Modeling of Relationships between Economic Performance and Environmental Quality by SOM and Growing Hierarchical SOM – the Case of the Czech Republic Regions

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Abstract: **-** The relationships between economic performance and environmental quality are complex. Therefore, we develop a model using self-organizing map (SOM) to visualize and investigate the relationships. This paper presents a design of economic and environmental parameters which characterize the regions of the Czech Republic. Based on these parameters we design models which are related to economic performance and environment. Using the SOM, it is possible to look for connections of economic performance and environmental quality of individual regions in the Czech Republic in the monitored period 2007-2010. The modeling as such is realized, in addition to SOM, also by a growing hierarchical self-organizing map (GHSOM) which models hierarchical relationships in input data, too.

Key-words: Economic performance, environmental quality, regions, modeling, SOM neural networks, GHSOM neural networks.

1 Introduction

The results of research in the area of modeling components of environment and modeling of relations between the environment, economy and social context in the regions of the Czech Republic have been presented in [1,2]. The results obtained in these studies are followed by work [3], which also contains a variety of such models on the global scale. The standard modeling tools of listed facts include decision-support systems, optimization and simulating models, general equilibrium models and other approaches to sustainable development modeling [1,2,3,4,5].

New approaches to modeling these relationships have been applied recently. This results from the complexness of decision-making which is highlighted at decision-making analyses on one side. On the other side the description of these processes involves uncertainty which is caused by our inability to exactly define basic terms. The basic principle of new approaches to modeling is utilization of tolerances, inaccuracy, uncertainty and partial truth in order to reach a robust system with low realization price. These systems work with uncertainty. Moreover, the data used are changing in time, are heterogeneous, inconsistent, missing and uncertain. Such data can be processed by neural networks [6,7,8]. Based on the mentioned research supported by e.g. works of air quality modeling by fuzzy sets [9], intuitionistic fuzzy sets [10] and by neural networks [11], this work is oriented on modeling economic performance in relation to quality of the environments by neural networks with unsupervised learning, precisely SOM [7] and GHSOM [12,13,14,15].

The application of the SOM is suitable since ecological data are considered to be difficult to analyze because numerous biological and environmental factors are involved in a complex manner in environment-organism relationships. Recent applications of the SOM, which are reviewed in [16], include the molecular, organism, population, community, and ecosystem scales. First attempts to model the relationships between economic and environmental indicators using the SOM include clustering of the ecological footprint of nations [17] and assessing the economic impact on biodiversity situation of the countries [18].

The structure of the SOM neural network is static in its nature. Moreover, it does not make it possible to represent hierarchical relationships in input data. The GHSOM structure of this neural network removes these restrictions by generating a hierarchical structure. This structure automatically determines the input data and, additionally, it mirrors the relationships within these data. The main advantage of these neural networks with unsupervised learning is both the problem-depending structure and the intuitive representation of hierarchical relationships in the data.

The article lists proposed economic and environmental indicators for regions of the Czech Republic. We would like to highlight that apart of these there are also other indicators which might have relevant influence on modeling; however, they are currently not measured in the Czech Republic. Further, the article is focused on basic terminology from the field of neural networks with unsupervised learning, i.e. for SOM [6,7,11] and GHSOM [12,13,14,15], which represent a suitable clustering approach to data defined in this way and express suitable classification of regions.

The remainder of the paper is organized as follows. Section 2 deals with the design of economic performance, environment and shared model design where relationships between economic performance and environmental quality are sought. Section 3 offers the basic notions of the SOM and GHSOM. Relationships between economic performance of regions and environmental quality in the Czech Republic result from modeling and analysis conducted in Section 4. Section 5 concludes the paper.

2 Problem Formulation

The design of economic and environmental parameters, based on previous correlation analysis and recommendations of notable experts, can be realized as presented in Table 1 and Table 2. These are datasets obtained from the Czech Statistical Office for regions of the Czech Republic between 2007 and 2010 (the capital of Prague (Hlavni mesto Praha - HMP), Central Bohemia (Stredocesky - SC), South Bohemian (Jihocesky - JC), Pilsen (Plzensky - P), Karlovy Vary (K), Usti (U), Liberec (L), Hradec Kralove (KH), Pardubice (PU), Vysocina (V), South Moravian (Jihomoravsky - JM), Olomouc (O), Zlin (Z), Moravia-Silesian (Moravskoslezsky - MS)) Based on the presented facts, the following data matrix **P** can be designed

$$\mathbf{P} = \begin{array}{c|ccccc:c} & x_1^t & \dots & x_k^t & \dots & x_m^t & \omega_{i,j}^t \\ \hline o_1^t & x_{1,1}^t & \dots & x_{1,k}^t & \dots & x_{1,m}^t & \omega_{1,j}^t \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ o_i^t & x_{i,1}^t & \dots & x_{i,k}^t & \dots & x_{i,m}^t & \omega_{i,j}^t \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ o_n^t & x_{n,1}^t & \dots & x_{n,k}^t & \dots & x_{n,m}^t & \omega_{n,j}^t \end{array},$$

where $o_i^t \in O$, $O=\{o_1^t, o_2^t, \dots, o_i^t, \dots, o_n^t\}$ are objects (regions) in time t, x_k^t is the k-th parameter in time t, $x_{i,k}^t$ is the value of the parameter x_k^t for the i-th object $o_i^t \in O$, $\omega_{i,j}^t$ is the j-th class assigned to the i-th object $o_i^t \in O$, $\mathbf{p}_i^t=(x_{i,1}^t, x_{i,2}^t, \dots, x_{i,k}^t, \dots, x_{i,m}^t)$ is the i-th pattern, $\mathbf{x}^t=(x_1^t, x_2^t, \dots, x_k^t, \dots, x_m^t)$ is the parameters vector. In the case of unsupervised learning, the classes $\omega_{i,j}^t$ are not known a priori, and they are assigned as a result of an unsupervised learning algorithm.

Table 1 Economic parameters

Economic Parameters
x_1^t is the general unemployment rate in [%].
x_2^t is GDP in common prices per capita.
x_3^t is the economic activity rate in [%].
x_4^t is the formation of gross fixed capital per capita.
x_5^t is net disposable household income per capita.
x_6^t is work productivity (GDP/employee).
x_7^t is public budget deficit in CZK per capita.
x_8^t is means small and medium enterprise, rate of employment in [%].
x_9^t is the gross value added in the services sector [%].
x_{10}^t is expenditure for research and development in CZK/capita.

Table 2 Environmental parameters

Environmental parameters
x_1^t is consumption of selected fuels in GJ/inhabitant in [%] (brown and black coal, coke).
x_2^t is the ratio of household expenditures on fuels and electricity in [%].
x_3^t is emission of nitride oxides (NO) [t/km^2].
x_4^t is communal waste in t/capita.
x_5^t is the relationship of produced industrial waste and GDP/capita.
x_6^t is the ratio of ecologically utilized area of the total area in [%].
x_7^t is the coefficient of ecological stability.
x_8^t is the consumption of industrial fertilizers in net nutrients in [t/km^2].
x_9^t is sulphur dioxide (SO_2) in [t/km^2].
x_{10}^t are environmental protection expenditures in CZK/capita.
x_{11}^t is consumption of electric energy in MWh/capita.
x_{12}^t are solid emissions in [t/km^2].
x_{13}^t is carbon monoxide (CO) in [t/km^2].
x_{14}^t is the ratio of areas with deteriorative air quality in [%].

3 Basic Notions of SOM and GHSOM

Based on the analysis presented in [6,7] the combination of the SOMs and K-means algorithm is a suitable unsupervised method for modeling of economic performance and environmental quality in regions of the Czech Republic.

The SOMs are based on competitive learning strategy. The input layer serves the distribution of the input patterns $\mathbf{p}_i^t=(x_{i,1}^t,x_{i,2}^t, \dots ,x_{i,k}^t, \dots ,x_{i,m}^t)$. The neurons in the competitive layer serve as representatives (Codebook Vectors), and they are organized into topological structure (most often as a two-dimensional grid) which designates the neighboring network neurons. First, the distances d_j are computed between pattern $\mathbf{p}_i^t$ and synapse weights $\mathbf{w}_{i,j}$ of all neurons in the competitive layer according to the relation

$$d_j = \sum_{i=1}^{n}(\mathbf{p}_i^t - \mathbf{w}_{i,j})^2 , \qquad (1)$$

where j goes over s neurons of competitive layer, $j=1,2, \dots ,s$, $\mathbf{p}_i^t$ is the i-th pattern, $i=1,2, \dots ,n$, $\mathbf{w}_{i,j}$ are synapse weights. The winning neuron j^* (Best Matching Unit, BMU), for which the distance d_j from the given pattern $\mathbf{p}_i^t$ is minimum, is chosen. The output of this neuron is active, while the outputs of other neurons are inactive. The aim of the SOM learning is to approximate the probability density of the real input vectors $\mathbf{p}_i^t \in R^n$ by a finite number of representatives $\mathbf{w}_{i,j} \in R^n$, where $j=1,2, \dots ,s$. When the representatives $\mathbf{w}_{i,j}$ are identified, the representative $\mathbf{w}_{i,j^*}$ of the BMU is assigned to each vector $\mathbf{p}_i^t$. In the learning process of the SOM, it is necessary to define the concept of neighborhood function, which determines the range of cooperation among the neurons, i.e. how many representatives $\mathbf{w}_{i,j}$ in the neighborhood of the BMU will be adapted, and to what degree. Activity of the neurons and neighborhood are described in [6,7]. After the BMUs are found, the adaptation of synapse weights $\mathbf{w}_{i,j}$ follows. The principle of the sequential learning algorithm is the fact, that the representatives $\mathbf{w}_{i,j^*}$ of the BMU and its topological neighbors move towards the actual input vector $\mathbf{p}_i^t$ according to the relation

$$\mathbf{w}_{i,j}(t'+1) = \mathbf{w}_{i,j}(t') + \eta(t') \times h(j^*, j) \times (\mathbf{p}_i^t(t') - \mathbf{w}_{i,j}(t')) , \qquad (2)$$

where $\eta(t') \in (0,1)$ is the learning rate. Gaussian neighbourhood function is in common use, which is defined as

$$h(j^*, j) = e^{\left(-\frac{d_E^2(j^*,j)}{\lambda^2(t)}\right)} , \qquad (3)$$

where $h(j^*,j)$ is neighbourhood function, $d^2_E(j^*,j)$ is Euclidean distance of neurons j^* and j in the grid, $\lambda(t)$ is the size of the neighbourhood in time t'.

The batch-learning algorithm of the SOM is a variant of the sequential algorithm. The difference consists in the fact that the whole training set passes through the SOM only once, and only then the synapse weights $\mathbf{w}_{i,j}$ are adapted. The adaptation is realized by replacing the representative $\mathbf{w}_{i,j}$ with the weighted average of the input vectors $\mathbf{p}_i^t$. The quality of the SOM results can be measured with quantization and topographic errors. The quantization error is computed as an Euclidean distance of the input vector $\mathbf{p}_i^t$ and the representative $\mathbf{w}_{i,j^*}$ of its BMU. The topographic error is a quotient of all the input vectors for which the first and second BMUs are neighbors in the map. The topographic error measures the rate of the SOM topology preservation. The GHSOM [12,13,14, 15,19] is a neural network with hierarchical structure composed of independent growing SOMs. The motivation was to provide neural network that adapts its structure during its unsupervised learning process according to the particular requirements of the input data. Navigation across branches is facilitated through a global orientation of the independently growing maps in the individual layers of the hierarchy. Such a system is divisive and dynamic at the same time [20]. A representation of a GHSOM is given in Fig. 1.

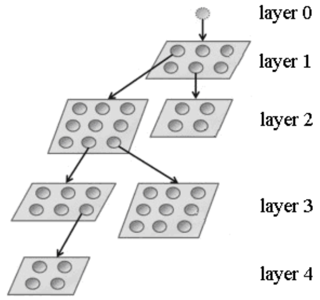

Fig. 1 A growing hierarchical self-organizing map

The layer 0 serves as a representation of the complete data set and it is necessary for the control of the growth process. The SOM in layer 1 consists of 3x2 neurons and it provides a rather rough organization of the main clusters in the input data. The two independent SOMs in the second layer offer a more detailed view of the data. The input data for one SOM may be mapped into a corresponding neuron on the higher layer. The two neurons on the second layer depict another expansion into the third layer. Such a hierarchical structure provides a granular input data representation. Furthermore, it can have various size with respect to input data.

The mean quantization error (mqe) [12,13,14,15] of a neuron j can be calculated as

$$mqe_j = 1/n_c \sum_{i=1}^{n_C} \|\mathbf{w}_j - \mathbf{p}_i^t\|, \; n_c = |\mathbf{P}_j|, \; \mathbf{P}_j \neq \emptyset, \qquad (4)$$

where mqe_j is the mean Euclidean distance between its model vector $\mathbf{w}_j$ (representative) and the n_c input vectors $\mathbf{p}_i^t$ that are the elements of the set of input vector $\mathbf{P}_j$ mapped onto this neuron j. At the start of the learning process, the mqe_0 is calculated for the neuron on the layer 0 of the given SOM according to the following formula [14]

$$mqe_0 = 1/n_\Lambda \sum_{j=1}^{n_\Lambda} \|\mathbf{w}_0 - \mathbf{p}_j^t\|,\ n_\Lambda = |\mathbf{P}|. \qquad (5)$$

The mqe measures the dissimilarity of the input data mapped on individual neurons, and this error is used to control the growth process in the neural network. A minimum quality of data representation for each neuron is defined as a fraction, and it is expressed by a parameter ψ of mqe_0. All the remaining neurons have to represent subsets of data at mqe smaller than the fraction ψ of mqe_0, i.e. it must hold that $mqe_j < \psi\ mqe_0$. The quantization error (qe_j) of the neuron is given by the equation (6) that can be used instead of mqe_j and it expresses a global termination criterion in the following way [14]

$$qe_j = \sum_{i=1}^{n_C} \|\mathbf{w}_j - \mathbf{p}_i^t\|,\ qe_j < \psi\ qe_0. \qquad (6)$$

The new generated SOM is learnt by a standard way. The growth process of a growing SOM can be characterized with $\mathbf{P}_j$ as a subset of $\mathbf{P}$ of the input data, which are mapped onto the neuron j, i.e. $\mathbf{P}_j \subseteq \mathbf{P}$, and of the vector $\mathbf{w}_j$ of the j-th neuron. Then the error of the r-th neuron is determined based on the neuron with the maximum qe assuming that the following equation holds [14]

$$r = \arg\max_j \left(\sum_{i=1}^{n_C} \|\mathbf{w}_j - \mathbf{p}_i^t\|\right),\ n_c = |\mathbf{P}_j|,\ \mathbf{P}_j \neq \emptyset. \quad (7)$$

The selection of this neuron is characterized by a dissimilar neighbor δ in this way

$$\delta = \arg\max_j (\|\mathbf{w}_r - \mathbf{w}_j\|),\ \mathbf{w}_j \in N_r, \qquad (8)$$

where N_r is the set of neighboring neurons of the error neuron r.

4 Modeling and Analysis of the Results

Three models were proposed for modeling of economic performance, quality of environment and relations of economic performance and quality of environment. The inputs to the model of economic performance are represented by proposed economic indicators, the inputs to the model of quality of environment by environmental parameters. The third model contains research of the influence of economic performance on environmental quality of the regions.

4.1 Modeling by SOM

Input parameters of individual SOMs are based on a number of experiments and are specified in Table 3.

Table 3 Input parameters of the SOM

Parameter	Init.	h(j*,j)	Initial λ(t')	Final λ(t')	η(t')	Epochs
Value	Linear	Bubble	10	1	0.01	10000

The structure of the neural network is limited by the number (200 neurons) with the aim to minimize quantization as well as topographical error. Such a high number of neurons also ensure visualization of changes in the status of regions in time t. The batch training algorithm was selected from SOM learning. The clustering by K-means algorithm with the aim to find clusters of similar regions is realized on the adapted SOM. The number of clusters comes from the value recommended according to the index of clustering quality [21]. U-matrix of square Euclidean distances of economic performance, environmental quality and relations of economic performance and environmental quality is shown in Fig. 2, Fig. 4 and Fig. 6. The U-matrix shows square Euclidean distances d_j between representatives $\mathbf{w}_{i,j}$. The K-means algorithm can be applied to the adapted SOM in order to find clusters as presented in Fig. 3 (economic performance), Fig. 5 (environmental quality) and Fig. 7 (relations between economic performance and environmental quality).

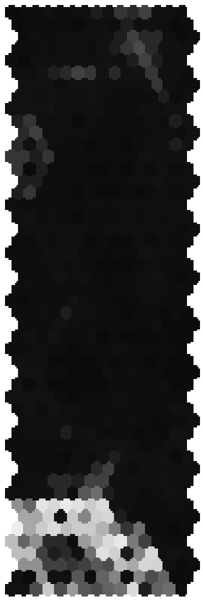

Fig.2

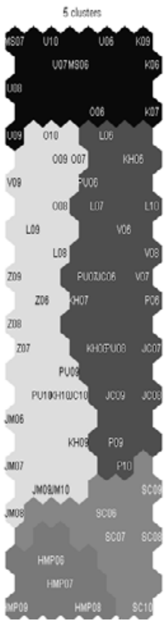

Fig.3

Fig.2 U-matrix of square Euclidean distances (economic parameters)

Fig.3 Clustering of the SOM by K-means algorithm (economic parameters)

The first step included modeling of economic performance and environmental quality separately. Fig. 3 shows clusters of regions sorted by economic parameters. The region of Prague is in the left lower corner as the best performing. Further, this region increases its distance from others in time t. As for economic performance, nearest regions to Prague are SC and JM. The worst performing regions, which are the farthest from Prague, are MS, U and K. We can see a negative trend in slow increasing of the distance of these to the well performing regions. Other regions are average from the viewpoint of economic performance, in time t the region O distance from the best performing is growing, while for the others it is decreasing.

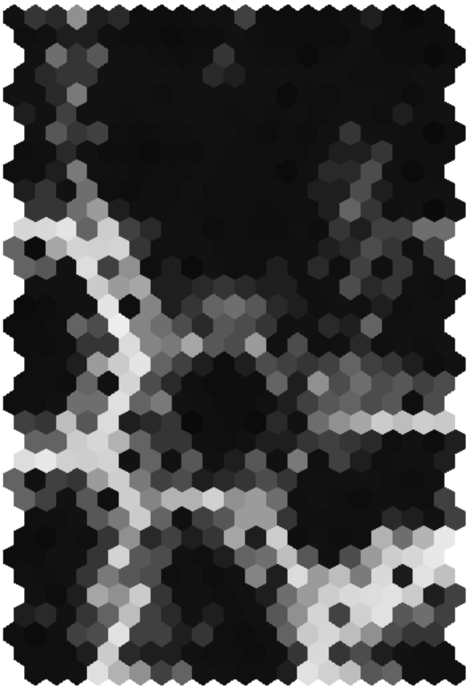

Fig.4 U-matrix of square Euclidean distances (environmental parameters)

Fig. 5 shows clusters of regions based on environmental parameters. The Prague region is typical by its high consumption of fuels and production of emissions and industrial waste. This goes together with high spending on environment protection. This region is getting near to region JM in time t, which means that the environment in Prague is improving. Region U shows high emissions of SO_2 and NO while MS it typical for high emissions of CO and consumption of selected fuels. The movement towards environmentally better conditions is visible especially for region U. In the second step, modeling of the relation of economic performance and environmental quality was carried our; i.e. modeling of economic performance and environmental quality together. Such a model enables evaluation of relations between economic and environmental parameters. While 5 clusters could be found in each of the individual models, the combination of models brings higher variability in the created map in the form of 6 clusters.

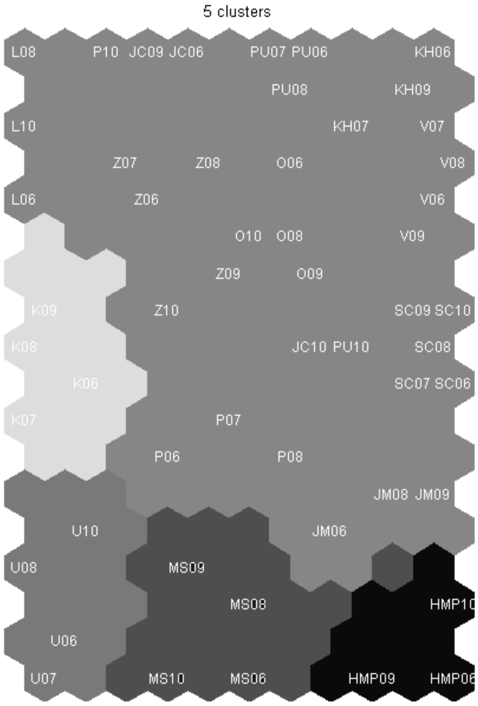

Fig.5 Clustering of the SOM by K-means algorithm (environmental parameters)

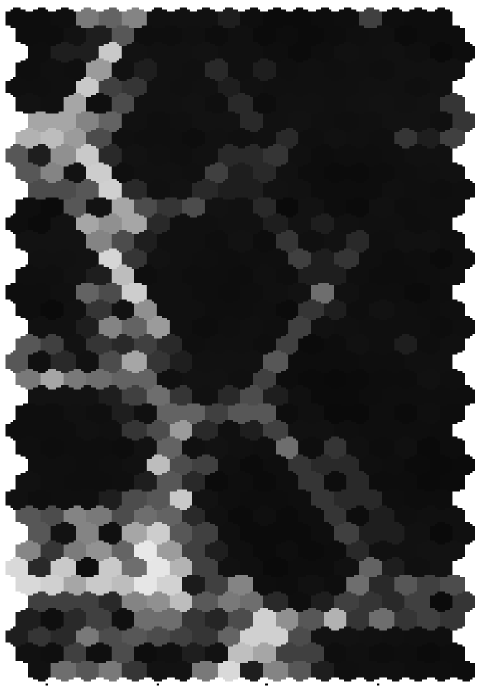

Fig.6 U-matrix of square Euclidean distances (relation of economic performance and environmental quality)

Both models influence classification of regions into these clusters. The Prague region is in one cluster, other clusters are formed by regions MS, U and K. Regions L, JC and P form another cluster and the rest of regions (KH, PU, JM, SC, V, Z, O) are located in the last cluster.

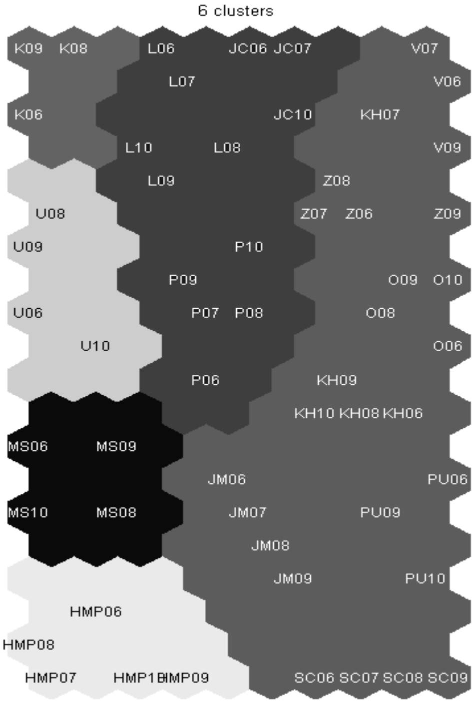

Fig.7 Clustering of the SOM by K-means algorithm (influence of economic performance on environmental quality)

The interpretation of dependencies between economic and environmental model can be realized based on the values of individual parameters listed in Appendix 1. The best performing region from the economic viewpoint is Prague. The economic performance is connected with high consumption of selected fuels, high CO, solid and NO emissions, high production of industrial waste and low coefficient of environmental stability. Negative environmental conditions come hand in hand with high expenditure on environment protection.

Regions MS and U are industrial regions with high unemployment rate and low ratio of small and medium enterprises. This is connected to high consumption of selected fuels and, therefore, also production of CO (region MS) or NO and SO_2 (region U). The upper part of the map shows regions with high coefficient of environmental stability and low consumption of fertilizers. There regions are oriented on the sector of services (K), primary sector (JC) or glass and processing industry (L). The maps shows that near the Prague region are especially region JM and, slowly getting farther, region SC. Region JM is oriented on small and medium enterprises especially in services. Region SC is typical by higher economic activity and spending on research and development. This is connected with orientation on automotive industry. From the environmental view, this region decreases spending on environmental protection and increases consumption of industrial fertilizers.

4.2 Modeling by Growing Hierarchical SOM

Input parameters of GHSOMs are also based on a number of experiments and are specified in Table 4.

Table 4 Input parameters of the GHSOM

Parameter	Init.	h(j*,j)	Initial $\lambda(t')$	Final $\lambda(t')$	$\eta(t')$	Epochs
Value	Linear	Gaussian	1.5	0.5	0.01	10000
Parameter	ψ_1	ψ_2	Units exp.			
Value	0.5	0.0001	4			

The fraction ψ_1 measures the breadth of maps, while the fraction ψ_2 controls the depth of maps. The value of ψ_1=0 would lead to huge maps, while ψ_1=1 would create only 2x2 maps. A new map is created for the data mapped onto one neuron if its qe>ψ_2 mqe. Setting ψ_2=0 would lead to very deep branches, while ψ_2=1 would result in no hierarchy. Finally, neurons with less than 4 data items were not allowed to be expanded. The values of neighborhood input parameters in Table 4 hold for the first layer. For the sub-layers, initial $\lambda(t')$ was set to 0.5 and final $\lambda(t')$ was 0.1.

For the economic performance, the Prague region (HMP) established one category with five representatives (Fig. 8). The evolution of this region suggests that the best economic performance was achieved in 2008 and then it declined due to the economic recession.

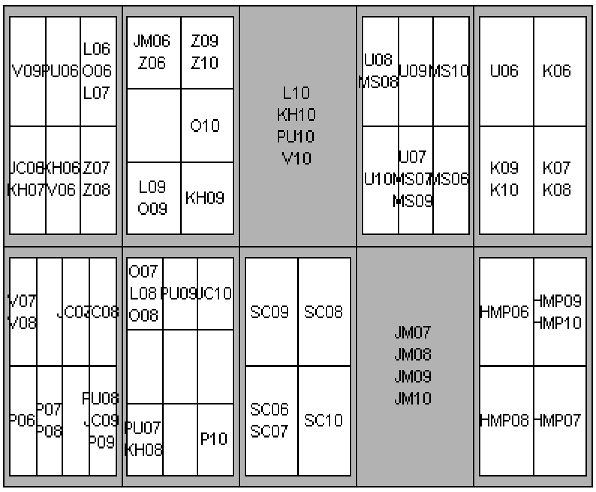

Fig. 8 GHSOM for economic performance

The second category (next to the HMP region) includes catching-up regions such as JM and SC. These regions have a similar economic performance. However, for example unemployment rate was higher in the JM region, while economic activity was higher in the SC region (Fig. 9). The third category (top right) covers the following regions: U, MS, and K, respectively. A low GDP per capita (x_2) and work productivity (x_6) was typical for these regions (Fig. 9).

The remaining regions are located on the left part of the GHSOM. Nevertheless, regions L, KH, PU, and V evolved from this category in the direction to the economically weakest regions in the year 2010. It was especially higher public budget deficits that were responsible for this development (Fig. 9).

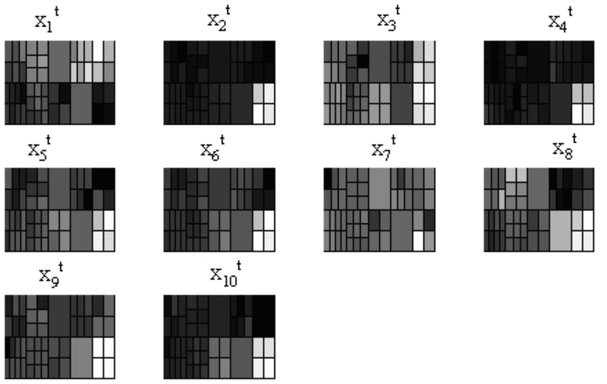

Fig. 9 Values of representatives for economic performance in GHSOM (high values are depicted in white, low values in black color)

Considering the environmental quality, the L, P, and JM regions provided good results (Fig. 10) with low air pollution and waste production. An above average environmental quality was also achieved by PU, KH, O, and Z regions. An improving environmental quality was typical for the JM region in 2010, too. On the contrary, the PU region deteriorated in 2010. The SC and V regions had an average quality of environment during the monitored period.

There is an empty space between the left and right part of the GHSOM. This suggests that the remaining regions (on the left) are significantly distant from the regions on the right part. The U and KV regions represent the first specific category (top left). These regions are energetically expensive with only slow decrease in air pollution (Fig. 11).

Still, the worst environmental quality was associated with the regions placed in central left and bottom left, respectively, of the GHSOM (MS and HMP regions). The environment of the MS region improved up to 2009. However, in 2010 it got worse to some extent (especially when considering the ratio of areas with deteriorative air quality.

Industrially oriented regions such as U, K, or MS regions did not have sufficient resources to fund the environmental protection. Therefore, the environmental quality remained low for the whole monitored period. On the other hand, the higher investment in environmental protection lead to decrease in some pollutants (e.g. NO and CO) in the Prague region (Fig. 11).

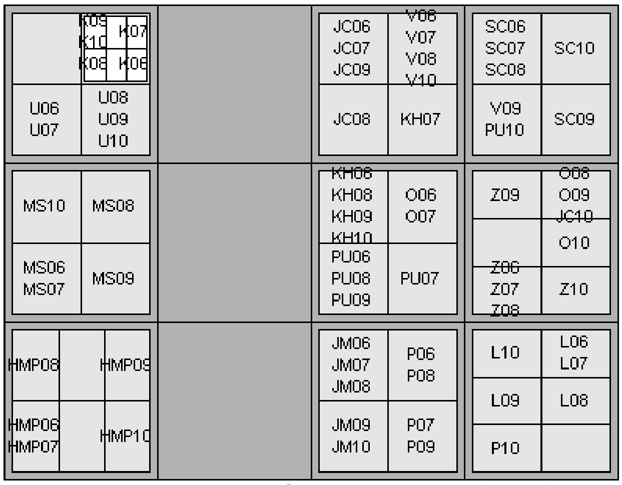

Fig. 10 GHSOM for environmental quality

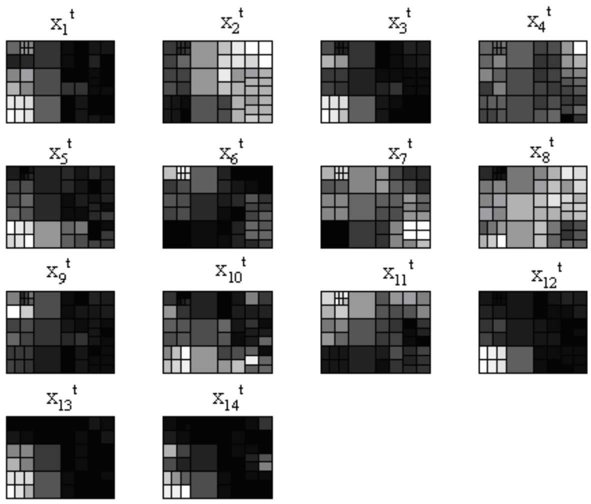

Fig. 11 Values of representatives for environmental quality in GHSOM

When relating the economic performance and environmental quality in one GHSOM, the Prague region (HMP) remained in a special category (Fig. 12). The most similar combined environment was in the MS region. Again, the values of representatives for the model studying relations between economic performance and environmental quality can be visualized as depicted in Fig. 13.

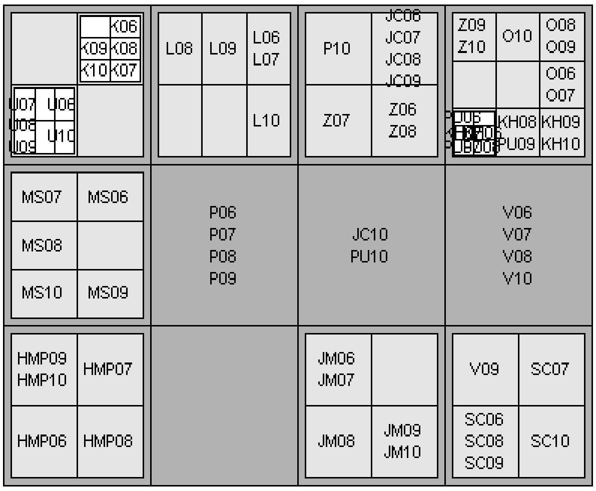

Fig. 12 GHSOM for the model combining economic performance and environmental quality

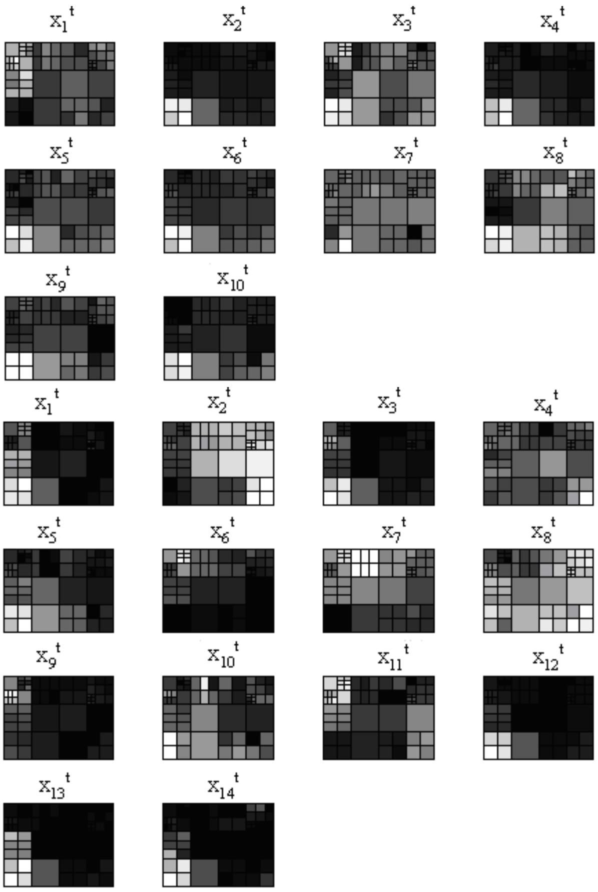

Fig. 13 Values of representatives for the model studying relationships between economic performance and environmental quality (top- economic performance, bottom- environmental quality)

Another category was created by the U and K regions with similar industrial and economic structures leading to similar environmental quality. The L region was also close to this category. However, there is a trend toward the right part of the GHSOM. The economically catching-up regions were placed to the right bottom part of the combined GHSOM. There were different economic strategies of the regions in this category. While the JM region was focused on increasing the expenditure for research and development, the SC region was oriented on the service sector. The close positions of the JC and PU regions in 2010 suggest that these regions chose the strategy of the JM region. On the other hand, the economic policy of the V region was closer to the SC region. The remaining regions were located in the top right position on the GHSOM. These regions were strong in environmental quality, but only average or below average in economic performance.

Our results may have some important policy implications. Our results suggest that it is possible to improve the economic performance without jeopardizing the environment quality. In the JM region, increasing expenditure for research and development and the growing employment in the SMEs, respectively, seem to be the drivers of economic performance. An alternative strategy with the orientation on the service sector was chosen in the SC region. However, we have to mention that the SC region economically profits from the spatial proximity to the Prague region.

5 Conclusion

Previous research has shown that SOMs represents a suitable method for modeling regional economic processes [22,23,24,25,26].

In this paper, we have demonstrated that the relationships between economic performance and environmental quality can be successfully modeled and visualized by neural networks with unsupervised learning. These were utilized for the design of the models of economic performance, environmental quality, and of the model which looks for relations between economic performance and environmental quality. The mentioned models were a function of economic and environmental parameters. The design of these models depends on their measurability.

Our results imply that economic performance influences the quality of the environment in the monitored regions as well as the direction if the development trend and movement of the regions to higher (or lower) quality of economic and environmental conditions.

This model may be used by regional governments to make effective decisions in the field of environmental financing. In addition, the model enables the simulation of regional policies and their impact on regional economic and environmental environment. Experimental results obtained by the presented methods and their visualization ensure a better understanding of the data and, thus, the relationship between economic performance and environmental quality. SOMs have been successfully applied to spatial data recently [27,28]. Therefore, in future we will address the issue of incorporating spatial information into our models.

The experiments were carried out in SOM and GHSOM Toolbox, Matlab 7.1 environment under MS Windows XP operational system.

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Appendix 1: Values of representatives for the model of researching relations between economic performance and environmental quality