Heliyon

Received:
6 November 2015
Revised:
29 December 2015
Accepted:
28 January 2016

Heliyon (2016) e00071

Impacts of a flash flood on drinking water quality: case study of areas most affected by the 2012 Beijing flood

Rubao Sun [1], Daizhi An [1], Wei Lu [1], Yun Shi, Lili Wang, Can Zhang, Ping Zhang, Hongjuan Qi, Qiang Wang [*]

Center of Hygiene Assessment and Research, Institute of Disease Control and Prevention, Academy of Military Medical Sciences, 20 Dongda Street, Beijing 100071, China

[*] Corresponding author.

E-mail address: wang76qiang@163.com (Q. Wang).

[1] The first three authors contributed equally to this work.

Abstract

In this study, we present a method for identifying sources of water pollution and their relative contributions in pollution disasters. The method uses a combination of principal component analysis and factor analysis. We carried out a case study in three rural villages close to Beijing after torrential rain on July 21, 2012. Nine water samples were analyzed for eight parameters, namely turbidity, total hardness, total dissolved solids, sulfates, chlorides, nitrates, total bacterial count, and total coliform groups. All of the samples showed different degrees of pollution, and most were unsuitable for drinking water as concentrations of various parameters exceeded recommended thresholds. Principal component analysis and factor analysis showed that two factors, the degree of mineralization and agricultural runoff, and flood entrainment, explained 82.50% of the total variance. The case study demonstrates that this method is useful for evaluating and interpreting large, complex water-quality data sets.

Keywords: Risk assessment processes, Pollution, Mathematics, Health sciences, Applied sciences

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

1. Introduction

On July 21, 2012, torrential rain hit the city of Beijing, China. The average rainfall over the whole city for the same period was 170 mm, the highest recorded rainfall since 1951. The rainfall event was caused by long-term regional rainfall and affected a significant part of Beijing. Within a day, there were many obvious effects of the flood, including damage to property and infrastructure. The floodwater killed 79 people (Gui-Feng, 2012), and 56,933 people were evacuated, causing damages of 11.64 billion Yuan and destroying at least 8,200 homes (Sha-Sha, 2012). Overall, more than 1.9 million people were affected by the flood (Liu, 2012). Fangshan District, in the southwest of Beijing, received a record-breaking 460 mm of rain and was the most heavily affected area. The torrential rain triggered at least three types of natural disasters in this district, including flash floods, ponding, and mudslides.

Inevitably, after a flash flood, there is an immediate response by government agencies, as relief operations get underway to try and restore basic infrastructure and provide the fundamental items that are necessary for survival and subsequent recovery. Floodwater will often produce many health problems because of, among other things, damage to water supply systems, insufficient drinking-water supplies, and disruption of transport systems (Michelozzi and de' Donato, 2014; Bich et al., 2011; Carroll et al., 2010; Fundter et al., 2008). However, the most serious consequence of flooding is large-scale contamination of drinking water (surface water, groundwater, and distribution systems). Drinking water can be contaminated with microorganisms such as bacteria, sewage, heating oil, agricultural or industrial waste, chemicals, and other substances that can cause serious illnesses (Murshed et al., 2014; Yard et al., 2014; Chaturongkasumrit et al., 2013). In such situations, water-borne illnesses that are usually associated with poor hygiene and sanitation can affect a large part of the population (Baig et al., 2012); therefore access to clean drinking water and adequate sanitation is a priority.

To improve our understanding of pollution patterns and to support decision making concerning effective control and prevention of disease, it is very important to be able to identify hidden sources of drinking water pollution. To date, principal component analysis (PCA) and factor analysis (FA) are the most commonly used, multivariate statistical tools in water environmental science (Shyu et al., 2011; Liu et al., 2011). These methods can be used to interpret complex databases to obtain an improved understanding of water quality. These techniques also permit identification of the possible factors or sources that are responsible for variations in water quality and that influence the water system; they can therefore support the development of appropriate strategies for effective management of water resources and provide rapid solutions for pollution issues

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

(Singh et al., 2004; Li et al., 2007; Kazi et al., 2009). However, to date, no studies have been carried out to determine either the safety of water for human consumption or the sources of water pollution after severe floods.

As stated above, the identification of hidden sources is critical to our understanding of water pollution patterns and to support decision making about site remediation. Therefore, multivariate statistical methods should be applied in disaster impact analysis. The objectives of this study were, i) to describe the changes in water quality because of the 2012 flash flood using laboratory analysis methods; ii) to use the PCA and FA method to identify hidden pollution sources and their contributions after the flash flood, and iii) to demonstrate the merits of the suggested method using a case study.

2. Materials and methods

2.1. Description of sampling sites

The villages of Dahanji, Louzishui, and Huangshandian are located in the rural zone of Beijing. These three villages are in the Fengtai District of Beijing, the area worst hit by the flash flood. The main drinking water source for the population of the region is groundwater. We carried out a detailed investigation of drinking water in the study area on July 27, 2012. Nine water samples were collected at key sites to be analyzed for a wide range of determinants that were considered to represent the water quality of the groundwater system. The first two sites (1 and 2) were in the area around Dahanji; four sites (3–6) were in the environs of Louzishui, and three sites (7–9) were in the area around Hangshandian (Fig. 1).

2.2. Sample collection

Samples were collected, preserved, and transported as outlined in the Chinese National Quality Standards for Drinking Water (GB/T 5750.2-2006). In brief, water samples were collected from the sampling sites using a sterilized sampler. After adding a preserving agent, the choice of which was dependent on the test variable, the samples were packed in sealed plastic bags, and then transported to the laboratory.

2.3. Analytical methods

The samples were analyzed in the laboratory of the Institute of Disease Control and Prevention, Academy of Military Medical Sciences, Beijing, following the methods outlined in the Chinese National Quality Standards for Drinking Water (GB/T 5749-2006 and GB/T 5750-2006). Samples were analyzed for turbidity by the scattering method; for total hardness by the titrimetric method; for total

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

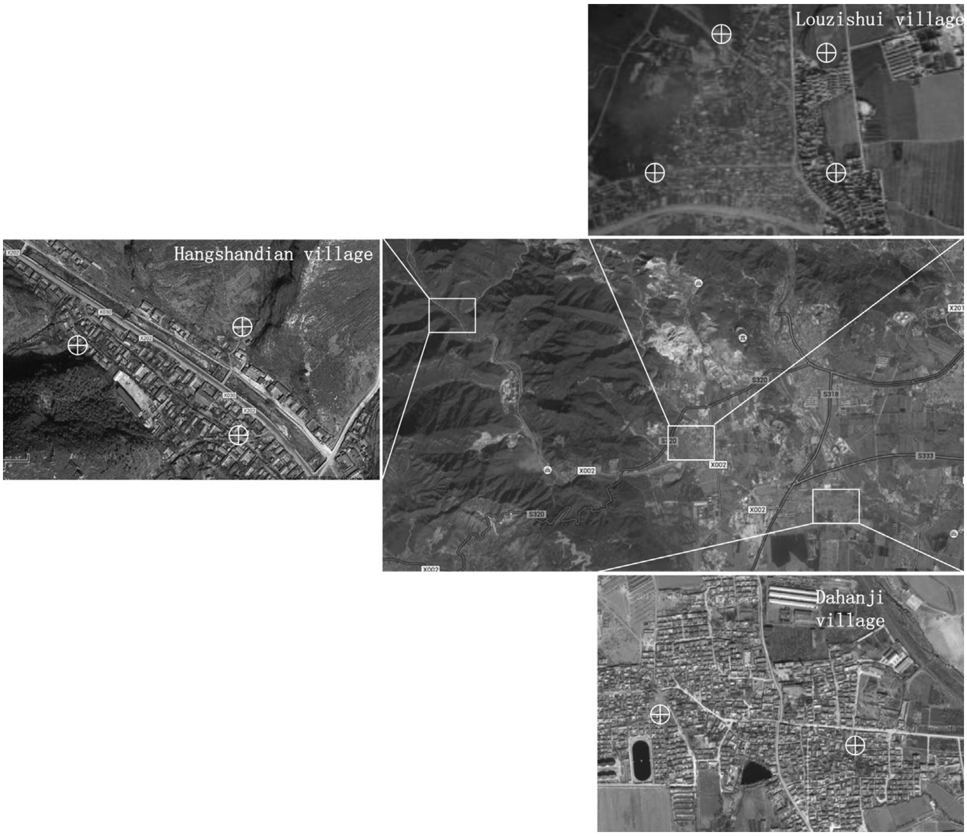

Fig. 1. Map of the study area and sampling sites.

dissolved solids by the gravimetric method; for sulfates, chlorides, and nitrates by spectrophotometry; for total bacterial counts (TBC) by the plate count method, and for total coliform groups by the multiple tube method. Data quality was ensured through careful standardization, procedural blank measurements, and spiked and duplicate samples. The laboratory also participates in regular national programs for analytical quality control. The analytical precision for replicate samples was within $\pm$10% and the measurement errors between determined and certified values were less than 5%.

2.4. Statistical analysis

Principal component analysis provides information on the most meaningful parameters, which describe the whole data set through data reduction with minimum loss of the original information (Alberto et al., 2001). It is a powerful technique for pattern recognition that attempts to explain the variance between a large set of inter-correlated variables and transforms it into a smaller set of independent (uncorrelated) variables (principal components). The principal component (PC) is expressed as:

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + \ldots + a_{im}x_{mj} \tag{1}$$

where a is the component loading; z is the component score; x is the measured value of a variable; i is the component number; j is the sample number, and m is the total number of variables.

Factor analysis attempts to extract a lower dimensional linear structure from the data set. It further reduces the contribution of the less significant variables obtained from PCA and extracts a new group of variables, known as varifactors (VFs), by rotating the axis defined by PCA. The basic concept of FA is expressed in Eq. (2):

$$z_{ji} = a_{f1}f_{1i} + a_{f2}f_{2i} + a_{f3}f_{3i} + \ldots + a_{fm}f_{mi} + e_{fi} \tag{2}$$

where z is the measured value of a variable; a is the factor loading; f is the factor score; e is the residual term accounting for errors or other sources of variation; i is the sample number; j is the variable number, and m is the total number of factors.

PCA and FA of water quality data were carried out using SPSS version 18.0 (SPSS Inc., Chicago, IL, USA). PCA of the normalized variables (water quality data set) was used to extract significant PCs and to further reduce the contribution of variables with minor significance; these PCs were subjected to varimax rotation (raw) to generate VFs. VFs can be hypothetical underlying, yet convenient, variables for the purposes of water quality assessment (Vega et al., 1998; Helena et al., 2000). Each original water quality variable is the linear combination of common factors and one unusual factor that explains the errors or other sources of variation.

3. Results and discussion

3.1. Water quality with parameter variations

Understanding drinking water quality is important, given that it is the main factor that determines its suitability for drinking (Wang, 2013; Kumar et al., 2007). Summary data for eight parameters, including the mean and standard deviation, are reported in Table 1. The maximum permissible limit for turbidity in drinking water is 1.0 nephelometric turbidity units (NTU). The values of turbidity varied widely and ranged from 0.48 to 9.99 NTU, with a mean of 3.26 NTU. Turbidity exceeded the permissible limit at six sites (sites 3–7, and site 9). Water hardness is primarily caused by the presence of cations, such as calcium and magnesium, and anions, such as carbonate, bicarbonate, chloride, and sulfate (Ravikumar et al., 2011). Drinking water with a hardness value that exceeds the limit of 450 mg/L is considered to be very hard. Total hardness (TH) ranged from 218 to 481 mg/L, with a mean value of 369.2 mg/L as $CaCO_3$ (Table 1). Samples from two sites (site 1 and site 2) fell into the very

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

Table 1. Description of water-quality parameters.

		Sampling location										
Parameters	**Standard values**	**Site 1**	**Site 2**	**Site 3**	**Site 4**	**Site 5**	**Site 6**	**Site 7**	**Site 8**	**Site 9**	**Mean**	**Standard deviation**
Turbidity (NTU)	≤1	0.48	0.91	2.76[a]	9.99[a]	5.42[a]	1.9[a]	4.12[a]	0.88	2.86[a]	3.26	3.00
Total hardness (mg/L)	≤450	481[a]	473[a]	410	218	409	394	367.6	258.1	311.8	369.2	90.6
Total dissolved solids (mg/L)	≤1000	587	586	318	250	247	278	522	243	282	368	151
Sulfates (mg/L)	≤250	211.6	194.9	104	87.7	86.5	114	201	60.7	121.3	131.3	56.3
Chlorides (mg/L)	≤250	137.2	144.5	24.5	13.6	13.5	21.2	103.8	13.0	17.5	54.3	56.8
Nitrates (by NO_3^-) (mg/L)	≤10	13.0[a]	11.4[a]	1.84	8.18	8.09	1.85	15.9[a]	7.6	12.1[a]	8.88	4.81
Total bacterial count (CFU/cm^3)	≤100	28	297[a]	500[a]	2000[a]	72	2000[a]	2000[a]	1376[a]	1457[a]	1081	8548
Total coliform group (CFU/cm^3)	not detected	not detected	not detected	170[a]	1000[a]	67[a]	1000[a]	1000[a]	1000[a]	890[a]	570	488

[a] Values indicate exceedances of standard values.

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

hard category, indicating that some of the water was unsuitable for drinking purposes. TDS in water are determined by evaporating a water sample to dryness, and weighing the residue that remains (Bahar and Reza, 2010). They comprise compounds of inorganic salts (principally calcium, magnesium, potassium, sodium, bicarbonates, chlorides, and sulfates) and small amounts of organic matter that are dissolved in water. TDS ranged from 243 to 587 mg/L and had an average value of 368 mg/L.

The abundance of the major anions in this study decreased in the following order: $SO_4^{2-}>Cl^->NO_3^-$. The concentrations of sulfate, the first dominant anion, ranged from 60.7 to 211.6 mg/L, and the average was 131.3 mg/L. Chloride was the second dominant anion. Its concentrations ranged from 13.0 to 144.5 mg/L and the average value was 54.3 mg/L. Nitrates are the end product of aerobic stabilization of organic nitrogen, and a product of the conversion of nitrogenous material, a phenomenon that occurs in polluted water. The nitrate concentrations of groundwater samples ranged from 1.84 to 15.9 mg/L, with an average value of 8.88 mg/L. Nitrate concentrations of four samples exceeded the maximum permissible limit of 10 mg/L.

Information about bacterial colonies in the water samples is also provided in Table 1. TBC ranged from 28 to 2000 CFU/cm^3, with an average value of 1081 CFU/cm^3 in the sampled drinking waters. Water samples from only two sites (site 1 and site 5) were within the maximum permissible limit of TBC, while all the others exceeded the limit. Coliform bacteria, which are not an actual cause of disease, are commonly used as a bacterial indicator of water pollution. In the study area, coliform groups (TCG) were detected in seven groundwater samples (from sites 3–9). When compared with the maximum limits for microbial parameters in drinking water, the data indicate that most of the samples were unsuitable for drinking water purposes. The above results show that it is imperative to have sufficient information to be able to make reliable statements about water quality. It is, however, often difficult to interpret and draw meaningful conclusions from a huge complex data set comprising a large number of parameters.

3.2. Source identification

Further, for effective pollution control and water resource management, pollution sources and their relative contributions need to be identified. PCA was used to support the identification and analysis of sources of water pollution. All of the data were standardized with a mean of 0 and variance of 1. The results of Kaiser–Meyer–Olkin (KMO = 0.548) and Bartlett's sphericity tests (P = 0) indicated that parameters of these samples were suitable for PCA (Table 2). The greater the calculated eigenvalues, the more significant the corresponding

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

Table 2. Results of KMO and Bartlett's tests.

Kaiser–Meyer–Olkin measure of sampling adequacy		0.548
Bartlett's test of sphericity	Approx. Chi-square	76.225
	df	28
	Sig.	0.000

factors. Following Pekey et al. (2004), only eigenvalues ≥1 were selected. The results of PCA after applying varimax rotation for the water-quality parameters are presented in Table 3, while Fig. 2 shows the variation diagram in rotated space. The results indicate that PCA reduced the number of variables to two principal components (PCs), which explained 82.503% of the data variance. PC1 and PC2 accounted for 59.225% and 23.278% of the total variance, respectively.

The rotated component matrix was then obtained by orthogonal rotation. VFs were obtained by applying FA to the PCs. The VFs and the corresponding variable loadings are presented in Table 4. According to Liu et al. (2003), factor loadings >0.75, between 0.5 and 0.75, and between 0.3 and 0.5 are considered to be strong, moderate, and weak, respectively. Out of the two VFs, VF1 had strong positive loadings for sulfates, TDS, chlorides, and nitrates (Table 4). Concentrations of TDS in water vary considerably in different geological regions owing to differences in the solubility of minerals (WHO, 2004). Further, agriculture is very developed in the study area, and agricultural fertilizers are extensively used. Therefore, VF1 could reflect both the mineral components of the drinking water and the influence of agricultural runoff from the soil. VF2 has strong positive loadings for TCG and TBC, a moderate loading for turbidity, and a strong negative loading for TH (Table 4). The communalities of TCG,

Table 3. Total variance explained.

	Initial eigenvalues		
Component	**Total**	**% of variance**	**Cumulative %**
1	4.738	59.225	59.225
2	1.862	23.278	82.503
3	0.830	10.369	92.873
4	0.421	5.263	98.136
5	0.127	1.587	99.723
6	0.017	0.213	99.935
7	0.003	0.036	99.971
8	0.002	0.029	100.000

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

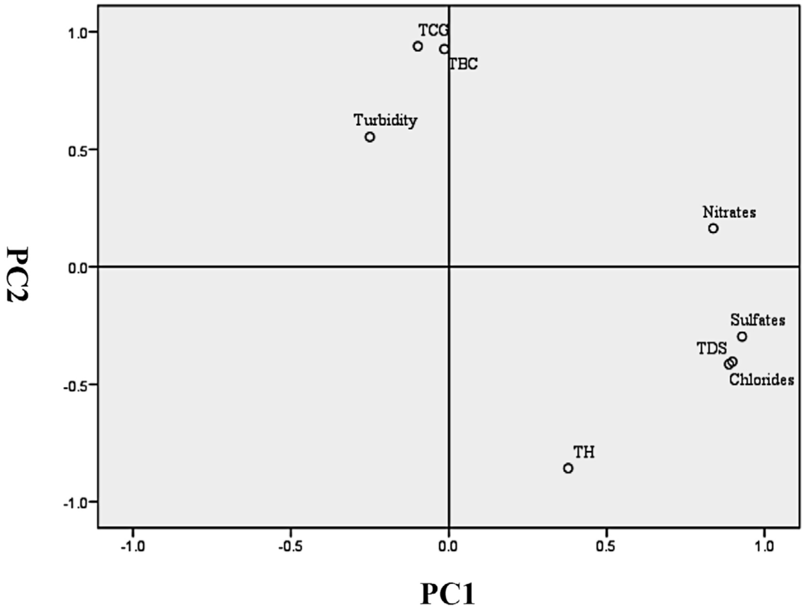

Fig. 2. Principal component analysis loading plot for the eight parameters.

TBC, and turbidity were relatively high, suggesting complex influences of multiple sources on these variables. However, the high microbial loads and turbidity arising from the floods resulted in water quality contamination. Therefore, the results show that several microorganisms were transferred via floodwater to different parts of this region and water for human consumption was cross-contaminated by floodwater.

3.3. Source spatial distribution

The factor score of each sampling point VF can easily be calculated when SPSS is used for FA. The factor score of each VF multiplied by its variance

Table 4. Rotated component matrix.

	Varifactors	
Variables	**VF1**	**VF2**
Sulfates	0.929	-0.297
TDS	0.898	-0.403
Chlorides	0.887	-0.414
Nitrates	0.838	0.163
TCG	-0.098	0.938
TBC	-0.014	0.926
TH	0.378	-0.857
Turbidity	-0.250	0.553

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

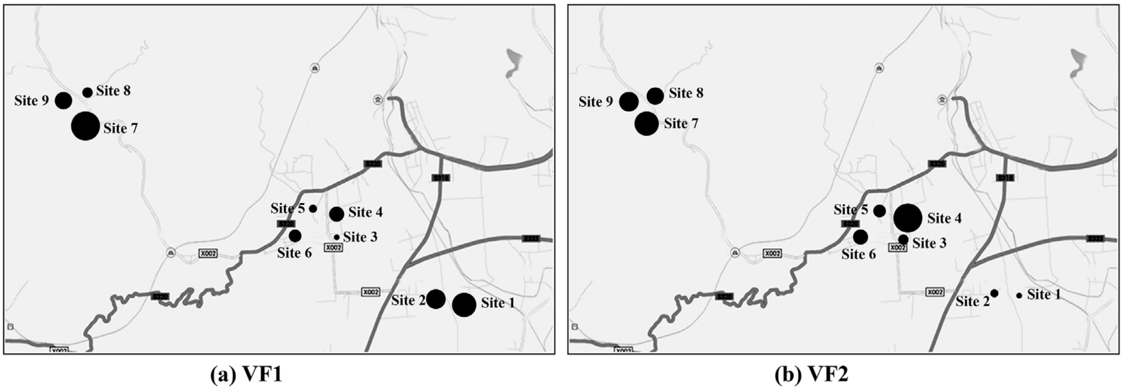

Fig. 3. Spatial distribution of the factor scores for each VF. The size of the circle represents the size of the factor score of each VF.

contribution rate accounts for the extraction of a common factor, which is then weighted to obtain composite scores for each sampling site. The higher the factor score of a sampling point, the more serious the pollution at that point. Fig. 3 shows clearly that the different sampling points had different sources of pollution. The common factor score of VF1, which represented the degree of mineralization and agricultural runoff of the sampling points, was highest at site 7, followed by site 1, site 2, site 9, site 4, site 6, site 8, site 5, and site 3 (Fig. 3), which shows that variations in this region were mainly influenced by geological conditions and agricultural production. Our survey also demonstrated that these spatial distributions represented the degree of variation in agricultural runoff from the soil. The common factor score of VF2 was highest at site 4, followed by site 7, site 9, site 8, site 6, site 5, site 3, site 2, and site 1 (Fig. 3). Previous analysis showed that VF2 mainly represented the effects of the flood. Results showed that the floodwater introduced large amounts of impurities and microbial contaminants into drinking water. These findings mirror those of the actual survey, and confirm that the different sampling points suffered flood damage to varying degrees. Thus, the method that we have presented appears to be an effective tool for water pollution source apportionment and identification, and may provide valuable reference information for pollution control and emergency management.

4. Conclusions

The aim of this study was to identify the sources and the geographical distribution of water pollution in the areas worst hit by a flash flood by interpreting analysis results of the major water-quality parameters. The main conclusions are as follows:

1. The eight parameters for which the samples were analyzed highlight the variations in water quality. The results indicate that the nine samples were

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

unsuitable for drinking purposes; the results also indicate that it is difficult to interpret and draw meaningful conclusions from a complex data set.

2. PCA and FA can provide useful information for assessing water quality. The combination of these two methods showed that the pollution levels in the study area were mainly influenced by two factors, the degree of mineralization and agricultural runoff, and flood entrainment. Moreover, maps can present information about spatial variations in drinking water quality in an easily understood format.

3. This study demonstrates that the combination of PCA and FA provides a useful and efficient method for summarizing data and reporting information to decision makers to ensure an improved understanding of the quality status of drinking water. This method should be very useful in the future.

Declarations

Author contribution statement

Rubao Sun: Performed the experiments; Analyzed and interpreted the data.

Daizhi An, Wei Lu: Performed the experiments.

Yun Shi, Lili Wang, Can Zhang, Ping Zhang, Hongjuan Qi: Contributed reagents, materials, analysis tools or data.

Qiang Wang: Conceived and designed the experiments; Wrote the paper.

Rubao Sun, Daizhi An and Wei Lu contributed equally to this study.

Competing interest statement

The authors declare no conflict of interest.

Funding statement

This project was supported by grants from the National Natural Science Foundation of China (81472478 and 81200298).

Additional information

No additional information is available for this paper.

References

Alberto, W.D., Del Pilar, D.M., Valeria, A.M., Fabiana, P.S., Cecilia, H.A., De Los Angeles, B.M., 2001. Pattern recognition techniques for the evaluation of

http://dx.doi.org/10.1016/j.heliyon.2016.e00071

spatial and temporal variations in water quality. A case study: Suquía River Basin (Cordoba-Argentina). Water. Res. 35 (12), 2881–2894.

Bahar, M., Reza, S., 2010. Hydrochemical characteristics and quality assessment of shallow groundwater in a coastal area of Southwest Bangladesh. Environ. Earth Sci. 61, 1065–1073.

Baig, S.A., Xu, X., Khan, R., 2012. Microbial water quality risks to public health: potable water assessment for a flood-affected town in northern Pakistan. Rural Remote Health 12 2196.

Bich, T.H., Quang, L.N., Ha Le, T.T., Hanh, T.T., Guha-Sapir, D., 2011. Impacts of flood on health: epidemiologic evidence from Hanoi, Vietnam. Glob. Health Action 4 6356.

Carroll, B., Balogh, R., Morbey, H., Araoz, G., 2010. Health and social impacts of a flood disaster: responding to needs and implications for practice. Disasters 34 (4), 1045–1063.

Chaturongkasumrit, Y., Techaruvichit, P., Takahashi, H., Kimura, B., Keeratipibul, S., 2013. Microbiological evaluation of water during the 2011 flood crisis in Thailand. Sci. Total Environ. 463-464, 959–967.

Fundter, D.Q., Jonkman, B., Beerman, S., Goemans, C.L., Briggs, R., Coumans, F., Lahaye, J.W., Bierens, J., 2008. Health impacts of large-scale floods: governmental decision-making and resilience of the citizens. Prehosp. Disaster Med. 23 (4), s70–s73.

Gui-Feng, G., 2012. Beijing 7.21 torrential rains victims toll to 79 [Press Release], Xinhua. Net. August, 6. (in Chinese). http://news.xinhuanet.com/politics/2012-08/06/c_112639461.htm.

Helena, B., Pardo, R., Vega, M., Barrado, E., Fernández, J.M., Fernández, L., 2000. Temporal evolution of groundwater composition in an alluvial aquifer (Pisuerga river, Spain) by principal component analysis. Water Res. 34 (3), 807–816.

Kazi, T.G., Arain, M.B., Jamali, M.K., Jalbani, N., Afridi, H.I., Sarfraz, R.A., Baig, J.A., Shah, A.Q., 2009. Assessment of water quality of polluted lake using multivariate statistical techniques: A case study. Ecotox. Environ. Safe. 72, 301–309.

Kumar, M., Kumari, K., Ramanathan, A.L., Saxena, R., 2007. A comparative evaluation of groundwater suitability for irrigation and drinking purposes in two intensively cultivated districts of Punjab, India. Environ. Geol. 5, 553–574.

 http://dx.doi.org/10.1016/j.heliyon.2016.e00071

Li, R., Dong, M., Zhao, Y., Zhang, L., Cui, Q., He, W., 2007. Assessment of water quality and identification of pollution sources of plateau lakes in Yunnan (China). J. Environ. Qual. 36, 291–297.

Liu, C.W., Lin, K.H., Kuo, Y.M., 2003. Application of factor analysis in the assessment of groundwater quality in a Blackfoot disease area in Taiwan. Sci. Total Environ. 313 (1–3), 77–89.

Liu, W.C., Yu, H.L., Chung, C.E., 2011. Assessment of water quality in a subtropical alpine lake using multivariate statistical techniques and geostatistical mapping: a case study. Int. J. Environ. Res. Public Health 8 (4), 1126–1140.

Jun, Liu., 2012. Great grief to city-"7.21" torrential rains in Beijing. Chinese. Weather. Net. (in Chinese). (accessed 28.01.2016.). http://www.weather.com.cn/zt/kpzt/1696696.shtml.

Michelozzi, P., de' Donato, F., 2014. Climate changes, floods, and health consequences. Recenti. Prog. Med. 105 (2), 48–50.

Murshed, M.F., Aslam, Z., Lewis, R., Chow, C., Wang, D., Drikas, M., van Leeuwen, J., 2014. Changes in the quality of river water before, during and after a major flood event associated with a La Niña cycle and treatment for drinking purposes. J. Environ. Sci-China 26 (10), 1985–1993.

Pekey, H., Karakas, D., Bakoglu, M., 2004. Source apportionment of trace metals in surface waters of a polluted stream using multivariate statistical analyses. Mar. Pollut. Bull. 49 (9-10), 809–818.

Ravikumar, P., Somashekar, R.K., Angami, M., 2011. Hydrochemistry and evaluation of groundwater suitability for irrigation and drinking purposes in the Markandeya River basin, Belgaum District, Karnataka State, India. Environ. Monit. Assess. 173 (1-4), 459–487.

Sha-Sha, H., 2012. The Beijing municipal government held a briefing on July 21 catastrophic natural disasters [Press Release], Beijing. Daily. August, 6. (in Chinese). http://www.scopsr.gov.cn/rdzt/bjbykbmlz/bjszxd/zxxx/201208/t20120806_176473.html.

Shyu, G.S., Cheng, B.Y., Chiang, C.T., Yao, P.H., Chang, T.K., 2011. Applying factor analysis combined with kriging and information entropy theory for mapping and evaluating the stability of groundwater quality variation in Taiwan. Int. J. Environ. Res. Public Health 8 (4), 1084–1109.

Singh, K.P., Malik, A., Mohan, D., Sinha, S., 2004. Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of Gomti river (India): A case study. Water Res. 38, 3980–3992.

 http://dx.doi.org/10.1016/j.heliyon.2016.e00071

Vega, M., Pardo, R., Barrado, E., Deban, L., 1998. Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis. Water Res. 32 (12), 3581–3592.

Wang, S., 2013. Groundwater quality and its suitability for drinking and agricultural use in the Yanqi Basin of Xinjiang Province, Northwest China. Environ. Monit. Assess. 185 (9), 7469–7484.

WHO, 2004. Guidelines for drinking water quality: training pack. WHO, Geneva, Switzerland.

Yard, E.E., Murphy, M.W., Schneeberger, C., Narayanan, J., Hoo, E., Freiman, A., Lewis, L.S., Hill, V.R., 2014. Microbial and chemical contamination during and after flooding in the Ohio River-Kentucky, 2011. J. Environ. Sci. Health A Tox. Hazard Subst. Environ. Eng. 49 (11), 1236–1243.

 http://dx.doi.org/10.1016/j.heliyon.2016.e00071