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The Analysis of the Patterns of Land Classification in Terms of the Application in the Valuation of Soilless Areas**

1. Introduction

In the applied in Poland way of diagnosing the quality of soil (valuation), its algorithm cannot be directly used in the classification of areas without soil cover, especially when the mineral substance consists of technogenic materials. In the scale of the country this is probably not a big problem, but in many cases, the situation is inconvenient, at least as far as administrative procedures are concerned. It is useful to build an algorithm, which would allow marking at least approximately the situation of land, object or its part in the valuation scale.

2. Classification Criteria

Regardless the approach to the issue of the soil quality assessment, there is a list of soil properties, being repeated as valuation criteria in different countries [14, 19, 23]. A striking, although understandable feature of different classification systems, is their adjustment to the kind of land use. There are different expectations in case of arable land, permanent green area or forest. Nevertheless, avoiding certain aspects specific to the way of land use, the basic consideration in the soil quality assessment can be regarded requirements in terms of arable land; in any case – soils highly classified as arable land will definitely meet the requirements for the forestry.

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Strzemski [19] is grouping different approaches to the problem of arable land classification within the deductive and inductive methodologies. Deductive methods a priori assume the classification of each, theoretically possible form of land, with the differentiation of relatively small list of patterns grouped in respective classes In this case, the classification means the indication of the closest (the most similar) pattern in terms of the features of the studied land. Inductive methods involve ranking each criterionand factor affecting the fertility or making a symptom of the land productivity, as well as the aggregation of quantitative indicators, according to the established algorithm.

Regardless the approaches to the classification model, it is necessary to find factors allowing the comparison of soil pattern (pedon) to the respective patterns or factors that would make qualitative or quantitative measures leading to its ranking.

One can list the requirements to the factors being potential soil quality indicators [17]:

- the easiness of the assessment (of measurement or estimation);
- the possibility to express the changes in the function of soil;
- the possibility to assess in a reasonable time;
- the availability of the analysis for many users: the best if made in field conditions;
- sensitivity to the soil-forming factors and land use;
- representation of physical, biological and chemical properties of soils;
- ability to make quantitative and/or qualitative assessment.

In Polish practice, in the description of the classified soil profiles, several characteristics are considered: the thickness of diagnostic horizons, character of transition to another horizon, granulation (mechanic group), colouration of the horizons (regarding their humidity), structure of horizons, texture of horizons, reaction, content of hydrocarbons in the horizons, presence, kind and degree of the concretion, presence, degree and kind of gley. It should be noticed that the mentioned above characteristics of soil refer to the profiles described during the classification work and the content of the documentation is smaller; this description can be roughly reconstructed based on the symbols of soil outlines, using proper instructions [14].

In the qualitative assessment, soils make a multi-dimension object [3, 18]. A certain finite number of factors make the assessment criteria. The problem is the algorithm leading from the criteria to valuation.

There are several models that can be seen as alternative prototypes of the algorithm of land quality assessment in soilless areas. Some of them refer to well-known general relationships between the properties of environment and crops. In general one can mention the following algorithms of getting inductiveassessment of land quality: additive approach, multiplicative approach and the approach based on the„minimum principle". We assume that the basis of the valuation assessment is the algorithm transforming n-element vector $\mathbf{x}$ representing n quantitative features, significant for the land in terms of its soilquality: $\mathbf{x} = (x_1, x_2, x_3, \ldots, x_n)$. The outcome of the algorithm is the ranking in the a priori establishedscale or other form of indirect indication of the place of a classified object in the valuation sequence.

In the additive procedure the final point ranking C_{add} is the sum of linear or non-linear functions of the input vector components, according to the formula $C(\mathbf{x}_{\text{add}} = a_1(x_1) + a_2(x_2) + a_3(x_3) + \ldots + a_n(x_n)$. Symbols a_i mean the established function transforming the values of individual features in a respective point ranking. The prototype of this valuation model includes the polynomial models of soil productivity [11], used in the assessment of the impact of chemical factors on crops The acceptation of such validation model includes the acceptation of the substitution of individual factors This means that the algorithm generally makes exception of the "rule of minimum" [1, 11]: negative individual assessments add up lowering the final ranking grade, while one negative factor does not ruin a high grade resulting from the high ranking level of the other. A characteristic feature is also the lack of plateau that is always present in the models of minimum.

In the multiplicative approach the point validation C_{mpl} is the function of the product

$$C_{mpl} = f(b_1(x_1) \cdot b_2(x_2) \cdot b_3(x_3) \ldots b_n(x_n)) \qquad (1)$$

The prototype of such an approach to the valuation, is a similar in form, Mitscherlich–Baule model [11, 15, 16], assuming exponential functions adequate to the characteristics of individual factors forming a final grade. Also this approach assumes the approval of the individual substitution factors, although, better than the additive algorithm regards the presence of unfavourable factors in the characteristic of lands In accordance with this approach is the way of the assessment of reclaimed grounds, with the application of the valuation index (WB) [7, 8], although it requires more multifaceted information and GIS/LIS environment. The procedure is inductive and involves the establishment of ranking based on: the characteristic of the formation (function of granulation and sorption of methylene blue), distribution of different formations in vertical, characteristics of the land slope. The ranking makes a scale 1–10 points and the algorithm has a multiplicative, not additive character. One can assess that it is consistent and well fixed towards the valuation ranking [20]. It can be treated as a good starting point in constructing methods of valuation classification for soilless areas.

The best known prototype of the relationships between the habitat features and crops in the von Liebig–Sprengler model, according to the original idea by [21], representing the relationship between the resources of the nutrients and crops This relationship takes the form

$$C_{\min} = \min[(m_1(x_1), m_2(x_2), m_3(x_3), \ldots, m_n(x_n), P)] \quad (2)$$

The individual functions are determined by smaller or bigger limitation of the quality, while the final land assessment is determined by the factor that is limiting to the highest extent. The P value is a plateau that carries the maximal grade. Some agricultural economists, analysing the usefulness of the von Liebig-Sprengler model as the principle of determining the fertilization level [1, 4, 5, 10, 11, 15, 16], assume that the "minimum principle" accepts the exclusiveness of LRP (Linear Response and Plateau) function as the only representation of the dependence between the growth factor and crops Nowadays this assumption is questioned even more because it does not result directly from von Liebig and Sprengler's ideas For several years Liebig–Sprengler "minimum principle" has been regarded a serious candidate for the position of the paradigm in the modelling of the crops' reaction to environmental factors, after a long time of being treated by agro-economists as a "historical curiosum". However, at present, the way of classification of natural or reclaimed land that would be entirely based on such a model of thinking remains unknown.

3. Data

The comment to the table of the class of land [14] is an official database of the relationships between macroscopically defined soil properties and their position in the validation series It contains all the available patterns of soil profiles in Poland, indicating their valuation classes The valuation classes make a ranking scale, according to the presumed values of their profitability of the agricultural land. They are discrete units in the table of ground classes According to the taxonomy by Strzemski [19], the Polish classification represents deductive approach to the valorisation of the productive space of agriculture. In this classification industrial soils do not occur. Thus at present it cannot be directly used in the assessment of the validation of soilless areas after reclamation.

Trying to interpret the information collected in the *Komentarz...* (*Commentary...*) as the source of knowledge requires assuming that the whole set of the patterns contained there reflects general rules of classification, possible to be detected and quantified by data mining techniques in databases Second assumption, referring to the concrete need of finding the rules of classification for the areas deprived of significant attributes characteristic to developed soils, makes it necessary to apply replacement criteria regarding typological and lithological attributes know from the *Komentarz...*. This issue results from the awareness of the occurrence in the reclamation of technogenic materials, where such basic characteristics as granulation distribution do not have to reflect all the relationships between them and other attributepp. This means that the granulation of the mineral formation of technogenic origin (e.g. waste products from the flotation of the ores of sulphur, zinc, lead or copper), formally classified to a definite mechanic group, in the range of other properties (filtration, water capacity, exchange capacity of cations), can have other characteristics than it is expected in natural soil formationpp. In these cases one should directly refer to such features, in case of which granulation makes a substitute.

Considering all the circumstances, a list was made. It included all the features significant from the point of view of the assessment of agricultural soils and linked with the basic criteria of land classification:

– $EAWC_{050}$: The water easily available in the layer of 0–50 cm, the difference of the water content in soil is reflecting the range of pressures 34 kPa to 200 kPa expressd in m^3/m^3. In formed and cultivated soils (apart from grain composition) it is formed by the depth and the amount of organic carbon on the detritus or ploughing level. In raw grounds, it can be expressed with quite a big certainty that this influence is limited to the granulation and the kind of mineral material. The interpretation of this value is direct: a big value *EAWC*050 is useful, its diminishing makes an unfavourable factor.
– $EAWC_{50100}$: The water easily available in the lithological layer 50–100 cm, difference of the water content in soil is reflecting the range of pressures 34 kPa to 200 kPa, expressed in m^3/m^3. The value of this feature depends on the properties of mineral material. This is the component implicating the degree of draining the upper layer of the ground. The bigger value of this feature improves the quality of land, the lower-decreases.
– $EAWC_{100150}$: The water easily available in the litological layer 100–150 cm, difference of the water content in soil is reflecting the range of pressures 34 kPa to 200 kPa expressed in m^3/m^3.
– *CEC*: Exchange capacity in the relation to cations in layer 0–30 cm in $cmol^{(+)}/kg$ of soil. This is the feature depending on mineral composition, reaction and the content of organic carbon in soils Big CEC value is generally a useful feature, apart from the cases of great saturation of grounds with acidifying components.

– AI_{050}: Percentage of air pores in the layer of 0–30 cm with sub-pressure 34 kPa. This is a structural feature deciding on air-water relationships. In arable soils minimal content of pores should not be smaller than 10%. The diminishing of this value influences worsening the level of aeration, Chile the growth of above 20% does not improve the quality.

The list of soil properties certainly contains features important for their usefulness quality. The disadvantage of the list is based on attributes requiring laboratory analyses.

The approximate value of the listed attributes can be estimated by the regression equations made for the database of soils in the European Union [24] according to the commonly known van Genuchten model [22]. *CEC* value can be estimated with quite a good reliability (R^2 = 0.739, n = 1930) with the regression equations obtained for relatively differentiated databases [12, 13].

The values of attributes for 747 patterns of the profiles of arable soils contained in the *Komentarz...* [14] were calculated taking the centres of mechanic groups, indicated in the descriptions and indicated there depths of detritus horizons It is obvious that the set of patterns does not meet the requirements of statistical examination, however it might be not enough for finding the regularity of the inter-relationships.

4. Results

In Poland, the valuation ranking of arable land covers 9 classes marked with symbols: I, II, IIIa, IIIb, IVa, IVb, V, VI and VIRz, respectively. They should form a profitability ranking (with average costs), which can indirectly be derived in an arbitrary point scale from a so-called conversion hectare: I: 9.75, II: 9.0, IIIa: 8.25, IIIb: 6.75, IVa: 5.5, IVb: 4.0, V: 1.75, VI: 1.0, VIRz: 0.0. This arbitrary 10-point scale, by definition, has a discrete character, although closer to the truth would be a continuous scale, reflecting undoubted fuzzy character of the differentiated valuation classes figure 1 presents the relationships between subsequent attributes and valuation classes The concept of 95% range of variability here is totally arbitrary, because the database does not represent random values The comparison between graphs allows confirming several regularities The graphs show that better valuation classes are characterized by higher values of attribute $EAWC_{050}$. This is a rather obvious relationship and – despite the dilution – very distinct. Less distinct, although visible is this relationship to $EAWC_{50100}$ and $EAWC_{100150}$. The shape of the relationship between value *CEC* and valuation class is very characteristic. It shows that above a certain value *CEC*, its further growth has no major effect on soil quality. It is easy to notice that the highest values *CEC* are characterized by medium valuation classes. The last graph indicates potential danger connected with the interpretation of the relationship between porosity and position in classification. It can only be interpreted as the illustration of negative correlation between water capacity of soils and the volume of macro-pores: in a three-phase system these both components compete with one another.

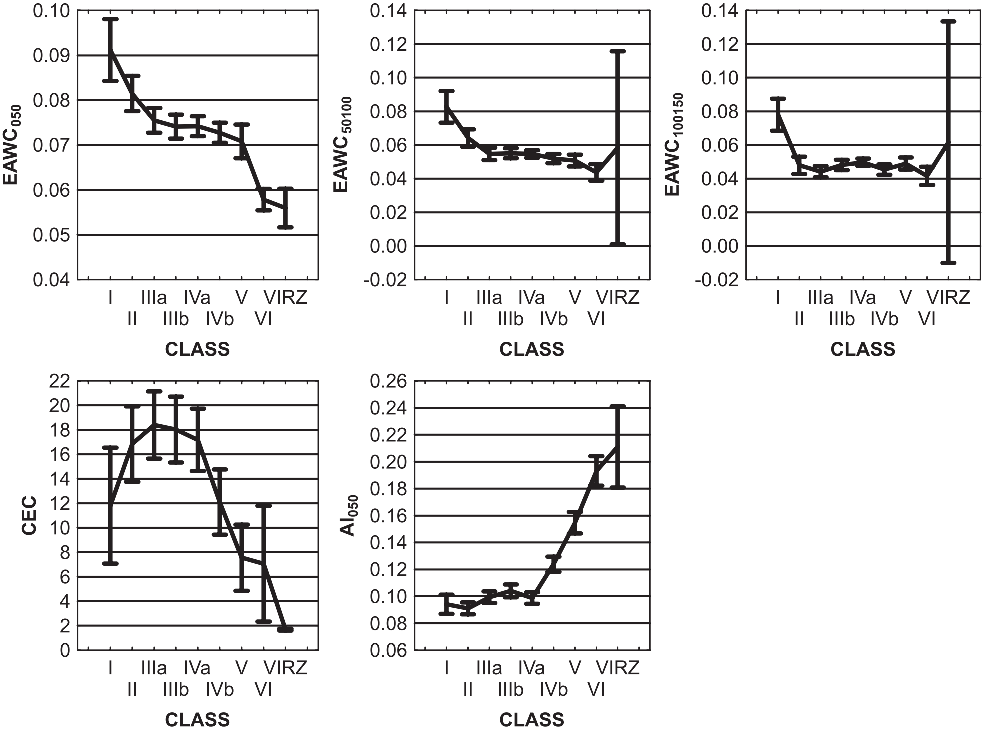

Fig. 1. 95% ranges of the variability of selected attributes for the arable land classes: based on empirical models

A significant question connected with the database analysis is the definition of joint algorithm of combined transformation of the characteristics of land on their position in validation ranking. To analyse this task as research instrument one can use classification and regression algorithms.

4.1. Classification Algorithms

Classification algorithms transform the vector of quantifiable or qualitative features, describing the object in nominal scale of classes, in this case literally the scale of valuation classes.

The most elementary algorithm of classification is Fisher's linear discrimination function. His method is applied to the obtained data and allows correct classification of almost 35 of soil patterns.

Table 1 presents general efficacy of algorithm with the combination of the correctness in the identification of subsequent classes It is worth stressing that, compared to other variables of the linear model, $EAWC_{050}$ has relatively small importance for the correctness of the class identification. It probably results from a strong correlation between $EAWC_{050}$ and AI_{050}.

Table 1. Efficacy of the identification of validation in percentage, with the use of Fisher's discrimination function. Option 1: probability *a priori* proportional to the abundance of the class; Option 2: probabilisty *a priori* identical for every class

Class	Option 1	Option 2
I	70.4	74.1
II	35.8	38.3
IIIa	16.3	17.0
IIIb	8.5	4.6
IVa	58.0	42,.5
IVb	38.3	19.1
V	35.0	50.0
VI	75.0	91.7
VIRz	33.3	66.7
Total	34.3	28.5

Fisher's algorithm is the reference point for other alternative procedures, including evolutionary ones, called artificial neural networks (ANN). A classical way to construct ANN is looking at the best (in terms of architecture, training parameters and construction details) solutions with the method of trials and errors In this area, however, ontogenic constructions appear, including networks changing its structure during the training. Due to the construction of the model, ANN are regarded universal approximators, allowing the recognition of every pattern of classification and regression, provided the relationship is continuous.

In the group of classical classifiers, with different types of architecture and parameters of training, algorisms: MLP (Multi Layer Perceptron), PNN (Probabilistic Neural Network) and the RBF (Radial Basis Function). With the limited number of training examples, the problem of this type of algorithms, is the tendency to overadjustment. To estimate generalization error the set of data was divided into three parts: a training part (380 random patterns), validation part (180 random patterns) and test part 207 (random patterns). This allows cross-validation hold-out.

ANN algorithms make significant development of classical Fisher's linear discrimination functions by introducing into classification non-linear transformation. This usually significantly improves the efficiency in the identification of objects Its further improvement is possible due to the application of ensembles (committees) of neural networks (or other algorithms of classification). Due to particular aspects of the functioning of individual classification algorithms, they can show correct functioning in different parts of identified sets The combination of the indications of classifiers of different architectures can lead into significant improvement in the recognition of objects In this case we used a pile of networks in their first layer consisting of two PNN (380 and 174 units in a hidden layer, respectively), and one MLP (22 hidden units) and RBF (150 hidden units). The second layer of the pile (transforming outputs from four networks of the first layers) was MLP network (9 hidden units), in other version it was PNN (125 hidden units). Table 2 contains information referring to the efficiency of the identification of individual sets through subsequent sets by subsequent algorithms.

Table 2. The degree of correct recognition of subsequent parts of the of patterns by models built with the application of evolutionary algorithms Tr: training set, Val: validation set, Tst: test set

Algorithm	Tr	Val	Tst
MLP	0.60	0.57	0.80
PNN	0.85	0.74	0.73
RBF	0.61	0.60	0.58
Stacked: MLP	0.90	0.86	0.84
Stacked: PNN	0.94	0.77	0.74

From the comparison it is seen that MLP algorithms and RBF, referring to this concrete set, provide smaller efficiency, but much better generalization compared to the probabilistic network. At the same time, a significant improvement of the functioning is done with the introduction of two-degree processing.

The additional advantage of ontogenic evolutionary algorithms in the GhostMiner pack is the possibility of identifying linguistic rules of classification of subsequent classes Like in the case of classical algorithms of classification, three procedures were studied – in a pure form and the combination of algorithms in the form of the committee of classifiers.

The worked-out classification algorithms were [9]: FSM (Feature Space Mapping) IncNet algorithm of the construction of the ensemble of classifiers and the algorithm of the decision tree – SSV Tree. The pack provides the validation tree with the 10-Folds method, which means ten repetitions of the construction of the classifier on 9/10 of the set of patterns and validation on the remaining 1/10, with the change of content of both setpp. It is a validation technique applied towards a small data set. It is in this case significant, because of the tendency to a considerable growth of networks changing their structure (Tab. 3).

Table 3. The Fraction of the correct recognition of individual parts of the set of patterns by different evolutionary algorithms; CVtr means training set, CVtest means test set in the validation procedure with 10-Folds method

Algorithm	CVtr	CVtest
FSM	0.80	0.73
SSV Tree	0.89	0.53
IncNet	0.49	0.44
Ensamble	0.86	0.67

Taking into account the purpose of the carried out analysis a conclusion can be formulated that classification algorithms can be successfully used in the transformation of the vector of land in the valuation scale, is a structure of the "black box" type made of a complex pile of neural networks It is also not meaningless that coming to the final result of the assessment. Non-linear procedures of classification can make attractive proposal of the classification of soilless areas, especially in systems of spatial information where data processing can be programmed properly. Table 4 also indicates that – despite a slightly worse result – mean PNN algorithm provides correct marking of all the valuation classes, in contrast to MLP algorithm.

Table 4. Percentage efficacy of the validation with the application of Fisher's discrimination function and non-linear classification algorithms

Class	Fisher	MLP	PNN
I	70.4	66.7	70.4
II	35.8	88.9	88.9
IIIa	16.3	79.3	80.0
IIIb	8.5	90.8	88.9
IVa	58.0	91.7	86.7
IVb	38.3	94.8	86.9
V	35.0	87.5	72.5
VI	75.0	100.0	91.7
VIRz	33.3	0.0	100.0
Total	34.3	88.1	85.0

4.2. Regression Algorithms

A direct connection between valuation classes and their profitability is assumed. An obvious assumption of the connection between the features of soils and their valuation position is also explaining the inductive approach. According to this, we are looking for the relationship between the characteristics of land and the ranking given to each valuation class This is a classic task within the range of regression of many variables, which can be solved in many ways with the use of linear and non-linear algorithms table 5 contains the overview of errors in the estimation of ranking with regression models obtained with different methods Except for linear regression the parameters of which were estimated with the smallest squares method, remaining algorithms have iteration character. The algorithm GMDH type (Group Method of Data Handling) [2] was applied in the form of a so-called Polynomial Neural Network that constructs regression equation by looking through generally defined class of polynomial models The validation of this model was carried out with the application of LOO (Leave-One-Out) procedure. The obtained result indicates good generalization, although not the best efficiency of the projection of relationship. Minimum algorithm (like in the case of linear regression, parameters were estimated with SAS – SAS Institute Inc. pack) makes the model of relationship, constructed according to the prediction by Sprengler–Liebig [15, 16]. Remaining models represent the approach based on evolutionary algorithms: MLP, RBF and GRNN (Generalized Regression Neural Network), respectively [6]. Similarly analogically, as in case of classification algorithms, also a "stacked" algorithm was applied, in which input values came from four different networks.

Table 5. Estimation errors in the ranking of validation classes, obtained with the application of different regression algorithms

Algorithm	R^2_{Tr}	$RMSE_{Tr}$	MAE_{Tr}	R^2_V	$RMSE_V$	MAE_V	R^2_{Tst}	$RMSE_{Tst}$	MAE_{Tst}
Linear	0.34	1.75	1.46	–	–	–	–	–	–
GMDH type	0.71	1.66	1.38	0.65	1.69	1.41	–	–	–
Minimum	0.66	1.66	1.37	–	–	–	–	–	–
MLP	0.64	0.83	1.00	0.66	0.74	1.02	0.46	0.84	1.21
RBF	0.59	0.63	1.05	0.56	0.68	1.25	0.53	0.73	1.22
GRNN	0.81	0.43	0.63	0.56	0.67	1.12	0.53	0.69	1.11
Stacked:MLP	0.94	0.24	0.33	0.90	0.32	0.44	0.89	0.32	0.43
Stacked:GRNN	0.95	0.21	0.21	0.88	0.35	0.32	0.92	0.29	0.29

Like in the case of classification algorithms the advantage of ANN over analytical models. One of the reasons is disproportion between the number of the degrees of freedom of two approaches A great disadvantage of ANN is a form of "black box”, while the methodological measure is indicating a simple transformation of quantitative features of land in a valuation scale. A large degree of the dilution of the relation blurs the picture of inter-relationship. However, the analysis of the results in figure 1 and the relationship between errors obtained with different methods, suggest the connection between 7 multiplicative algorithm (generally compliant with the algorithm of processing ANN) with some form of minimum principle. In particular, the relation CEC and validation indicate that these relationships are more complicated than simple linear regression.

5. Recapitulation

The set of soil patterns attributed to individual valuation classes can indirectly be a carrier of information on the approved rules of land classification. The abundance of patterns indicates that it used to be difficult to establish quantitative criteria of classification, together with their proper algorithms, contrary to the interpretation of the ensembles of macroscopic features.

The degree of the complexity of the relationship between quantitative attributes of arable land and their classification is well illustrated by figures 2 and 3.

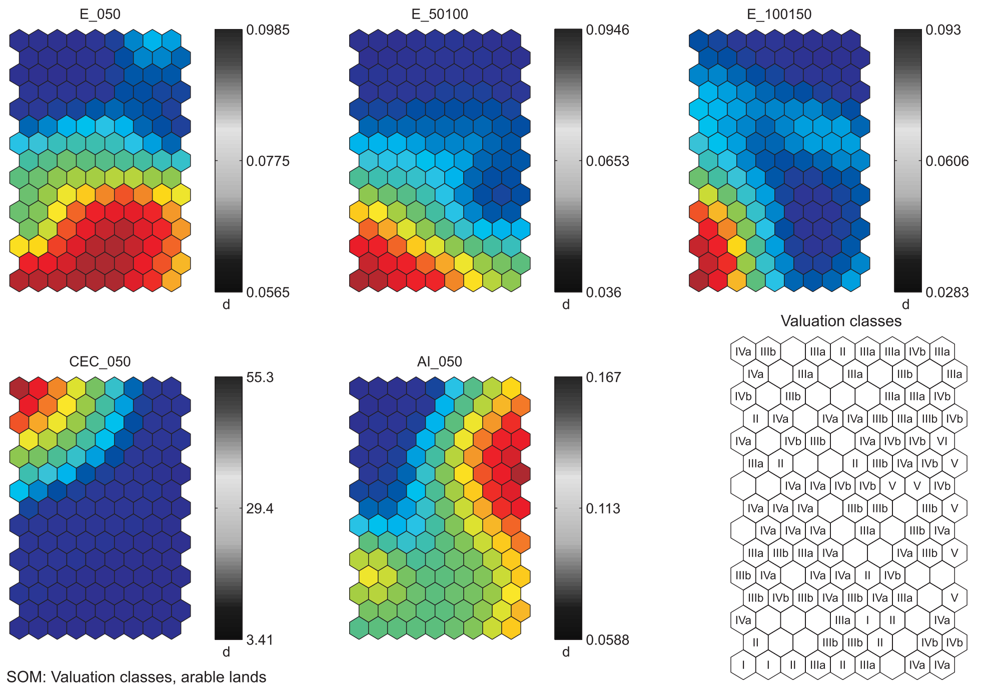

Fig. 2. The distribution of the features of land in the space of the self-organizing Kohonen’s map

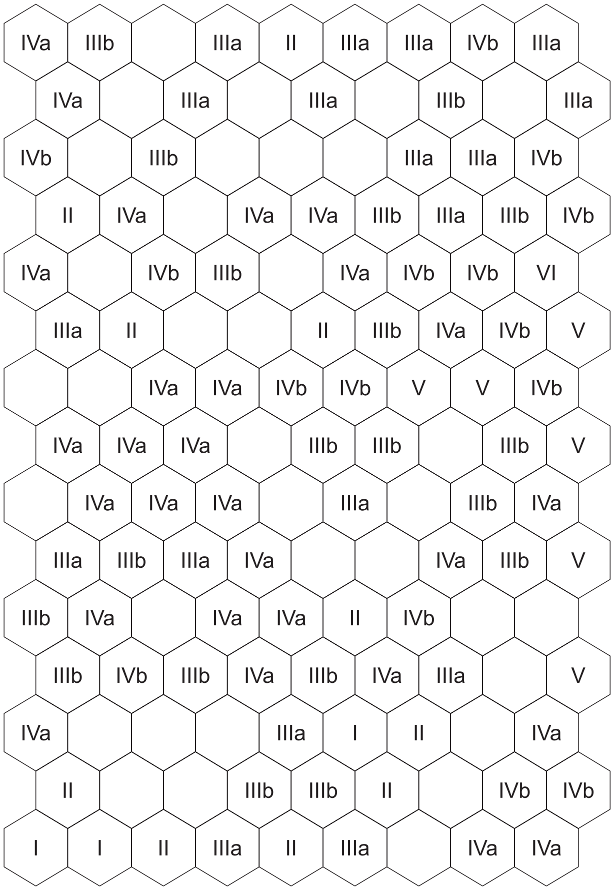

Fig. 3. SOM map of the classes of arable land obtained in the Kohonen's clusterisation procedure

The first one is showing distribution of the values of individual features on the background of result Kohonen's map of features The construction of Kohonen's SOM is based on distance criterion of individual patterns, understood as the criterion of similarity. For instance, analysing subsequent variables (in the nomenclature referring to the ideas of correctly oriented map) in this map maximal values $EAWC_{050}$ are located in its "southern" fragment, while the smallest values of this variable are located in the "NW" part. The distributions of the values of other features, especially CEC_{050} and AI_{050} is different. The result of the established similarity is generating the image of the similarity of soil patterns, seen in the figure 3. Following a general rule: higher valuation rather in a "southern" zone, worse in "east" and "north-west" part, the dominant picture is the presence of "islands" of higher validation in larger fragments of lower valuation and vice versa. The obvious consequence of this phenomenon are relatively good results of the application of evolutionary algorithms, usually characterised by a larger number of the degrees of freedom than alternative, purely statistical models of a closed structure. This is also confirmed by the observations with the application of ontogenic classification algorithms, where merely satisfactory results were obtained at the structures counting above 200 transforming unitpp. The growth of this structure was at the same time causing excessive adjustment of the model to the data, visible as a result of cross-validation. Building proper decision trees and algorithms of extraction of logical rules lead into sets counting above 120 rules, with their efficiency limited to about 60% of correct identifications.

The solution of the dilemma of the structure of inference on the quality of land based on quantitative features is – regarding the carried out analyses – very difficult. Of course, in many possible cases it would be reasonable to apply the obtained evolutionary model. This solution, however is not very useful in fragment-oriented studies, single samples and rough analyses Based on the knowledge of structure of processing in neural networks and the interpretation of results, one can conclude that a proper model of land classification based on quantitative features takes a multiplicative approach, although one cannot overlook a relatively good result obtained with a "minimum" approach.

5.1. Conclusions

The carried out analyses of the relationship between model values of quantitative patterns of the profiles of soils of arable land allow the following conclusions:

1) Satisfactory results of modelling the classification of land are provided by evolutionary algorithms, especially in the form of the set of classifiers and ensembles of approximators.
2) It is very difficult to obtain an unambiguous pattern of relationships in the valuation relations in a traditional regression analysis Relatively good results are given by the model obtained with the use of GMDH algorithms and the approach based on "minimum principles".
3) It seems justifiable to look at good model of classification, referring to compulsory in Poland validation of soil in the framework of multiplicative approach with the application of "minimum principle" elements

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