultural use, and their spontaneous afforestation. The other reason for the overall afforestation is the termination of clearcutting in the forests of the nature park. In these climatic and soil conditions, 15 years is enough time for the felled area to become a young forest.

Changes in ploughed fields versus fallows and grassland were counted relative to the area of agricultural land on the base map. According to our estimates, 47% of agricultural land was ploughed in spring 1985. The corresponding number in 2000 was only 10%. The definite estimate for the year 2000 is 6.5%, but 3.5% was added from weighted fuzzy decisions (Fig. 2). In addition, in the case of woodland most pixels are classified firmly either to wood or open natural land, and the share of fuzzy decisions is even less. Fuzzy decisions

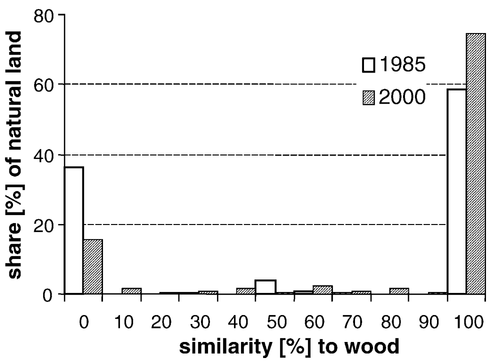


Fig. 1. Estimated share of wood as percentage of natural land at Otepää study area in May 1985 and 2000, according to the similarity level of decision.

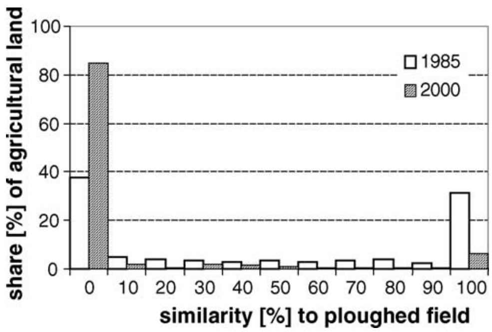


Fig. 2. Estimated share of ploughed fields as percentage of agricultural land at Otepää study area in May 1985 and 2000, according to the similarity level of decision.

in binominal exemplar-based decisions mean that among the most similar exemplars to the pixel were representatives of both classes. A pixel was classified to the class whose sum of similarities among the most similar exemplars to the pixel was greatest.

4. Selection and application of spatial indicators for the Wenger Moor case study site (Austria)

The Wenger Moor comprises the largest remaining mire complex of the pre-alpine region in Austria’s Salzburg province. The overall size of the entire area is 298 ha with a mean elevation above sea level of 510 m. Several habitat types according to Annex I of the FFH Directive occur on the Wenger Moor site. The main areas of interest are small remnants of active raised bogs still capable of natural regeneration (FFH code: 7110), which have largely been altered to degraded raised bogs (FFH code: 7120) due to a change in vegetation and bush encroachment.

One of the groups of spatial indicators to be tested and applied within the SPIN project are the so-called structural indicators based on landscape metrics. Although the quantitative assessment of landscape structure using landscape metrics is frequently mentioned as holding much potential for nature conservation (Blaschke, 2001), there are currently only very few operational applications of landscape metrics in European nature conservation.

For the application and testing of landscape metrics to function as structural indicators, we followed

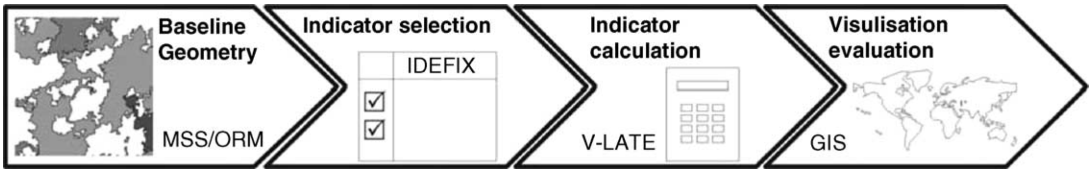


Fig. 3. Schematic workflow from the establishment of a baseline geometry, indicator selection, indicator calculation to visualisation and evaluation of the indicators. In smaller letters, the respective tools used in the process.

several methodological steps, from the generation of the baseline geometry to the actual calculation and evaluation of the metrics. These steps are summarised in Fig. 3 captions.

For the calculation of landscape metrics and the subsequent development of meaningful structural indicators applied to categorical maps, the quality and consistency of the baseline geometry derived from the classification procedure is of crucial importance. It is important which class definitions are applied to the dataset, as the results of landscape metrics depend on the thematic resolution and the classification scheme used. In the absence of a consistent FFH-specific spatial database for all case study areas, the EUNIS classification key (EEA, 2003) was chosen as a common denominator for comparative studies within the SPIN project.

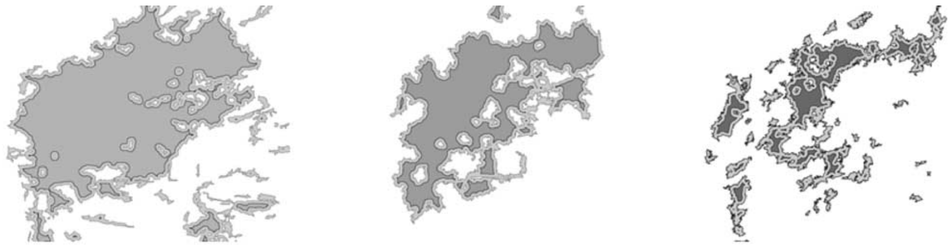
As a classification method for the case study area Wenger Moor, we applied the multiscale segmentation/object relationship modelling (MSS/ORM; Burnett and Blaschke, 2003) methodology. This classification is based on a multiscale segmentation using the software eCognition (Definiens, 2001). Subsequently, a supervised classification combined with object relationship modelling is performed to include expert knowledge in a rule base. The method and its advantages are discussed in detail by Burnett and Blaschke (2003), and are compared to alternative methods of multiscale landscape analysis by Hay et al., 2003. How MSS/ORM was used in the Wenger Moor to delineate FFH habitat types, as well as subsequent degradation stages, has been described in Lang and Langanke (2004).

Many landscape metrics are statistically correlated, and it was often attempted to identify a small set of statistically independent metrics that capture all aspects of a landscape pattern (Riitters et al., 1995; Herzog and Lausch, 1999). However, these approaches neglect the fact that many metrics have been developed for particular ecological questions, which in turn may only be addressed sufficiently by specific metrics. We therefore identified abstracted ideas (“the essence of the metric”) in order to communicate the potential of those measures. We assume that these key issues (Table 4) address all relevant major structural aspects of the site under investigation. Table 4 gives an example for one group of metrics (core area analysis).

There are a number of software packages available for the structural analysis of landscape patterns. Some landscape metrics offered are well documented (McGarigal and Marks, 1995) but usually without

Table 4
Key issues, questions and related metrics for the group of core area metrics

Parameter/key issue	Question answered by metric	Metric/indicator
Size and number of remaining core areas	How large is the ecologically effective area for edge-sensitive species in the entire landscape?	TCA/TCCA (total core area and total class core area)
Important when considering habitat requirements of either ‘interior species’ or ‘edge species’	Of how many disjunct core areas are all patches of one class comprised?	NCA (number of core areas)
	Which percentage of the patch is core area?	CAI (core area index)
	What is the degree of decimation? Does a core area exist and in how many parts is it split?	Cority (Lang and Klug, submitted for publication)



	NP	CA	MPS	PSSD	NCA	TCCA	CAI	N*	N^0	Cority
1953	25	98327.69	3933.11	17323.51	41	65868.92	66.99	3	18	0.171
1976	3	59769.53	19923.18	27431.89	17	36958.96	61.84	2	1	0.118
1999	28	30957.6	1105.63	3935.3	52	7098.59	22.93	2	23	0.096

Fig. 4. Area and core area analysis (edge effect 5 m) for FFH type 7110 (active raised bog). Metrics characterizing core area are marked in grey shaded column headings. NP: number of patches; CA: class area (m^2); MPS: mean patch size; PSSD: patch size standard deviation; NCA: number of core areas; TCCA: total core area (m^2); CAI: core area index (%); N^*: number of habitats with disjunct core areas; N^0: number of habitats with no core area; Cority = (NP − N^0)/NCA.

any pre-selection mechanism for the end user. To improve the selection and documentation of landscape metrics, a database tool named indicator database for scientific exchange (IDEFIX) was developed and will shortly be available in the public domain (Klug et al., 2003). IDEFIX provides storage and search functionality on all relevant aspects of a certain metric (e.g. general information; selection and review; formula; Natura 2000 context; references; etc.).

As part of the SPIN project, the metrics selected for further analysis were implemented in the ArcGIS extension vector-based landscape analysis tool extension (V-LATE) and calculated within the ArcGIS 8.x software environment (Lang and Tiede, 2003). This tool provides a selected set of the most common metrics to be calculated directly in vector format.

Results of the calculation of landscape metrics were visualised in graphs and tables, as well as map-representations for better visual comparison and evaluation. Fig. 4 shows an example for a core area analysis of the FFH priority habitat ‘‘open raised bog’’ as classified on the 1953, 1976 and 1999 aerial photographs. A core area distance of 5 m was used in this example, and a significant decrease (6.59–0.71 ha) in the remaining core area of the open bog habitat can be observed.

The results of an evaluation of the metrics applied as structural indicators were documented in table form and is available for download from the SPIN homepage (www.spin-project.org). Certain requirements are summarised, and these have to be considered when using landscape metrics as structural indicators. According to these categories, metrics can show various restrictions for applicability as indicators, regarding calculation or interpretability. One of the most important issues concerns ambiguity (the metric value can indicate either favourable or unfavourable states of a habitat type). For example, a high value for edge density can be considered as positive or negative depending on whether edge-sensitive species or species that need a high structural richness are concerned. A second important issue is the species and/or habitat type data required for interpretation. In many cases, the results of a metric calculation do not make sense as a pure numeric value. They need to be interpreted in the context of a certain species or habitat type (or recorded for comparative reasons only). Additionally, most indices are sensitive to the thematic resolution of the underlying baseline geometry (classification). Only results obtained at a similar thematic depth can be compared. Dependency on thematic resolution in a stricter sense can occur when class aggregation leads to a reversal of the trend in results. As a last point, some metrics (such as core area and proximity) require parameterisation before calculation. In these cases, it is necessary to agree on a core area distance or a proximity buffer for the habitat type and/or species under consideration.

5. Disaggregating and downscaling of soil information (the Postojna case study area, Slovenia)

Protection of water resources, natural ecosystems, habitats and environmental modelling require more and more detailed information on soil properties from the spatial as well as from the attribute point of view. The accessible soil data, even the large-scale soil maps, are often considered unsuitable enough for applications in environmental modelling. Generally, soil maps are mostly available at too small a scale, while polygon interpretations are often too complex. Soil mapping units (SMU) contain information on the composition of different soil types (EC, ESB, 1998), often described as a percentage of the SMU area occupied by a particular soil type (soil typological units, STU). Properties are usually well described in the attribute tables, but the unknown spatial distribution of individual soil types within the SMU polygons makes the interpretation of data difficult for nature protection purposes and other activities at a detailed level.

Soil-developing properties are defined firstly by the physical and chemical properties of the parent material (Jenny, 1941, 1980) and by topography, of which the slope angle and the aspect are strongly correlated to soil properties (Gerrard, 1992). Catena is defined as a grouping of soils that differ greatly in the natural system of classification but are linked by conditions of topography in their occurrence. In the catena concept, slope plays a dominant role, as slope steepness is one of the most important factors that causes moisture conditions, surface wash, soil creep and down-slope movements of solutions, nutrients and masses.

The aim of this case study was: (a) to develop a GIS model that will enable the spatial prediction of soil types within the landscape and the individual SMU's; (b) elaboration of a raster soil map composed of STUs occupying the areas of high probability for each individual STU; (c) to produce thematic maps of selected basic soil properties (organic matter content, texture class, pH measurements and average soil depth) of better spatial resolution in comparison to the original soil map-derived thematic maps.

The Postojna Test Area (PTA) measures approximately 880 km^2 and lies in the SW part of Slovenia. Extensive woods predominantly cover 72% of the area. The relief of the area is diverse, with altitudes ranging from 439 to 1272 m. Slopes range from completely flat and gently undulating to very steep and precipitous. In the PTA, the different Triassic and Jurassic Limestone and Dolomite are dominant, while Tufa and Flysh sedimentary parent material can be found in the SW part. Convergent Continental, Alpine and sub-Mediterranean climatic influences characterise the area; the 30 years average precipitation is between 1500 and 2000 mm on the Javorniki Mountains. Predominating limestone and high precipitation are the primary reasons for many well-developed Karst phenomena (cave, dolina, polje, intermittent lakes). Apart from parent material and climatic conditions, the relief dominates pedogenetic influences in the PTA. The soils show wide heterogeneity. The most common soil types in the PTA are Chromic Cambisol, Rendzic Leptosol, Eutric Cambisol, Gleysoils, Planosols and Lithosols. The natural richness of the PTA was the reason that part of the area is in the process of being establishing as a regional park.

The data used were a vector digital soil map at the nominal scale 1:25,000 (DSM25); a vector soil map at the scale 1:10,000 (DSM10); point soil profile data with a description of soil horizons and standard soil analytical data; a digital elevation grid (DEM) in 100 and 25 m resolution, a grid of precipitation data in 1 km resolution; a 1:100,000 lithological map and land use map at the scale 1:5000. All data were converted and/or resampled to 25 m Arc/Info grids. Panchromatic enhanced IKONOS, Landsat TM image (1996, bands 4–5–3 composite) and 0.5 m ground resolution ortho-rectified airborne images were used for visual verification of the model results. DSM25 was used as a source of soil data in the model. SMUs are the smallest polygonal elements of the DSM25. Each SMU is composed of up to three different soil types named soil typological units, which cannot be shown separately because their polygons are too small for the scale of the map (Vrščaj and Prus, 1994).

The DSM25 of the PTA has been checked and examined. Thirty-six different SMUs were found in one or several polygons comprising 49 different soil typological units (=soil types). The STU properties/attributes of each STU have been verified and supplemented. For each STU, the attribute related to the geomorphologic features/landforms have been defined. For that purpose, we elaborated the form showing 11 landforms and indications of geomorphologic processes. The probabilities of STU appearance for each of 11 landforms have been determined using empirical knowledge. The probability data were entered in an MS ACCESS database and processed later as a source of parameters in the model.

The computer model has been elaborated in an ESRI Arc/Info 7.2.1 environment within the GRID module, using Arc/Info AML language. The AML routines have been developed in a parametric manner that enables the application of cell-based datasets (grids) with different spatial resolution. The GIS model for the spatial prediction of certain soil types (STUs) within soil map mapping units was developed, and consists of six AML routines. The aim of the model is to predict locations—the position and spatial extent of individual STU within SMU on the basis of the probability of STU presence on a certain type of relief. The model processes each SMU separately, passing through the following stages:

- extraction of SMU areas from the vector soil map, rasterisation using the same origin point;
- analysis of STU probability and comparison to the DEM grid parameters;
- creation of probability grids for each STU present in the SMU using parameters from an ASCII database;
- evaluation of separate STU probability grids—cells hold the probability of STU for the cell locations;
- cell-by-cell evaluation and combining separate STU probability grids in one common SMU grid where the highest probability values are preserved.

The number of iterations was equal to the number of different SMUs in the original soil map covering the PTA. Repeating the procedure has resulted in separate SMU grids that have been merged into a united grid – a soil map covering the whole PTA – the extent of DSM25. The attribute table of the united grid has, on the basis of the STU code, been related to the original DSM25 STU attribute table using relations in Arc Map. The extended dataset was the basis for the elaboration of thematic maps of selected STU properties. Visualisation of data and model output testing were completed using ArcMap, Spatial Analyst and 3D extensions.

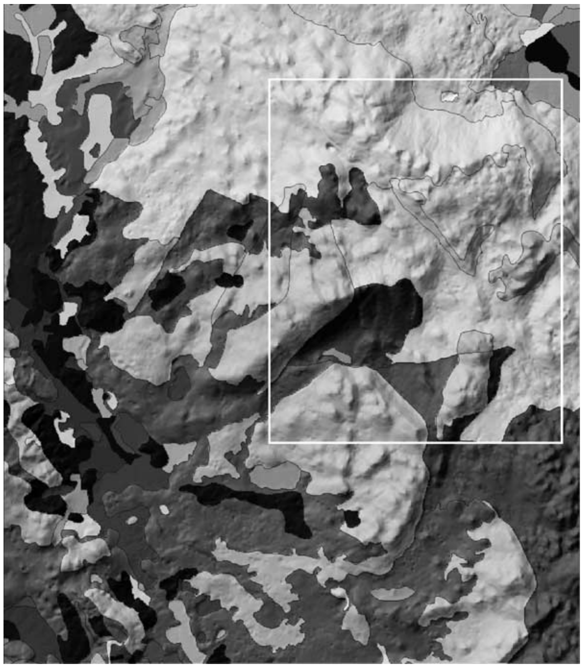


Fig. 5. Variegated 25 m relief overlaid by DPK25 polygons. The frame shows the area of Fig. 6.

The main result of the work was a new, predicted soil map (PSM) where the SMUs have been disaggregated to the map of 38 individual soil types (STUs). Spatial resolution (grid cell size is 25 m) is improved (Fig. 6) compared to the original vector polygons of DSM25 (Fig. 5). In addition, the PSM grid was used to derive 25 m grids—thematic maps of selected soil properties: (a) organic matter content in horizon A; (b) the predominant texture class of A and B horizons; (c) pH in A and B horizons; (d) average soil depth, rootable depth.

The comparison between DSM25 and PSM is presented in Table 5.

The total number of polygons in PSM increased. The main reason for this is the high heterogeneity of the relief. The larger total PSM area is a consequence of treating urbanised areas in DSM25 as non-polygon areas. DSM25 has a smaller minimum polygon size due to the presence of a few sliver polygons, which were generated during extraction of DK25 from the country's soil database. PSM minimum patch size represents the area of one 25 m grid cell. The larger maximum PSM polygon size is a result of the amalgamation of the SMU with similar STU structure.

Table 5
Comparisons of spatial parameters between DSM25 and PSM

	Digital soil map 1:25,000 (DSM25) vector	Predicted soil map (PSM) 25 m grid converted to vector
No. of polygons/patches	145	25.329
Total area (m^2)	224,000,000	224,750,625
Minimum polygon/patch size (m^2)	560	625
Mean polygon/patch size (m^2)	1,454,545	8838
Maximum polygon/patch size (m^2)	33,065,796	33,148,124

The model was designed and adapted to the SMU-based structure of the input DSM25. Processing each SMU one by one has several advantages and disadvantages. Each SMU covers a uniform lithological area, and thus there was no soil variability caused by the different parent material. The information concerning the SMU composition—STU presence is preserved. The neighbouring borders of the polygons in which similar STUs are present in some areas disappear, while the DPK25 polygon borders between SMU with diverse STU remained (Fig. 6).

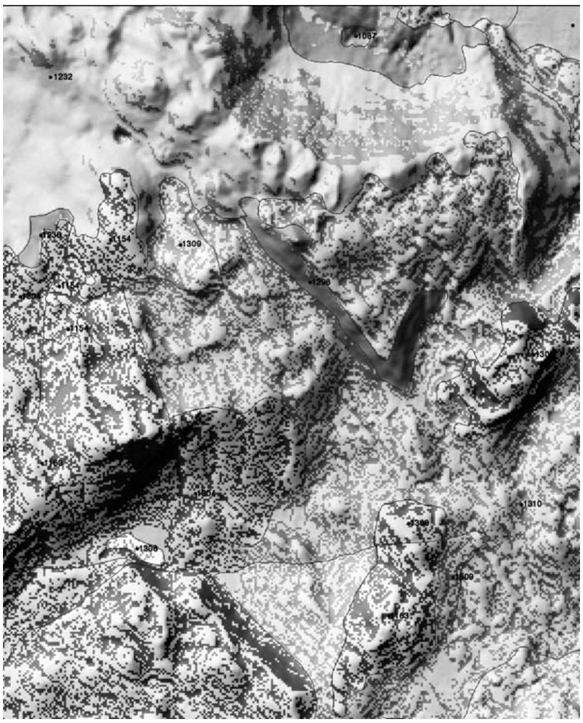


Fig. 6. PSM in 25 m raster grid and DPK25 polygon borders (enlarged).

The disadvantage of the model is that only the STUs presented in the original SMUs are evaluated, and thus STUs not described in SMUs, but present in the area, are not evaluated.

Regarding the spatial resolution, the result of the map is refined and quite detailed, and hence it is more suitable for the purposes of environmental research. The model was designed for use in an area well known to the author, and thus the applicability of the model in this stage is limited to the PTA. Recently, new software products for DEM analyses and automatic computation of new, landform-based spatial entities have been developed. The results are more advanced data layers in grid format describing different facets of landform types (MacMillan, 2001; MacMillan et al., 2000). Apart from additional data, landform-based approaches should be included in the development of more robust models for the disaggregation of soil vector-based information.

6. Conclusions and discussion

The management and monitoring of nature conservation sites takes place at different administrative levels. For these, ecologically relevant information has to be provided in different aggregations. The results of the SPIN project demonstrate the benefits and information gain through the integration of remote sensing-, biodiversity- and geo-data in multiple scales by various applications and modelling approaches for the development of spatial indicators for nature conservation.

- The application of object-oriented classification for mapping of habitats has proven to be efficient in terms of the level of detail and accuracy obtained. The appearance of homogenous objects rather than "salt and pepper" structure is considered very valuable due to the fact that the pattern of homogenous objects more likely relates to land use patterns in the landscape. Integration of additional knowledge using fuzzy rules allows the classification of more specific detail than is revealed by classification algorithms based on a statistical model. Once a classification hierarchy is set up, it can be transferred to other scenes, provided that the definition of fuzzy rules have to be adapted for their values. In practical work, the calibration of fuzzy rules to include expert knowledge can be very time-consuming, insecure and sometimes even arbitrary. Problems for the transferability of classification hierarchies arise especially from the phenological differences that occur between 2 years; even if the acquisition dates are very similar the specific phenology of each year can be very different and may complicate the spectral distinction of classes. On the regional scale, an accurate EUNIS level 1 habitat map for quite a large area of about 4000 km^2 was produced for 2001, and the methodology was transferred for the production of habitat maps of the years 1995 and 1990. On the local scale, a promising object-oriented classification concept was developed that will now be transferred to a larger dataset and statistically validated.

- In cases where a large number of different data sources is available and empirical observations exist, case-based and machine-learning methods are promising for mapping land cover units, the spatial distribution of species, habitat suitability; case-based methods have advantages over other methods if the response variable has a multimodal distribution relative to any explanatory variable, if the predictable classes are heterogeneous, if both numerical and nominal features have to be combined, and if values of multiple response variables have to be predicted. Land cover change analysis at the Otepää study area confirmed the drastic decrease in the area of ploughed fields, and revealed the reduction of open natural habitats between the years 1985 and 2000.
- For the monitoring of ecologically important aspects of landscape patterns, landscape metrics are in principal applicable as structural indicators. However, understanding the exact impacts of pattern on process has often been identified as the greatest challenge for the application of landscape metrics (Haines-Young and Chopping, 1996). Therefore, the process of selection and application of structural indicators is difficult. With the IDEFIX indicator database and the vLATE ArcGIS extension, two user-friendly tools are provided to support the selection and application process. The set of structural indicators needs to be chosen specifically for the habitat type and/or species under consideration, and issues of ambiguity, data requirements, thematic resolution and necessary parameterisation need to be taken into account. Therefore, we suggest that there is not one set of universally applicable structural indicators that is applicable to all Natura 2000 sites. Further research on the expected ranges of indicator values under various composition and configuration scenarios is needed to agree on thresholds for certain structural indicators. This would allow direct conclusions to be drawn concerning the conservation status of specific habitat types and habitats of species. Thresholds would, however, very likely need to be locally or regionally adapted. Nonetheless, we suggest that even in the absence of specifically defined thresholds, a set of metrics can be monitored over time, and dramatic changes in the values at a certain point could serve as a red flag indicating the necessity of a more detailed assessment.
- Soil data are considered to be indispensable information for ecologically sound nature conservation management, and a comprehensive description of habitats. Nevertheless, the soil data commonly available is in most cases too general. Thus, downscaling and disaggregating soil data are an important means to improve soil datasets from the spatial point of view. The modelling of soil type distribution within SMUs has shown to be practicable on the basis of the probabilities of STU appearance for 11 geomorphologic landforms. The model has to be prepared for the adoption of further improved additional geo-coded information that can improve the accuracy of predicted soil parameters. Important datasets (lithological information, climatic data and relief climatic-derived data to describe the climatic conditions on micro locations as well as remote sensing data) and landform approach should be included in the future. At present, the new model-derived information can be used as a good approximation of a more detailed soil

map and can help to bridge the gap of missing data and help in situations when high resolution soil information is not available. It is important that procedures and techniques of downscaling soil information be further developed. They can enable the updating and improvement of existing soil databases more efficiently in a shorter time and at a lower cost than expensive and time-consuming soil mapping.

Further information about the SPIN project, detailed information on all case studies, as well as reports and developed software tools are available at the project's website: www.spin-project.org.

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