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Feature Map Classifier – a possible approach to morphological/ geological evaluation of terrain

Janez HAFNER
Republic of Slovenia, Ministry of Defense, Kardeljeva ploščad 25, SI-1000 Ljubljana, Slovenia
E-mail:janez.hafner@pub.mo-rs.si

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Abstract

This paper investigates the practicability of new classification approach to image processing. Landsat TM image of Slovene coastal area was used to perform lithological classification. Standard classification methods, based on statistical principles do not always give satisfactory results. Therefore a variety of new approaches are being tested in order to achieve better accuraccy. One of the most promising fields is artificial intelligence where artificial neural networks (ANNs) have proven to be usefull. An artificial neural network represents a limited analogy of the neural functioning of the biological brain (Sejnowski, Koch and Churchland, 1988). Several ANN methods have been developed to solve classification problems. The one represented in this article is a combination of two methods: Self Organising Maps and Backpropagation network. This kind of ANN, also called Feature Map Classifier, is not the best in sence of accuraccy but has one big advantage in comparison with other ANNs – it is much more transparent.

In comparison with standard approach better results were gained especially in more complicated cases, where classes are not linearly separable. The separability of classes is shown to be one of the most important factors. ANN methods tend to give better results as statistical clustering technique especially in cases when classes overlap and are not easily separable.

Introduction

The morphologic/geologic mapping of a territory is one of the preliminary steps in selecting the optimal highway route. Slovene geologists are under pressure to provide planners with fast solutions, for all intended areas of the extensive highway construction program covering the entire country. Mapping requires extensive fieldwork, the cost and duration of which is directly linked with the feasibility study. Developed is an morphologic/geologic map. It, being derived by the interpretation of field data, is subject to many different influences such as the availability of data, impassability of a territory, it's overgrowth, and human expertise. The question then remains, whether it is possible to obtain a low cost and relatively quick solution that would be independent of human subjectivity. The solution consists of two parts.

First, there is a problem of input data. The acquisition should be based on already existing or easily derived data. One of the fastest ways is to use remotely sensed data. Nowadays, there are a variety of commercial satellites supplying a multitude of data that can be used in different ways. High-resolution satellite multispectral imagery (LANDSAT, SPOT, Ikonos) is useful for the analysis of vegetation and soil characteristics, whilst radar (RADARSAT, ERS) and stereoscopic pairs (SPOT, Ikonos) imagery can be used for the creation of digital elevation models. In the work presented hereafter, an attempt was made to compensate for the contribution of lithology with the use of the LANDSAT Thematic Mapper image. Besides satellite data, other already existing sources of data were considered, including digital geologic and geodetic maps that were used to derive various derivative data layers. The classical approach to aerophoto imagery was also used to delineate different vegetation cover types.

Second, the processing of data should be automatic. This means that all data should be gathered or converted into a digital format, then processed at a later stage by computer. The digital georeferenced data can be considered as digital imagery, whilst the procedural methods can be considered as digital image processing. In order for them to be performed, a knowledge base about examined phenomena, must be designed. Several different designs exist. For instance, expert systems try to incorporate expert knowledge, in the form of IF-THEN rules. The problem arises, when one makes an attempt to reshape expert know-how to comply with strict rules. Mapping is usually described as a highly intuitive process, which is often very difficult to describe. Therefore, a methodology with self-learning capabilities is needed. In the field of digital image processing, various parametric and non-parametric methods (classifiers) have won wide recognition, and are now widely used. With this work, an attempt was made to investigate the application of a special non-parametric method, inspired by the human brain – artificial neural networks.

Study area

The study area occupies approximately 50 square kilometres of the Slovene coastal area, near the Italian border (Fig.1). It bears all the morphological, lithological and vegetation properties of the whole coastal region, and can be considered to be representative.

The examined territory was first mapped using standard techniques, such as fieldwork and aerophoto interpretation. The mapping produced a morphologic/geologic map, where 7 different area categories were extracted: stable areas, labile areas, landslides, sinkholes, debris, moist areas and erosion zones. In the later course of work, this map was used for the random extraction of learning, and for testing samples.

The resulting map is mainly an interpretation of lithological and morphological factors. In this place it should be pointed out that the morphological shape of terrain exibits strong correlation with lithology. The flysch, composed of sandstone and marl, is less resistant to weathering than limestone. As a consequence, clastic sediments are covered with a thick, overgrown, weathering cover and the morphological shape of flysch area is heavely ditched and full of ravines. Areas with limestone are re-

Figure 1. Geographical position of Črni Kal region.

sistant to mechanical but non-resistant to chemical weathering. Ordinarily, they are seldom found with any significant weathering cover and are marked with a variety of karstic phenomena such as sinkholes and doline.

In the mapping (classification) process the problems arise because it is possible that certain areas belong to multiple categories at once. For instance, labile areas and landslides are much alike. Furthermore, erosion zones and debris areas are often subject to sliding. The problem is twofold. First, logic of the model obliges us to select only one category, and second, categories are highly overlapping. Consequently, decisions are made by experts, according to their knowledge and experience.

Input data

Lithological data

Lithological mapping of the entire Slovene coastal area in a scale of 1:5000 took place in 1994. The authors (Ribičič et al, 1994) found 12 different lithological units. For the purposes of this project, they were combined to form 5 units (Fig. 2a): alluvium, limestone, deluvium, and two types of flysch – one with a majority content of sandstone, the other with majority content of marl.

Digital elevation model and derivatives

A digital elevation model (DEM) with 5 meters of spatial resolution was made using isolines from base topographic plans in a scale of 1:5000. The information derived from a DEM (see Fig. 3 – shaded relief) does not alone contribute heavily to a model, but is very important as a foundation for several DEM based derivatives. The slope data layer is expressed as the change in elevation over a certain distance. In this case, the distance is the size of a pixel. The slope of the terrain is directly connected with weathering, erosion and deposition. It was expected to directly influence in the occurrence of landslides and labile areas. The aspect data layer describes the direction of the slope at each pixel. The aspect data was not expected to have a direct influence on the model, but is important nevertheless for the creation of related statistic layers. Both slope and aspect data layers were derived using 1st order derivative filters (gradient operators). By employing a 2nd order derivative filter (Laplacian operator), data layers describing convexity/concavity of landscape morphology were made. Two different filters, using neighbourhood sized 7×7 and 11×11 cells were used to produce two different data layers. The curvature data layer was produced using the 4th polynomial function (ESRI, 1992) to describe curvature of landscape morphology. This calculation uses the neighbourhood sized 3×3 cells and is closely related to convexity/concavity of data layers. The outputs were three data layers: general curvature, planform curvature – curvature perpendicular to the slope direction and profile curvature – and curvature of the surface in the direction of the slope. Curvature, convexity/concavity, slope and aspect data layers are all strongly related to the physical characteristics of a drainage basin and can be used to describe erosion and runoff processes. The slope affects the overall rate of downslope movement, whilst the aspect defines its direction. The profile curvature affects the acceleration and deceleration of flow, therefore influencing erosion and deposition. The planform curvature, together with convexity/concavity, influences convergence and the divergence of flow. The flowlength data layer details the downstream distance along a flow path of the hypothetical rainfall/runoff events. This layer is used with the intent of extracting erosion zones that are typically formed in the upper flow areas of flysch lithology. In calculating the standard deviation for slope and aspect data layers using two different neighbourhood sizes (5×5 and 8×8 cells), four standard deviation data layers were derived. The variability within the aspect data layer is closely connected with ridge/ravine detection, where slope direction opposes one another. The variability of slope is related to the undulation of the surface – a typical phenomena for unstable areas.

Distance to surface waters

This layer, made by a calculation within an individual cell, measures the minimum distance to surface waters, and could assist in defining the process of erosion in non-karst areas.

Vegetation data

The coarse vegetation map (Fig. 3b) separating three different categories (dense, medium and non-overgrown areas) was compiled using aerophoto interpretation.

LANDSAT TM image

Two models, the first using a lithological map, the second using a LANDSAT Thematic Mapper image, were made in order to study the application of a model in cases where no lithological data was accessible. The LANDSAT TM image consists of 7 spectral bands: blue, green, red, near infrared, thermal infrared and 2 mid-infrareds, with an 8-bit radiometric and 30 meter spatial resolution (except thermal infrared – 120 meters). The satellite image was, due to coarse spatial resolution and occasional cloud cover, not expected to completely substitute lithological data contribution.

Methodology

The modelling of a terrain is primarily a classification process. The input data is clustered into homogeneous and separable groups according to an appropriate measure of similarity.

With the intention to improve the classification process, new methods, among them

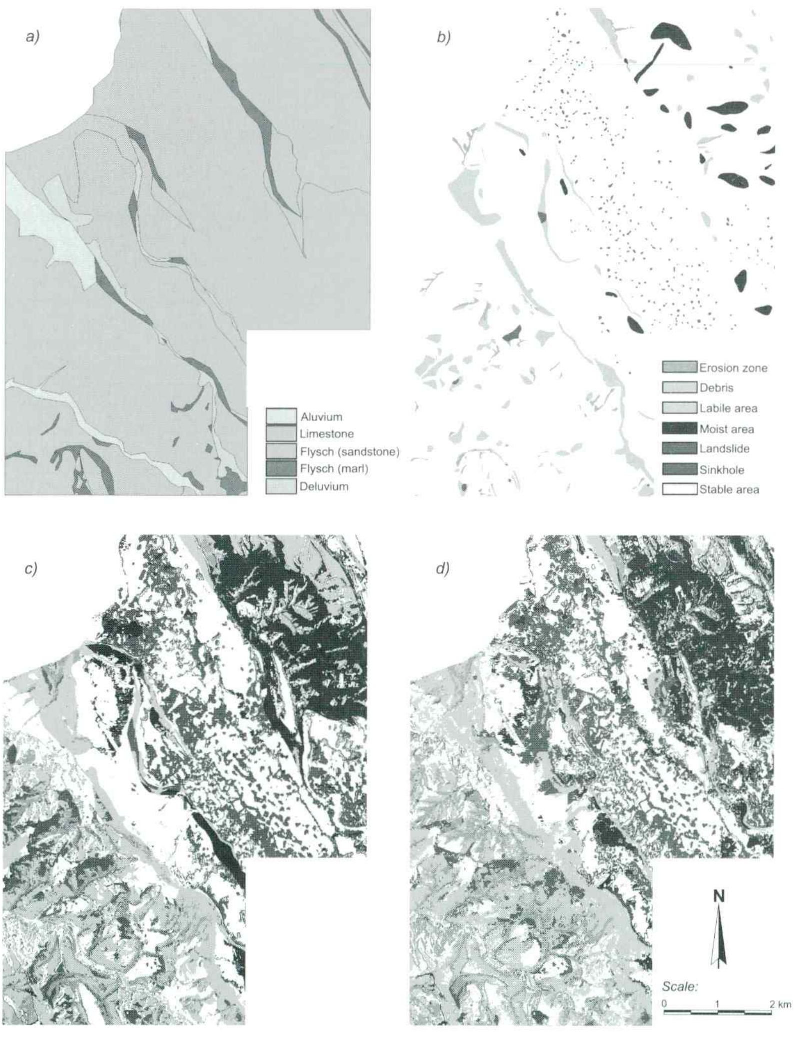

Figure 2. Lithological input data (a), morphological/ geological map obtained by standard mapping methods (b), result of classification using lithological data (c) and result of classification using satellite data (d).

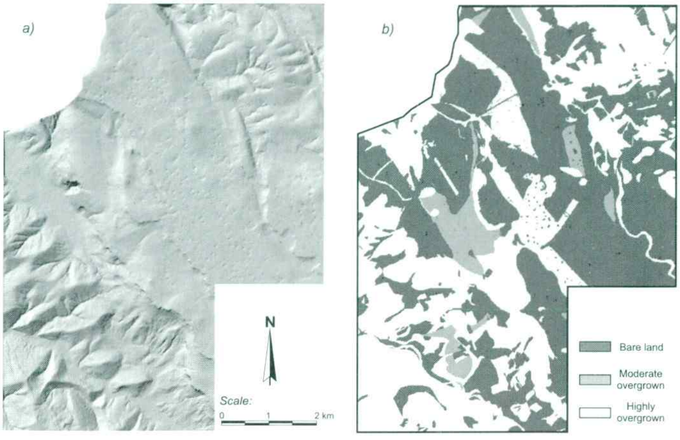

Figure 3. Shaded relief (a) and vegetation data layer (b).

also the subject of this article – artificial neural networks (ANNs), are being developed. Although similar to the k-NN, they are more efficient and require less data for training. The distribution free nature enables them to join remote sensing and geographic data of multiple type/statistical distributions, in the single classification model. The overall objective of this paper is to investigate and discuss their application in the morphological/geological evaluation of an examined area.

An artificial intelligence technique, ANN, inspired by the human brain, has shown promising results and is now considered to be an alternative method in digital image processing. The human brain forms a massive communication network, consisting of billions of nerve cells, known as neurones. In functional terms a neuron can be seen as a processing unit receiving and transmitting electrical impulses. Learning, and the storage of knowledge take place by modifying the conductivity between the neuron connections. ANNs are mathematical models that try to mimic the biologic brain. Artificial neurons, also called processing elements, or *PEs*, are interconnected through numerical weights that function analogously to conductivity connections.

The selected ANN method FMC (Feature Map Classifier) combines great representational and analytical power of Self Organising Maps (SOM) with the classification abilities of Backpropagation (BPG) networks. A backpropagation network can be used as a classifier itself, and as such it remains the most popular ANN classification method, but there is an inherent problem. That is, it is very difficult to give physical meaning to the weights connected to the neurones. The use of an SOM method makes the evaluation of classes and the classifier itself much easier. When confronted with multidimensional data it is often very difficult to determine how the data is structured; therefore, it is desired to reduce the dimensionality. The statistical method usually used in performing this task is factor analysis. However, as with parametric statistical classifiers, there is again a problem of normal distribution and linear relations among variables. To solve this problem a special ANN, Self Organising Map was developed by Tuevo Kohonen (Kohonen, 1984). It reduces a multivariable space into two (sometimes three) dimensions in such a manner that makes it possible for every n-dimensional input pattern to occupy its place in a 2-D map.

Results

Two FMC models were made, the first for the classification using lithological data, whilst the second substituting lithological data with 7 bands of LANDSAT TM image. Both artificial neural networks constituted of an input neural layer (with 20 and 22 neurones), Kohonen's layer (matrix of 20×20 neurones) and an output layer (7 neurones representing 7 categories).

After the learning stage, the recall procedure took place to actually perform the classification of the studied area. Results are shown in figure 2.

Classification accuracy

The assessment of classification accuracy of multivariate data unfortunately does not reach the ability to produce digital land cover classification. In fact, this problem sometimes precludes the application of automated land cover classification techniques, even when their cost compares favourably with a more traditional means of data collection (Lillesand & Kiefer, 1994). Methods originate from the field of image processing and are often described in expert literature. The most common way to represent the classification accuracy is in the form of an error matrix (Congalton, 1991).

Accuracy assessment results

Accuracy was assessed using a test sample taken by stratified sampling. This kind of accuracy is not dependent upon categories existent in the examined territory. The solution is a general model that describes the model's behaviour, not just in this case but also for any other resembling region. Another fact in favour of the general model is the nature of input data. All the data, except the satellite image, is independent of the acquisition time and, therefore, dependant only upon the mode of acquisition. Ideally, where procedures are standardised, input data generation should yield identical or at least similar results. This leads to the conclusion that the model using lithological data is general and the model using satellite images is less so.

The error matrixes of both models were used as the basis for an accuracy table (Table 1 and Table 2) generation. The equality of average produced accuracy and overall accuracy is the result of equivalent sample sizes for singular categories. The results show satisfactory accuracy. Significant difficulties arise only in the case of labile and stable areas. Whilst the stable areas in both models show similar proclivity to moist areas, the labile areas in the model with lithological data are mixed with a debris category, and the model using satellite images is mixed with erosion zones. Despite the mixing problem, both of the models are within the borders of serviceability, especially in the feasibility stage of study where one strives to yield a fast and low-cost outcome.

The comparison of models (Table 3) shows that the model using satellite images yields a somewhat weaker result than the model using lithological data. This confirms the conjecture of the ability of LANDSATs TM images to substitute the contribution of the lithological data.

Table 1. Accuracy table for the classification – usage of lithological data

	REFEREN	CLASSIFIED	CORRECT	PROD. A.	USER. A.	KHAT
EROS	250	260	197	78,80%	75,77%	71,73%
DEBRIS	250	278	223	89,20%	80,22%	76,92%
LABIL	250	195	106	42,40%	54,36%	46,75%
MOIST	250	301	216	86,40%	71,76%	67,05%
LANDS	250	254	207	82,80%	81,50%	78,41%
SINKH	250	275	240	96,00%	87,27%	85,15%
STABIL	250	186	109	43,60%	58,60%	51,70%
AVERAGE:				74,17%	72,78%	68,24%
OVERALL KHAT:				69,87%		
OVERALL ACCURACY:				74,17%		

Table 2. Accuracy table for the classification – usage of satellite image

	REFEREN	CLASSIFIED	CORRECT	***PROD. A.***	***USER. A.***	***KHAT***
EROS	*250*	*311*	*200*	*80,00%*	*64,31%*	*58,36%*
DEBRIS	*250*	*224*	*139*	*55,60%*	*62,05%*	*55,73%*
LABIL	*250*	*216*	*94*	*37,60%*	*43,52%*	*34,10%*
MOIST	*250*	*289*	*208*	*83,20%*	*71,97%*	*67,30%*
LANDS	*250*	*263*	*213*	*85,20%*	*80,99%*	*77,82%*
SINKH	*250*	*278*	*236*	*94,40%*	*84,89%*	*82,37%*
STABIL	*250*	*168*	*91*	*36,40%*	*54,17%*	*46,53%*
AVERAGE:				***67,49%***	***65,99%***	***60,31%***
OVERALL KHAT:				***62,07%***		
OVERALL ACCURACY:				***67,49%***		

Table 3. Comparison of accuracies

ACCURACY	LITHOLOGICAL DATA	SATELLITE DATA
Overall acc.	74,17%	67,49%
Overall KHAT	68,87%	62,07%
Average Prod	74,71%	67,49%
User	72,78%	65,99%
KHAT	68,24%	60,31%

Another way to evaluate the application of the model is to use expert opinion. In spite of the fact that such judgements are heavily affected by human subjectivity, it can still be used as a quick and approximate method. In this case, expert opinion is in favour of both models. The thick vegetation cover of flysch terrain makes it difficult to investigate. This affected the quality of learning/testing data. The resulting classification for this region, therefore, is evaluated to be even better than the actual input (reference) data. The explanation could lie in the ability of ANNs to reduce the noise of learning data, and thus produce a highly generalised solution. The classification of moist areas is inappropriate. That is why it would be reasonable for this category to be either excluded from the model, or to be joined with the stable area category.

The feature map classifier has proven to be a useful tool. High delimitation abilities of input feature space and a capacity to work with distribution free data of various data types makes it superior in comparison with statistical classifiers. ANNs in general are criticised because of nontransparent functioning – the black box effect. Fortunately in the case of FMC, this statement does not apply. While the usual classification of ANNs enables users to perform only one single analytical operation – impact analysis, it is the SOM part of FMC, which is known for its great power to present data in the form of 2D matrices.

Impact analysis

Impact analysis is a technique where the relevance of each input variable is determined using the leave-one-out method. The effect of disabling each input neuron in turn is determined in terms of its percentage reduction in the accuracy of the classification. Figure 4 and table 4 illustrate the results of impact analyses for both models. The Y coordinate is defined as a portion of accuracy reduction when an input neuron for a certain category is turned off. On the X-axis, all the individual and, in cases where they constitute a logical unit, joint categories (preceded by SUM) are presented.

The result for the first model indicates lithology to be the most important input data. Seven bands of LANDSAT TM satellite image do not represent proper compensation. Nevertheless, the accuracy of the second model is affected to a smaller extent than expected. The contribution of lithological data is compensated by the increased importance of other factors, particularly vegetation, ridge/ravine data and wa-

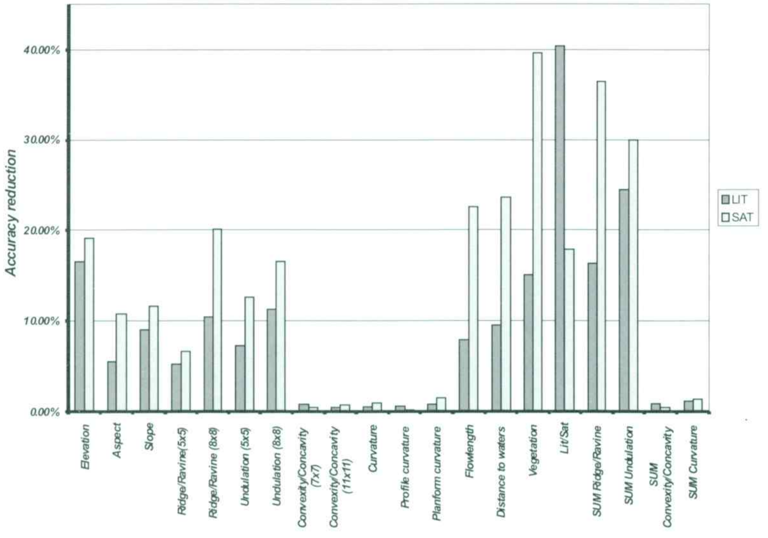

Figure 4. Result of impact analyses.

Table 4. Importance of input variables according to impact analysis

	LITHOLOGICAL DATA	SATELLITE DATA
IMPORTANT	*Lithology* *Undulation* *Elevation* *Ridge/Ravine* *Vegetation*	*Vegetation* *Ridge/Ravine* *Undulation* *Flowlength* *Distance to surface waters*
LESS IMPORTANT	*Distance to surface waters* *Slope* *Flowlength*	*Elevation* *Satellite image* *Aspect*
UNIMPORTANT	*Aspect* *Curvature* *Convexity/Concavity*	*Slope* *Curvature* *Convexity/Concavity*

ter related factors. The examined territory is especially characterised by high lithology-vegetation correlation, bare limestone and highly overgrown flysch. Data on the basis of standard deviation, ridge/ravine and undulation data, shows that the neighbourhood of 8×8 cells is more important than the neighbourhood of 5×5 cells. The low importance of slope data (Table 4) upon analysis gave an unexpected result. It was expected that the slope would strongly affect the stability of the ground. This presumption however, holds only for flysch areas. An imbricated limestone region is, on the other hand, characterised with almost vertical, but fully stable slopes.

An important point to note here is that there still exists a variety of attributes not included in this model. Human intervention especially in the form of irrigation, civil engineering activities, tree cutting and water dams often decisively influence the nature of environment.

Competitive layer analysis

While the impact analysis gives an impression about the importance of the input variables, questions about their mutual relationship, the separability of output categories and the impact of input variables on a particular category remained unanswered. Self-organising maps, as a part of FMC, offer perhaps the best solution at this point in time, that artificial neural networks are able to produce. The unsupervised learning that takes place in the self-organising phase forms so-called Kohonen's maps, where bright tones represent characteristic regions, and dark tones uncharacteristic regions. Organising data into groups depends of course upon the purpose we are seeking to achieve. Groups can be organised according to output categories. In this way Kohonen's maps, describing categories, are made (Fig. 5). Examination of their mutual relationship enables a resemblance/separability study of the classification model to be made. Ideally, each category would occupy its own part of the Kohonen's map, and would not overlap with any other categories.

The importance of input variables can be studied by partitioning data into classes, according to individual variable values. The Kohonen's maps in this case represent inner-variable groups (Fig. 5). Variables can be differentiated either by their individual class values (vegetation: dense, medium, non-overgrown areas) or by some other kind of arbitrary values (curvature: concave $[-\infty, -1]$, flat $[-1,1]$, convex $[1,\infty]$). The differentiation of inner-variable groups serves as an indicator of variable importance – the better the discrimination, the more important the variable. For instance, the differentiation of variable *Slope* (Fig. 6) shows that three different groups for slope: $<10°$, $10°$ to $20°$ and $>20°$ exist.

The comparison of inner-variable Kohonen's maps of different variables is used for the study of their relationships, whilst the comparison of inner-variable Kohonen's maps with output category Kohonen's maps is used to estimate the influence that the individual inner-variable group has on the particular category (Fig. 5). Visual comparison of Kohonen's maps is useful only in cases where there is a likeness/dissimilarity of the two maps. Obviously, in

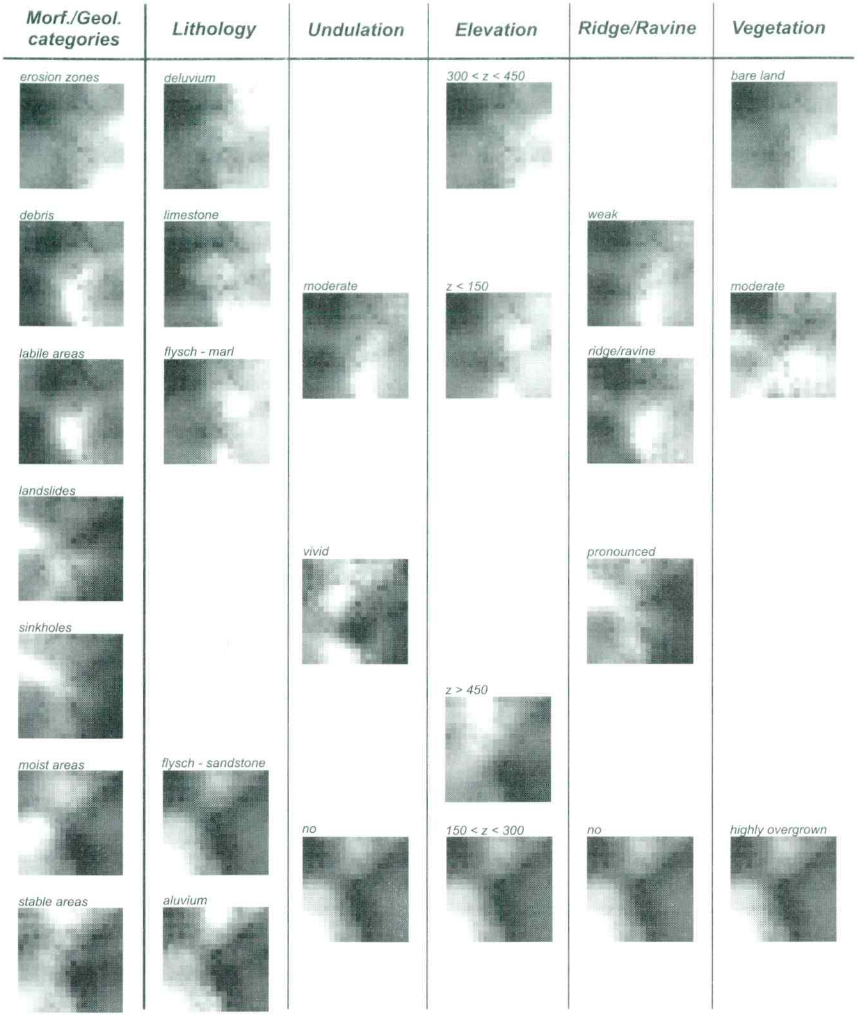

Figure 5. Kohonen's maps for output categories and 5 most important input variables (usage of lithological data).

vague cases, one requires a distinct measure of separability. The proposed separability measure is

$S_{a,b} = 1 - r_{a,b}$,

where $r_{a,b}$ is the Pearson correlation coefficient for classes a and b. The range of values for $S_{a,b}$ is [0,2], where values close to 0 indicate high overlapping, values around 1 indicate that there is no significant relationship and values close to 2 indicate high dissimilarity.

Figure 5 and the corresponding separability table (Table 5) illustrate the functionality of Kohonen's maps, for a model using lithological data. The leftmost column contains output category maps and the following 5 columns display Kohonen's maps for the 5 most important factors, as determined by impact analysis. The less important factors are shown in Figure 6.

The similarity study of output categories shows evident resemblance between debris – labile areas, landslides – sinkholes and stable – moist areas. The comparison of lithological units shows that the model is able to discriminate between two lithological groups: alluvium + flysch-sandstone and deluvium + limestone + flysch-marl. On the basis of other factors it is possible to infer with some certainty that the first lithological group is identified as being a highly overgrown, flat region with an altitiude of 150 to 300 meters above sea level. All together they serve as the identifier for stable and moist areas.

On the other hand the identifiers for sinkholes and landslides are much less frequent.

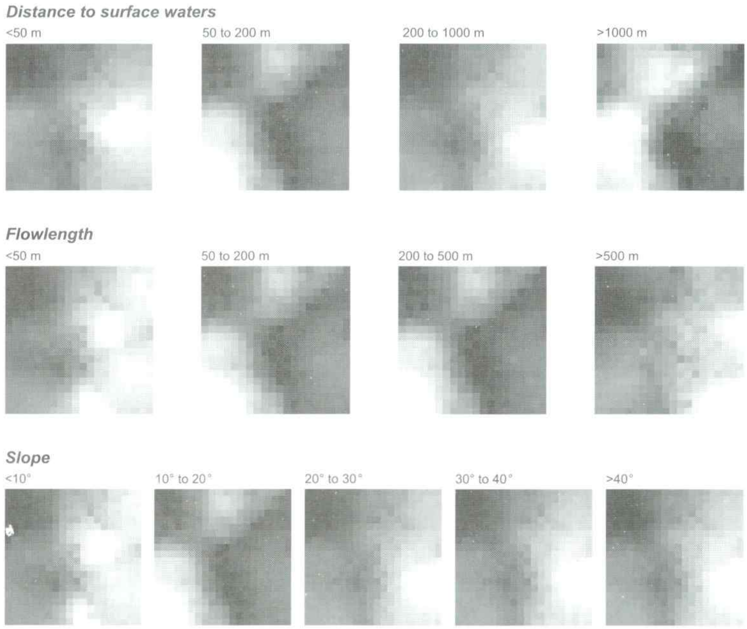

Figure 6. Kohonen's maps for less important input variables (usage of lithological data).

Both categories are marked with vivid undulation and pronounced ridge/ravine occurrences. Debris and labile areas are viewed as moderately overgrown limestone and flysch-marl lithology, with moderate undulation and intermediate configuration. Erosion zones show similarities with debris and labile areas, but represent the category most distinctive of all. Usually these are high, upper-stream and poorly vegetated areas marked with a short flowlength. The analysis of Kohonen's maps is a useful tool that can be used for studying operational aspects of FMC. The application strongly depends upon purpose of the work to be undertaken and, therefore, differs from case to case.

Summary and conclusions

This paper has demonstrated the possible use of alternative classification algorithms for the morphological/geological classification of the Slovene coastal region. A specially developed artificial neural network classificator – FMC (feature map classificator) has proven itself to be a useful tool for the morphologic/geologic category predictions. Its main advantage over classical statistical methods includes the use of freely distributed data, thus enabling one to incorporate multisourced data, without almost any restrictions. The artificial neural networks, as massively parallel and highly distributed computational models, exhibit features such as fault tolerance and generalising abilities. The resulting model, made on the basis of a small territorial area, is general in its nature even when employing site (elevation) and acquisition time (satellite) dependent data. Therefore, it can be used for any other region of similar geomorphological and lithological characteristics.

The most common criticism made of artificial neural network classifiers is the unintelligible mode of operation. It was clearly demonstrated that this does not apply to the feature map classifier. While the impact analysis offers a common ANN tool for the evaluation of input-variable contribution, the self-organising part of FMC is much more powerful. The use of visual and statistical analysis of Kohonen's maps to evaluate the distinctive abilities of input variables, relationships among them, their influence on output and separability of output categories, turned out to be a clear and accurate technique of great analytical power.

Altogether, the employment of FMC is recommended in the feasibility phase of such works. Combining the ability to use

Table 5. Separability table of important factors for the classification using lithological data

		Ridge/Ravine No	Weak	R/R	Pron	*Elevation* <150	<300	<450	>450	*Undulation* Vivid	Moder	No	*Vegetation* High	Moder	Bare	*Lithology* Alluv	Lime	Fl-s	Fl-m	Deluv	*Morph./Geol. categories* Eros	Debris	Labil	Moist	Landsl	Sinkh	Stab
Ridge	No	0,00	1,48	1,52	0,76	1,28	0,00	1,18	0,64	0,45	1,48	0,00	0,00	0,78	1,16	0,12	1,45	0,00	1,29	1,34	1,14	1,56	1,59	0,20	0,70	0,94	0,27
	Weak	1,48	0,00	0,08	1,51	0,15	1,48	0,30	1,82	1,44	0,00	1,48	1,48	0,40	0,27	1,48	0,13	1,48	0,16	0,32	0,33	0,09	0,28	1,79	1,35	1,56	1,65
	Ridge/Ravine	1,52	0,08	0,00	1,45	0,27	1,52	0,28	1,83	1,64	0,08	1,52	1,52	0,36	0,30	1,55	0,16	1,52	0,26	0,33	0,32	0,08	0,18	1,80	1,26	1,51	1,70
	Pronounced	0,76	1,51	1,45	0,00	1,76	0,76	1,83	0,37	0,45	1,51	0,76	0,76	1,13	1,81	0,56	1,70	0,76	1,76	1,79	1,84	1,41	1,09	0,52	0,13	0,06	0,47
Elevation	<150	1,28	0,15	0,27	1,76	0,00	1,28	0,19	1,73	1,38	0,15	1,28	1,28	0,57	0,11	1,32	0,14	1,28	0,01	0,14	0,20	0,33	0,67	1,61	1,66	1,79	1,54
	<300	0,00	1,48	1,52	0,76	1,28	0,00	1,18	0,64	0,45	1,48	0,00	0,00	0,78	1,16	0,12	1,45	0,00	1,29	1,34	1,14	1,56	1,59	0,20	0,70	0,94	0,27
	<450	1,18	0,30	0,28	1,83	0,19	1,18	0,00	1,75	1,56	0,30	1,18	1,18	0,46	0,09	1,40	0,15	1,18	0,18	0,22	0,01	0,34	0,61	1,51	1,59	1,83	1,54
	>450	0,64	1,82	1,83	0,37	1,73	0,64	1,75	0,00	0,32	1,82	0,64	0,64	1,65	1,79	0,49	1,74	0,64	1,71	1,62	1,74	1,72	1,57	0,21	0,65	0,29	0,26
Undul.	Vivid	0,45	1,44	1,64	0,45	1,38	0,45	1,56	0,32	0,00	1,44	0,45	0,45	1,22	1,52	0,25	1,46	0,45	1,42	1,45	1,54	1,50	1,49	0,36	0,67	0,50	0,20
	Moderate	1,48	0,00	0,08	1,51	0,15	1,48	0,30	1,82	1,44	0,00	1,48	1,48	0,40	0,27	1,48	0,13	1,48	0,16	0,32	0,33	0,09	0,28	1,79	1,35	1,56	1,65
	No	0,00	1,48	1,52	0,76	1,28	0,00	1,18	0,64	0,45	1,48	0,00	0,00	0,78	1,16	0,12	1,45	0,00	1,29	1,34	1,14	1,56	1,59	0,20	0,70	0,94	0,27
Veget.	Highly overgr.	0,00	1,48	1,52	0,76	1,28	0,00	1,18	0,64	0,45	1,48	0,00	0,00	0,78	1,16	0,12	1,45	0,00	1,29	1,34	1,14	1,56	1,59	0,20	0,70	0,94	0,27
	Moderate ov.	0,78	0,40	0,36	1,13	0,57	0,78	0,46	1,65	1,22	0,40	0,78	0,78	0,00	0,42	0,94	0,56	0,78	0,59	0,79	0,48	0,51	0,57	1,24	0,80	1,35	1,23
	Bare land	1,16	0,27	0,30	1,81	0,11	1,16	0,09	1,79	1,52	0,27	1,16	1,16	0,42	0,00	1,35	0,20	1,16	0,12	0,24	0,09	0,46	0,76	1,53	1,59	1,84	1,58
Lithology	Alluvium	0,12	1,48	1,55	0,56	1,32	0,12	1,40	0,49	0,25	1,48	0,12	0,12	0,94	1,35	0,00	1,46	0,12	1,34	1,36	1,34	1,55	1,55	0,26	0,69	0,77	0,10
	Limestone	1,45	0,13	0,16	1,70	0,14	1,45	0,15	1,74	1,46	0,13	1,45	1,45	0,56	0,20	1,46	0,00	1,45	0,15	0,18	0,16	0,18	0,43	1,76	1,64	1,72	1,53
	Flysch-sands.	0,00	1,48	1,52	0,76	1,28	0,00	1,18	0,64	0,45	1,48	0,00	0,00	0,78	1,16	0,12	1,45	0,00	1,29	1,34	1,14	1,56	1,59	0,20	0,70	0,94	0,27
	Flysch-marl	1,29	0,16	0,26	1,76	0,01	1,29	0,18	1,71	1,42	0,16	1,29	1,29	0,59	0,12	1,34	0,15	1,29	0,00	0,12	0,20	0,32	0,65	1,60	1,66	1,78	1,55
	Deluvium	1,34	0,32	0,33	1,79	0,14	1,34	0,22	1,62	1,45	0,32	1,34	1,34	0,79	0,24	1,36	0,18	1,34	0,12	0,00	0,22	0,40	0,70	1,59	1,75	1,78	1,50
Morph./Geol. categories	Erosion zone	1,14	0,33	0,32	1,84	0,20	1,14	0,01	1,74	1,54	0,33	1,14	1,14	0,48	0,09	1,34	0,16	1,14	0,20	0,22	0,00	0,38	0,66	1,49	1,62	1,86	1,48
	Debris	1,56	0,09	0,08	1,41	0,33	1,56	0,34	1,72	1,50	0,09	1,56	1,56	0,51	0,46	1,55	0,18	1,56	0,32	0,40	0,38	0,00	0,09	1,77	1,26	1,43	1,61
	Labile areas	1,59	0,28	0,18	1,09	0,67	1,59	0,61	1,57	1,49	0,28	1,59	1,59	0,57	0,76	1,55	0,43	1,59	0,65	0,70	0,66	0,09	0,00	1,69	0,93	1,11	1,55
	Moist areas	0,20	1,79	1,80	0,52	1,61	0,20	1,51	0,21	0,36	1,79	0,20	0,20	1,24	1,53	0,26	1,76	0,20	1,60	1,59	1,49	1,77	1,69	0,00	0,57	0,54	0,24
	Landslides	0,70	1,35	1,26	0,13	1,66	0,70	1,59	0,65	0,67	1,35	0,70	0,70	0,80	1,59	0,69	1,64	0,70	1,66	1,75	1,62	1,26	0,93	0,57	0,00	0,21	0,72
	Sinkholes	0,94	1,56	1,51	0,06	1,79	0,94	1,83	0,29	0,50	1,56	0,94	0,94	1,35	1,84	0,77	1,72	0,94	1,78	1,78	1,86	1,43	1,11	0,54	0,21	0,00	0,60
	Stabile areas	0,27	1,65	1,70	0,47	1,54	0,27	1,54	0,26	0,20	1,65	0,27	0,27	1,23	1,58	0,10	1,53	0,27	1,55	1,50	1,48	1,61	1,55	0,24	0,72	0,60	0,00

generalisation and already existing data, it serves as an efficient tool to produce fast, low-cost estimations of morphologic/geologic properties. This kind of modelling is, however, constrained for usage in the preliminary stages of such works, and should be in the later course of work, combined with standard fieldwork.

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