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Recognizing the Relationship between Spatial Patterns in Water Quality and Land-Use/Cover Types: A Case Study of the Jinghe Oasis in Xinjiang, China

Fei Zhang [1,2,3,*], Juan Wang [4] and Xiaoping Wang [1,2,3]

1 College of Resources and Environment Science, Xinjiang University, Urumqi 830046, China; wxp4911@163.com
2 Key Laboratory of Oasis Ecology, Xinjiang University, Urumqi 830046, China
3 Key Laboratory of Xinjiang Wisdom City and Environment Modeling, Urumqi 830046, China
4 College of Geography and Remote Sensing Science, Beijing Normal University, Beijing 100875, China; wangjuan6231@163.com
* Correspondence: zhangfei3s@xju.edu.cn; Tel.: +86-135-7992-5126 or +86-991-8581281

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Abstract: To understand the relationship between spatial water quality patterns and changes in land-use/cover types in the Jinghe Oasis, 47 water sampling sites measured in May and October 2015 were divided into six cluster layers using the self-organizing map method, which is based on non-hierarchical *k*-means classification. The water quality indices included the chemical oxygen demand (COD), biological oxygen demand (BOD), suspended solids (SS), total phosphorus (TP), total nitrogen (TN), ammonia nitrogen (NH_3-N), chromaticity (SD), and turbidity (NUT). Data was also collected on the changes in the farmland, forest–grassland, water body, salinized land, and other land types during the wet and dry seasons. Then, we combined these data with the classification results of the GF-1 remote sensing satellite data obtained in May and October 2015 and analyzed the influences of land-use/cover type on water quality for different layers and seasons. The results indicate that Clusters 1 to 3 included monitoring samples from the wet season (May 2015), whereas Clusters 4 to 6 included monitoring samples from the dry season (October 2015). In general, the COD, SS, NUT, TN, and NH_3-N values were high around the Ganjia Lake *Haloxylon* natural conservation area in the southern Ebinur Lake region, east of Ebinur Lake, and around the Kuitun River during the wet season. The SD values around these areas were high. Moreover, high BOD and TP values were mainly concentrated around the Ganjia Lake *Haloxylon* natural conservation area, as well as the Kuitun River, during the dry season. In the discussion on the relationship between the different water quality parameters and land-use/cover type changes, we determined that farmland, forest–grassland, and salinized land significantly influenced the water quality parameters in the Jinghe Oasis. In addition, the influences of various land-use/cover types on the water quality parameters in the research zone during the different seasons exhibited the following descending order of magnitude: farmland → forest–grassland → salinized land → water body → others. Moreover, their influences were lower during the wet season than the dry season. In conclusion, developing research on the relationship between the spatial framework of the water quality in the Jinghe Oasis and land-use/cover type changes is significant for the time sequence distribution of water quality in arid regions from both theoretical and practical perspectives.

Keywords: self-organizing map method; water quality spatial distribution; land use/cover; correlation analysis; GIS

1. Introduction

Water quality is of great importance to the study of water resources in arid regions. Accurate information on the spatial distribution of surface water quality is imperative for assessing environmental monitoring, land-surface water management, and watershed changes [1,2]. Land use/cover changes in drainage basins significantly influence the water quality of rivers, lakes, river mouths, and coastal areas [3–5]. Surface water resources, through runoff or infiltration, will always carry a large amount of pollutants; therefore, the spatial allocation of land use/cover changes in drainage basins frequently influences or even endangers water quality frequently through non-point source pollution [6]. However, the regional differences and complexity of land-use/cover types result in various relations between land use/cover and water quality in different regions [7]. Therefore, it is very important to explore the relationship between land-use/cover types and water quality for the development and management of the basin [8–10]. At present, numerous scholars have extensively applied statistical methods to determine the mutual relations between land use/cover changes and water quality in various research zones [11–13]. These methods included correlation analysis [14,15], multiple regression [16], and redundancy analysis [17,18].

A self-organizing map (SOM) is a type of artificial neural network algorithm, which is a self-organizing and self-learning network visual method, and it can express multi-dimensional spatial data in low-dimensional points through non-linear mapping [19]. A SOM is an all-purpose classification tool that can connect samples with variables [20,21]. In recent years, SOMs have become increasingly popular in environmental research on account of their capacity to address non-linear relations. Kalteh [22] and Céréghino [11] discussed the application of the SOM method in environmental science, particularly in water resource classification. Chon [23] evaluated the application of SOM technology in the field of ecology. The high-dimensional, non-linear, and uncertain features of water quality monitoring data are resulted in a certain complexity during the analysis and evaluation of surface water quality data. Therefore, data mining and the modern mode recognition method have been introduced to analyze and explain water quality monitoring data, which can to a certain extent offset the deficiency of the traditional method [24].

In the Xinjiang Uygur Autonomous Region, most of the rivers are characterized by a low water yield, short flow, small water environmental capacity, poor self-cleaning capability, and low tolerance to pollution. Hence, an artificial change in the land use and exploration of resources in lake regions leads to an evident correlation between land-use/cover types and water quality. In addition, the scientific utilization and protection of the water resources of Ebinur Lake and the scientific application of chemical fertilizers and improvement of their application rates are important actions, which should be addressed to achieve sustainable development in the agricultural irrigation zones of the Jinghe Oasis and rivers of Xinjiang. The Jinghe Oasis, which comprises an oasis and a desert, is a typical mountainous zone in an arid region and an important part of the northern slope of the Tianshan Mountains. Under the influence of drought climate and human activities, the agricultural and domestic use of water sources under the influence of drought climate and human activities has result in the discharge of water and the pollution of the regional ecological environment, which has become an urgent problem related to the sustainable socioeconomic development in Xinjiang. Therefore, a typical section of the Jinghe Oasis in the plain area of the arid region was selected as the research object of this study. The SOM method was applied to recognize the spatial distribution of water quality in the Jinghe Oasis. Based on the result, this study offers a tentative exploration of the relationships between water quality and land use/cover changes in different clusters, and provides new insights on controlling, managing, and protecting the ecological environment of the Jinghe Oasis.

The main objectives of this study were to: (1) analyze the spatial framework of water quality using the self-organizing map (SOM) method, based on non-hierarchical k-means classification; (2) explore the relationship between the water quality parameters and land-use/cover types in different clusters; and (3) analyze the relationship between water quality parameters and land-use/cover types in different stages.

2. Materials and Methods

2.1. Study Area

The Jinghe Oasis is in the center of Eurasia in the northwest of the Xinjiang Uygur Autonomous Region, at 44°02′~45°10′ N and 81°46′~83°51′ E (Figure 1). The Jinghe Oasis is composed of wetland and desert oasis vegetation and wildlife, and it is a national desert ecological reserve. The study area has a unique wetland ecological environment, and it has been listed as the "wetland nature reserve" in the Xinjiang Uygur Autonomous Region. The region has 385 kinds of desert plants, which is approximately 64% of the vast amount of desert plants in China. The Jinghe Oasis was once fed by 12 river branches, which belong to three major river systems: the Bortala River, the Jing River, and the Kuytun River, which were mainly rivers connected with Ebinur Lake. Due to natural environmental changes and human activities (i.e., modern oasis agricultural development), many rivers gradually lost their hydraulic connections with Ebinur Lake, and the Bortala River and the Jing River currently supply water to the lake. The climate in the Jinghe Oasis is a typical continental arid climate, with an annual average temperature of 7.36 °C, an average precipitation of 100~200 mm, and an average mean evaporation of 1500~2000 mm [25]. In recent years, under the dual influence of natural and human factors, the water resources of the Jinghe Oasis have degraded seriously, causing an extreme decrease in the natural oasis and water area, desertification of the land, salinization of the farmland, serious grassland degradation, and water quality salinization [26]. At the same time, under the effect of the strong winds in Alashankou, the region has become a main source of dust; this affects the ecological environment of northern Xinjiang.

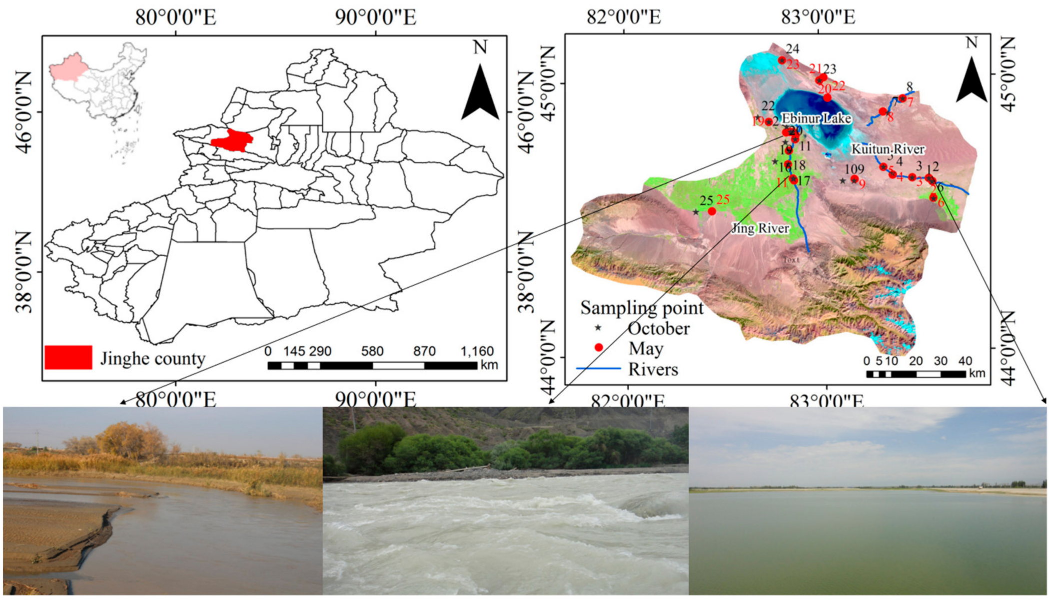

Figure 1. Location and sampling points of the study area.

2.2. Data Acquisition and Processing

(1) As the data sources, this study applied GF-1 remote sensing images obtained in May and October 2015 (see http://www.cresda.com/CN/). These images were not influenced by clouds, fog, or snow cover, and their quality was good. It conducted radiation and orthographic corrections for the remote sensing image data combined with 1:50,000 scale digital elevation model (DEM) data. We established five land-use/cover types by using the Environment for Visualizing Images software (ENVI Version 5.0), namely: farmland, forest–grassland, water body, salinized land, and others, based on the actual conditions of the research zone. Finally, we generated a vector data map of the land-use/cover types for two stages of the research zones.

(2) In total, this study collected 47 water sampling points, with 23 points collected in May 2015 and 24 points collected in October 2015. The samples were taken in a wide range of hydrological environments in May and October, which included the Kuitun and Jing River (P1, P2, P3, P4, P5, P6, P11, P13 (just in October), P14, P15, P16, P17, P18, P19, P20), the ditches of these rivers (P9, P10), and Ebinur Lake (P7, P8, P21, P22, P23, P24, P25). The surrounding land-use/cover types of the inflowing rivers contained farmland, forest–grassland and others, while that of the ditches contained salinized land and farmland, as well as others. Thus, these sampling points were collected mainly out of concern for the effects of different land-use/cover types on the surrounding surface water. Besides, the river water flows into Ebinur Lake and affects its water quality. It is not certain whether the inflowing rivers and surrounding land-use/cover types affect the water quality of the lake. Thus, it is necessary to take water from the inflowing rivers and its ditches as well as from Ebinur Lake itself. The information about the land-use/cover types within the one-km buffer zone of the water quality sampling points in the research area was obtained. The sampling points from the inflowing rivers were used to test the monitoring indices, including: chemical oxygen demand (COD), five-day biological oxygen demand (BOD_5), suspended solids (SS), total phosphorus (TP), total nitrogen (TN), ammonia nitrogen (NH_3-N), chromaticity (SD), and turbidity (NUT). The pillar industries in the Jinghe Oasis include salt production and *Artemia* breeding. Non-heavy industry is present; thus, point source pollution from industrial wastewater was not considered in the research zone. All of the polyethylene bottles were used to store the samples. The bottles were cleaned, dried, and sealed with deionized water before sampling. The samples were taken to the laboratory for measurements and analyses after collection. We applied dichromate titration, dilution, inoculation, gravimetry, ammonium molybdate spectrophotometry, alkaline potassium persulfate decomposition UV spectrophotometry, and Nessler's reagent spectrophotometry to measure the COD, BOD_5, SS, TP, TN, and NH_3-N, respectively. The analyses of all of the samples were entrusted to and completed by Urumqi Jincheng Measurement Technology Co., Ltd. (Urumqi, China). Research samples were collected from agricultural land in Jinghe County and Tuotuo Village, which surround Ebinur Lake; a national ecological zone in Ebinur Lake called Bird Isle; and the Ganjia Lake *Haloxylon* natural conservation area.

2.3. Recognition of Water Quality Spatial Characteristics Based on the SOM Method with Non-Hierarchical K-Means Classification

At present, classifications, based on the SOM neural network, are mainly unsupervised and applied to fault analyses, text clustering, and water quality evaluations. The method, which does not require a consistent data distribution, is simple, and can address detailed information without the influence of minor local problems. The results distributed the features of the input mode and topological structures [27]. A typical SOM network generally consists of input and output clusters. All of the nerve cells in the input cluster and the weight vectors in the output cluster are connected and classified as typed data using the SOM via a learning process. Accordingly, the *k*-means algorithm is applied to keep each cluster compact and separate the clusters from each other. The Davies–Bouldin clustering index was used to determine the optimal number of clusters for the dataset [16,28]. The lower the Davies–Bouldin index value is, the better the clusters are differentiated. The K-means cluster analysis was combined with the Davies–Bouldin index (DBI) to select the clustering number [21].

The SOM method, based on non-hierarchical *k*-means classification, was applied to the spatial framework of the water quality in the research zone by implementing the following steps: (1) input the water sample data for clustering from May and October 2015 to the SOM network. It applied the topological values for calculating the network size to select the quantity of nerve cells and determine the output results based on the minimum values of the quantization error (QE) and topological error (TE). The QE was used to determine the capacity of the established neural network in distinguishing the original input data, whereas the TE was used to measure the neural network quality, i.e., to evaluate whether the network was applicable for training [19]. After determining the network size, we conducted network training and obtained a set of weight values. (2) The weight value obtained from the SOM clustering results was considered the initial cluster center, and the *k*-means algorithm was initialized to execute this algorithm and, combined with the DBI index, selected the clustering number. This clustering combination algorithm maintains the self-organizing features of the SOM network, inherits the high efficiency of the *k*-means algorithm, and offsets the poor clustering effects that result from the excessive convergence time of the SOM network and the inappropriate selection of the initial clustering center for the *k*-means algorithm. The SOM requires a SOM toolbox and some basic functions in the Matrix Laboratory (MATLAB) [29]. This study used MATLAB 2013a as the calculation platform.

2.4. Spatial Analysis of the Influences of Land Use/Cover Change on Water Quality

As an artificial system disturbance, land-use/cover type is the second major boundary condition that influences hydrologic processes directly or indirectly, and exerts a considerable effect on the drainage water environment. First, we obtained information on the land-use/cover types within the one-km buffer zone of the water quality sampling points in the research area, using the spatial analysis function of ArcGIS 9.3. Based on the results, we discussed and analyzed the correlation between water quality and land-use/cover type changes at different levels and periods. For different levels, we established the correlation between water quality and land-use/cover types in each layer, and discussed the influence of land-use/cover type changes on water quality. In different periods, it analyzed the land-use/cover type information and eight types of water quality indices during the dry and wet seasons. The land-use/cover type information and eight water quality indices were imported into Canoco 4.5 [30] to test the Detrented Correspondence Analysis (DCA) gradient axis. The results showed that the DCA gradient shaft length was less than three. Based on the research results of Wang et al. [31], when the DCA gradient shaft length is less than three, the redundancy analysis (RDA) method can explore the relationship; therefore, the redundancy analysis (RDA) method was applied to determine the influence trend of land-use/cover changes on the water quality within the buffer area of Ebinur Lake. This method indicates that the contribution rate of a single land-use/cover variable on water quality, and can directly demonstrate the correlation between land-use/cover type and water quality parameters via a two-dimensional (2D) ordination graph. The methodology is explained in the following section, and a conceptual flow chart describing the methodology is shown in Figure 2.

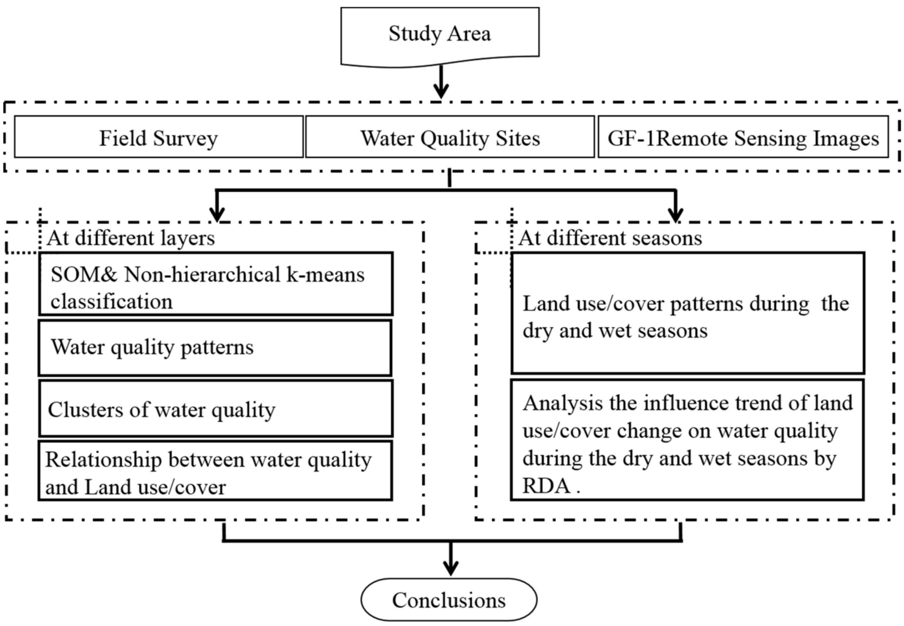

Figure 2. Conceptual model of the methodology.

3. Results and Analysis

3.1. Spatial Framework of Water Quality in the Jinghe Oasis

Regarding the network structure selection, neural networks with a more complicated structure generally have a better capability to address complicated non-linear problems, but require a longer training time [20]. Increasing the number of water quality indices can provide more abundant information; however, the correlations among the indices will also increase. The topological values were selected to determine the grid size in this study, and the *k*-means clustering method was adopted to obtain the results. After the standard processing of the water quality data, the best network training effect was obtained from 35 (7 × 5) nerve cells, and the QE and TE values were 1.033 and 0.001, respectively.

When the average variance values are less than 5% for different clusters, the DBI is low; thus, the corresponding clustering number can be regarded as the best clustering result. Therefore, this study input the trained weights of the neuron nodes through the K-means cluster analysis, which combined with the DBI to select the clustering number. The results are shown in Figure 3a. Six clusters were formed because this number yielded the minimum DBI value (Figure 3a).

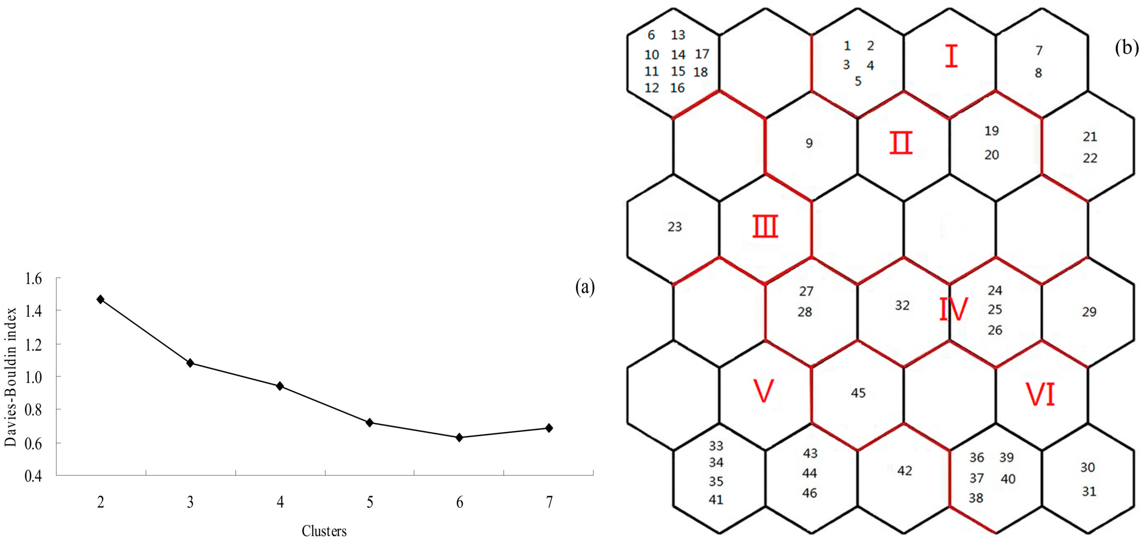

Figure 3. (**a**) Davies–Bouldin index (DBI) plot; (**b**) Results of the self-organizing map (SOM) clustering of the cells on the map plane (distribution of the sampling sites on the SOM according to the eight water quality parameters and clustering of the trained SOM).

Figure 3b presents the results of the SOM clustering of the cells on the map plane, which exhibited similarities among the different monitoring stations. Cluster 1 included the sampling points around the Ganjia Lake *Haloxylon* natural conservation area in the southern Ebinur Lake region, and points east of Ebinur Lake and around the Kuitun River during the wet season. Cluster 2 included the monitoring stations in the Jing River and around the agricultural ditch in the western Ebinur Lake region. Cluster 3 comprised samples of water from melted ice in the southwestern corner of the research zone, which were grouped into only one type. Cluster 4 included the sampling points within the Ganjia Lake *Haloxylon* natural conservation area during the dry season. Cluster 5 included the sampling points in the Jing River, the agricultural ditch, and around Ebinur Lake. Cluster 6 contained points located around the Kuitun River and Ebinur Lake Bird Isle, which had more pools. In general, individual points may interfere with the explanation of the results; the classification results can identify the time sequence features in the research zone. Clusters 1 to 3 entirely included samples from the wet season (May 2015), whereas Clusters 4 to 6 contained the monitoring samples from the dry season (October 2015). To further observe the information on the water quality parameters of the Jinghe Oasis, based on the responses of different nerve cells, the water quality information from the various cluster groups was visualized. The results are shown in Figure 4.

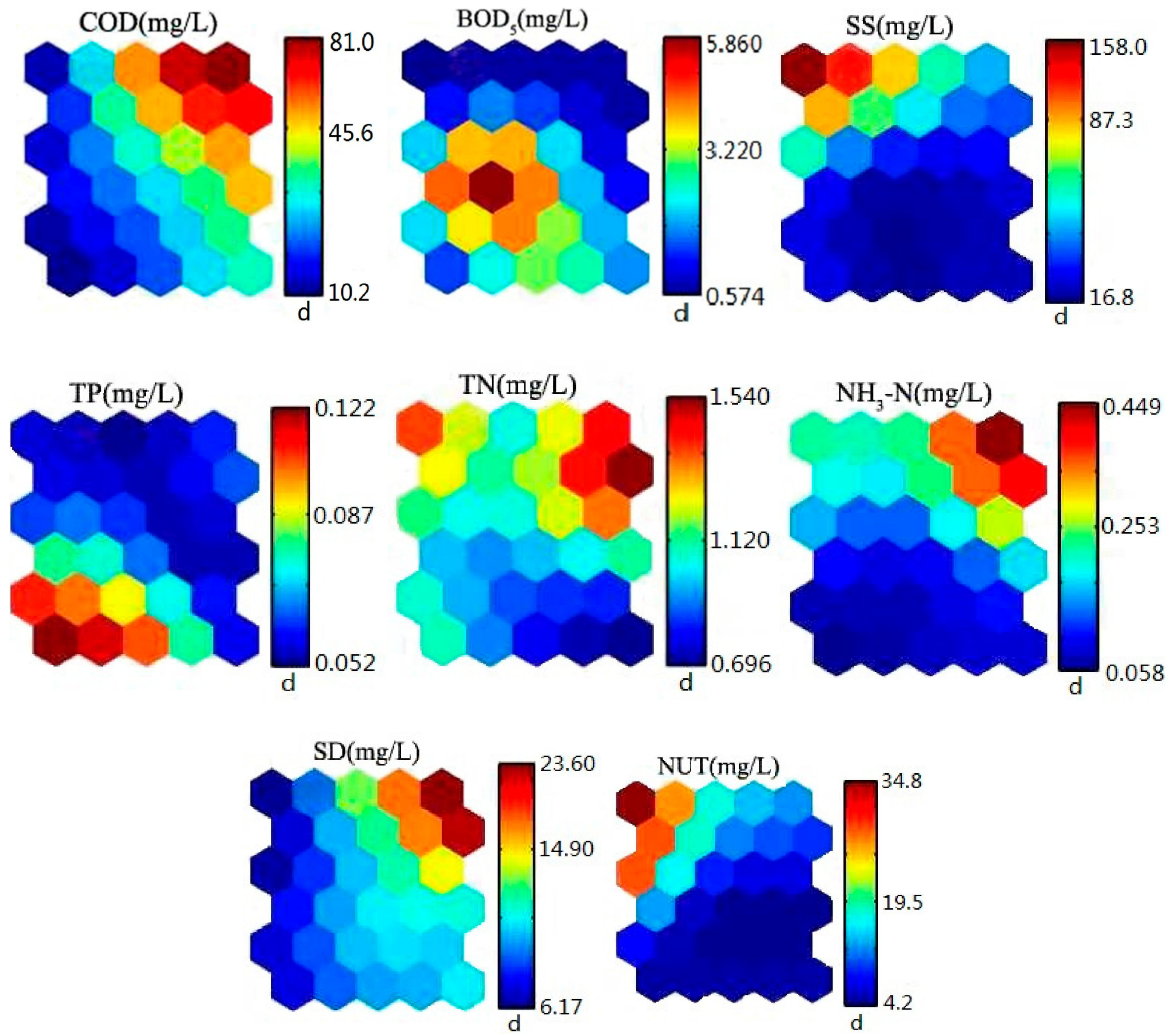

Figure 4. The patterning results for the water quality parameters on the SOM plane.

Figure 4 describes the distribution of different water quality parameters on the SOM. High COD, TN, NH_3-N, and SD values were recorded in the right corner of the SOM network, thereby indicating a declining trend in the southern Ebinur Lake region and the surrounding Kuitun River. The right corner of the SOM locates this trend in Clusters 4 to 6 in May 2015, and the left corner locates this trend in Cluster 1 to 3 in October 2015 (Figure 3b). The values during the wet season (May 2015) were higher than those during the dry season. High values of SS and NUT were observed in the left corner of the SOM network, which falls within the scope of the agricultural ditch and the Jing River areas during the dry season; thus, these are increasing trends. This region is mainly distributed around the agricultural land area and is significantly influenced by human activities. High TP values were observed within the scope of the lower left corner, which mainly focuses on the agricultural ditch and Jing River during the dry season. Crops were mature during the dry season (October 2015), and the farmland area was increased, which thereby increased the TP value. In contrast, the distribution of the BOD_5 was different, indicating a declining trend from the center to the surrounding area. High BOD_5 values were mainly observed downstream of the Ganjia Lake *Haloxylon* natural conservation zone, which is surrounded by a salt field, thereby exerting a certain influence on the surrounding water quality. The regional change in the water quality of the Jinghe Oasis was reflected clearly and directly through the SOM. During the wet season (May) in the Jinghe Oasis, melted water from mountain ice and snow promote the flow in the Jing River, thereby resulting in a significant increase in surface runoff, leading to an improved water quality in the rainy season compared with the dry season (Figure 4). To observe the distribution of the water quality parameters directly, we collected different values of the water quality parameters at various layers (Figure 5).

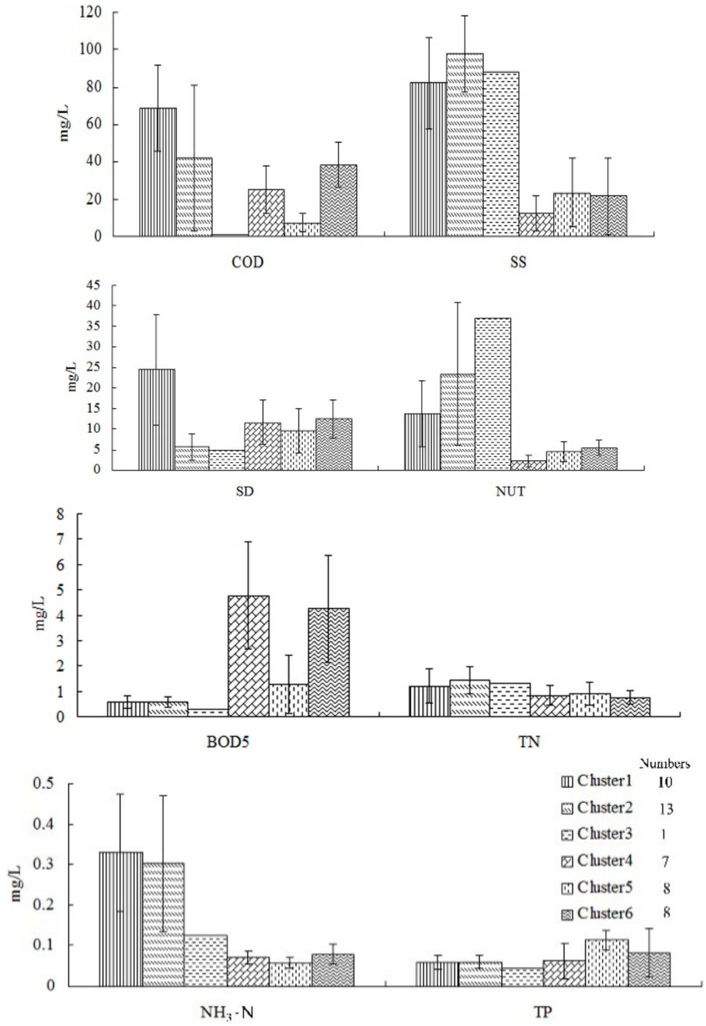

Figure 5. Average values for the water quality parameters.

Figure 5 shows that the distribution of water quality parameters varied in different clustering layers. Among the six clusters, water quality was generally relatively better in Cluster 3; however, Cluster 3 only had one sampling point, which comprised ice and snow water. Therefore, its water quality was not considered. In addition, the COD, SS, NUT, TN, and NH_3-N contents were high in Clusters 1 and 2, which indicated a relatively lower water quality, compared with the water downstream of the Ganjia Lake *Haloxylon* natural conservation zone, the surrounding Ebinur Lake region, and the agricultural land. The SD values were high in Clusters 1, 4, and 6. Meanwhile, high BOD_5 values were mainly concentrated in Clusters 4 and 6, which were around the Ganjia Lake *Haloxylon* natural conservation zone and Ebinur Lake Bird Isle. To a certain extent, many pools in these clusters are influenced by the water area. The concentration difference in the TP of each layer was minimal and considerably influenced by human activities, particularly changes in the agricultural land area. Based on these results and the Chinese Environmental Quality Standards for Surface Water

(GB3838-2002), we evaluated the grades of the water quality parameters, including the COD, BOD_5, TN, NH_3-N, and TP, at different layers (Table 1).

Table 1. The classes of water quality parameters in each cluster. COD: chemical oxygen demand; BOD: biological oxygen demand; TN: total nitrogen; NH_3-N: ammonia nitrogen; TP: total phosphorus.

Water Quality Parameters	Cluster 1	Cluster 2	Cluster 4	Cluster 5	Cluster 6
COD	Exceed V	Exceed V	I	IV	V
BOD_5	I	I	IV	I	IV
TN	IV	IV	III	III	III
NH_3-N	II	II	I	I	I
TP	II	II	II	III	II

As shown in Table 1, according to the Chinese Environmental Quality Standards for Surface Water (GB 3838-2002), Clusters 1 to 6 did not satisfy the potable water quality level. Clusters 1 and 2 had an identical water quality classification level, and their COD and TN contents were higher than the standard values. The COD content exceeded level V. Meanwhile, the BOD_5 and COD contents were excessive in Clusters 4 and 5, respectively. In Cluster 6, both the COD and BOD_5 contents were excessive, but the COD content was higher.

3.2. Analysis of Land-Use/Cover Type and Its Relation to Water Quality at Different Layers

In this study, historical data, high-resolution Google Earth images, and field survey data were selected. It is verified that more than 100 pixels of each land-cover type were used for the training data, and the confusion matrix was used to verify the classification results. For the classification results obtained in May and October 2015 (Figure 6), precision increased to 89.9750% and 86.2848%, respectively, and the kappa coefficients based on the confusion matrix were 0.8681 and 0.8184 (Table 2), which indicates an accurate classification result that satisfies the research requirements. Accordingly, ArcGIS was used to establish a one-km buffer zone around the water sampling points. The composition of land use/cover at different layers was analyzed according to the hierarchical results of the water quality parameters, and the results are presented in Figure 7.

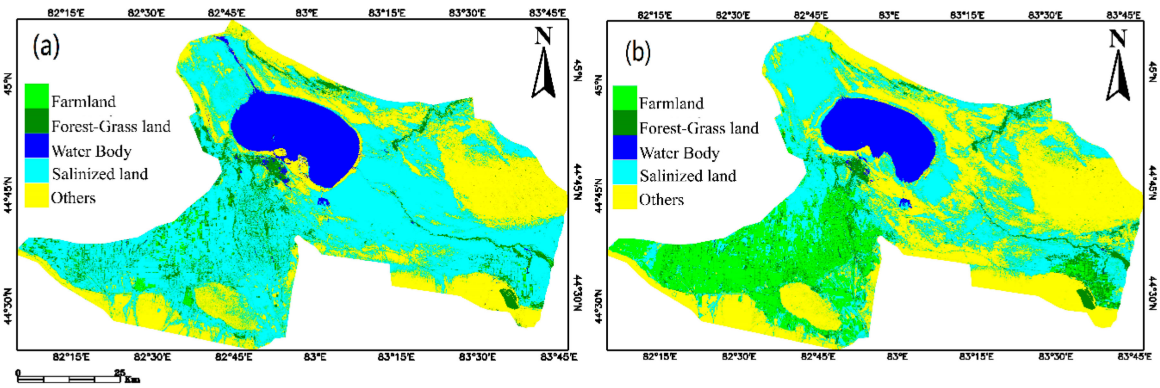

Figure 6. The change in land use/cover of the Ebinur Lake area during the rainy (May) and dry (October) seasons in 2015 (**a**) May; (**b**) October.

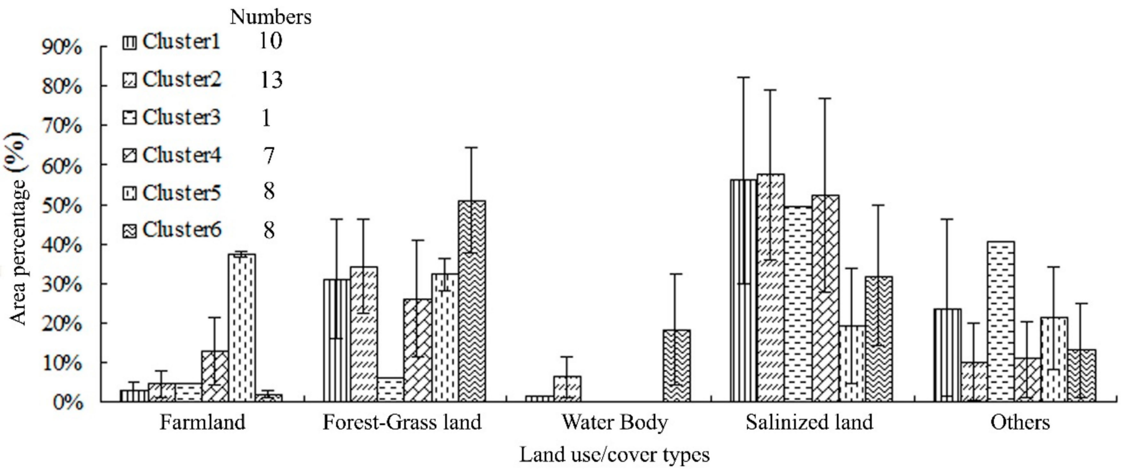

Figure 7. The area of land use/cover for each cluster.

Table 2. The confusion matrix calculation with a maximum likelihood supervised classification.

Time	LULC	Water Body	Saline Land	Farmland	Forest Grassland	Other Land	Total	User's Accuracy (%)
May	Water body	144	0	0	0	0	144	100
	Saline land	0	77	0	0	16	93	82.79
	Farmland	0	36	101	0	0	137	73.72
	Forest–grassland	0	36	0	101	0	137	73.72
	Other land types	1	0	0	0	87	88	98.96
	Total	145	149	101	101	103	Overall = 89.9750%	
	Producer's accuracy (%)	99.31	51.67	100	100	84.46	Kappa = 0.8681	
October	Water body	144	0	0	0	0	144	100
	Saline land	0	57	0	0	26	83	86.67
	Farmland	0	16	101	0	0	117	86.32
	Forest–grassland	4	16	0	101	0	117	86.32
	Other land types	0	0	0	0	77	77	100
	Total	148	89	101	101	103	Overall = 86.2848%	
	Producer's accuracy (%)	97.29	64	100	100	74.75	Kappa = 0.8184	

Figure 7 shows that the land-use/cover modes are at different layers. In general, the salinization phenomenon was serious across the entire research zone. Among the six clusters, Cluster 1 mainly included the sampling points around the Ganjia Lake *Haloxylon* natural conservation area, the eastern Ebinur Lake region, and the Kuitun River. The major land type in this cluster was forest–grassland. The monitoring site in Cluster 2 was in the irrigation ditch of the Jinghe Oasis and in the Jing River. In May, crops do not grow abundantly in this zone, and the major land type in this cluster was forest–grassland. Cluster 4 mainly included the Ganjia Lake *Haloxylon* natural conservation area and the sampling points in Tuotuo Village during the dry season, which included farmland and forest–grassland. The sampling points in Cluster 5 were in the agricultural ditch, the Jing River, and the surrounding Ebinur Lake. The land types mainly included forest–grassland and farmland, which was larger than the other land type. Cluster 6 was mainly located in the Kuitun River and the surrounding Ebinur Lake Bird Isle. A considerable number of plants, such as reed, grow in some of its pools. The percentages of the forest–grassland and salinized land within the 1-km buffer were large, based on the actual conditions in the research zone and the distribution of the sampling points. Based on these results, the correlation between land-use/cover type and water quality parameters from Clusters 1 to 6 was analyzed. The results are presented in Table 3.

Table 3. The correlation coefficients between the land use/cover and water quality parameters in each cluster.

Title	Parameters	Farmland	Forest–Grassland	Water Body	Salinized Land	Others
Cluster 1	COD	−0.161	0.240	**0.986** *	−0.110	−0.361
	BOD_5	0.074	0.492	−0.439	−0.613	0.552
	SS	−0.271	**−0.710** **	0.801	0.619	−0.384
	TP	−0.195	0.453	0.371	0.444	0.623
	TN	0.464	0.524	**−0.721** *	−0.224	0.121
	NH_3-N	−0.491	0.039	0.071	−0.066	0.291
	SD	−0.296	0.448	0.415	−0.426	0.396
	NUT	−0.261	**−0.724** **	0.550	**0.756** **	−0.612
Cluster 2	COD	**−0.581** *	**0.613** *	0.916	**−0.693** **	0.442
	BOD_5	−0.004	0.455	0.055	−0.545	0.242
	SS	0.493	−0.512	**−0.983** **	0.386	0.047
	TP	−0.222	0.531	0.850	−0.129	0.382
	TN	0.351	0.415	−0.867	−0.356	−0.311
	NH_3-N	−0.467	0.121	0.122	−0.269	0.284
	SD	−0.226	−0.073	−0.051	−0.217	0.473
	NUT	**0.639** *	−0.446	**−0.990** **	0.513	−0.236
Cluster 4	COD	**−0.652** *	0.484	/	0.375	−0.048
	BOD_5	−0.482	−0.402	/	0.505	0.688
	SS	−0.155	0.658	/	−0.179	−0.167
	TP	**0.872** **	−0.398	/	**−0.791** *	0.868 *
	TN	0.336	0.468	/	−0.571	−0.124
	NH_3-N	−0.202	−0.540	/	0.398	0.352
	SD	−0.543	**0.825** *	/	0.214	−0.549
	NUT	0.578	0.469	/	**−0.819** *	−0.129
Cluster 5	COD	0.094	−0.372	/	0.325	−0.400
	BOD_5	**−0.881** **	0.503	/	0.774 *	−0.044
	SS	0.621	−0.533	/	−0.284	−0.380
	TP	0.587	−0.702	/	−0.565	0.136
	TN	0.735	−0.588	/	−0.184	−0.604
	NH_3-N	−0.675	0.108	/	0.487	0.308
	SD	−0.632	0.330	/	0.208	0.576
	NUT	0.311	0.076	/	−0.459	0.154
Cluster 6	COD	0.489	0.401	**0.980** *	−0.454	0.289
	BOD_5	−0.256	**−0.884** **	−0.660	0.367	0.327
	SS	−0.481	0.194	0.341	−0.150	−0.062
	TP	−0.545	−0.656	0.269	−0.060	0.206
	TN	−0.158	−0.364	−0.022	0.516	0.313
	NH_3-N	−0.553	−0.366	0.517	−0.090	0.603
	SD	0.811	−0.037	−0.857	0.249	−0.282
	NUT	0.450	0.165	0.764	−0.497	0.636

* $p < 0.05$ (two-tailed) ** $p < 0.01$ (two-tailed).

In Cluster 1, which included the area around the Ganjia Lake *Haloxylon* natural conservation area and Kuitun River in May, the forest–grassland exhibited a negative correlation with the SS and NUT under the significance level of 0.01, with coefficients reaching up to −0.710 and −0.724, respectively. At a significance level of 0.05, the water body type exhibited an obvious positive correlation with the COD and a negative correlation with the TN, with coefficients of 0.986 and −0.721, respectively. At a confidence level of 0.01, the salinized land demonstrated a positive correlation with the NUT, with a coefficient of 0.756. In Cluster 2, which included the Jing River and around the agricultural ditch in the western Ebinur Lake region in May, the farmland presented a negative correlation with the COD and a positive correlation with the NUT at a confidence level of 0.05, and the coefficients were −0.581 and 0.639, respectively. Under the same conditions, the forest–grassland exhibited a positive correlation with the COD, and the coefficient was 0.613. At the confidence level of 0.01, the water body type exhibited an evident negative correlation with the SS and NUT, and the correlation coefficients were −0.983 and −0.990, respectively. In Cluster 4, which included the Ganjia Lake *Haloxylon* natural conservation area in October, several water quality parameters were mainly influenced by the farmland, forest–grassland, and salinized land types. At a confidence level of 0.05, the farmland exhibited a negative correlation with the COD, with a coefficient of −0.652. At a confidence level of 0.01, the farmland demonstrated an evident positive correlation with TP, and the coefficient was 0.872. At a confidence level of 0.05, salinized land showed a clear negative correlation with TP and NUT, and the coefficients were −0.791 and −0.819, respectively. In this layer, the other land types exhibited a positive correlation with the TP, with a coefficient of 0.868. The sampling points in this layer were mainly located within the one-km buffer zone of the water quality sampling points in Tuotuo Village, where the influences of human activities are considerable; therefore, in Cluster 4, the correlation percentage of the other land types with TP was high. In Cluster 5, which included the Jing River and the agricultural ditch and around Ebinur Lake, farmland demonstrated an evident negative correlation with the BOD_5 at a 0.01 confidence level, with a correlation coefficient reaching up to −0.881. At a confidence level of 0.05, the salinized land showed a positive correlation with the BOD_5, with a correlation coefficient of 0.774. In Cluster 6, which included the area around the Kuitun River and Ebinur Lake Bird Isle in October, the forest–grassland showed a clear negative correlation at a confidence level of 0.01, and the correlation coefficient reached −0.884. At a confidence level of 0.05, the water area exhibited a positive correlation, with a correlation coefficient of 0.980.

A comprehensive analysis of the results indicated that the farmland, forest–grassland, and salinized land types have a considerable influence on the water quality parameters in the Jinghe Oasis. In Clusters 1, 2, and 6, the size of the water area, to a certain extent, also influenced the changes in the water quality parameters to a certain extent. Given the unbalanced distribution of the sampling points at different layers, the effect of the land-use/cover composition on the water quality in the research zone varied, so it can only indicate influences to a certain extent. Therefore, considering the actual conditions in Ebinur Lake, different land-use/cover types and water quality influences must be understood, and the correlation between the land-use/cover types and water quality in the Jinghe Oasis at different periods is further discussed.

3.3. Analysis of Land-Use/Cover Changes in the Jinghe Oasis and their Correlation with Water Quality at Different Seasons

The constituents of the land-use/cover types at different seasons exerted diverse influences on the water quality. Therefore, the analysis of the influences of land-use/cover type changes on water quality was conducted. The results are presented in Figure 8.

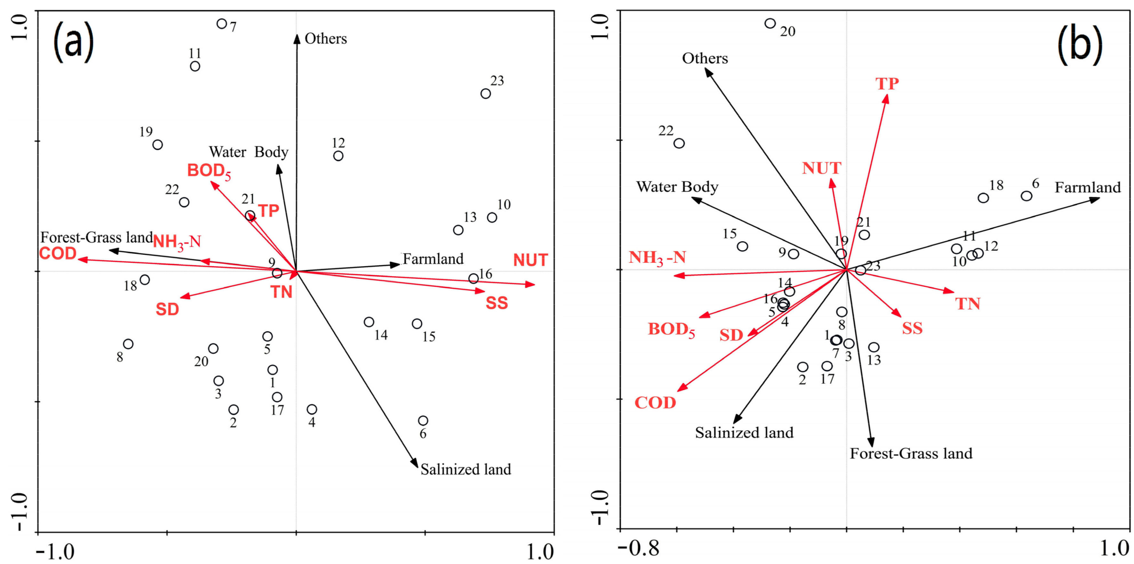

Figure 8. Redundancy analyses (RDA) of comprehensive land use/cover and water quality (**a**) wet season; (**b**) dry season.

As shown in Figure 8, the farmland exhibited a negative correlation with the COD at a confidence level of 0.01 during the wet season and a correlation coefficient of −0.543. In contrast, it showed a positive correlation with the NUT, with a correlation coefficient of 0.555. At a confidence level of 0.05, the farmland demonstrated a negative correlation with the NH_3-N; the correlation coefficient was −0.461. At a confidence level of 0.05, the forest–grassland showed a positive correlation with the BOD_5 and TP, with correlation coefficients of 0.470 and 0.518, respectively. They exhibited a negative correlation with the SS and NUT, with correlation coefficients of −0.529 and −0.498, respectively. At a confidence level of 0.05, the salinized land demonstrated a positive correlation with the BOD_5 and TP, with correlation coefficients of −0.503 and 0.518, respectively. In contrast, it presented a negative correlation with the SS and NUT, with correlation coefficients of 0.449 and 0.449, respectively. During the dry season, the influence of the farmland on various water quality parameters evidently increased because of crop growth. At a confidence level of 0.01, the farmland presented a clear negative correlation with the COD and an evident positive correlation with the TP, with correlation coefficients of −0.620 and 0.616, respectively. At a confidence level of 0.05, the farmland showed a positive correlation with the TN and a negative correlation with the BOD_5, NH_3-N, and SD, with correlation coefficients of 0.543, −0.495, −0.522, and −0.526 for TN, BOD_5, NH_3-N, and SD, respectively. At a confidence level of 0.01, the salinized land demonstrated a negative correlation with the NUT and TP; the correlation coefficients were −0.543 and −0.603, respectively. In contrast, it presented a positive correlation with the BOD_5 at a confidence level of 0.05 and a correlation coefficient of 0.522. Similarly, during the wet and dry seasons, the correlation between the water body and other land types with the water quality parameters was small. Based on these results, the influences of the various land-use/cover types in the research zone on the water quality parameters exhibited the following order, in descending order of influence: farmland → forest–grassland → salinized land → water body → others. Moreover, the influence was lower during the wet season than during the dry season.

4. Discussion

In the present study, SOM clustering analyses were used to visualize the water quality of the Jinghe Oasis during different seasons; the unbalanced distribution of precipitation resulted in an apparent variation in the surface runoff and further imbalanced the spatial distribution of the water quality in the research zone [32–34]. During the dry season, the aquatic plants in rivers and lakes grow as the temperature rises, which can absorb and purify part of the water quality parameters to a certain degree. Therefore, significant and seasonal changes in the surface runoff at the research zone are important factors, which result in noticeable differences in the spatial distribution of water quality characteristics during the wet and dry seasons. However, the information about the flow rate of the water was not available, as the flowing rate of the inflowing river was not consistent with its ditches; it was controlled by the government. The additional analysis about the flowing rate would be further analyzed in our future research.

Another major factor that causes differences in the spatial distribution of water quality is the change in land use/cover, especially in farmland. During the dry season, farmland areas have a greater influence on more water quality variables than they do during the rainy season, because of their intensive fertilization and agricultural runoff from soil erosion [35–37]. Multiple factors threaten the ecological safety of the Jinghe Oasis system; especially in recent years, the lakeside desertification zone has rapidly expanded on account of the decrease in the Ebinur Lake area and the degradation of lakeside vegetation under the influence of the strong winds in Alashankou. In the current overall situation, the human activities influencing land-use/cover changes are directly related to the development of the vulnerable ecological area that surrounds Ebinur Lake.

Recent statistics indicate that the annual growth rate of the population in the Jinghe Oasis is approximately 2.49%, which is slightly higher than previous growth rates [38]. Under the stress of a large population, the amount of inappropriate activities that negatively impact land use/cover in the Jinghe Oasis will increase. For the last 30 years, cotton has been the major crop in the Jinghe Oasis.

The results of the current study indicate that the sampling points surrounding the farmland in the research zone have lower water quality values than the other studied regions. The primary livelihoods of the urban residents around the Ebinur Lake area are agricultural and animal husbandry industries. Pollutants that result in high TP and NH_3-N contents in water include the excessive application of chemical fertilizers on farmlands, the production of livestock manure in rural villages, randomly stocked garbage, and domestic wastewater. The improper application of chemical fertilizers and pesticides to a vast area leads to high water nitrogen and phosphorus contents, resulting in the spread of algae in river sections. Consequently, the amount of dissolved oxygen in the river may decrease, the water quality may deteriorate, and eutrophication may occur.

Furthermore, this scenario poses a serious salinization problem. Certain measures have been implemented for the ecological protection of Ebinur Lake, such as returning farmland to forest, cultivating ecological forests, and promoting efficient irrigation and water-saving technologies. However, these measures promote the gradual expansion of the lake area, and result in different degrees of negative consequences. The most apparent result has been the rise of the underground water level, which has aggravated land salinization in the lowland areas and resulted in vast expanses of uncultivated former agricultural lands. Statistics indicate that soil salinization in the Ebinur Lake area mainly occurs in the Bortala River, the Jing River, the villages and towns surrounding Ebinur Lake, areas downstream of the Daheyanzi River, and areas north of Bole City [39]. Severe soil salinization has seriously affected the farming of crops; therefore, some farmers have increased the amount of chemical fertilizers that they apply to increase yield, which also increases the pollution of the water and soil. Others have even abandoned their land, thereby, causing land-use/cover change.

Although SOM has been successfully used to classify the different metals in many research studies [40–43], the spatial assessments of water quality were first attempted to use SOM in the Jinghe Oasis in Xinjiang. Previous studies [44] found that the clustering results between conventional clustering analysis and SOM were generally similar. However, SOM can offer a variety of advantages; it showed the spatio-temporal changes of water quality in just one figure and explained it clearly. Therefore, SOM was chosen as the main tool to assess the water quality of the Jinghe Oasis.

5. Conclusions

The spatial distribution characteristics of water quality in the Jinghe Oasis and their correlation with land-use/cover types were analyzed, and the following conclusions were drawn.

(1) Based on non-hierarchical *k*-means classification, 47 water quality sampling points were divided into six clusters using the SOM method, and the time sequence characteristics of the research zone were better recognized in the classification results. Clusters 1 to 3 comprised samples from the wet season (May 2015), whereas Clusters 4 to 6 comprised monitoring samples from the dry season (October 2015). In general, the COD, SS, NUT, TN, and NH_3-N contents were high. The SD value was high in Clusters 1, 4, and 6. In addition, high BOD and TP values were mainly concentrated in Clusters 4 and 6. Based on these results, the water quality at different clusters of the research zone was further evaluated. The results show that Clusters 1 to 6 do not satisfy potable water quality standards.

(2) The correlations between the land-use/cover types and water quality parameters for Clusters 1 to 6 were analyzed, according to the hierarchical results of the water quality parameters. The comprehensive analysis indicates that the farmland, forest–grassland, and salinized land exerted significant influences on the water quality parameters of the Jinghe Oasis. In Clusters 1, 2, and 6, the size of the water area, to a certain extent, also influenced changes in the water quality parameters.

(3) During the wet and dry seasons, the influences that various land-use/cover types in the research zone had exhibited the following descending order of influence: farmland → forest–grassland → salinized land → water body → others, on the water quality parameters. Moreover, the influences were lower during the wet season than during the dry season.

In general, the land-use/cover type, area percentage, and water quality in the Jinghe Oasis demonstrated apparent correlations. The results of this study can tentatively explain the relationship between water quality and land-use/cover types in different clusters by the SOM method. This work provides new insight for further studies on the correlation between land use/cover and water quality in the Jinghe Oasis, as well as a scientific reference for formulating regulations and control policies for the spatial development and water environmental protection of the Jinghe Oasis.

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