ASSESSMENT OF WATER QUALITY OF EDO CASTLE OUTER MOAT USING PRINCIPAL COMPONENT ANALYSIS

Cheng Chen[1], Daiki Kakinuma[1], Tadashi Yamada[2]

[1]Graduate school of Science and Engineering, Chuo University
(1-13-27 Kasuga, Bunkyo-ku, Tokyo 112-8551 Japan)
[2] Faculty of Science and Engineering, Chuo University
(1-13-27 Kasuga, Bunkyo-ku, Tokyo 112-8551 Japan)
E-mail: a15.gyxe@g.chuo-u.ac.jp

Edo Castle Outer Moat is an important area providing precious water environment in central Tokyo. However, due to the limited water exchange and combined sewer overflow, the hydraulic retention time becomes very long. As a result, the water quality is becoming considerably serious.

Principal component analysis is an effective statistical instrument able to identify the variables explaining most variation within a sample and simplify the structure to provide a basis for the following work. Because of these advantages, it is applied to assess the water quality of Outer Moat. The results show that the order of importance of water quality objectives for changing in water quality in Outer Moat is Chl-a, SS, TP > TN, NO_3-N, NO_2-N > pH, DTP > COD, NH_4-N. And it is inferred that SS and TP greatly influence the amount of algae, which can be represented by Chl-a; pH has a positive effect on dissolved state of phosphorus; there is a positive correlation between NH_4-N and organic matters.

Therefore, principal component analysis is a good method of the assessment of water quality when involving many factors.

Key Words: *Outer Moat, Principal component analysis, SPSS*

1. INTRODUCTION

Edo Castle Outer Moat (shown as Outer Moat in the following), was an artificial channel excavated to prevent enemy from invasion about 400 years ago, and it was defined as a historical site in 1956. Thus, the Outer Moat is important spatially and historically.

However, the water quality of the Outer Moat becomes increasingly worse recently, exceeding the Environmental Quality Standards for Surface Water proposed by Ministry of the Environment because of combined sewage system within the area, and when rainfall is beyond the capacity of sewage treatment plants, combined sewer overflow is directly released into the Outer Moat, and pollutants are accumulated at the bottom without outflow in that the Outer Moat is enclosed [1,2]. Among them, chronic loading of nutrients, such as nitrogen and phosphorus, causes severe eutrophication.

In order to have a better understanding of the reason of changing in water quality, this study is focused on identifying the key water quality objectives using principal component analysis by SPSS software.

2. DATA COLLECTION AND ANALYSIS

2.1 Study area

Fig. 1 shows the catchment area of sewage and observation point in the Outer Moat The Outer Moat is divided into three parts, that is, Ushigome Moat, New Mitsuke Moat and Ichigaya Moat respectively, and flows into downstream river. The distance and elevation difference between A and C is about 1.3km and 12m, respectively. According to field observations and literatures, there are 18 outlets along the Outer Moat, among which 10 outlets are from combined sewage system.

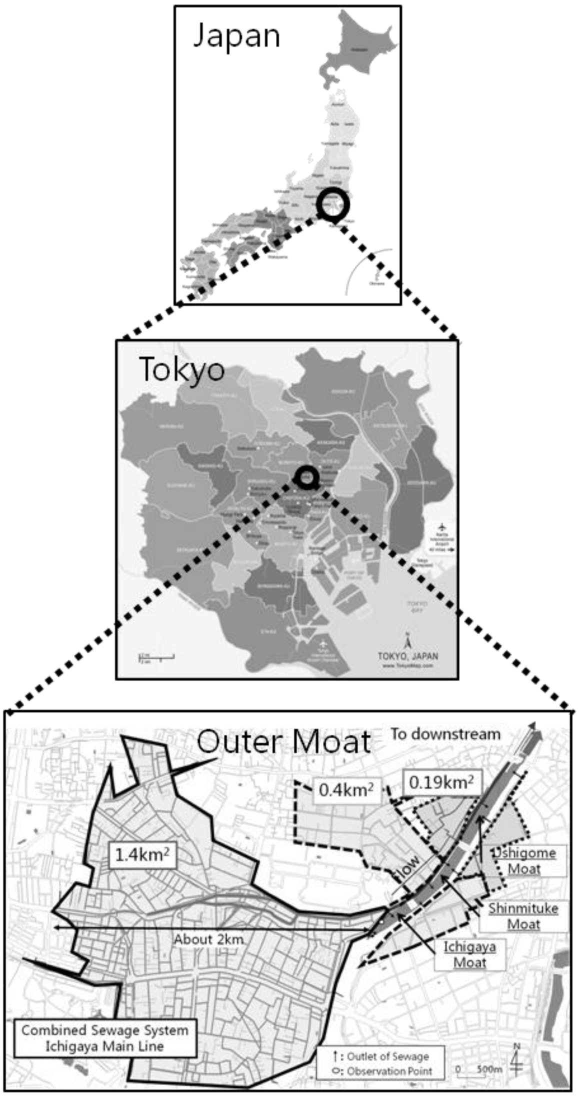

Fig. 1. Sewer pipeline network in Outer Moat

The field observations were carried out from September 2014 to May 2016. In this paper, Ichigaya Moat is selected as the study area because the eutrophication problem of Ichigaya Moat is the most significant shown as Fig. 2.

Table 1. Features of Edo Castle Outer Moat

Name	Ichigaya Moat	Shinmitsuke Moat	Ushigome Moat
Length (m)	324	470	612
Surface area (m^2)	16,450	28,800	32,580
Catchment area of sewage (km^2)	1.40	0.40	0.19

2.2 Water sampling and analysis method

Water samplings were carried out at 10:00 from September 2014 to May 2016. The samples were obtained at the surface water within Ichigaya Moat, kept cool and taken back to laboratory to be analyzed. Among them, pH was measured in the field. Chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), dissolved total-P (DTP), suspended solids (SS), nitrate nitrogen (NO_3-N), nitrite nitrogen (NO_2-N) and ammonia nitrogen (NH_4-N) were measured by absorption photometer (DR3900, TOA DKK). Chlorophyll-a (Chl-a) were measured by UNESCO method.

Fig. 2. Eutrophication problem of Ichigaya Moat (Photo was taken in May 12nd, 2016)

2.3 Analysis of observation results

As shown in Table 2, the number of cases is 32, however, there are different degrees of deletion within each water quality objectives.

Table 2. Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
pH	31	96.9%	1	3.1%	32	100.0%
COD	27	84.4%	5	15.6%	32	100.0%
TN	28	87.5%	4	12.5%	32	100.0%
TP	28	87.5%	4	12.5%	32	100.0%
DTP	28	87.5%	4	12.5%	32	100.0%
SS	22	68.8%	10	31.3%	32	100.0%
NO_3-N	17	53.1%	15	46.9%	32	100.0%
NO_2-N	16	50.0%	16	50.0%	32	100.0%
NH_4-N	16	50.0%	16	50.0%	32	100.0%
Chl-a	30	93.8%	2	6.3%	32	100.0%

The Pearson correlation matrix was prepared within the 10 water quality objectives and shown in Table 3. It was observed that the correlation coefficient between TP and Chl-a is the largest (66.7%), indicating that TP is the most important limiting factor for the amount of algae, represented by Chl-a. In addition, the correlation coefficient between COD and NH_4-N is also very large (61.4%), indicating that there is a large and positive correlation between NH_4-N and organic matters, which consume oxygen so as to result in increased COD.

Table 3. Correlation Matrix[a]

	pH	COD	TN	TP	DTP	SS	NO_3-N	NO_2-N	NH_4-N	Chl-a
pH	1.000									
COD	.039	1.000								
TN	-.139	.120	1.000							
TP	-.422	.207	.121	1.000						
DTP	-.434	.131	-.194	.592	1.000					
SS	-.268	.266	-.233	.535	.124	1.000				
NO_3-N	-.310	.237	.574	.430	.021	-.052	1.000			
NO_2-N	-.492	-.309	.449	-.183	-.009	-.550	.387	1.000		
NH_4-N	-.034	.614	.378	-.274	.127	-.322	.046	.215	1.000	
Chl-a	-.244	.092	.082	.667	-.044	.537	.434	-.072	-.524	1.000

a. Determinant = 5.777E-5

3 PRINCIPAL COMPONENT ANALYSES (PCA)

PCA is a statistical method aiming for reducing the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set [3]. In SPSS software, the process of PCA is carried out as follows [4]:

(1) Data Standardization;

(2) Calculating the correlation coefficient matrix;

(3) Calculating eigenvalues and eigenvectors of correlation coefficient matrix R;

Table 4. Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
F_1	2.910	29.105	29.105	2.910	29.105	29.105	2.666	26.659	26.659
F_2	2.441	24.409	53.513	2.441	24.409	53.513	2.280	22.804	49.463
F_3	1.737	17.370	70.884	1.737	17.370	70.884	1.822	18.217	67.680
F_4	1.426	14.256	85.140	1.426	14.256	85.140	1.746	17.460	85.140
F_5	.679	6.785	91.925						
…	…	…	…						
F_{10}	.021	.211	100.000						

Extraction Method: Principal Component Analysis.

(4) Determine the number of new principal components:

Select the top m of all the principal components whose eigenvalues $\lambda_j \geq 1$, and it is valid if their cumulative contribution rate is more than 85%. If not, add principal components as less as possible to make cumulative % exceed 85%.

(5) Obtain Rotated Component Matrix by "Varimax with Kaiser Normalization" (a kind of rotation method, among which "Varimax" is the abbreviation of "variance max").

4 RESULTS AND DISCUSSIONS

4.1 Determination of principal components for assessment of water quality of Outer Moat

According to the above rule, the top four principal components are selected (shown in Table 4) and the rest can be ignored. It is observed that four principal components explain 85.140 % of total variation.

Among them F_1 accounts for 26.659 %, F_2 explains 22.804 %, F_3 accounts for 18.217 % and F_4 explains 17.460 % of total variation as calculated by loadings for a cumulative percentage of variance by SPSS. The component matrixes extracted from the data by SPSS for the calculation of Fs are given in table 5. The load values in each column show the correlation coefficient between each variable and its corresponding principal component.

Table 5. Component Matrix[a]

	Component			
	F_1	F_2	F_3	F_4
pH	-.532	-.443	.142	.513
COD	.227	.148	.876	.283
TN	.047	.781	-.009	.399
TP	.930	.048	.078	-.094
DTP	.429	.076	.313	-.760
SS	.710	-.463	.186	.099
NO_3-N	.465	.677	-.093	.344
NO_2-N	-.161	.798	-.437	-.237
NH_4-N	-.361	.541	.729	-.074
Chl-a	.806	-.057	-.281	.383

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

And then, Rotated Component Matrix can be obtained by Varimax with Kaiser Normalization and it converges in 7 iterations (See Table 6).

Table 6. Rotated Component Matrix[a]

	Component			
	F_1*	F_2*	F_3*	F_4*
pH	-.137	-.332	-.782	.145
COD	.206	.069	.003	.935
TN	-.081	.845	-.093	.204
TP	.755	.157	.527	.099
DTP	.062	-.209	.887	.179
SS	.800	-.288	.131	.148
NO_3-N	.302	.829	.107	.110
NO_2-N	-.474	.691	.304	-.341
NH_4-N	-.558	.213	.127	.766
Chl-a	.870	.302	.003	-.174

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 7 iterations.

Assume that each variable in Table 6 is shown as W_{ij} , where i and j is number of rows and columns, respectively. Then,

$$\begin{cases} \sum_{i=1}^{4} W_i^2 \approx 1 \\ \sum_{j}^{10} W_j{}^2 \approx \lambda_j \end{cases} \tag{4-1}$$

The reason why it is not equal to 1 is that this calculation contains only four principal components, and it will reach 1 if all the components are calculated.

In the three-dimensioned component plot in rotated space shown as Fig. 3, three axes represent F_1*, F_2* and F_3*, respectively.

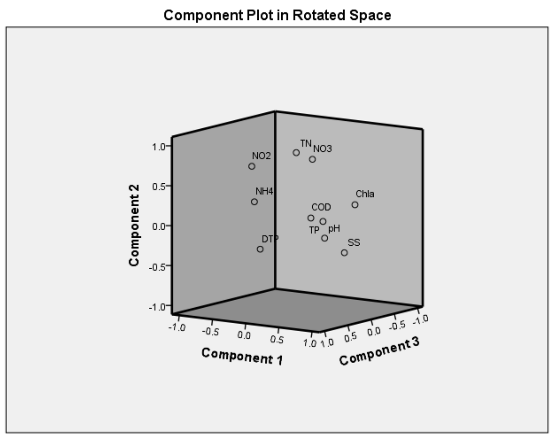

Fig. 3. Three-dimensioned Component Plot in Rotated Space

Fig. 4 is obtained by spreading Fig. 3 to two-dimensioned plots. It shows that the component F_1* is mainly decided by Chl-a, SS and TP; the component F_2* is mainly decided by TN, NO_3-N and NO_2-N; and the component F_3* is mainly decided by pH and DTP. Likewise, the component F_4* is mainly decided by COD and NH_4-N. Therefore, F_1* represents algae factor, F_2* represents nitrogen factor, F_3* represents phosphorus factor, and F_4* represents organic matter factor.

Based on above, it can be concluded that the order of importance of water quality objectives for changing in water quality in Outer Moat is Chl-a, SS, TP > TN, NO_3-N, NO_2-N > pH, DTP > COD, NH_4-N.

And it can be inferred that: SS and TP greatly influence the amount of algae, which can be represented by Chl-a; nitrogen is the second important factor effecting water quality. pH has a positive effect on dissolution of phosphorus; there is a positive correlation between NH_4-N and organic matters. However, this factor is less important relatively.

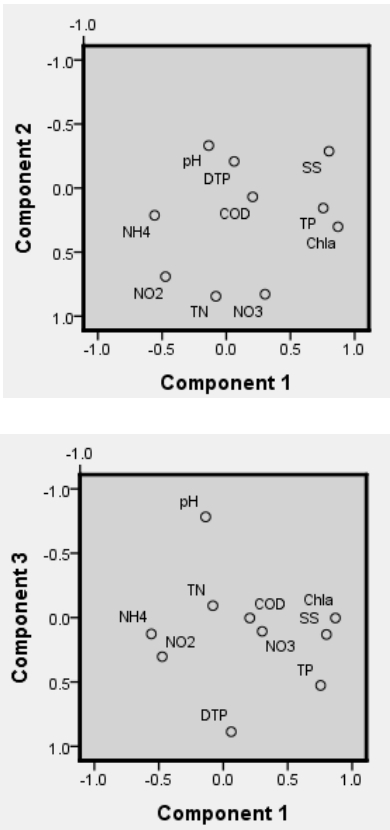

Fig. 4. Two-dimensioned Component Plot in Rotated Space

5 CONCLUSIONS

Principal component analysis can distinguish variables according to their similarity, and the results can be shown as one, two, or three dimensioned plane plot, which is particularly visualized.

In this study, a large number of observation data are classified into algae factor, nitrogen factor, phosphorus factor and organic matter factor, which it is benefit for work in the future.

The order of importance of water quality objectives for changing in water quality in Outer Moat is Chl-a, SS, TP > TN, NO_3-N, NO_2-N > pH, DTP > COD, NH_4-N.

And it can be inferred that:

(1) SS and TP greatly influence the amount of algae, which can be represented by Chl-a;

(2) Nitrogen is the second important factor effecting water quality.

(3) pH has a positive effect on dissolution of phosphorus;

(4) There is a positive correlation between NH_4-N and organic matters. However, this factor is less important relatively.

Therefore, principal component analysis is a good method of the assessment of water quality when involving many factors.

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