DOI:** 10.5846/stxb201607221487

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Date: 2017-10-30T00:00:00+00:00

Abstract

Spatiotemporal evolution pattern analysis of time-series land use constitutes a current research hotspot. By applying the Self-Organizing Map (SOM) neural network method for integrated spatiotemporal representation and evolution pattern analysis of multi-temporal land use changes, regional land use change patterns are explored. Based on five-phase remote sensing classification data of land use in Beijing for the years 2005, 2007, 2009, 2011, and 2013, a Self-Organizing Map neural network was constructed and its clustering and dimensionality reduction visualization capabilities were employed to simultaneously train and output the land use data for all five years, thereby discovering clustering patterns of construction land, cultivated land, forest land, grassland, and garden land. Through secondary clustering of the output neurons and land use change trajectory analysis, the spatiotemporal evolution characteristics of land use changes in suburban Beijing across the five monitoring periods were obtained. The results reveal that land use changes in suburban Beijing from 2005 to 2013 exhibited distinct evolution characteristics: plain areas demonstrated a transition from cropland-dominated to construction land-dominated patterns, while mountainous areas showed a transition toward forest land-dominated patterns, with each district' s development exhibiting temporal sequentiality. Overall, six categories of land use evolution trajectories were formed.

Full Text

DOI: 10.5846/stxb201607221487

Qi Jianchao, Liu Huiping, Yi Yaoguo. Spatiotemporal evolution analysis of land use in Beijing from 2005 to 2013 using a self-organizing map. *Acta Ecologica Sinica*, 2017, 37(19): 6346–6354.

Qi J C, Liu H P, Yi Y G. Land use spatial-temporal evolution analysis using a self-organizing map in Beijing, 2005—2013. *Acta Ecologica Sinica*, 2017, 37(19): 6346-6354.

Spatiotemporal Evolution Analysis of Land Use in Beijing from 2005 to 2013 Using a Self-Organizing Map

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Abstract: Analysis of the spatiotemporal evolution patterns of time-series land use is currently a research hotspot. By applying a self-organizing map neural network method, this study conducts an integrated spatiotemporal expression of multi-temporal land-use change and analyzes its evolution patterns, in order to explore regional land-use change modes. Based on remote-sensing classification data of land use in Beijing for five periods—2005, 2007, 2009, 2011, and 2013—a self-organizing map neural network was constructed, and its clustering and dimensionality-reduction visualization functions were used to train and output the land-use data for the five years simultaneously. Aggregation patterns of construction land, farmland, forest land, grassland, and garden land were identified. Through secondary clustering of output neurons and analysis of land-use change trajectories, the spatiotemporal evolution characteristics of land-use changes in the suburban areas of Beijing over the five monitoring periods were obtained. The results indicate that, from 2005 to 2013, land-use change in the suburban areas of Beijing showed distinct evolutionary characteristics: in plain areas, farmland tended to develop into construction land, while in mountainous areas, land use evolved toward forest land; moreover, development in different regions exhibited temporal sequentiality. Overall, six types of land-use evolution trajectories were formed.

Keywords: self-organizing map (SOM); land-use change; multiple time series; spatiotemporal analysis; trajectory analysis

Land use spatial-temporal evolution analysis using a self-organizing map in Beijing, 2005–2013

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Abstract: Multiple time series land using spatial-temporal evolution analysis is an important research area. In this study, we investigated the spatial-temporal integrated expression of multiple time series land use change. A self-organizing map (SOM) neural network was used to explore regional land use change modes and to analyze what has driven these changes. Remote sensing data for five land use classification data periods (2005, 2007, 2009, 2011, and 2013) for Beijing were used to train the network, and the outputs identified the aggregation modes for building land, farmland, forest land, grassland, and gardens by using the clustering, dimension-reducing, and visual functions of the SOM. Then we conducted second-step clustering to produce the neuron and build the land use change trajectories that are needed to analyze the spatial-temporal features of Beijing suburban land use changes during the five monitoring periods. The results revealed that

Funding projects: Special Fund for Basic Scientific Research Business Expenses of Central Universities; Beijing Municipal Co-construction Project Special Funding; National Natural Science Foundation of China project (40671127); Ministry of Land and Resources public welfare industry research project (201411015-03)

Received date: 2016-07-22; **Online publication date:** 2017-05-27

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http://www.ecologica.cn

there were two land use changes in the Beijing suburbs between 2005 and 2013. One was the development of buildings on farmland located on the plains and the other was the development of forest land in mountainous areas. Furthermore, development in each district had its own time sequences. This meant that we eventually obtained six land use change trajectories in total.

Key Words: self-organizing map (SOM); land use change; multiple time series; spatial-temporal analysis; trajectory analysis

The spatiotemporal evolution of land use refers to changes over time in the spatial distribution of various land-use types. As time-series data increase, the difficulty and complexity of analyzing their evolution also increase. The self-organizing map method, which is commonly used to analyze high-dimensional spatiotemporal data, can simultaneously process multiple time-series datasets, thereby facilitating the analysis of spatiotemporal evolution laws and development patterns of land use across multiple time series, and providing support for the rational optimization of the spatial layout of land use.

At present, many achievements have been made in research on land-use change. Yang Guoan et al.[1] used a fractal model to study changes in the spatial pattern of land use in Beijing by comparing the fractal dimensions and instability indices of various land-use types in Beijing over two periods; Fu Hao et al.[2], Long Hualou et al.[3], and Fan Q et al.[4] all adopted pairwise comparisons between adjacent periods of multi-period data, quantitatively analyzing and explaining land-use change by calculating land-use change dynamics, transition matrices, and other methods; Liu H et al.[5], Huang Yong et al.[6], and Rong Fangfang et al.[7] used change-trajectory analysis methods to study the changing laws of spatial land-use patterns. Spatiotemporal analysis of land-use change includes both temporal and spatial dimensions. Although most current studies analyze from the temporal perspective, the integration of the two is still not very complete: spatial studies often focus on distribution patterns, while temporal studies mostly analyze in the form of time slices. Current research on the spatial distribution patterns of land use is relatively mature, whereas the processing of time-series data is mostly based on comparisons between single-period or two-period data. For multi-temporal land-use change data with more than two monitoring moments, the integrated spatiotemporal expression and comparative analysis still require further in-depth study. At the same time, trajectories of land-use change are currently mostly expressed by a map-algebra method, that is, by using trajectory codes to represent the change from one land type to another. This form of expression makes it difficult to directly conduct quantitative analysis and visual representation of trajectories.

The self-organizing map (SOM) is an artificial neural network that uses unsupervised learning to train input sample data and discretely represents high-dimensional data in the input space in low dimensions (usually two dimensions). The theory was first proposed in 1982 by Kohonen[8] of Helsinki University of Technology, Finland. What distinguishes the self-organizing map method from other artificial neural network methods is that it uses a neighborhood function to preserve the topological properties of the input space, thus allowing secondary clustering and trajectory construction directly on its output panel. As a neural-network clustering algorithm, SOM is often used to explore clustering patterns of spatial objects[9-11]; in addition, as a tool for dimensionality reduction and visualization, SOM is also often used to express and analyze potentially identifiable patterns[12-15]. In current research, the dual functions of SOM—clustering and visualization—are often used in combination, and it is frequently applied in various fields to analyze and process high-dimensional spatiotemporal data. For example, SOM has been widely applied in spatiotemporal evolution and trajectory analysis, as well as visualization studies, of socioeconomic change[16-18], epidemics[19], crime[20], airline routes[21], meteorology[22], and other fields. To date, however, studies applying the SOM method to spatiotemporal analysis of land use remain relatively scarce. Abroad, Arribas-Bel et al.[23-24] have begun to use SOM to study urban expansion and urban spatial structure, while domestically Jiao Limin et al.[25] have also begun to use SOM to conduct comparative analysis of the expansion characteristics of major Chinese cities. However, this work remains at a relatively preliminary stage: most studies use the SOM output panel to express the clustered distribution and differences of indicators that reflect urban expansion characteristics, whereas further in-depth research is still needed on the comparison of multi-temporal data and the analysis and expression of change trajectories.

Based on land-use data for Beijing in five periods—2005, 2007, 2009, 2011, and 2013—this paper uses the neural-network clustering function of SOM to input the five time-series datasets into the network simultaneously for training, obtaining output clustering results for different time-series data that are comparable in both time and space. These results are then visually represented and comparatively analyzed on the SOM output panel and in geographic space. With the aid of SOM' s topology-preserving characteristics, change trajectories are constructed on its output panel, allowing direct quantitative analysis and intuitive expression of the direction of trajectory change. Thus, by applying the SOM method, this study provides a new attempt and exploratory perspective for the integrated spatiotemporal expression and comparative analysis of multi-temporal land-use change, and on this basis further analyzes and reveals the spatiotemporal patterns and development laws of land-use change in the districts of Beijing from 2005 to 2013.

1 Study Area and Research Data

The study area of this paper comprises 14 suburban districts of Beijing Municipality, including Chaoyang District, Haidian District, Fengtai District, Shijingshan District, Shunyi District, Tongzhou District, Daxing District, Fangshan District, Changping District, Mentougou District, Huairou District, Miyun District, Yanqing District, and Pinggu District. The research data consist of land-use classification data interpreted from SPOT remote-sensing images for five periods—2005, 2007, 2009, 2011, and 2013—of Beijing Municipality (Fig. 1). Except for 2005, when the fusion of SPOT4 panchromatic-band images and multispectral-band images was used as the data source, all other periods used SPOT5 multispectral-band images as the data source. The spatial resolution was 10 m, and the classification accuracy was above 82% in all cases. The research data come from the long-term land-use monitoring project of the Beijing Rural Economy Research Center, undertaken by the research group over the past 20 years. Considering the consistency of the remote-sensing data sources and the fine-scale monitoring that began in 2005, this paper selects the five monitoring years after 2005 for study. Owing to the continuity and consistency of the long-term land-use monitoring project, the land-use classification standard adopts the eight major categories in the *Technical Regulations for Survey of Current*

Land Use Status formulated by the National Agricultural Regionalization Committee in 1984. In combination with the characteristics of remote-sensing data classification, the land categories were ultimately divided into seven classes: construction land (residential areas, industrial and mining land, and transportation land were merged and termed construction land), cultivated land, forest land, grassland, garden land, water bodies, and unused land.

2005 **2007** **2009**

2011 **2013**

Legend

- Forest land
- Grassland
- Garden land
- Cultivated land
- Construction land
- Water bodies
- Unused land

0 20 40 km

Fig. 1 Land use classification data of Beijing, 2005–2013

2 Research Methods

The overall technical workflow of this paper is shown in Fig. 2, mainly including the construction of the SOM network, secondary clustering, and analysis of land-use change trajectories.

2.1 SOM Method

The SOM network is a two-layer network composed of an input layer and an output layer (also called the competitive layer). The input layer is used to receive the input training samples, while the neurons in the output layer are generally arranged in a two-dimensional array. Bidirectional connections are established between the neurons of the two layers. The SOM network classifies the set of input patterns by finding the optimal weight vector, that is, the best-matching neuron. The steps of the SOM algorithm are: initialize each weight vector, that is, for

Fig.2 Overall flow chart of this study

Figure 1: Fig.2 Overall flow chart of this study

assign small random numbers to the weight vectors of the output layer and normalize them; find the winning neuron for the input data; adjust the weight vectors within the winning neighborhood; and repeatedly find the winning neuron for the input data and perform the subsequent steps until the iteration stopping criterion is satisfied.

In the experiment, the SOM algorithm was implemented through Matlab programming. To determine the size parameter of the SOM output panel, because the trajectories of change needed to be plotted and visualized, the SOM output panel was set sufficiently large so that, as far as possible, each input node in the output panel space would have a unique winning node corresponding to it. The input data in this paper consisted of the seven land-class attributes for 14 districts in Beijing in five years; that is, there were (5a $\times$14) districts (= 70) input records. Based on previous research experience and multiple experiments, the size of the SOM output panel was set to (20 $\times$20 = 400); that is, 400 neurons were output, far more than the number of input nodes. The number of training iterations of the SOM network was set to 10,000 to ensure the stability of the training results, thereby obtaining the component planes of each feature variable and the positions of the best-matching neurons.

Fig. 2 Overall flow chart of this study

2.1.1 SOM output component planes

The SOM input data are seven-dimensional vectors composed of proportional data for the seven land classes. These seven land-class attributes are regarded as seven feature variables. After network training, the weight vector of each output neuron is composed of these seven feature variables. By displaying the value of each feature variable according to the location of each output neuron, the component plane of each feature variable is obtained, allowing the clustering condition of the values of each feature variable to be observed intuitively.

Figure 3 shows the respective distributions and clustering patterns of the seven land-class attributes on the SOM output panel after network training. Each panel represents one land class; the darker the color, the higher and more concentrated the proportion of that land class. It can be found that, on the SOM output panel, the distributions of construction land, cultivated land, forest land, grassland, and garden land are relatively clustered, whereas the distributions of water bodies and unused land are relatively disordered. Among them, high values of the proportion of construction land cluster in the upper-right corner of the SOM output panel (Fig. 3a); high values of the proportion of cultivated land cluster in the upper-left corner (Fig. 3b); high values of the proportion of forest land cluster in the lower-right corner (Fig. 3c); high values of the proportion

Fig. 3 Output component planes of SOM

Figure 2: Fig. 3 Output component planes of SOM

of grassland cluster in the lower-left corner (Fig. 3d); and high values of the proportion of garden land cluster on the left side (Fig. 3e). It can thus be seen that, after SOM network training, the patterns of the input data in the input space can be identified and expressed in the output space.

2.1.2 Best-matching neurons

By calculating Euclidean distance, the output neuron closest to the input data is identified as its best-matching neuron. According to the positions of the best-matching neurons of the input data on the SOM output panel, the input data for each year are represented on the output panel (Fig. 4). In combination with the component planes in Fig. 3 for comparative analysis, it can be found overall that, in all time phases of this study, Chaoyang District, Haidian District, Shijingshan District, and Fengtai District mainly cluster in areas with relatively high proportions of construction land; Daxing District, Tongzhou District, and Shunyi District generally cluster in areas with relatively high proportions of cultivated land; Yanqing District, Miyun District, Huairou District, and Mentougou District mainly cluster in areas with relatively high proportions of forest land; and Pinggu District is mainly located in an area with a relatively high proportion of garden land.

2.2 Secondary clustering

The 400 output neurons were subjected to secondary clustering according to their weight vectors. The secondary clustering used the k-means algorithm. After repeated trials, it was determined that clustering into seven classes had good interpretability, and the results were visualized separately in SOM output space and geographic space. The regional divisions of the SOM output panel in Fig. 5 represent the results of the secondary clustering; the line charts in Fig. 6 show the seven attribute values of each clustering result, that is, the area proportions of the seven land classes. Based on these proportions, the land-use structure type of each cluster was determined. Among them, forest-land transition types I and II indicate that their forest-land proportions are lower than that of the forest-land type, but forest land still occupies the dominant proportion. In forest-land transition type II, construction land and cultivated land also account for considerable proportions. Figure 7 visualizes the clustering results for the five years in geographic space and uses multiple maps to express changes among different years. Because the land-use data for the different years and different districts were used simultaneously as input data for network training, in the output results, the clustering results for different periods and different regions have comparability.

Fig. 3 Output component planes of SOM

For comparison, the contents shown in Fig. 5, Fig. 6, and Fig. 7 all correspond to the same seven clusters, so as to facilitate spatiotemporal comparative analysis. As shown in Fig. 6, the differences among the clusters are mainly manifested in construction land, cultivated land, and forest land, followed by grassland and garden land, while water bodies and unused land make relatively small contributions.

2.3 Trajectory analysis

According to the positions of the best-matching neurons for the input data of each district in different periods on the SOM output plane, the output points corresponding to each district in different periods are connected in sequence. In this way, the trajectory of land-use change for each district is constructed in the low-dimensional space, i.e., on the SOM output plane, and the change trajectories are then subjected to cluster analysis. At this point, the proportional data for the land-use structure of each district in each year are arranged in chronological order to form a vector, which represents the change trajectory of that district and is used as the data input for trajectory clustering. Based on the trajectory-clustering results, the development patterns of land use in the study area are examined, and they are also visualized in both the SOM output space and geographic space.

3 Analysis of the Spatiotemporal Evolution of Land Use in Beijing

Analysis of the spatiotemporal evolution of land use includes two aspects: space and time. The spatial clustering pattern of land use can be expressed and explained by combining the clustering status of the attributes of each land category in the SOM output plane with the positions of the best matching neurons for the input data of each year. Meanwhile, according to the secondary clustering results of the output neurons, the spatial distribution pattern of land use in each year can be obtained. Through comparison of multi-temporal sequence data and construction, analysis, and visualization of change trajectories, the spatiotemporal change patterns of land use can be explained.

3.1 Spatial Clustering Pattern of Land Use

First, by combining the positions of the best matching neurons and the distributions of the attribute values of each land category in the SOM output component planes, the clustering status of different districts in different years can be intuitively identified; see Section 2.1.2. According to the secondary clustering results, the similar clustering status of the land-use structures of different districts in each year can be quantitatively determined, as shown in Fig. 7. It can be found that during the study period, the outer districts of Beijing mainly developed in two directions. One is the development pattern in which the southeastern plain area shifted toward the construction-land type, manifested as a decrease in the cultivated-land-type cluster and an increase in the construction land/cultivated land-type cluster. The other is the development pattern in which the northwestern mountainous area shifted toward the forest-land type, manifested as a decrease in the forest-land transition type II cluster and an increase in the forest-land-type cluster.

3.2 Spatiotemporal Change Patterns of Land Use

3.2.1 Analysis of the Evolution of Spatial Patterns

(1) The development pattern in which the southeastern plain area shifted toward the construction-land type. From Fig. 7, it can be seen that the cultivated-land type in Shunyi District, Tongzhou District, and Daxing District in 2005 and 2007 changed into the construction land/cultivated land type; among them, Shunyi District changed earlier (2009), while Tongzhou District and Daxing District changed later (2013). This change was mainly characterized by a decrease in the proportion of cultivated land and an increase in construction land, forest land, and grassland, indicating that Shunyi District, Tongzhou District, and Daxing District have the characteristics of newly developing urban areas. Chaoyang District and Fengtai District in the plain area always belonged to the construction-land type, while Haidian District and Shijingshan District, located in the transition zone between mountains and plains, always belonged to the construction-land transition type; the proportion of forest land in this type was significantly higher.

Fig. 4 Best matching unit of SOM

Fig. 5 Regional division of SOM output plane by second-step clustering

(2) The development pattern in which the northwestern mountainous area shifted toward the forest-land type. From Fig. 7, it can be seen that Fangshan District, Changping District, and Pinggu District changed from forest-land transition type II in 2005 to forest-land transition type I; Yanqing District and Miyun District changed from forest-land transition type I in 2005 to forest-land type; and Huairou District and Mentougou District always belonged to the forest-land type. This change was mainly characterized by a gradual increase in the proportion of forest land and a decrease in the proportions of cultivated land and other land categories, indicating that all five districts had a land-use change trend dominated by forest-land growth.

In general, from 2005 to 2013, the land-use changes in Pinggu District, Fangshan District, Changping District, Yanqing District, and Miyun District exhibited a change pattern from forest-land transition type II to forest-land transition type I and then to forest-land type. The land-use changes in Shunyi District, Tongzhou District, and Daxing District exhibited a change pattern

Fig. 6 Percent of different land use type in second-step clustering result

Figure 3: Fig. 6 Percent of different land use type in second-step clustering result

Fig. 7 Geospatial visualization of clustering result in different years

Figure 4: Fig. 7 Geospatial visualization of clustering result in different years

from cultivated-land type to construction land/cultivated land type. Huairou District and Mentougou District always belonged to the forest-land type; Haidian District and Shijingshan District always belonged to the construction-land transition type; and Chaoyang District and Fengtai District always belonged to the construction-land type.

3.2.2 Land-Use Change Trajectories For the 14 trajectory lines corresponding to the 14 districts, trajectory-direction similarity was analyzed through clustering. In this paper, the k-means algorithm was adopted, and after multiple iterations,

The experiment determined that clustering the 14 trajectories into 6 classes had very good interpretability: Chaoyang District and Fengtai District formed one class; Haidian District and Shijingshan District formed one class; Shunyi District, Tongzhou District, and Daxing District formed one class; Changping District and Fangshan District formed one class; Pinggu District formed one class; and Huairou District, Mentougou District, Yanqing District, and Miyun District formed one class. The land-use change trajectories of the districts are shown in Fig. 8. The colors of the trajectory lines in the left panel correspond one-to-one with the colors of the districts in the right panel; that is, the same color indicates the same trajectory cluster.

From the trajectory clustering map in the left panel of Fig. 8, it can be seen that the change trajectories of Chaoyang District, Fengtai District, Haidian District, and Shijingshan District all tend to extend toward the upper-right corner of the SOM output panel, indicating that these areas are more inclined toward the development of a land-use pattern with a high proportion of construction land —that is, they are more oriented toward development as central urban areas. Shunyi District, Tongzhou District, and Daxing District tend to develop in the direction of Chaoyang District, Fengtai District, Haidian District, and

Fig. 6 Percent of different land use type in second-step clustering result

Fig. 7 Geospatial visualization of clustering result in different years

Shijingshan District and follow closely thereafter, showing a transitional stage toward the construction-land type. The change trajectories of Huairou District, Mentougou District, Yanqing District, and Miyun District all tend to extend

Fig. 8 Land use change trajectories and visualization

Figure 5: Fig. 8 Land use change trajectories and visualization

toward the lower-right corner of the SOM output panel, indicating that these areas are more inclined toward the development of a land-use pattern with a high proportion of forest land—that is, they are more oriented toward the development of ecological conservation functions. The trajectory directions of Changping District and Fangshan District lie between those of Haidian District and Shijingshan District and those of Miyun District and Yanqing District, while Pinggu District consistently remains in an area with a relatively high proportion of garden land. In combination with the SOM panel of the second-step clustering results shown in Fig. 5, the land-use change patterns of the districts can be revealed more intuitively. Moreover, the trajectory lines can represent not only changes among the second-step clustering categories, but also changes within a given category. For example, Chaoyang District and Fengtai District, while still within the construction-land type, continue to develop toward a higher proportion of construction land.

Fig. 8 Land use change trajectories and visualization

4 Conclusions and Discussion

The SOM method is a highly effective visual data-mining method. It can map high-dimensional data onto a two-dimensional plane, thereby enabling more intuitive representation and identification of potential patterns. This study applied the SOM method to explore and analyze the spatiotemporal evolution patterns of district-level land use in Beijing. By setting a sufficiently large SOM output panel, and by making use of the topology-preserving property of SOM to input multi-temporal sequence data simultaneously into the SOM network for training and output, an integrated spatiotemporal expression and comparative analysis of land-use change was realized. This provides a new solution to the current problem in land-use change studies that the processing of multi-period data is mostly based on single periods or pairwise comparisons between adjacent periods [1-4].

The results of clustering and trajectory analysis are generally consistent with the "Eleventh Five-Year Plan" functional regional development plan for Beijing issued in 2006. Through secondary clustering of the SOM output neurons and the construction of land-use change trajectories on the output panel, some more detailed results can be found. For example, Chaoyang District, Fengtai District, Haidian District, and Shijingshan District are all urban functional expansion areas; however, compared with Haidian District and Shijingshan District, Chaoyang District and Fengtai District are closer to the development of the central urban area. In addition, although Fangshan District and Changping District are planned as new urban development areas, their current dominant land-use type is still forest land, and the proportion of forest land shows a certain increasing trend. Nevertheless, judging from the trajectory direction, they also show a certain development trend toward Haidian District and Shijingshan District. For Shunyi District, Tongzhou District, and Daxing District, in the course of their regional development, the transformation of Shunyi District occurred earlier. In summary, the characteristics of land-use change in Beijing from 2005 to 2013 are mainly manifested as the year-by-year increase in construction land and forest land and the year-by-year decrease in cultivated land. This indicates a structural change of mutual increase and decrease among land categories during the outward expansion of the city, as well as the occupation of agricultural land by construction land. Therefore, the application of this method can effectively reveal the spatiotemporal patterns of regional land-use change, and at the same time provides an alternative, more intuitive and convenient exploratory method for the integrated spatiotemporal expression and comparative analysis of land-use change data across longer time series.

The input data in this study consisted of 70 records, and the number of output neurons was set to 400. However, when the study area is larger or the input spatial units are divided more finely, the amount of input data will increase substantially. At that time, the number of output neurons must also be increased accordingly, meaning that a larger SOM output-panel size will be required. In this way, the computational load during SOM network training will increase greatly, and it will therefore be necessary to consider the algorithmic efficiency of SOM.

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Note: Figure translations are in progress. See original paper for figures.