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Characteristics of nutrients in natural wetland in winter: a case study

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Abstract The transformation, composition, and distribution characteristics of nutrients in natural wetlands are significantly affected by human activities, such as large-scale water conservancy projects and agricultural activities. It is necessary to reveal the composing and distribution characteristics of nutrients for elucidating its complex removal and retention mechanisms in natural wetlands. In this study, the composition and the spatial distribution characteristics of nitrogen in a natural wetland in central China were illustrated and analyzed. The self-organizing map (SOM) model was used in this study to assess the water quality dataset of the wetland. The relationships between nitrogen and other water quality parameters were revealed by the visualization function of the SOM model with the pre-processed data; the modeling result was in agreement with the linear correlation analysis. The results indicated that the SOM model was suitable for the assessment of field-scale date of natural wetlands, and finally a potential approach for predicting the nutrients concentrations in natural wetlands was also found.

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Introduction

Natural wetlands, which generally consist of water, soil, vegetation, and microorganism systems, are important for maintaining aquatic ecosystem biodiversity of surface water (Zhang et al. 2010). The global research of wetlands mainly focuses on ecological biodiversity and conservation (Whitehouse et al. 2008), water quality improvement (USEPA 2000), circulation of materials (biogeochemical cycle) (Raich and Schlesinger 1992), and environmental restoration (Suding et al. 2004). Based on the bibliometric analyses, the popular wetland research issues and wetland research changes were roughly found; the nutrients transformation through water, soil, and vegetation in wetlands was the most active research issue during the past two decades (Zhang et al. 2010). Smith and McCormick (2001) investigated the long-term relationships between changes in nutrient inputs and wetland nutrient concentrations in a northern everglades marsh. A natural wetland in eastern Lake Taihu, China, was separated into five subzones with different macrophyte structures to investigate their nutrient removal dynamics; the results indicated that a higher nutrient removal potential in wetland was dominated by Typha orientalis Presl, Zizania latifolia Turcz, and Hemarthria sibirica under high nutrient load (Hu et al. 2010).

The transformation, composition, and distribution characteristics of nutrients in natural wetlands are significantly affected by human activities, such as large-scale water conservancy projects and agricultural activities (Garcia-Garcia et al. 2009; Garnier et al. 2010; Xu et al. 2010). The mechanisms of the nutrients transformation in natural wetlands are hard to reveal because of the high variability of complex environmental systems (Hu et al. 2010). The nutrients were difficult to be removed in winter, especially for nitrogen removal, both nitrification and denitrification rates were slow in cold climates; it is significant to study the characteristics of nutrients in wetland in cold climates (USEPA 2000; Vymazal 2007; Zhang et al. 2008). Modeling the nutrients transformation and distribution processes are significant for elucidating the complex nutrient removal and retention mechanisms and assessing the corresponding water treatment potential of wetlands (USEPA 2000; Scholz 2006; Zhang et al. 2008). It is also important for optimizing the design, operation, and management of the water quality improvement and ecological restoration engineering projects, especially in winter (Zhang et al. 2008). The accuracies of the modeling results are greatly affected by the quality of the data (Zhang et al. 2009). However, it is difficult to assemble a large, robust, and multivariate dataset. Even if the experiments have been planned well, there will always be times when something goes wrong, such as equipment malfunctioning and human error, resulting in gaps in the data, especially in the field scale experiments data (Burke 1999; Zhang et al. 2009). Missing values occur commonly in large environmental datasets of natural wetlands. Since the conventional modeling approaches require complete input dataset, those data groups containing missing values are always removed from the dataset before modeling; this largely shortens the available dataset and embarrasses the modeling processes. A model, which is not affected by missing values, is necessary for processing the incomplete input dataset to reveal the nutrients transformation, composition, and distribution characteristics in natural wetlands (Zhang et al. 2009). The self-organizing map (SOM) model, which has advantages for information extraction (i.e., without prior knowledge) and the efficiency of presentation (i.e., visualization), is not affected by missing values and could process with incomplete input datasets (Chon 2011). It has been well applied for the monitoring and assessment for constructed wetland outflow (Zhang et al. 2008; 2009), stormwater runoff (Ki et al. 2011), river water (Astel et al. 2007), ecosystem level (Chon 2011), etc. Conventional multivariate methods are somewhat limiting for revealing the nonlinear and complex environmental data because of the rough data quality. Moreover, compared to other similar data mining techniques, the SOM is an efficient means to show the complex data in a more comprehensive fashion and in fewer dimensions (Kohonen et al. 1996; Chon 2011). The self-organizing map algorithm was compared with some conventional statistical methods (polar ordination; principal components analysis; correspondence analysis; non-metric multidimensional scaling) for ecological community; the result indicated that the SOM could perfectly complete classical techniques for exploring data and enabled both the visualization of the sample units and the visualization of species abundance (Giraudel and Lek 2001). Principal components analysis, cluster analysis, and SOM were applied to a large environmental dataset of chemical indicators of river water quality; the advantages of SOM algorithm and its classification and visualization ability for large environmental datasets were also stressed (Astel et al. 2007).

The aims of this study are to assess the composition and distribution characteristics of the nitrogen in winter, identify the relationship between nitrogen and other water quality variables in the natural wetland, and then find a potential approach for predicting the nutrients concentrations in natural wetlands.

Materials and methods

Study area

Honghu Lake wetland (113°17′ E and 29°48′ N as its geographic center), which is located in Honghu County and Jianli County in the southeast of Hubei Province, is the largest natural wetland in Jianghan Plain in central China (Fig. 1). It has an area of approximately 344 km^2, with an average water depth of 1.34 m and a maximum depth of 2.3 m (Li et al. 2009). The wetland is also located at the north bank of the middle reaches of Yangtze River and near the Three Gorges Dam Project. Enclosure culture for fish

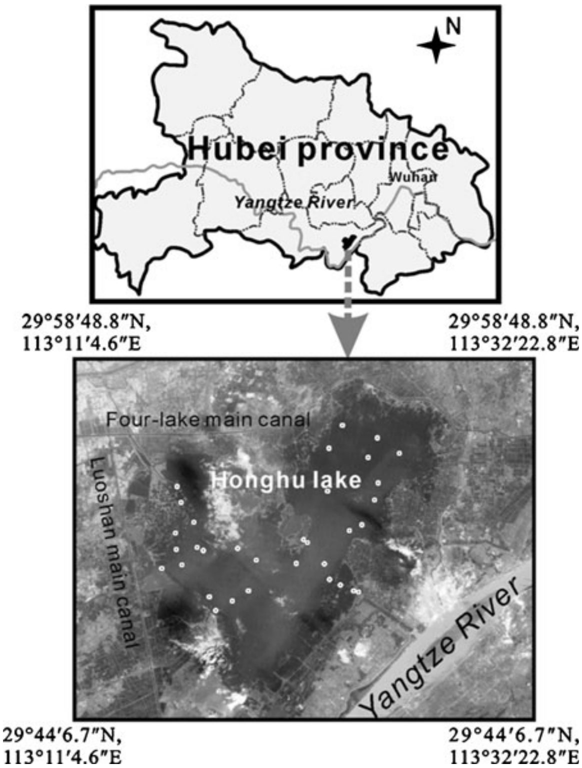

Fig. 1 Location of Honghu Lake wetland and the water quality monitoring sites

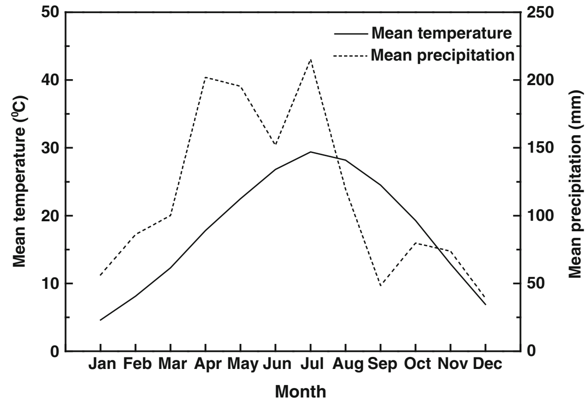

Fig. 2 The monthly variations of mean precipitation and mean temperature of the study area during 2001–2010

started at the end of the 1980s and increased sharply from the year 2000, which caused many environmental problems such as deterioration of water quality and biodiversity reduction (Chen and Xu 1995; Cheng and Li 2006). The study area (Fig. 1) had a subtropical monsoon climate. The average air temperature and annual rainfall were 16.3°C and 1,100–1,300 mm, respectively (Chen and Xu 1995). The monthly variations of mean precipitation and mean temperature of the study area during 2001–2010, obtained from China Meteorological Data Sharing Service System, are shown in Fig. 2.

Dataset

Data were collected by monitoring the water quality parameters of Honghu Lake wetland in January 2010. According to water current, depth, vegetation species, and density, protection, and utilization of the wetland, the locations of stations from Nos. 1 to 33 were selected (Fig. 1) (Mo et al. 2009; Li et al. 2009).Water samples were analyzed for temperature, pH, conductivity, and dissolved oxygen (DO) by using a calibrated Hydrolab DS5 Multi-probe Water Quality Sonde made by Hach Co., USA. Transparency (SD) was determined using Secchi disk. Chemical oxygen demand of the water sample was measured by the method of permanganate oxidation. Total nitrogen (TN) was measured by persulfate digestion and oxidation-double wavelength (220 and 275 nm) method by a spectrophotometer. Ammonia–nitrogen (NH_4^+–N) was determined by Nessler's reagent photometry. Nitrate–nitrogen (NO_3^-–N) was measured by UV spectrophotometry. Nitrite–nitrogen (NO_2^-–N) was determined by using *N*-(1-naphthyl)-ethylenediamine spectrophotometric method (APHA 1998).

Statistical analyses

All statistical analyses were performed using the standard software packages Origin 7.0 and Matlab 7.0. Significant differences ($p<0.05$, if not stated otherwise) between datasets were indicated where appropriate. The Shapiro–Wilk Normality Test was used to determine whether or not a dataset followed a normal distribution (Shapiro and Wilk 1965).

Self-organizing map

The SOM is a competitive learning neural network model and algorithm that implements a characteristic nonlinear projection method from the high-dimensional space of sensory or other input signals onto a low-dimensional regular lattice of neurons. The SOM models have been widely applied for the visualization of dimensional systems and data mining

Table 1 Summary statistics of the main water quality parameters in Honghu Lake in winter 2010

Parameter	Unit	Sample number	Mean	Standard deviation	Minimum	Median	Maximum
SD	cm	32	79	21.9	18	81	110
Temperature	°C	29	8.0	0.49	6.3	8.0	8.9
pH	–	28	8.8	0.29	8.0	8.8	9.2
Conductivity	mS/cm	28	0.5	0.08	0.3	0.5	0.6
DO	mg/L	29	14.9	3.74	8.0	14.2	25.1
NH_4^+–N	mg/L	33	0.834	0.4368	0.475	0.688	2.630
NO_3^-–N	mg/L	33	0.668	0.2507	0.063	0.745	1.101
NO_2^-–N	mg/L	33	0.011	0.0091	0	0.011	0.044
TN	mg/L	33	2.010	0.6569	0.511	2.088	3.241

(Kohonen et al. 1996, Vesanto et al. 1999). The SOM is based on unsupervised learning, which indicates that no human intervention is required during the model learning process and that little information needs to be known about the characteristics of the input data (Alhoniemi et al. 1999). In the SOM algorithm, the topological relations and the number of the neurons or nodes are fixed from the beginning. Each neuron contains a weight vector. At the beginning of the model, the weight vectors are initialized to random values. During the training, each weight vector is calculated using a distance measure such as the Euclidian distance. After a competitive learning process, the clusters corresponding to characteristic features can be shown on a U-matrix map.

The SOM toolbox (version 2) for Matlab 7.0 developed by the Laboratory of Computer and Information Science at Helsinki University of Technology was used in this study. The toolbox is available online at http://www.cis.hut.fi/projects/somtoolbox (Vesanto et al. 1999).

Results and discussion

Data pre-processing and analysis

Table 1 summarizes the main water quality parameters in Honghu Lake in January 2010. Approximate 33 measurements per variable were taken. According to the mean, median, minimum, and maximum values of the water quality parameters shown in Table 1, the water quality of Honghu Lake wetland was not satisfactory in winter. The serious pollution might be caused by the increased enclosure culture for fish and uncontrolled non-point source wastewater discharged into Honghu Lake wetland (Cheng and Li 2006).

Several missing values were observed, in the dataset for SD, temperature, pH, conductivity, and DO, due to equipment malfunctioning; these missing values would potentially mislead the data analysis. Modeling results could be promoted by using suitable pre-processing methods considering the presence of anomalies and the requirement for data distribution normality (Obu-Cann et al. 2001; Zhang et al. 2009). SOM algorithms could be improved considerable when the input data are pre-processed appropriately; one way in which the data can be pre-processed is normalization (Obu-Cann et al. 2001). In this study, the data were pre-processed by utilizing a log transformation method before modeling (Eq. 1). The raw datasets were pre-processed if the raw dataset did not follow a normal distribution. The Shapiro–Wilk

Table 2 Result of the normality test

Variable	Normality test result	
	Raw data	Transformed data
SD	No	Yes (a=0)
Temperature	Yes	–
pH	Yes	–
Conductivity	Yes	—
DO	Yes	–
NH_4^+–N	Yes	–
NO_3^-–N	No	Yes (a=0)
NO_2^-–N	Yes	–
TN	No	Yes (a=0)

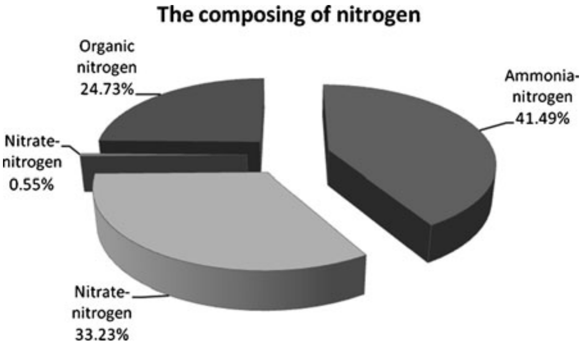

Fig. 3 Composition of nitrogen in Honghu Lake wetland

Normality Test was used to determine whether or not the input dataset follows a normal distribution.

$$x(\text{new}) = \log(x + a); \quad a \in R \tag{1}$$

where

x(new), pre-processed data; and x, raw data.

As shown in Table 2, the dataset of SD, NO_3^-–N, and TN were normalized by this log transformation method. Raw temperature, pH, conductivity, DO, NH_4^+–N, NO_2^-–N data, which followed normal distributions, and normalized SD, NO_3^-–N, and TN data were used in the subsequent analyses and SOM modeling.

Composing and spatial distribution of nitrogen

The composing of total nitrogen in the Honghu Lake wetland in the period of monitoring is shown in Fig. 3. Nitrogen had a complicated biogeochemical cycle with various biotic and abiotic transformations. In the natural wetlands, surface water had little or negligible particulate inorganic nitrogen, the important form of nitrogen in wetlands was inorganic nitrogen, which occurred predominantly as NH_4^+–N, NO_3^-–N, and NO_2^-–N (Vymazal 2007; Shen et al.

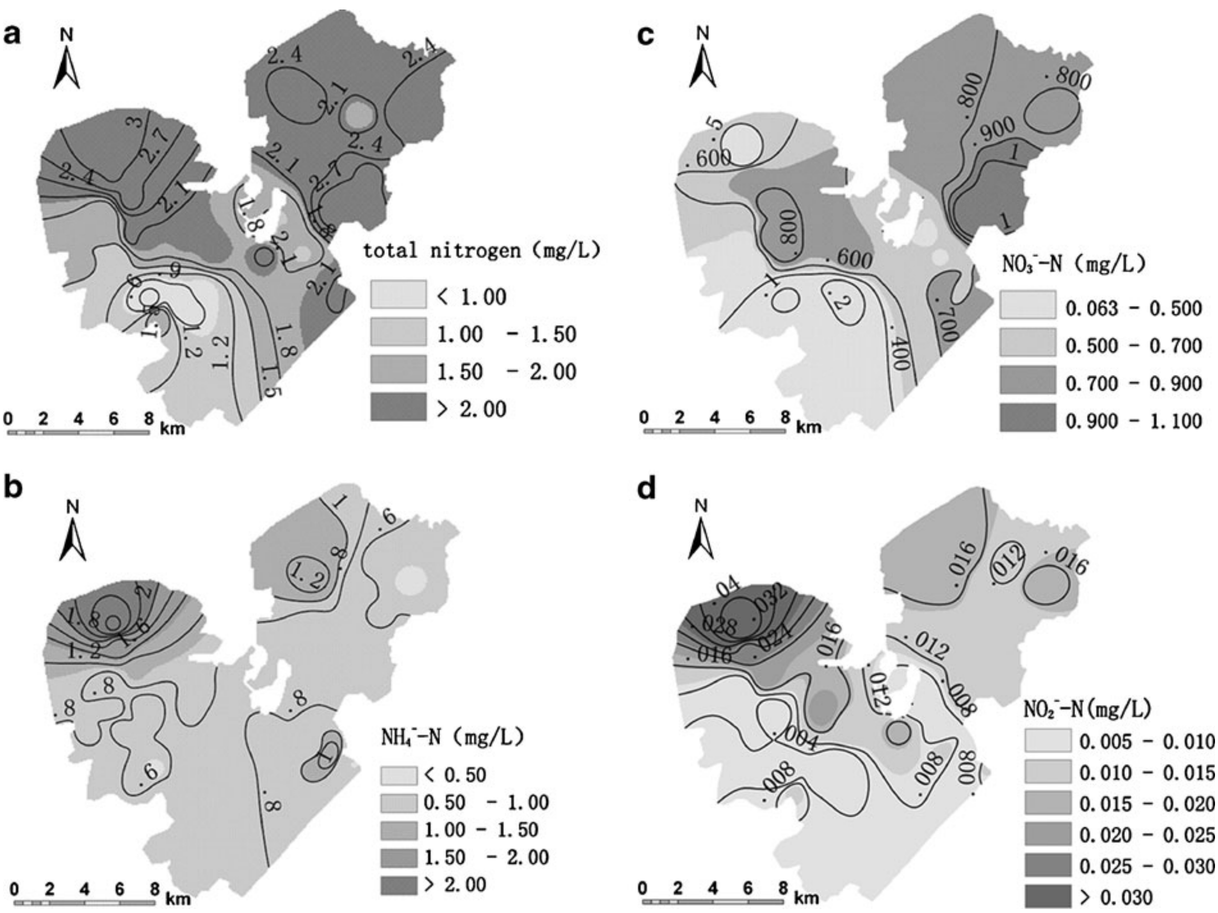

Fig. 4 The spatial distributions of **a** total nitrogen; **b** NH_4^+–N; **c** NO_3^-–N; **d** NO_2^-–N in Honghu Lake wetland

2003). Here the concentration of organic nitrogen was calculated by the relatively total nitrogen and inorganic nitrogen concentrations (Shen et al. 2003). Over the period of monitoring, the 75% of nitrogen occurred as inorganic nitrogen, while 25% were organic nitrogen, in the Honghu Lake wetland.

The spatial distribution characteristics of total nitrogen, NH_4^+–N, NO_3^-–N, and NO_2^-–N are illustrated in Fig. 4a–d, respectively. The gray shade scaling of the figures show the concentrations of the parameters in each map unit; for example, the lighter gray shades are associated with the low relative concentrations of the corresponding parameter. This helps to directly identify and subsequently illustratively show the spatial distribution characteristics of the Honghu Lake wetland. The nitrogen concentrations in the north corner of Honghu Lake wetland were highest. It might be because of the uncontrolled non-point source agricultural waste discharges from the four-lake main canal (Fig. 1), which is also a main channel of Jianghan Plain, which linked to the north corner of Honghu Lake wetland (Li et al. 2009; Garnier et al. 2010).

Relationships between nitrogen and other water quality variables

The SOM model was applied to identify the relationships between the incomplete pre-processed normalized input dataset of water quality parameters of Honghu Lake wetland. The component planes for each variable of the SOM model are shown in Fig. 5. The unified distance matrix (U-matrix) representation of the SOM visualizes the distances between the map neurons (Vesanto et al. 1999; Lee and Scholz 2006). The distances between the neighboring map neurons were calculated and visualized with gray shades between them in Fig. 5. The component plane shows the value of the variable in each map unit (Lee and Scholz 2006). For example, the lighter gray shades are linked to the high relative component value of the corresponding weight vector.

The relationships between NH_4^+–N, log (NO_3^-–N), NO_2^-–N, TN, and other input variables could be

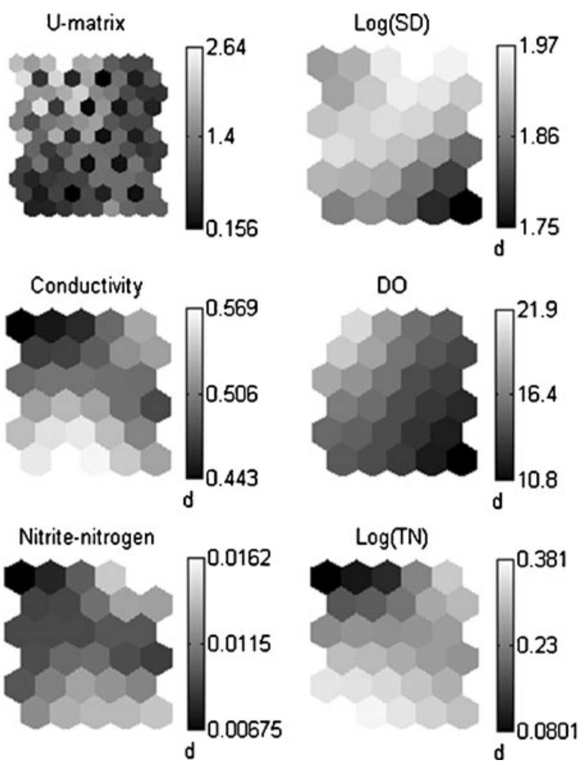

Fig. 5 Abstract visualization of the relationships between the incomplete normalized input data set of water quality parameters of Honghu Lake wetland using a self-organizing map model

Table 3 Correlation coefficients (R) and corresponding p values, variable pairs (in brackets) related to a correlation analysis comprising input (column headings) and target (row headings) variables

Variables	Log (SD)	Temperature	pH	Conductivity	DO
NH_4^+–N	−0.273 (0.130, 32)	−0.620 (<0.01, 29)	−0.434 (0.025, 28)	0.306 (0.113, 28)	−0.071 (0.714, 29)
Log (NO_3^-–N)	−0.059 (0.749, 32)	−0.379 (0.043, 29)	0.173 (0.380, 28)	0.713 (<0.01, 28)	−0.289 (0.129, 29)
NO_2^-–N	−0.303 (0.091, 32)	−0.690 (<0.01, 29)	−0.288 (0.137, 28)	0.580 (<0.01, 28)	−0.274 (0.150, 29)
Log (TN)	−0.279 (0.122, 32)	−0.584 (<0.01, 29)	−0.061 (0.758, 28)	0.743 (<0.01, 28)	−0.338 (0.073, 29)

identified and illustratively showed. As shown in Fig. 5, high NH_4^+–N values (>0.86) were linked to low log (SD) values (<1.86), temperature values (<8.01), pH values (<8.71), and DO values (<16.4), indicating that NH_4^+–N concentrations correlated negatively with SD, temperature, pH, and DO concentrations in Honghu Lake wetland in winter. Low log (NO_3^-–N) values (less than −0.314) were associated with high temperature values, high pH values, high DO values and low conductivity values, indicating that NO_3^-–N concentrations correlated negatively with temperature, pH, and DO concentrations in the wetland but correlated positively with conductivity concentrations. The relationship between log (NO_3^-–N) and log (SD) was weak. High NO_2^-–N values (>0.012) were linked to low log (SD) values (<1.86), low temperature values (<8.01), low pH (<8.71), low DO concentrations (<16.4), but linked to high conductivity values (>0.506). The results indicated that SD, temperature, pH, and DO concentrations had a negative relationship with NO_2^-–N concentrations; conductivity had a positive relationship with NO_2^-–N concentrations. Low log (TN) values (less than −0.314) were associated with high temperature values, high pH values, high DO values, and low conductivity values, indicating that TN concentrations correlated negatively with temperature, pH, and DO concentrations in the wetland but correlated positively with conductivity concentrations.

Table 3 summarizes the results from a correlation analysis for the input variables Log (SD), temperature, pH, conductivity, DO, and the target variables NH_4^+–N, log (NO_3^-–N), NO_2^-–N, TN. Unlike the SOM model, the missing values of each pair were disregarded in this analysis. Findings were in agreement with the key relationships revealed by the SOM in Fig. 5. The linear relationships between NH_4^+–N values and temperature (R=−0.620), pH (R=−0.434); log (NO_3^-–N) and temperature (R=−0.379), conductivity (R=0.713); NO_2^-–N and temperature (R=−0.690), conductivity(R=0.580); TN and temperature (R=−0.584), conductivity (R=0.743), were statistically significant (p<0.05).

Multivariable linear regression simulation

According to the analysis results of Fig. 5 and Table 3, it seems that nitrogen in Honghu Lake wetland could be easily removed and retentive if DO, temperature, and pH values were high and conductivity values were low. The transformations mechanisms within wetlands are highly complex and include microbial, biological, physical, and chemical processes that may

Table 4 Multivariate linear regression equations for ammonia–nitrogen, log (nitrate–nitrogen), nitrate–nitrogen, total nitrogen as functions of log (SD), temperature, pH, conductivity, and DO in Honghu Lake wetland in winter 2010

Linear regression equation for determining nitrogen values	Variable pairs	r^2	p Value
NH_4^+-N=0.076×Log(SD)−0.362×Temperature−1.214×pH+1.475 ×Conductivity+0.074×DO+12.329	28	0.5757	0.001
Log(NO_3^-–N)=0.138×Log(SD)−0.0038×Temperature+0.348×pH +1.224×Conductivity−0.031×DO−3.669	28	0.6566	< 0.001
NO_2^--N=0.001×Log(SD)−0.008×Temperature−0.009×pH+0.039 ×Conductivity+0.0001×DO+0.123	28	0.5306	0.003
Log(TN)=−0.020×Log(SD)−0.059×Temperature+0.126×pH+0.890 ×Conductivity−0.015×DO−0.556	28	0.6142	<0.001

occur sequentially or simultaneously (Scholz 2006; Vymazal 2007). The processes of nitrogen transformations in wetlands include ammonia volatilization, nitrification, denitrification, nitrogen fixation, plant and microbial uptake, mineralization (ammonification), nitrate-ammonification, anaerobic ammonia oxidation, ammonia adsorption, and burial (Vymazal 2007). Those processes are significantly affected by the crucial factors of water quality, such as temperature, DO, pH, and conductivity. Multivariable linear regression model was also applied to determine the nitrogen values by using other more cost-effective, rapid, and easier to measure water quality variables such as SD, temperature, pH, conductivity, and DO. The results of the regression analysis are shown in Table 4. Ammonia-nitrogen, log (nitrate–nitrogen), nitrate–nitrogen, total nitrogen values in Honghu Lake wetland over the period of monitoring were determined well by the selected variables with r^2 of 0.5757, 0.6566, 0.5306, and 0.6142, respectively ($p<0.05$) (Table 4).

Conclusions

1. The composition of nitrogen and the spatial distribution characteristics of total nitrogen, ammonia–nitrogen, nitrate–nitrogen, and nitrite–nitrogen in the Honghu Lake wetland were illustrated, respectively. Over the period of analysis, the 75% of nitrogen occurred as inorganic nitrogen, while 25% were organic nitrogen, in the Honghu Lake wetland; the nitrogen concentrations in the north corner of Honghu Lake wetland were highest.
2. The relationships between ammonia–nitrogen, nitrate-nitrogen, nitrate-nitrogen, total nitrogen and other water quality parameters could be well identified and illustratively showed by using the pre-processed data with SOM model. The key relationships revealed by SOM model, which was not affected by missing values in the input data, were in agreement with the linear correlation analysis results.
3. Cost-effective, rapid, and easily measurable online variables, such as SD, temperature, pH, conductivity, and DO were chosen for the prediction of ammonia–nitrogen, nitrate–nitrogen, nitrite–nitrogen, total nitrogen concentrations with a multivariable linear regression model, respectively. The relative high r^2 values indicated that this model could be used as a potential approach for predicting the nutrients concentrations in natural wetlands.
4. Further research is required to assess the microcosmic impact and dynamic mechanisms of SD, temperature, pH, conductivity, and DO on microbial, biological, physical, and chemical processes of nitrogen transformation and removal in Honghu Lake wetland.

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References

Alhoniemi, E., Hollmen, J., Simula, O., et al. (1999). Process monitoring and modeling using the self-organizing map. *Integrated Computer-Aided Engineering, 6*(1), 3–14.

APHA (1998) *Standard methods for the examination of water and wastewater, 20th edition. American Public Health Association (APHA)*, American Water Works Association and Water and Environmental Federation, Washington D.C.

Astel, A., Tsakouski, S., Barbieri, P., et al. (2007). Comparison of self-organizing maps classification approach with cluster and principal components analysis for large environmental data sets. *Water Research, 41*(19), 4566–4578.

Burke, S. (1999). *Missing values, outliers, robust statistics and non-parametric methods*. LC*GC Europe Online Supplement, 19–24

Chen, Y. Y., & Xu, Y. X. (1995). *Hydrobiological Resources and Environment in Lake Honghu* (p. 15). Beijing: Science Press.

Cheng, X. Y., & Li, S. J. (2006). Evolution and character of the representative lakes in the middle and lower reaches regions of Yangtze River. *Chinese Science Bulletin, 51* (7), 848–855.

Chon, T. S. (2011). Self-Organizing Maps Applied to Ecological Sciences. *Ecological Informatics, 6*(1), 50–61.

Garcia-Garcia, V., Gomez, R., Vidal-Abarca, M. R., et al. (2009). Nitrogen retention in natural Mediterranean wetland-streams affected by agricultural runoff. *Hydrology and Earth System Sciences, 13*(12), 2359–2371.

Garnier, M., Recanatesi, F., Ripa, M. N., et al. (2010). Agricultural nitrate monitoring in a lake basin in Central Italy: a further step ahead towards an integrated nutrient management aimed at controlling water pollution. *Environmental Monitoring and Assessment, 170*(1–4), 273–286.

Giraudel, J. L., & Lek, S. (2001). A comparison of self-organizing map algorithm and some conventional statistical methods for ecological community ordination. *Ecological Modelling, 146*(1–3), 329–339.

Hu, L. M., Hu, W. P., Deng, J. C., et al. (2010). Nutrient removal in wetlands with different macrophyte structures in eastern Lake Taihu, China. *Ecological Engineering, 36* (12), 1725–1732.

Ki, S. J., Kang, J. H., Lee, S. W., et al. (2011). Advancing assessment and design of stormwater monitoring programs using a self-organizing map: Characterization of trace metal concentration profiles in stormwater runoff. *Water Research, 5*(14), 4183–4197.

Kohonen, T., Oja, E., Simula, O., et al. (1996). Engineering applications of the self organizing map. *Proceedings of the IEEE, 84*(10), 1358–1384.

Lee, B.-H., & Scholz, M. (2006). Application of the self-organizing map (SOM) to assess the heavy metal removal performance in experimental constructed wetlands. *Water Research, 40*(18), 3367–3374.

Li, T., Cai, S. M., Yang, H. D., et al. (2009). Fuzzy comprehensive-quantifying assessment in analysis of water quality: a case study in Lake Honghu, China. *Environmental Engineering Science, 26*(2), 451–458.

Mo, M., Wang, X., Wu, H., et al. (2009). Ecosystem health assessment of Honghu Lake Wetland of China using artificial neural network approach. *Chinese Geographical Science, 19*(4), 349–356.

Obu-Cann, K., Fujimura, K., Tokutaka, H., et al. (2001). Data mining of power transformer database using self-organizing maps. *Proceedings of International Conference on Info-tech & Info-net (ICII2001),* Beijing 2001, Oct. 29 – Nov. 1, Beijing, China. 4, 44–49. Available online at http://ieeexplore.ieee.org/iel5/7719/21162/00983717.pdf

Raich, J. W., & Schlesinger, W. H. (1992). The global carbon-dioxide flux in soil respiration and its relationship to vegetation and climate. *Tellus Series B-Chemical and Physical Meteorology, 44*(2), 81–99.

Scholz, M. (2006). *Wetland systems to control urban runoff.* Amsterdam: Elsevier.

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika, 52*(3/4), 591–611.

Shen, Z. L., Liu, Q., & Zhang, S. M. (2003). Distribution, variation and removal patterns of total nitrogen and organic nitrogen in the Changjiang River. *Oceanologia et Limnologia Sinica, 34*(6), 577–585.

Smith, E. P., & McCormick, P. V. (2001). Long-term relationship between phosphorus inputs and wetland phosphorus concentrations in a northern everglades marsh. *Environmental Monitoring and Assessment, 68* (2), 153–176.

Suding, K. N., Gross, K. L., & Houseman, G. R. (2004). Alternative states and positive feedbacks in restoration ecology. *Trends in Ecology & Evolution, 19*(1), 46–53.

USEPA. (2000). *Constructed wetlands treatment of municipal wastewater.* United States (US) Environmental Protection Agency (EPA), Office of Research and Development, Cincinnati, OH, USA

Vesanto, J., Himberg, J., Alhoniemi, E., et al. (1999). Self-organizing map in matlab: the SOM toolbox. In: *Proceedings of the Matlab DSP Conference*, November 1999, Espoo, Finland, pp. 34–40. Software available online at http://www.cis.hut.fi/projects/somtoolbox/

Vymazal, J. (2007). Removal of nutrients in various types of constructed wetlands. *Science of the Total Environment, 380*(1–3), 48–65.

Whitehouse, N. J., Langdon, P. G., Bustin, R., et al. (2008). Fossil insects and ecosystem dynamics in wetlands: implications for biodiversity and conservation. *Biodiversity and Conservation, 17*(9), 2055–2078.

Xu, Y. Y., Cai, Q. H., Han, X. Q., et al. (2010). Factors regulating trophic status in a large subtropical reservoir, China. *Environmental Monitoring and Assessment, 169* (1–4), 237–248.

Zhang, L., Scholz, M., Mustafa, A., et al. (2008). Assessment of the nutrient removal performance in integrated constructed wetlands with the self-organizing map. *Water Research, 42*(13), 3519–3527.

Zhang, L., Scholz, M., Mustafa, A., et al. (2009). Application of the self-organizing map as a prediction tool for an integrated constructed wetland agroecosystem treating agricultural runoff. *Bioresource Technology, 100*(2), 559–565.

Zhang, L., Wang, M. H., Hu, J., et al. (2010). A review of published wetland research, 1991–2008: ecological engineering and ecosystem restoration. *Ecological Engineering, 36*(8), 973–980.