



Water Quality Analysis and Evaluation of Eutrophication in a Swamp Wetland in the Permafrost Region of the Lesser Khingan Mountains, China

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Abstract

Wuyiling Nature Reserve is located at the edge of a frozen soil area and has abundant vegetation resources. It is an important area for evaluating the impact of frozen soil degradation on the environment. Analyzing the water quality and eutrophication characteristics of different swamps and water bodies can provide a basis for protecting the water environment of frozen soil areas. The pollution characteristics of different swamps and water bodies were analyzed and the Levenberg–Marquardt back-propagation neural network was used to evaluate water quality and eutrophication. Finally, the eutrophication evaluation was compared with the nutritional status index. The results demonstrated that (1) the highest concentrations of the total phosphorus (TP), total nitrogen, ammonia nitrogen (AN), permanganate index (PI), chemical oxygen demand, and chlorophyll were all present in the Tangwang River, which could be caused by the effects of human and agricultural activities along the river. The maximum average concentrations of TP, AN, and PI in the four wetland swamps appeared in the shrub swamp; (2) The water quality category of shrub, grass, and forest swamps in Wuyiling Nature Reserve was Class II, and the water quality category of floating swamps and the Tangwang River was Class I. The nutrient levels of the four marsh swamp wetlands and the Tangwang River were in the mid-range for many nutrients; and (3) the LM–BP neural network model, which was used to evaluate water eutrophication, and the results of a comprehensive evaluation of a nutritional status index were similar, further demonstrating the credibility of the evaluation results.

Keywords Permafrost region · LM–BP model · Water quality evaluation · Water eutrophication evaluation

Wetlands serve as transition zones between terrestrial and aquatic ecosystems. Sometimes called “the cradle of life” or “the kidneys of the earth,” wetlands play an indispensable role in balancing hydrological and climatic cycles as well as in protecting biodiversity and water resources (Broeck et al. 2015; Li et al. 2020a, b). In cold areas of the northern hemisphere, the unique periodic freeze/thaw processes of water and soil have a significant impact on the hydrological processes of swamps that affects the development of high-latitude and high-altitude swamp ecosystems (Grogan et al. 2004; Sharma et al. 2006; Song et al. 2019). The Lesser Khingan Mountains possess one of the most concentrated

areas of wetlands in the cold regions of China. Seasonal permafrost is widely distributed here and is very sensitive to climate change. With the increase of temperature and the intensification of human disturbance, permafrost has undergone serious degradation (Xiao et al. 2016; Wei et al. 2011), so it is important to understand the effects of permafrost degradation on wetland water quality. Most of the surface water in the Lesser Khingan Mountains, including a large amount of water in the marsh area, was previously frozen to a thickness of 90–130 cm during winter, and this water was slowly released from April to June of the following year; this was conducive to the retention of water in the swamps (Shen et al. 2019). At the same time, wetlands are highly sensitive ecosystems that can retain and decompose pollutants from various sources, so are easily polluted when exposed to various types of pollution (Mao et al. 2014). In addition, most of the world’s freshwater resources have experienced eutrophication due to excessive inputs of nitrogen and phosphorus, primarily from human activity (Janssen et al. 2017;

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Xu 2013). Therefore, scientists need to clearly understand the status and environmental quality of wetland ecosystems, necessitating the monitoring and analysis of the characteristics of water pollution in these swamps. Studying the spatial distribution and eutrophication levels of different types of swamp water bodies will provide a basis for protecting wetland ecosystems.

Water quality research in regions with permafrost involves two types of water: surface water and groundwater. The geological origin of water (which may release uranium and arsenic) has a significant impact on the quality of surface water in subarctic regions with permafrost (Elliott et al. 2020). Lindsay et al. (2019) simulated the effects of permafrost loss on wetlands, showing that for every 10% reduction in permafrost area, the total annual flow of ditch and tidal flats decreased by 2.5%. Marion et al. (2019) studied the hydrogeochemical characteristics of groundwater in regions with permafrost. The contribution of shallow and deep groundwater to surface water has changed significantly over time, characterized by decreased dissolved organic carbon and increased total amount of dissolved solids in the Big Fish rivers. This is related to the reduction of permafrost coverage. Jasmina et al. (2020) demonstrated that water quality changes related to the thawing of frozen soil significantly affect zooplankton in small Arctic lakes. At present, past research on the eutrophication of wetlands and related water quality has mainly focused on lakes, rivers, reservoirs, and constructed wetlands (Yang et al. 2020; Anthony et al. 2020; Chang and Yu 2020; Feng et al. 2018; Li et al. 2020a, b). Therefore, there is a very urgent need to understand the water quality characteristics and eutrophication of swamp wetlands in permafrost regions. Permafrost degradation has varying degrees of impact on water quality and eutrophication of marsh wetlands in the permafrost regions of the Wuyiling Nature Reserve. Analyzing the pollution levels in different marsh wetlands and water bodies will provide a reference for water quality evaluation in permafrost regions.

Materials and Methods

Wuyiling Nature Reserve, located in the northeastern part of Heilongjiang Province, lies in the northern part of the eastern section of the Lesser Khingan Mountains at 48°33–50' N, 129°00–30' E (Fig. 1). Low mountains and hills dominate the local terrain with an average elevation of 350–400 m. The temperate continental monsoon climate features an average annual temperature of -1.1°C and a soil freezing period of about 220 days. Areas of seasonally frozen soil and island-shaped permafrost layers have a maximum freezing depth of 250 cm. The zonal soil in the area is dark brown soil, and non-zonal soil includes meadow, swamp, and peat soil. The zonal vegetation is a mixed coniferous

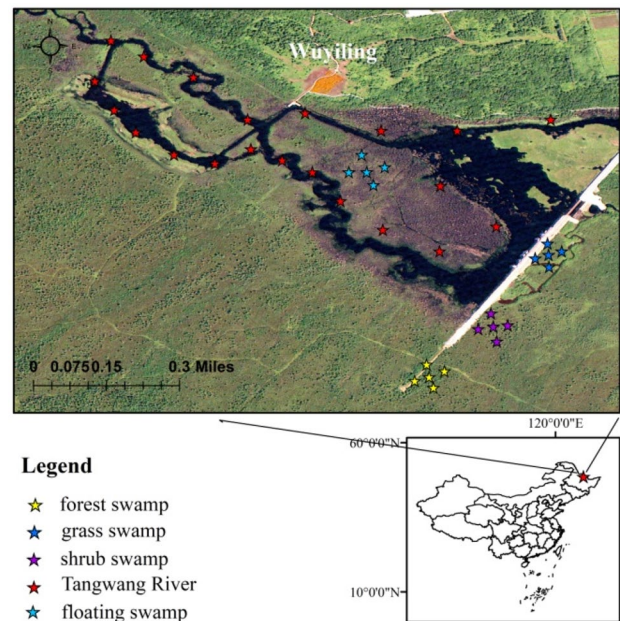


Fig. 1 Aerial photo and layout of the study area showing the location of collection sites; an inset map shows the location of the study site within an outline map of the provinces and other administrative regions of China

and broad-leaved deciduous forest dominated by Korean pine. The Wuyiling area has representative wetlands in the northeastern mountains, including forested, shrub, and grass swamps, in addition to swamps dominated by floating vegetation.

In August 2019, 20 water samples were collected along the Tangwang River in Wuyiling Nature Reserve; in addition, 20 water samples were collected in each of the four types of swamps. The samples were placed in light-proof bottles. A total of 100 samples were collected.

Water sample pretreatment and analysis tests were completed based on China's surface water environmental quality standard GB3838-2002. Among them, TN was measured using alkaline potassium persulfate digestion ultraviolet spectrophotometry (detection limit, 0.001 mg/L), and TP was measured using potassium persulfate digestion ultraviolet spectrophotometry (detection limit, 0.001 mg/L). Nessler's reagent colorimetric method was used to measure AN (detection limit, 0.001 mg/L), and COD was measured using rapid catalytic digestion spectrophotometry (detection limit, 10 mg/L). Chl-a was measured using the frozen extraction method (detection limit, 0.01 $\mu\text{g/L}$), PI with the potassium permanganate method (detection limit, 0.01 mg/L), dissolved oxygen (DO) with the iodometric method (detection limit, 0.01 mg/L), and suspended solids (SS) with the gravimetric method (detection limit, 1 mg/L).

An artificial neural network can be used for nonlinear mapping and has good fault tolerance, self-adaptation,

self-organization, and self-learning abilities, among other positive characteristics. This type of network is suitable for solving high-dimensional and nonlinear system problems. A back-propagation (BP) network is undoubtedly one of the most commonly used neural network models for artificial neural networks and has been widely used in the study of the status of nutrients in lakes and reservoirs (Deng et al. 2007). Since a standard gradient BP algorithm declines quickly in the first few steps, as it approaches an optimal value the gradient trends toward zero, resulting in a slow decline in the error function. Meanwhile, Newton’s law can produce an ideal search direction near the optimal value. The Levenberg–Marquardt (LM) method is a combination of the gradient descent and Newtonian methods. Compared to a traditional BP network and other improved algorithms, an LM–BP network has the advantage of requiring fewer iterations with faster convergence and higher accuracy.

After standardizing the data, random interpolation was used to generate 30 samples between each grading threshold. Next, 20 samples were randomly selected as training samples and 10 as test samples. A total of 120 samples were randomly interpolated in the calculation and evaluation of water quality, including 80 training samples and 40 test samples. A total of 150 samples were randomly interpolated in the calculation of eutrophication evaluation, including 100 training samples and 50 test samples.

According to the existing monitoring data and the specific conditions of the evaluation indicators in GB3838-2002, this method selected the DO, PI, AN, TP, and TN evaluation

index input model and used the expected output values to calibrate the model (Table 1).

The degree of eutrophication and pollution of lakes was mainly determined by the amount of nutrients present in the lake, such as nitrogen and phosphorus. Indicators that can directly or indirectly reflect or affect the nutritional status of water bodies or lakes include Chl-a, TN, TP, and PI. This study selected these same four water quality evaluation factors, which have been widely used to evaluate the eutrophication of wetland water bodies and to classify the nutritional status of water bodies (Wang et al. 2015; Xie et al. 2015). The standards (He 2010) are shown in Table 2, and the model was calibrated with the expected output value.

The indicators used to evaluate model performance in this paper were two statistical indicators: the average and maximum relative error. The smaller the evaluation indicators, the better the performance of the model. Equations (1) and (2) were used to calculate each statistic as follows:

$$e_{MRE} = \frac{1}{n} \sum_{i=1}^n \frac{|\hat{y}_i - y_i|}{y_i} \times 100\% , \tag{1}$$

$$e_{MaxRE} = \max_{1 \leq i \leq n} \frac{|\hat{y}_i - y_i|}{y_i} \times 100\% , \tag{2}$$

where e_{MRE} is the average error, e_{MaxRE} is the maximum relative error, \hat{y}_i is the simulated value of the i th sample, y_i is the measured value of the i th sample, $i = 1, 2, \dots, n$, and n is the number of simulated samples.

Table 1 Water quality evaluation standards and expected output values of the model

Water quality classification	Ranges (mg/L)					Training/test sample	Expected output
	DO	PI	AN	TP	TN		
I	7.5–12	0–2	0.05–0.15	0–0.01	0–0.2	1–30	1
II	6–7.5	2–4	0.15–0.5	0.01–0.025	0.2–0.5	31–60	2
III	5–6	4–6	0.5–1	0.025–0.05	0.5–1	61–90	3
IV	3–5	6–10	1–1.5	0.05–0.1	1–1.5	91–120	4

DO dissolved oxygen, *PI* permanganate index, *AN* ammonia nitrogen, *TP* total phosphorus, *TN* total nitrogen

Table 2 Water quality indicator status, classification standards, and expected output values of the model for water bodies

Nutrition classification	Chl-a (mg/m ³)	TP (mg/m ³)	TN (mg/m ³)	PI (mg/L)	Training/test sample	Expect output
I Poor nutrition	≤ 2	≤ 10	≤ 100	≤ 1	1–30	1
II Medium nutrition	≤ 10	≤ 50	≤ 500	≤ 4	31–60	2
III Mild eutrophication	≤ 26	≤ 100	≤ 1000	≤ 8	61–90	3
IV Moderate eutrophication	≤ 64	≤ 200	≤ 2000	≤ 10	91–120	4
V Severe eutrophication	> 64	> 200	> 2000	> 10	121–150	5

Chl-a chlorophyll a, *TP* total phosphorus, *TN* total nitrogen, *PI* permanganate index

Based on the MATLAB environment, this study created and trained an LM–BP model to evaluate water quality and lake nutritional status. The model has a structure of 5-10-1, and the transfer functions of the hidden and output layers adopted tansig and purelin, respectively. The learning rate (lr) was 0.01, and the expected error was set to 0.0001. The model reached a better evaluation effect when the maximum training cycle was 1000 times.

The LM–BP model had good evaluation accuracy for water quality and eutrophication evaluation of training samples and test samples (Table 3).

The comprehensive nutritional status index provides an evaluation method that can be used to analyze lake or reservoir eutrophication and is recommended by the China Environmental Monitoring Station (Yang et al. 2007). Based on water quality indicators such as Chl-a, TP, TN, PI, and Secchi disk transparency, the degree of eutrophication of a water body can be evaluated using Eq. (3):

$$TLI(\sum) = \sum W_j \cdot TLI(j), \tag{3}$$

where $TLI(\sum)$ represents the comprehensive nutritional status index, W_j represents the relative weight of the nutritional status index of the j th parameter; and $TLI(j)$ represents the nutritional status index of the j th parameter.

Taking Chl-a as the reference parameter, the normalized correlation weight calculation formula of the j th parameter is

$$W_j = \frac{r_{ij}^2}{\sum_{j=1}^m r_{ij}^2}, \tag{4}$$

where r_{ij} represents the correlation coefficient between the j th parameter and the benchmark parameter Chl-a, and m represents the number of evaluation parameters.

The nutritional status index formulas are as follows (Yang et al. 2007):

$$TLI(chl - a) = 10(2.5 + 1.086\ln chl - a), \tag{5}$$

$$TLI(TP) = 10(9.436 + 1.624\ln TP), \tag{6}$$

$$TLI(TN) = 10(5.453 + 1.694\ln TN), \tag{7}$$

$$TLI(SD) = 10(5.118 - 1.94\ln SD), \tag{8}$$

$$TLI(PI) = 10(0.109 + 2.66\ln PI), \tag{9}$$

where the SD unit is m, the Chl-a unit is mg/m^3 , and the other index units are mg/L . A series of continuous numbers from 0 to 100 was used to classify the nutritional status of the water body. The higher the index value, the greater the nutrient concentration. A TLI below 30 represents low nutrient levels, 30–50 represents moderate nutrition, and > 50 represents eutrophication, of which 50–60, 60–70, and > 70 indicate mild, moderate, and severe eutrophication, respectively.

The Kaiser–Meyer–Olkin (KMO) and Bartlett test methods in SPSS were used to conduct principal component analysis on the concentration of water quality indicators and the Shapiro–Wilk test method was used to test the normal distribution of the concentrations of water quality indicators in five swamp wetlands and water bodies. The first principal component contributed 52.4% of the variance in the data. TN and AN had higher positive loads on the first principal component at 0.78 and 0.65, respectively. Other water quality indicators had higher positive loads on the second principal component.

Results and Discussion

The spatial distributions of TP, TN, AN, COD, Chl-a, SS, DO, and PI concentrations in the Wuyiling wetland are shown in Fig. 2. The concentration of TP ranged from 0.003 to 0.262 $mg L^{-1}$ (average, 0.043 $mg L^{-1}$). The highest concentration appeared in the Tangwang River, and the lowest appeared in the forest swamp. The concentrations in the four wetland types and the average concentration of Tangwang River showed a trend of scrub swamp > Tangwang River > grass swamp > floating swamp > forest swamp. The concentration of TN ranged from 0.001 to 0.399 $mg L^{-1}$ (average, 0.117 $mg L^{-1}$). The highest concentration was recorded in the Tangwang River. Among the concentrations in the four wetland types and the average concentrations of Tangwang River, the TN concentration

Table 3 Levenberg–Marquardt Back Propagation (LM–BP) model used to evaluate the accuracy of training and test samples

Evaluation index	Training/test samples	Average relative error (%)	Maximum relative error (%)
Water quality evaluation	Training samples	0.29	2.53
	Test samples	0.42	5.6
Eutrophication evaluation	Training samples	0.33	3.41
	Test samples	0.45	6.03

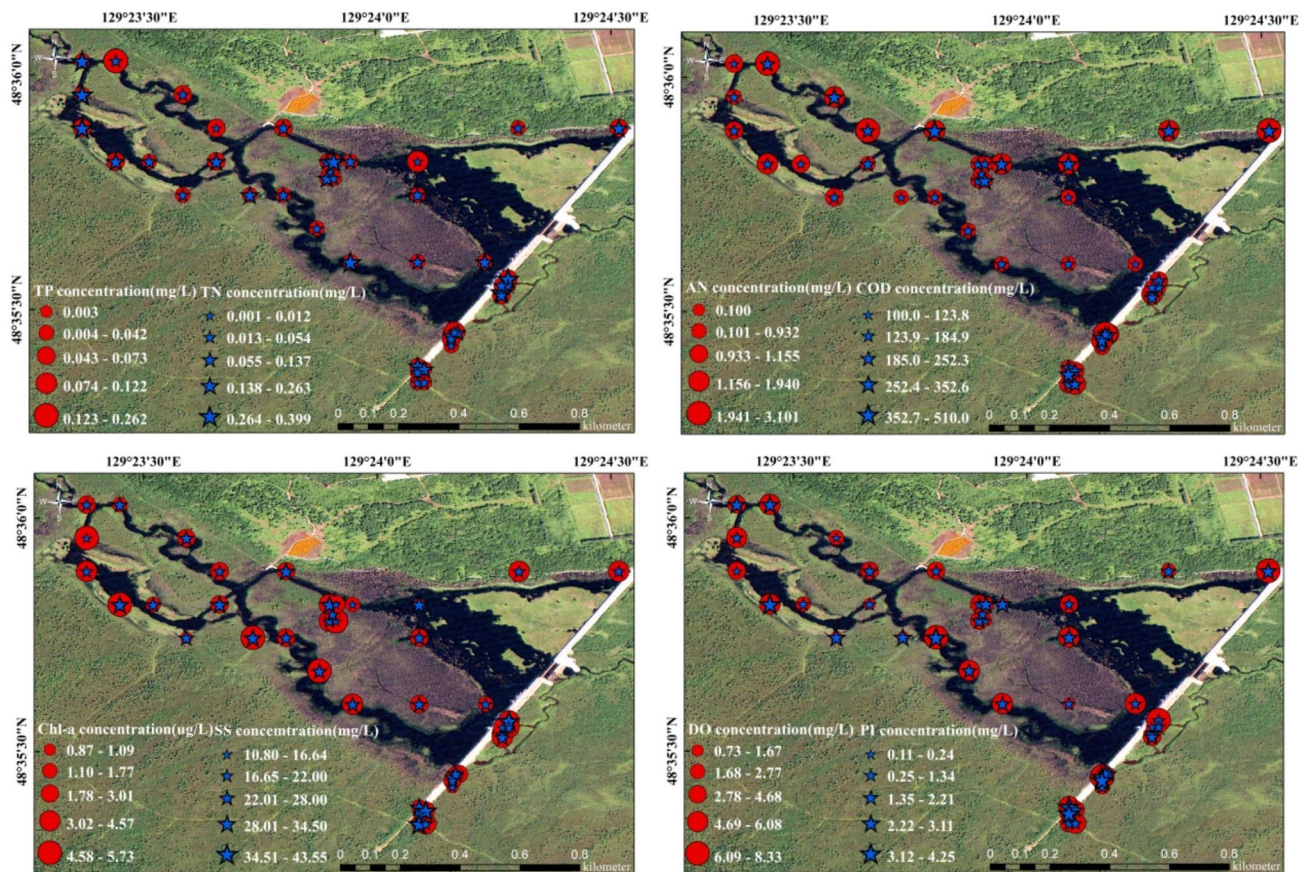


Fig. 2 Spatial distribution maps of water quality indicators in Wuyiling wetlands: concentrations of **a** TP total phosphorus, TN total nitrogen; **b** AN ammonia nitrogen, COD chemical oxygen demand; **c**

Chl-a chlorophyll, SS suspended solids; **d** DO dissolved oxygen, PI permanganate index

was highest in grass swamps, followed by floating swamps, the Tangwang River, forest swamps, and shrub swamps. The concentration of AN ranged from 0.1 to 3.101 mg L⁻¹ (average, 1.124 mg L⁻¹). The highest concentration was present in the Tangwang River, four wetlands showing a trend of scrub swamp > grass swamp > floating swamp > forest swamp. The COD concentration ranged from 100 to 510 mg L⁻¹ (average, 190.75 mg L⁻¹). The highest concentration at the sampling point also appeared on the Tangwang River, but among the wetland types, the highest average concentration occurred in the forest swamps. Chl-a concentrations ranged from 0.87 to 5.73 µg L⁻¹ (average, 2.85 µg L⁻¹). SS concentrations ranged from 10.8 to 43.55 mg L⁻¹ (average, 24.05 mg L⁻¹). The highest average concentrations of Chl-a and SS in wetlands were present in grass and forest swamps, respectively. The average concentrations of DO and PI were 3.75 mg L⁻¹ and 1.87 mg L⁻¹, respectively. The maximum concentrations of DO appeared in grass and forest swamps, and the highest average concentrations of PI appeared in forest and shrub swamps.

The original monitoring data of the seven water quality indicators passed the KMO and Bartlett tests, with a KMO value of 0.651, which was greater than 0.5. The Bartlett test value was 172 (sig. = 0.000; $p < 0.05$), so the null hypothesis of the Bartlett sphericity test was rejected, indicating that the data were suitable for principal component analysis (Shao et al. 2008). The cumulative contribution rate of the first two principal components was 73.5% of the total variance in the data, meaning these two principal components explained nearly 75% of the information in the original data (Fig. 3). Relatively high positive loads were observed for TN and AN on the first principal component. AN and TN in wetland water originate from agriculture and human activities (Asgher et al. 2021).

The eight water quality indicators in different types of wetlands and water bodies were significantly different ($p < 0.05$), while the TP concentration of shrub swamps was significantly higher than that of forest swamps (Fig. 4a). The TN concentration of grass swamps was significantly higher than that of shrub swamps (Fig. 4b). The concentration of AN in shrub swamps was significantly higher than that in

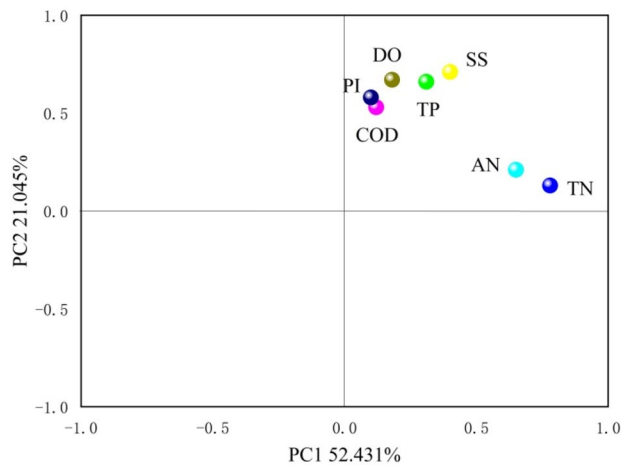


Fig. 3 Principal component (PC) analysis diagram of water quality indicators in Wuyiling wetlands and water bodies; percentages show the amount of variance accounted for in each PC

forest swamps and floating swamps (Fig. 4c). The COD concentrations of forest and shrub swamps were significantly higher than those of floating swamps and the Tangwang River (Fig. 4d). The concentration of Chl-a in grass swamps was significantly higher than that in forest and shrub swamps (Fig. 4e). The concentration of SS in forest marshes was significantly higher than that in floating marshes (Fig. 4f). The DO concentration of forest swamps was significantly higher than that of grass and floating swamps (Fig. 4g). The concentrations of PI in forest and shrub swamps were significantly higher than those in grass and floating swamps (Fig. 4h).

When compared with the Environmental Quality Standards for Surface Water of China (GB3838-2002), the average value of AN was higher than the standard limit for Class III surface water, while the COD and DO concentrations were higher than the standard limits for Class V and Class IV water bodies, respectively. The TP and PI concentrations did not exceed the surface water environment Class I standard. Table 4 shows the results of the above-trained LM–BP water quality evaluation model used to evaluate the water quality of different swamps and the Tangwang River. In 2019, the water quality category of shrub, grass, and forest swamps in Wuyiling Nature Reserve was Class II, and the water quality category of floating swamps and the Tangwang River was Class I, the best water quality classification available.

In this study, the main factors affecting water quality classification (Chl-a, TN, TP, and PI) were used as the main parameter indicators for establishing the evaluation model. The above-mentioned model, a trained LM–BP eutrophication evaluation model, was used to evaluate the degree of eutrophication of different swamp wetlands and the Tangwang River. The nutrient levels of the four marsh swamp

wetlands and the Tangwang River were in the mid-range for various nutrients (Table 5).

A comprehensive nutritional status index method was calculated. Then, based on the evaluation criteria used to analyze eutrophication, the eutrophication levels of the four swamp wetlands in the Wuyiling Nature Reserve and Tangwang River were obtained (Fig. 5). Among them, the average degree of eutrophication for shrub and forest swamps was in the mid-range for various nutrients. The other two swamps and Tangwang River had low levels of nutrients. The degree of eutrophication in forest, shrub, and grass swamps was quite different, which may be caused by the different flooding conditions and the degree of permafrost degradation in the swamp wetlands.

Swamp wetlands provide important protective barriers for wetland ecosystems and have important functions in conserving water, protecting ecosystems, and developing permafrost. According to the restricted classification criteria of nutrients in water proposed by Guildford and Hecky (2000), phosphorus and nitrogen restriction were indicated by the TN/TP ratios of ≥ 22.6 and $\text{TN/TP} \leq 9.0$ (mass ratios), respectively. The four types of swamps and the Tangwang River were nitrogen-restricted, which was different from the typical phosphorus-limited swamp waters of the middle and low latitudes (Wahlstrom et al. 2020). Wuyiling Nature Reserve is surrounded by forests and a lesser amount of farmland. Nitrogen limitation in the swamps could be caused by permafrost melting in summer. In the present study, grass, floating carpet swamps, and the Tangwang River had higher nitrogen and phosphorus ratios, while forests and shrub swamps had lower ratios. In summer, plants grow vigorously and require more nutrients. At the same time, they are also affected by the decomposition of plant litter and other complex factors that influence nutrient loading.

The highest concentrations of several water quality indicators, including TP, TN, AN, and COD, all appeared along the Tangwang River. Compared to the other four types of wetlands, the Tangwang River is more polluted in some areas, which could be caused by the effects of human and agricultural activities along the river (Nicholas et al. 2015). The maximum average concentrations of TP, AN, and PI in the four wetland swamps appeared in the shrub swamp. This could be caused by the proximity of this habitat to the river, uneven drainage patterns, and the fact that nutrients are easily stored in this type of habitat. Due to the continuous increase of human activities, wetlands face serious threats. The impact of human activities on wetlands decreases with increasing elevation (Asgher et al. 2021). The water quality category of shrub, grass, and forest swamps in Wuyiling Nature Reserve was Class II, and the water quality category of floating swamps and the Tangwang River was Class I, the best water quality classification available. The nutrient levels of the four marsh swamp wetlands and the Tangwang

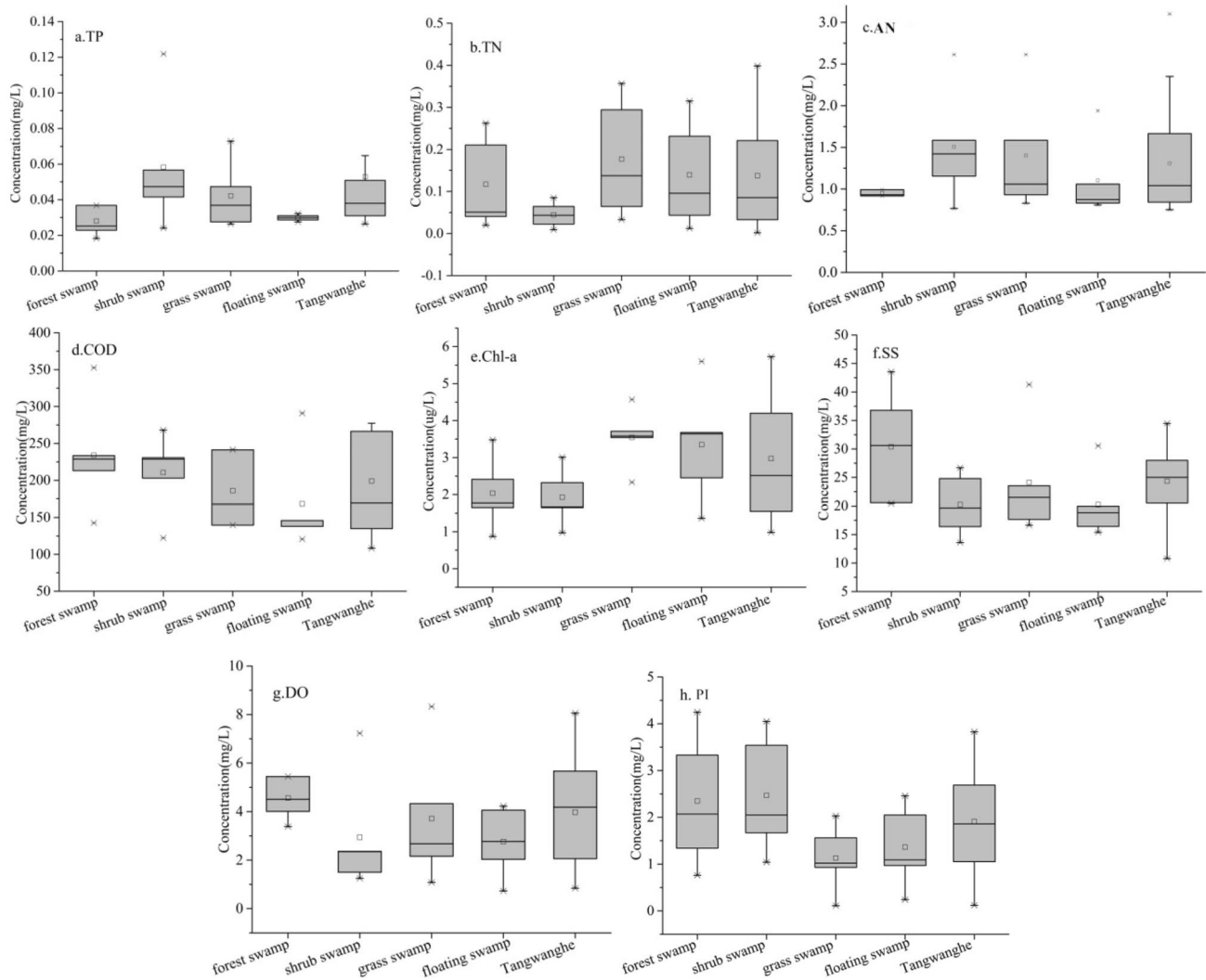


Fig. 4 Analysis on different concentrations of water quality indicators in Wuyiling wetlands and Tangwang River; concentrations of **a** TP total phosphorus; **b** TN total nitrogen; **c** AN ammonia nitrogen;

d COD chemical oxygen demand; **e** Chl-a chlorophyll a; **f** SS suspended solids; **g** DO dissolved oxygen; **h** PI permanganate index

Table 4 Levenberg–Marquardt Back Propagation (LM–BP) model water quality evaluation results of different swamp wetlands and Tangwang River

Types	LM–BP output value	Expected output value	LM–BP evaluation results
Floating swamp	1.0156	1	I
Grass swamp	1.9807	2	II
Scrub swamp	2.1033	2	II
Forest swamp	2.0561	2	II
Tangwang River	1.2543	1	I

Table 5 Levenberg–Marquardt Back Propagation (LM–BP) model eutrophication evaluation results of different marsh wetlands and Tangwang River

Types	LM–BP output value	Expected output value	LM–BP evaluation results
Floating swamp	1.9013	2	Medium nutrition
Grass swamp	2.1301	2	Medium nutrition
Scrub swamp	2.4102	2	Medium nutrition
Forest swamp	1.1864	2	Medium nutrition
Tangwang River	2.0566	2	Medium nutrition

River were in the mid-range for various nutrients. Agriculture, urbanization, and climatic warming have caused the degradation of water resources. The maximum average

concentrations of TN and Chl-a appeared in grass swamps, which could be related to the degradation of permafrost. The maximum average concentrations of COD, DO, and SS

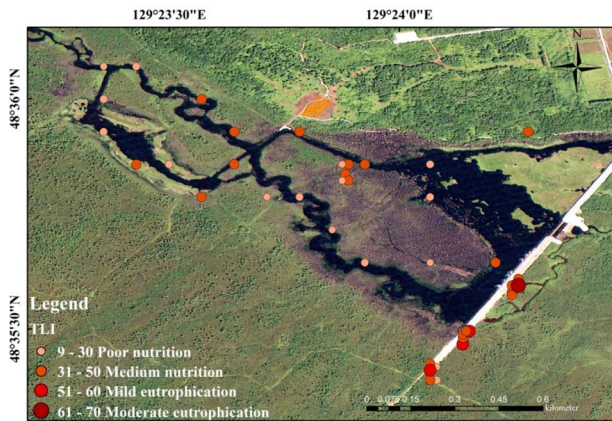


Fig. 5 Results of a comprehensive nutrient status index and evaluation

all appear in forest swamps, indicating that the water here contains large amounts of reducing substances, primarily organic pollutants. The results of the water quality evaluation show that although the maximum concentrations of some water quality indicators appeared along the Tangwang River so that the overall water quality was Class I, the water bodies of the Tangwang River and the four types of swamp wetlands had relatively high concentrations of some nutrients in some sampling points. Discovering whether this is related to the degree of melting of underground permafrost will require further research. The results of the comprehensive nutritional status index showed that the Tangwang River, floating swamps, and grass swamps contained low levels of nutrients, which was consistent with the results of water quality evaluation. The majority of eutrophic water is located in Africa, Oceania, South America, North America, Europe, and Asia (Wang et al. 2018; Murphy et al. 2000), including Lake Victoria in Africa and Lake Erie in North America (Pearl and Huisman 2008). Oceania has the highest proportion of large lakes with oligotrophication (23.1%), Europe has the highest proportion of large lakes with mesotrophication (35.2%), and Africa has the highest proportion of large lakes with eutrophication (88.8%; Zhang et al. 2021). The results of an evaluation of eutrophication based on a BP neural network model were consistent with the evaluation results of a comprehensive nutritional status index.

(1) The four types of swamps and the Tangwang River were nitrogen-restricted. Nitrogen limitation in the swamps could be caused by permafrost melting during the summer. Grass swamps, floating carpet swamps, and the Tangwang River had higher TN/TP ratios, while forest and shrub swamps had lower ratios. Compared to the other four types of wetland, the Tangwang River is more polluted in some areas, which could be due to the effects of human and agricultural activities along

the river. The maximum average concentrations of TP, AN, and PI in the four wetland swamps appeared in the shrub swamps, which could be caused by the proximity of this habitat to the river, uneven drainage patterns, or the fact that nutrients are easily stored in this type of habitat.

(2) The water quality category of shrub, grass, and forest swamps in Wuyiling Nature Reserve was Class II, and the water quality category of floating swamps and the Tangwang River was Class I, the best water quality classification available. The nutrient levels of the four marsh swamp wetlands and the Tangwang River were in the mid-range for most nutrients. The comprehensive nutritional status index revealed that Tangwang River, floating swamps, and grass swamps had low levels of nutrients, which was consistent with the results of water quality evaluation.

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