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FACTORS AFFECTING SEASONAL AND SPATIAL PATTERNS OF WATER QUALITY IN LITHUANIAN RIVERS

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Abstract. In this study the main processes influencing water quality of the Lithuanian rivers have been identified. Factor analysis was tested on river hydrochemical data from 108 sites for the period of 1999–2004. It enabled the identification of main factors determining water quality each season. As a result, monitoring stations were grouped into clusters each representing the influence of relevant factor.
The tested multivariate statistical procedures can be applied in practice when the reasons for water quality impairments are to be investigated. The findings reveal that Wastewater factor is prominent in small rivers downstream larger towns; Agro-geological factor – in Northern Lithuania's rivers of heavy carbonated soils and intensive agriculture lands as well as in South eastern Lithuania's rivers of more acidic soils; Hardly degradable organics factor – in Northern and Middle Lithuania's rivers of heavy-textured and fertile agricultural soils. The photosynthesis-vegetation and Aeration factors are predominant in major rivers.

Keywords: factor analysis, multivariate statistics, water quality, Lithuanian rivers.

Introduction

In the year 2000 the EU Directive 2000/60/EC (further referred to as WFD) came into force obliging all member states to carefully identify water status problems, the reasons behind them and to elaborate programs of measures to solve those problems (Directive 2000/60/EC… 2000). Implementation of measures is a very costly activity, therefore it is very important to have a correct identification of problems and their causes and thus avoid unnecessary costly actions. Ideal reasoning for water status problems could be achieved by the use of good accounting data on point source pollution, diffuse pollution inputs and detailed process-based water quality models. Unfortunately, in many cases and in Lithuania in particular the aforementioned information is far from complete and the run of detailed models is impossible or not feasible in terms of precision of the results (Vaikasas 2010). One of the solutions to help find causes with limited information could be the use of proper statistical methods, applied on water monitoring data. The methods could be employed in conjunction with modeling to create a broader picture on possible problems and the reasons behind them. However, monitoring data contains a huge array of parameters (in this work – 27), some of which are very much intercorrelated. Consequently, conventional univariate statistical methods are unfit to analyze their complexity and detect meaningful structures in data, which could shed light on processes affecting water status. Luckily, multivariate statistical methods are perfectly designed to solve such kind of problems. Among them Factor analysis (FA) is one of the most reliable tools to deal with such tasks and therefore it has been utilized by a number of authors (Alberto *et al.* 2001; Aruga *et al.* 1995; Azzellino *et al.* 2006; Boyacioglu *et al.* 2007; Boyacioglu, H., Boyacioglu, H. 2008; Brodnjak-Voncina *et al.* 2002; Charkhabi, Sakizadeh 2006; Fitzpatrick *et al.* 2007; Kannel *et al.* 2007; Koklu *et al.* 2010; Kowalkowski *et al.* 2006; Kunwar *et al.* 2005; Marques da Silva *et al.* 2001; Mendiguchia *et al.* 2004; Morales *et al.* 1999; Omo-Irabor *et al.* 2008; Ouyang *et al.* 2006; Papatheodorou *et al.* 2006; Qadir *et al.* 2008; Razmkhah *et al.* 2010; Reisenhofer *et al.* 1998; Santos-Roman *et al.* 2003; Schaefer *et al.* 2010; Simeonov *et al.* 2002; Simeonov *et al.* 2003; Singh *et al.* 2006; Sojka *et al.* 2008; Spanos *et al.* 2003; Tarrado *et al.* 2006; Vega *et al.* 1998; Vidal *et al.* 2000; Voutsa *et al.* 2001; Zhang *et al.* 2009; Zhou *et al.* 2007). The strength of the method hides in its ability to extract meaningful structures from measurement data of numerous parametres that after qualified examination can be interpreted as particular factors or processes affecting water chemistry.

In a number of occasions factor analysis is combined with cluster and even discriminant function analysis, where the latter only pinpoint to parametres that differ the most among clusters (discriminate best) (Alberto *et al.* 2001; Boyacioglu H., Boyacioglu H. 2008; Kannel *et al.* 2007; Koklu *et al.* 2010; Kowalkowski *et al.* 2006; Kunwar *et al.* 2005; Qadir *et al.* 2008; Santos-Roman *et al.* 2003; Simeonov *et al.* 2002; Simeonov *et al.* 2003; Singh *et al.* 2006; Sojka *et al.* 2008; Zhou *et al.* 2007). Finally, factor analysis is sometimes used to complement modelling, like it was done in Spain with QUAL2E model (Azzellino *et al.* 2006).

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Although factor analysis was found to be a suitable tool in many applications, the situation with its use in Lithuania is a bit different. Apart from some exceptions (Povilaitis 2003), the method has almost not been used in Lithuania in the context of the analysis of physico-chemical data.

Therefore, the goal of the research was to assess the impacts different factors have on the state of Lithuanian rivers water and identify their spatial patterns by using system-oriented approach. This work aims to uncover external landuse, landcover and internal ecosystem processes and their affects on water physico-chemical parameters. Although this work is targeted at rivers, the results are important to the Curonian Lagoon and Baltic Sea as well, since river-born pollution is the main cause of water quality problems there.

1. Methodology

State monitoring physico-chemical data from the Lithuanian Environmental Protection Agency for 108 river sites have been used in this study (Fig. 1; Table 1).

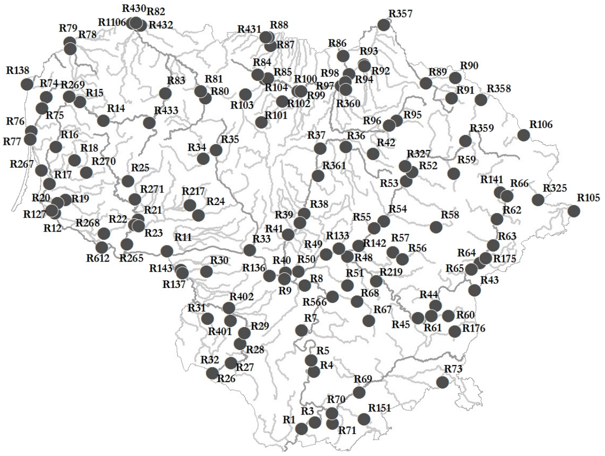

Fig. 1. Location of river water quality monitoring stations

The water samples were collected monthly, however for the analysis not always raw data was used – for significant part of the analysis raw data was aggregated as multi-annual seasonal data. The measured parameters include flow velocity (V), discharge (Q), suspended matter (SM), transparency (SK), pH, dissolved oxygen (O_2), oxygen saturation (O_2%), biochemical oxygen demand in 7 days (BOD_7), chemical oxygen demand using dichromate (COD_{Cr}) or permanganate (COD_{Mn}), total organic carbon (TOA), ammonia nitrogen (NH_4-N), nitrite nitrogen (NO_2-N), nitrate nitrogen (NO_3-N), organic nitrogen (N_{org}), phosphate phosphorus (PO_4-P), organic and adsorbed phosphorus (P_{org}), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), silica (Si), bicarbonate (HCO_3^-), sulphate (SO_4), chlorine (Cl) and total iron (Fe). The selection of parameters for this study was based on the idea to uncover as many water quality determining processes and as precisely as possible. In this sense, the guiding principle for parametre selection was the more of relevant parameters are included, the better. In addition, GIS layers of river basin boundaries and rivers (Lithuanian georeference database and the data of the Lithuanian Environmental Protection Agency) have been used.

The aforementioned data was subject to a multivariate statistical technique called Factor analysis, which have been applied by the use of Statsoft STATISTICA software as well as the PAST software. There were two types of Factor analysis used in this study. First of all, the spatial Factor analysis was employed, which was based on seasonal averages of physico-chemical data of all 108 monitoring stations combined for the whole study period of 1999–2004. Autumn-winter season was represented by the period from September to February months, spring – by March to April and summer – by May to August. Spatial FA was applied to identify main factors affecting river water quality and spatially group them according to the affecting factor and its strength. The other type of FA - local FA was employed only for a limited number of selected monitoring stations representing different groups, formed by means of spatial FA. Local FA was performed using the dataset of all data for particular selected station, covering the period of 1992–2004. Local FA results were utilized for more detailed description of processes affecting the aforementioned groups of stations.

The idea of factor analysis is to reduce intercorrelating variables into a few new representative uncorrelated integrated variables or the so-called principal components, which take a form of the 1st-order equation. The components then are orthogonally rotated in space to transform into latent factors that are explained by variables that correlate with them. The FA mathematical model is based on the assumption that the behaviour of each variable X_i is influenced by m common factors ($F_1, F_2, ..., F_m$). The interrelationship between factors and variables ($X_1, X_2, ..., X_k$) is expressed by the 1st-order equations:

$$X_i = \sum_{j=1}^{m} \lambda_{ij} F_j \; ; \qquad (1)$$

$$X_k = \sum_{j=1}^{m} \lambda_{kj} F_j \; , \qquad (2)$$

where λ_{ij} ($i=1, ..., k; j=1, ..., m$) = $cov(X_i,F_j)$ – factor loadings (the higher the loading, the more a variable is related to the factor).

2. Results and discussion

Factor analysis from Lithuanian river monitoring data discovered six factors for each season that have been affecting river water quality indices. Some of them are common for all seasons, whereas some of them are season specific unique ones. Further in this chapter each common factor is represented only by the season in which it is most pronounced, while the unique ones are represented by the season for which they have been identified. Three factors are common for all seasons. *Wastewater factor* is the most pronounced one in all periods and in autumn-winter period in particular. In autumn-winter, for instance, it is remarkable through high positive loadings

Table 1. Water quality monitoring stations from which the hydrochemical and river basin data have been used

Code	Monitoring station	Code	Monitoring station	Code	Monitoring station
R1	Nemunas upstream Druskininkai	R41	Šušvė at the mouth	R80	Venta upstream Kuršėnai
R3	Nemunas downstream Druskininkai	R42	Juosta downstream Jackagalis	R81	Venta downstream Kuršėnai
R4	Nemunas upstream Alytus	R43	Neris at Buivydžiai	R82	Venta downstream Mažeikiai
R5	Nemunas downstream Alytus	R44	Neris upstream Vilnius	R83	Virvytė downstream Patekla
R7	Nemunas upstream Prienai	R45	Neris downstream Vilnius	R84	Mūša upstream Kulpė
R8	Nemunas upstream Kaunas	R48	Neris upstream Jonava	R85	Mūša downstream Kulpė
R9	Nemunas downstream Kaunas	R49	Neris downstream Jonava	R86	Mūša downstream Saločiai
R11	Nemunas downstream Smalininkai	R50	Neris upstream Kaunas	R87	Sidabra downstream Joniškis
R12	Nemunas upstream Rusnė	R51	Lomena downstream Kaišiadorys	R88	Sidabra at the border to Latvia
R14	Minija upstream Plungė	R52	Šventoji upstream Anykščiai	R89	Nemunėlis downstream Panemunis
R15	Minija downstream Plungė	R53	Šventoji downstream Anykščiai	R90	Juodupė downstream Juodupė
R16	Minija downstream Gargždai	R54	Šventoji upstream Ukmergė	R91	Laukupė downstream Rokiškis
R17	Minija downstream Priekulė	R55	Šventoji downstream Ukmergė	R92	Tatula upstream Biržai
R18	Veiviržas at Veiviržėnai	R56	Širvinta upstream Širvintos	R93	Tatula below Biržai
R19	Šyša upstream Šilutė	R57	Širvinta downstream Širvintos	R94	Tatula at Trečionys
R20	Šyša downstream Šilutė	R58	Siesartis-Malkėstas downstream Molėtai	R95	Lėvuo upstream Kupiškis
R21	Jūra upstream Tauragė	R59	Vyžuona downstream Utena	R96	Lėvuo downstream Kupiškis
R22	Jūra downstream Tauragė	R60	Vilnia upstream N.Vilnia	R97	Lėvuo upstream Pasvalys
R23	Šešuvis at Skirgailiai	R61	Vilnia at the mouth	R98	Lėvuo at the mouth
R24	Šaltuona downstream Raseiniai	R62	Žeimena at Kaltanėnai	R99	Daugyvėnė at the mouth
R25	Lokysta downstream Šilalė	R63	Žeimena downstream Švenčionėliai	R100	Kruoja at the mouth
R26	Šešupė at the border to Poland	R64	Žeimena upstream Pabradė	R101	Obelė downstream Radviliškis
R27	Šešupė downstream Kalvarija	R65	Žeimena downstream Pabradė	R102	Obelė at the mouth
R28	Šešupė upstream Marijampolė	R66	Būka upstream Baluošas	R103	Kulpė downstream Šiauliai
R29	Šešupė downstream Marijampolė	R67	Strėva downstream Semeliškės	R104	Kulpė at the mouth
R30	Siesartis downstream Šakiai	R68	Strėva at Liūtonys	R105	Birvėta at the border to Belarus
R31	Šeimena downstream Vilkaviškis	R69	Merkys upstream Varėna	R106	Laukesa downstream Zarasai
R32	Šelmenta at the border to Poland	R70	Merkys downstream Puvočiai	R127	Skirvytė upstream Rusnė
R33	Dubysa upstream Seredžius	R71	Skroblus downstream Dubininkai	R133	Šventoji at the mouth
R34	Kražantė upstream Kelmė	R73	Šalčia downstream Šalčininkai	R136	Nemunas downstream Kaunas at Kulautuva
R35	Kražantė downstream Kelmė	R74	Akmena-Danė at Tubausiai	R137	Šešupė at the border to the Kaliningrad region
R36	Nevėžis upstream Panevėžys	R75	Akmena-Danė downstream Kretinga	R138	Šventoji at the mouth at the Baltic Sea
R37	Nevėžis downstream Panevėžys	R76	Akmena-Danė upstream Klaipėda	R141	Švogina-Žeimena upstream Vaišniūnai
R38	Nevėžis upstream Kėdainiai	R77	Akmena-Danė at the mouth	R142	Širvinta at the mouth
R39	Nevėžis downstream Kėdainiai	R78	Bartuva upstream Skuodas	R143	Siesartis at the mouth
R40	Nevėžis upstream Raudondvaris	R79	Bartuva downstream Skuodas	R150	Jiesia at Jiestrakis

of BOD_7, NH_4-N, NO_2-N, N_{org}, P_{org}, Na^+, K^+, Cl^-, PO_4-P and high negative loadings of O_2 and O_2% (Fig. 2). Similar parameters are related to this factor in other seasons as well. The factor is especially profound in small rivers downstream larger settlements where low dilution capacity translates into high pollutant concentrations (Figs 3–4). The process was also confirmed by the results of the local factor analysis. It can be noticed from the Table 2 almost the same correlating parameters and situations, when pollutant concentrations ascent as a consequence of reduced flow and dilution capacity in drier periods.

Agro-geological factor is the second most pronounced one in terms of variables explained and is common for all periods as well. It is expressed by high positive loadings on NO_3-N, SO_4^{2-}, Ca^{2+}, Mg^{2+} and high negative ones on total Fe and Si among others (Fig. 2).

Elevated concentrations of NO_3-N, SO_4^{2-}, Ca^{2+} and Mg^{2+} are found in northern Lithuanian karstic zone with prevailing limestone, dolomite or gypsum bedrock (Figs 3–4). This zone is also characterized by fertile lowlands with sod-gley soils and wide tracts of arable lands – this is one of the most intensive agricultural regions in Lithuania. Consequently, nitrates pose an acute water quality problem there. On the other hand, geological processes also determine relatively high concentrations of total Fe and Si, although this occurs mostly in rivers flowing through eastern and southeastern Lithuanian region of podzolic soils, sandy bedrock, marshes or pastures (Figs 3–4).

Elevated total Fe and Si levels are related to more acid conditions there. Low pH guarantees greater weathering and solubility of those elements from different chemical compounds and soil minerals. The main agents here are humic and fulvic acids, which tend to create colloidal organic complexes with Fe, Al and Si that do not precipitate. Although in general eastern Lithuanian rivers are less enriched with organic matter than the rivers from other regions, the former are more abundant with acid organic compounds.

Table 2. Wastewater factor loadings at the river monitoring sites where there is a well-pronounced wastewater impact

	River monitoring stations										
Parameter	R101	R103	R104	R87	R88	R91	R30	R98	R37	R85	R31
Q	**–0.70**	–0.46							**–0.53**		
SK				**–0.51**		**–0.94**					
SM				**0.75**		**0.84**					
pH							**–0.66**				
O_2						**–0.62**					
O_2%						**–0.55**					
BOD_7						**0.90**		**0.87**			
COD_{Cr}					**0.55**	**0.77**					
COD_{Mn}					0.44	**0.91**					
NH_4-N	**0.61**		**0.52**	**0.57**	**0.82**	**0.68**	**0.75**	**0.67**			**0.84**
NO_2-N		**0.74**	0.41						0.46	**0.68**	
N_{org}	**0.77**			**0.72**	**0.62**						
PO_4-P				**0.59**	**0.73**		**0.81**		**0.62**	**0.73**	**0.58**
P_{org}	**0.57**			0.46	**0.59**					**0.70**	
Ca^{2+}							**-0.56**				
Mg^{2+}					0.41						**0.71**
Na^+	**0.77**	**0.77**	**0.79**	**0.61**	**0.87**		**0.86**		**0.90**	**0.89**	**0.66**
K^+		**0.70**	**0.50**	**0.62**	**0.85**		**0.83**		**0.87**	**0.79**	**0.76**
Si							**0.83**				
HCO_3^-			**0.59**		**0.60**						
SO_4^{2-}		**0.82**	**0.74**	0.46	**0.78**					**0.87**	
Cl^-	**0.78**	**0.72**	**0.80**	**0.51**	**0.75**		**0.86**		**0.79**	**0.84**	**0.88**
Fe				**0.75**		**0.57**	**0.76**				
Max.*	–	–	–	–	S–W	–	S–W	–	–	–	–

*Max. – the season of maximum wastewater impact on river water quality; S – summer; W – autumn-winter; - no seasonal variation.

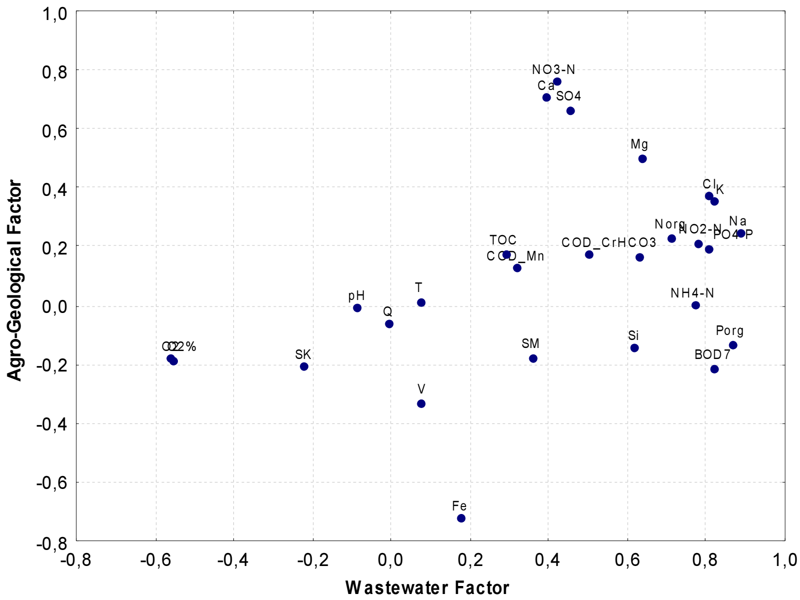

Fig. 2. The wastewater and the agro-geological factor loading plot (autumn-winter season)

The last common factor for all time periods is named as *hardly degradable organics (HDO)* one. It shows up with high loadings on TOC, COD_{Cr} and COD_{Mn} (Fig. 5).

The HDO factor is particularly strongly expressed in northern and central Lithuanian region of fertile soils where the biggest amounts of seasonal vegetation are produced (Figs 6–7). Vegetational detritus finds its way to rivers already partially decomposed on the way, leaving the remaining organic material that breaks down much slower. As expected, the process manifests itself most strongly in summer period when the bulk of vegetation is being produced.

There are also a number of factors that are characteristic only to particular seasons. The *photosynthesis-vegetation factor* is of particular relevance in the summer period. It is reflected by high positive loadings on BOD_7,

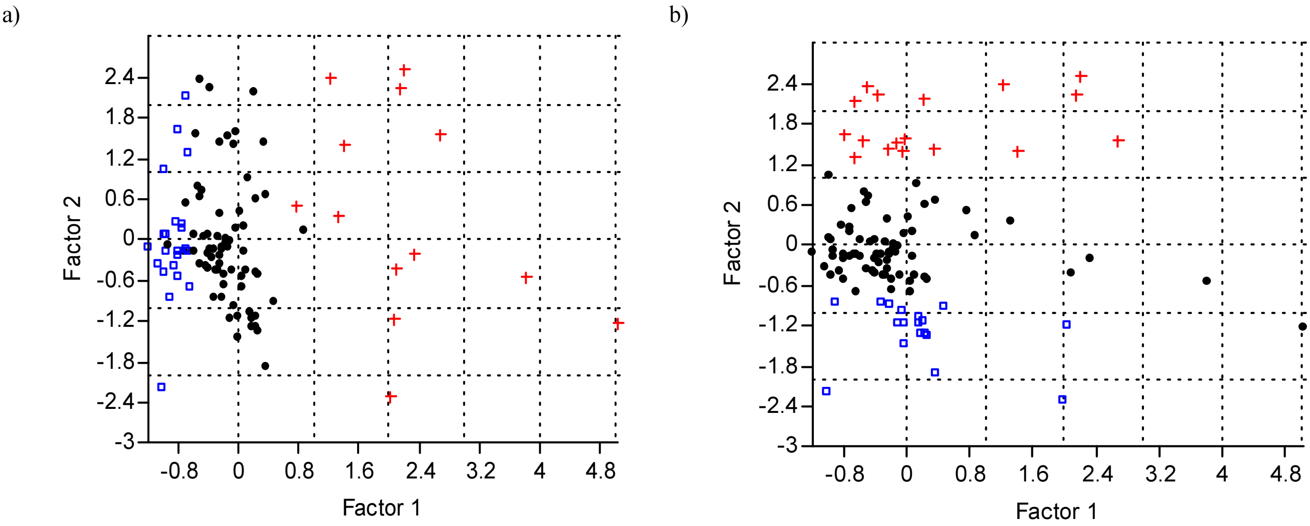

Fig. 3. Groupings of river monitoring stations along the axis of the wastewater (1st) (a) and the agro-geological (2nd) (b) factors in autumn-winter season (boxes – stations with most negative coordinates (factor scores), crosses – stations with most positive coordinates)

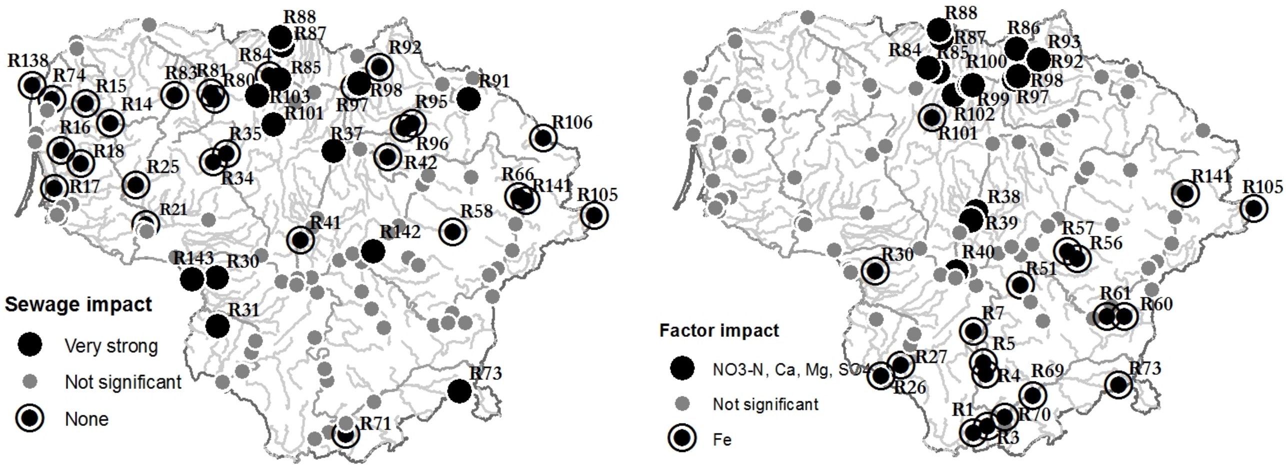

Fig. 4. River monitoring stations significantly affected by the wastewater (sewage, left) and the agro-geological factors (right) in the autumn-winter season

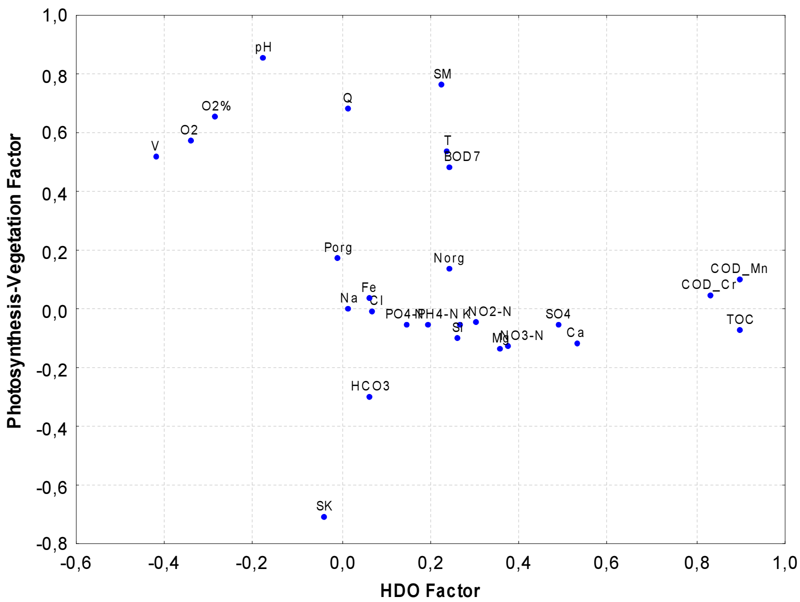

Fig. 5. The hardly degradable organics (HDO) and the photosynthesis-vegetation factor loading plot (summer season)

SM, pH, O_2, O_2%, Q, V, T and high negative loadings on SK (Fig. 5). The process of photosynthesis and production of vegetation organics is driven by intensive proliferation of phytoplankton, which manifests itself in elevated levels of SM and BOD_7 in river water. Photosynthetic reactions push up pH values as well as dissolved oxygen content. This happens despite the rule of thumb that in normal conditions when oxygen is not artificially added and the T increases, O_2 levels usually decrease because of the lower carrying capacity for this element in warmer waters. Greater Q, V and T values indicate big rivers, the waters of which warm up more in the summer. The factor is confined only to the Nemunas and Neris – Lithuanian largest rivers (Figs 6, 7). Here the conditions partly resemble lakes, where a big depth limits growth possibilities for macrophytes. Therefore, the lack of competition and warmer water creates perfect conditions for phytoplankton to thrive.

The conclusions are further confirmed by the results of the local factor analysis at separate monitoring stations in the Neris and Nemunas rivers. As seen from the Table 3, the photosynthesis-vegetation factor is also very much visible – upsurge of BOD_7, SM, pH, O_2, O_2% coincides with higher temperatures, indicating warmer season.

Aeration-organic decay factor is characteristic to autumn-winter period. It scores high on pH, O_2, O_2% as well as on V and Q (Fig. 8). The factor lifts pH, O_2 and O_2% by means of increased turbulence in more water abundant and fast flowing rivers, which include the Nemunas and some western Lithuania rivers that flow from highlands. Turbulence enhances water aeration. It also make it harder for ice to form, therefore conditions for aeration are enhanced while those for organic matter accumulation and decay are significantly worsened. The opposite situation is found in smaller and slower rivers of the Lithuanian north, where weak connection with groundwater makes it even easier for ice to form.

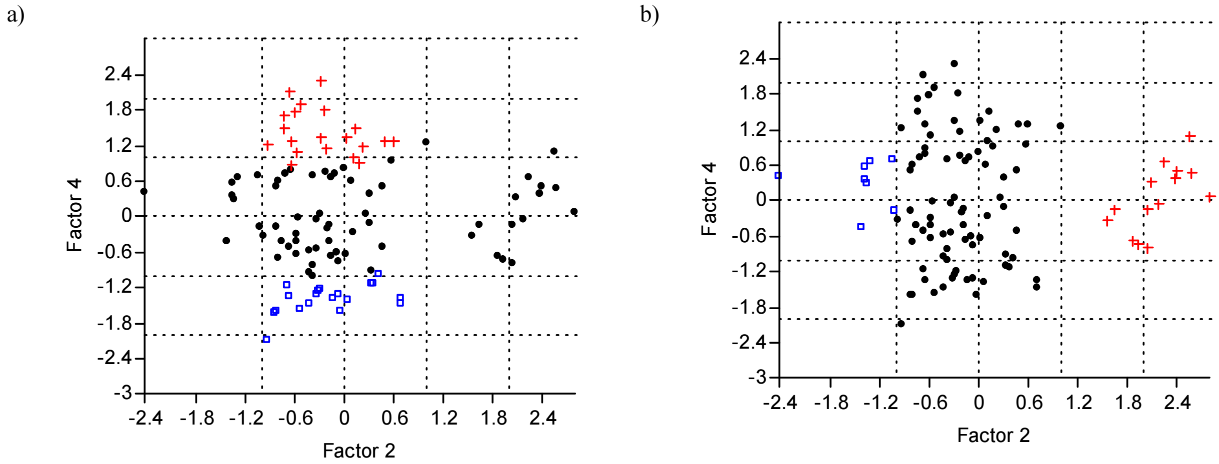

Fig. 6. Groupings of river monitoring stations along the axis of the hardly degradable organics (4^{th}) (a) and the photosynthesis-vegetation (b) factor (2^{nd}) in the summer season (boxes – stations with most negative coordinates (factor scores), crosses – stations with most positive coordinates)

Table 3. Photosynthesis-vegetation factor loadings at the river monitoring sites where photosynthesis processes are well pronounced in the summer period

	River monitoring stations					
Parameter	R11	R4	R48	R1	R44	R43
T	**0.81**	**–0.77**	**0.68**	**–0.79**	**–0.90**	**0.86**
SK	**–0.83**		**–0.82**	**0.82**	**0.78**	**–0.85**
SM	**0.81**	**–0.61**	**0.75**	**–0.68**	**–0.73**	**0.62**
pH	**0.80**	–0.42		**–0.75**	**–0.62**	**0.62**
O_2	**0.51**	**0.63**			–	
O_2%	**0.88**		0.44	–0.47	**–0.77**	**0.66**
BOD_7	**0.87**	**–0.85**	**0.87**	**–0.55**	**–0.83**	**0.78**
COD_{Cr}	**0.58**	**–0.52**	**0.70**		–0.45	
COD_{Mn}	**0.80**	**–0.65**	**0.65**	**–0.61**	–0.47	
NH_4-N				0.40		**–0.69**
NO_2-N	–0.43			**0.88**		**–0.55**
NO_3-N		**0.67**		**0.85**	**0.72**	**–0.85**
N_{org}				**–0.56**		
PO_4-P	**–0.77**	0.48	–0.45	**0.87**	**0.74**	**–0.64**
P_{org}	**0.75**		**0.84**			
Ca^{2+}	–0.49	**0.74**				
Si	**–0.81**				**0.75**	**–0.73**
Max.**	S–Sp	S	S	Sp–S	S–Sp	S–Sp

**Max. – Season of intensive photosynthesis process; S – summer; Sp – spring.

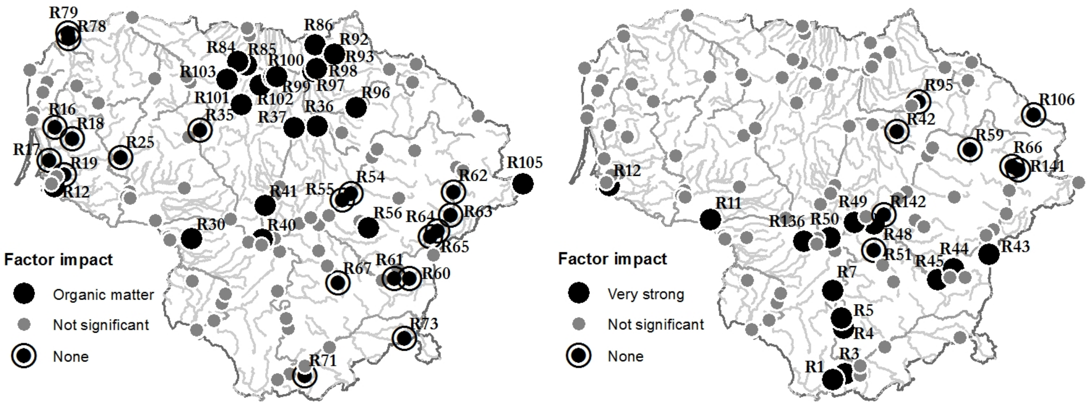

Fig. 7. River monitoring stations significantly affected by the hardly degradable organics (left) and the photosynthesis-vegetation factor (right) in the summer season

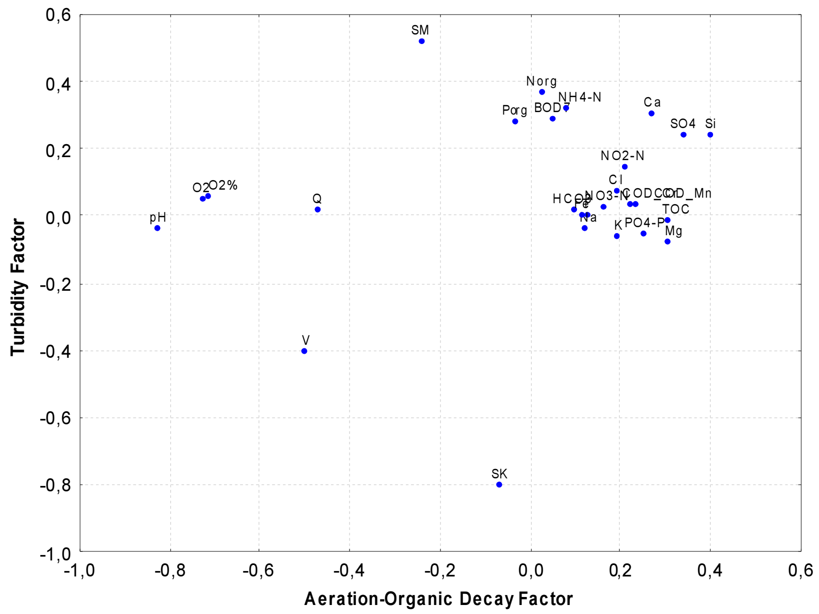

Fig. 8. The aeration-organic decay and the turbidity factor loading plot

Turbidity factor is also an autumn-winter process, which involves high positive loadings on SM and high negative loadings on SK (Fig. 8). The origin of high SM is variable. Strong factor influence in western Lithuanian rivers is related to hilly landscape and frequent floods, what translates into influx of erosion materials (Figs 9, 10). Larger factor scores in some small northern Lithuanian rivers might be due to heavy hardly permeable surfaces, leading to effective flushing of surface runoff to rivers together with SM particles. SM in the Nemunas might be related to turbulence and pick up of material from the river bed.

There are also other factors influencing water quality in different seasons, however they are of less importance. It can be said in general that in all seasons the six factor structure explained approximately 80% of common variation, which seems to be a relatively good result. Na^+, Cl^+ and K^+ are especially well explained parameters. However, there are some indicators, like Fe, Si or HCO_3^-, the explanation of which falls to the lows of 60% in some seasons. In those instances it is clear, that there are some unexplained factors behind those parameters, which are not related to all other quality indicators.

It can be seen from the results that factor analysis is capable of uncovering natural as well as human induced processes that affect water quality of rivers and can be successfully applied to Lithuanian situation.

The soundness of the FA has been subjected to a wide range of applications in water quality studies. One group of researchers (Papatheodorou *et al.* 2006; Spanos *et al.* 2003) used time series at one particular sampling location as input for factor analysis, termed as local factor analysis in this study. This makes it possible to distinguish among season dependent factors and the independent ones. The samples then are usually grouped according to affecting factors. This approach enables a detailed examination of processes in a particular location. Another group of authors (Alberto *et al.* 2001; Aruga *et al.* 1995; Boyacioglu, H., Boyacioglu, H. 2007; Brodnjak-Voncina *et al.* 2002; Charkhabi *et al.* 2006; Fitzpatrick *et al.* 2007; Kannel *et al.* 2007; Kowalkowski *et al.* 2006; Marques da Silva *et al.* 2001; Mendiguchia *et al.* 2004; Morales *et al.* 1999; Omo-Irabor *et al.* 2008; Ouyang *et al.* 2006; Qadir *et al.* 2008; Santos-Roman *et al.* 2003; Schaefer, Einax 2010; Simeonov *et al.* 2002; Simeonov *et al.* 2003; Singh

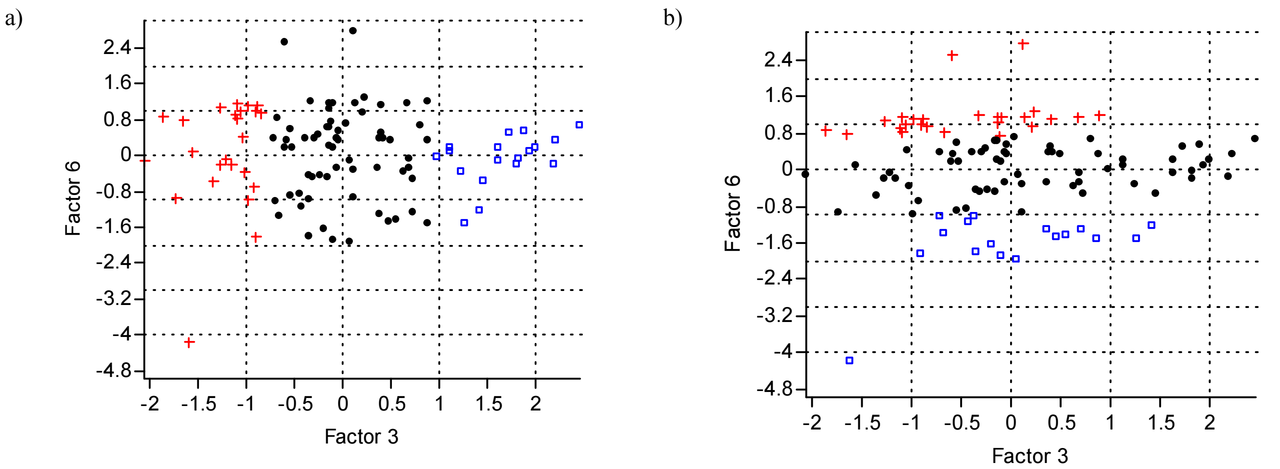

Fig. 9. Groupings of river monitoring stations along the axis of the aeration-organic (a) decay (3rd) and the turbidity (b) factor (6th) in the autumn-winter season (boxes – stations with most negative coordinates (factor scores), crosses – stations with most positive coordinates)

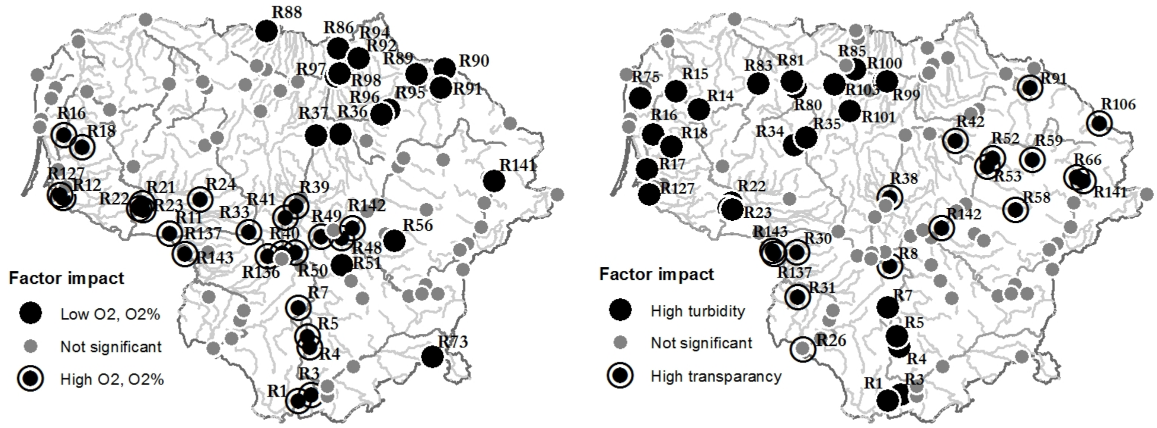

Fig. 10. River monitoring stations significantly affected by the aeration-organic decay (left) and the turbidity factor (right) in the autumn-winter season

et al. 2006; Spanos *et al.* 2003; Tarrado *et al.* 2006; Vega *et al.* 1998; Vidal *et al.* 2000; Voutsa *et al.* 2001; Zhou *et al.* 2007) pool the data from many sampling sites together to act as an input for factor analysis, termed as spatial factor analysis in this study. This type of method application is more common since it provides an opportunity to extract spatial factors acting in space and to group sampling sites and even samples according different factors. This type of method utilization prooved to be very convenient in terms of visualisation. For instance, Tarrado *et al.* (2006) visualized factor scores gradient along the river Ebro in Spain.

In addition to solitary use the method can be succesfuly applied in conjunction with other multivariate techniques. The most often combination is with cluster analysis, when factor analysis is applied to search for affecting processes in separate clusters (Fitzpatrick *et al.* 2007; Kannel *et al.* 2007; Reisenhofer *et al.* 1998; Schaefer *et al.* 2010; Simeonov *et al.* 2002; Zhang *et al.* 2009) or to confirm the designated clusters (Alberto *et al.* 2001; Boyacioglu, H., Boyacioglu, H. 2008; Mendiguchia *et al.* 2004; Omo-Irabor *et al.* 2008; Razmkhah *et al.* 2010; Simeonov *et al.* 2003; Singh *et al.* 2006; Vidal *et al.* 2000).

In practice when investigating river water status and the reasons behind it, it is recommended to apply factor analysis in combination with water quality modeling and other multivariate statistical methods. When using those methods in combination, modeling approach has an advantage in quantification of inputs and impacts of different pollution sources on river water quality – this is a feature needed for the selection of water status enhancing measures and the estimation of their potential effectiveness. However, factor analysis could potentially identify impacts and processes that the models could not reveal. This is quite a common occurrence, because modeling results are very much dependent on their structure and the input data – if there is a lack of information on particular sources of substances or it is even not expected that particular pollution sources exist in the investigated area, then this contaminant flow will not be taken into account in the modeling results. Another advantage of factor analysis is its ability to uncover situations, when water quality problems are caused by natural processes and it is not feasible to take any measures to improve water quality.

It is recommended to consider factor analysis as one of possible tools when optimizing river monitoring network and the parameters analyzed. In this case factor analysis tool would be most appropriate if the task is to select stations, representative of particular types of human impacts or natural processes as well as to select the most important processes-related parameters to measure there. However, when the task is to identify stations representative of stations groups with different levels of physico-chemical elements concentrations, the combination of cluster (CA) and discriminant analysis (DA) is recommended. CA and DA will enable to group stations according to the similarity of the concentrations of the substances as well as to identify parameters that differ the most among clusters. The identified parameters should be subject to monitoring afterwards. If there is a need to satisfy all the aforementioned needs then a combined use of FA, CA and DA methods is recommended.

Conclusions

1. The status of water ecosystems and the reasons behind it can be determined in a confident and complex way by simultaneously assessing all physico-chemical data and its interrelationships by the use of appropriate multivariate statistical methods. Such kind of the analysis empowers the understanding of not only separate water ecosystem components but also of the whole interacting system, enabling to take better water management decisions.

2. The combination of spatial and local factor analysis can be successfully applied as a tool, which can simultaneously group river monitoring sites into groups of similar values of particular water quality parameters and identify main processes that determine water quality in those groups.

3. The *Wastewater*, *Agro-geological* and *Hardly degradable organics* factors are the main ones affecting Lithuanian river water quality in all seasons.

4. *Wasterwater* factor is prominent in small rivers downstream larger towns and is reflected by low oxygen and high NH_4-N, NO_2-N, N_{org}, PO_4-P, P_{org}, COD_{Cr}, Na^+, K^+, Cl^- concentrations in water.

5. *Agro-geological* factor is pronounced in northern Lithuania's rivers of heavy carbonated soils and intensively used agricultural lands in their catchments which determine elevated Ca^{2+}, Mg^2+, HCO_3^- and SO_4^{2-} content in streamwater, as well as in south-eastern Lithuania's rivers where more acidic soils prevail in their watersheds determining higher abundance of Fe and Si.

6 *Hardly degradable organics* factor is mostly evident in northern and middle Lithuania's rivers draining heavy-textured soils in fertile agricultural areas securing increased quantities of COD_{Cr}, COD_{Mn} and TOC.

7 The *photosynthesis-vegetation* factor is acting only in the summer season and only in Lithuanian largest rivers, and is represented by abundance of suspended organics (SM, BOD_7), elevated pH and dissolved oxygen levels, resulting from intensive algal photosynthetic activity that is common in big rivers.

8. The *Aeration* and *Turbidity* factors represent the processes that take place in autumn-winter only. The former being noticeable by relatively high dissolved oxygen content in large Lithuanian rivers, while the latter being known for turbid waters of hilly region of western Lithuania.

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 spatial and temporal variations in water quality. a case study: Suquia river basin (Cordoba-Argentina), *Wat. Res*. 35: 2881–2894. http://dx.doi.org/10.1016/S0043-1354(00)00592-3

Aruga, R.; Gastaldi, D.; Negro, G.; Ostacoli, G. 1995. Pollution of a river basin and its evolution with time studied by multivariate statistical analysis, *Analytica Chimica Acta* 310: 15–25. http://dx.doi.org/10.1016/0003-2670(95)00101-5

Azzellino, A.; Salvetti, R.; Vismara, R.; Bonomo, L. 2006. Combined use of the EPA-QUAL2E simulation model and factor analysis to assess the source apportionment of point and non point loads of nutrients to surface waters, *Science of the Total Environment* 371: 214–222. http://dx.doi.org/10.1016/j.scitotenv.2006.03.022

Boyacioglu, H.; Boyacioglu, H. 2007. Surface water quality assessment by environmetric methods, *Environ. Monit. Assess*. 131: 371–376. http://dx.doi.org/10.1007/s10661-006-9482-4

Boyacioglu, H.; Boyacioglu, H. 2008. investigation of temporal trends in hydrochemical quality of surface water in Western Turkey, *Bulletin of Environmental Contamination and Toxicology* 80: 469–474. http://dx.doi.org/10.1007/s00128-008-9439-0

Brodnjak-Voncina, D.; Dobcnik, D.; Novic, M.; Zupan, J. 2002. Chemometrics characterisation of the quality of river water, *Analytica Chimica Acta* 462: 87–100. http://dx.doi.org/10.1016/S0003-2670(02)00298-2

Charkhabi, A. H.; Sakizadeh, M. 2006. Assessment of spatial variation of water quality parameters in the most polluted branch of the Anzali wetland, Northern Iran, *Polish Journal of Environmental Studies* 15: 395–403.

Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy. *Official Journal (OJ L 327).*

Fitzpatrick, M. L.; Long, D. T.; Pijanowski, B. C. 2007. Exploring the effects of urban and agricultural land use on surface water chemistry, across a regional watershed, using multivariate statistics, *Applied Geochemistry* 22: 1825–1840. http://dx.doi.org/10.1016/j.apgeochem.2007.03.047

Kannel, R. P.; Lee, S.; Kanel, S. R.; Kahn, S. P. 2007. Chemometric application in classification and assessment of monitoring location of an urban river system, *Analytical Chimica Acta* 582: 390–399. http://dx.doi.org/10.1016/j.aca.2006.09.006

Koklu, R.; Sengorur, B.; Topal, B. 2010. water quality assessment using multivariate statistical methods-a case study: melen river system (Turkey), *Water Resources Management* 24: 959–978. http://dx.doi.org/10.1007/s11269-009-9481-7

Kowalkowski, T.; Zbytniewski, R.; Szpejna, J.; Buszewski, B. 2006. Application of chemometrics in river water classification, *Water Research* 40: 744–752. http://dx.doi.org/10.1016/j.watres.2005.11.042

Kunwar, P. S.; Malik, A.; Sinha, S. 2005. Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques – a case study, *Analytica Chimica Acta* 538: 355–374. http://dx.doi.org/10.1016/j.aca.2005.02.006

Marques da Silva, A. M.; Sacomani, L. B. 2001. Using chemical and physical parameters to define the quality of Pardo river water (Botucatu – SP-Brazil), *Water Research* 35: 1609–1616. http://dx.doi.org/10.1016/S0043-1354(00)00415-2

Mendiguchia, C.; Moreno, C.; Galindo-Riano, M. D.; Garcia-Vargas, M. 2004. Using chemometric tools to assess anthropogenic effects in river water. a case study: Guadalquivir river (Spain), *Analytica Chimica Acta* 515: 143–149. http://dx.doi.org/10.1016/j.aca.2004.01.058

Morales, M. M.; Marti, P.; Llopis, A.; Campos, L.; Sagrado, S. 1999. An environmental study by factor analysis of surface seawaters in the gulf of Valencia (Western Mediterranean), *Analytica Chimica Acta* 394: 109–117. http://dx.doi.org/10.1016/S0003-2670(99)00198-1

Omo-Irabor, O. O.; Olobaniyi, S. B.; Oduyemi, K.; Akunna, J. 2008. Surface and groundwater water quality assessment using multivariate analytical methods: a case study of the Western Niger Delta, Nigeria, *Physics and Chemistry of the Earth* 33: 666–673. http://dx.doi.org/10.1016/j.pce.2008.06.019

Ouyang, Y.; Nkedi-Kizza, P.; Wu, Q. T.; Shinde, D.; Huang, C. H. 2006. Assessment of seasonal variations in surface water quality, *Water Research* 40: 3800–3810. http://dx.doi.org/10.1016/j.watres.2006.08.030

Papatheodorou, G.; Demopoulou, G.; Lambrakis, N. 2006. A long-term study of temporal hydrochemical data in a shallow lake using multivariate statistical techniques, *Ecological Modelling* 193: 759–776. http://dx.doi.org/10.1016/j.ecolmodel.2005.09.004

Povilaitis, A. 2003. Pagrindinių jonų koncentracijų karstinio regiono upėse panašumų ir skirtumų statistinis įvertinimas [Statistical assessment of similarities and differences in the concentrations of the main ions in the carstic region rivers], *Vandens ūkio inžinerija* 22(44): 5–14.

Qadir, A.; Malik, R. N.; Husain, S. Z. 2008. Spatio-temporal variations in water quality of Nullah Aik-tributary of the river Chenab, Pakistan, *Environ. Monit. Assess.* 140: 43–59. http://dx.doi.org/10.1007/s10661-007-9846-4

Razmkhah, H.; Abrishamchi, A.; Torkian, A. 2010. Evaluation of spatial and temporal variation in water quality by pattern recognition techniques: a case study on Jajrood River (Tehran, Iran), *Journal of Environmental Management* 91: 852–860. http://dx.doi.org/10.1016/j.jenvman.2009.11.001

Reisenhofer, E.; Adami, G.; Barbieri, P. 1998. Using chemical and physical parameters to define the quality of karstic freshwaters (Timavo River, North-eastern Italy): a chemometric approach, *Water Research* 32: 1193–1203. http://dx.doi.org/10.1016/S0043-1354(97)00325-4

Santos-Roman, D. M.; Warner, G. S.; Scatena, F. 2003. Multivariate analysis of water quality and physical characteristics of selected watersheds in Puerto Rico, *Journal of the American Water Resources Association* 39: 829–839. http://dx.doi.org/10.1111/j.1752-1688.2003.tb04408.x

Schaefer, K.; Einax, J. W. 2010. Analytical and chemometric characterization of the Cruces River in South Chile, *Environmental Science and Pollution Research* 17: 115–123. http://dx.doi.org/10.1007/s11356-009-0116-6

Simeonov, V.; Einax, J. W.; Stanimirova, I.; Kraft, J. 2002. Environmetric modeling and interpretation of river water monitoring data, *Analytical and Bioanalytical Chemistry* 374: 898–905. http://dx.doi.org/10.1007/s00216-002-1559-5

Simeonov, V.; Stratis, J. A.; Samara, C.; Zachariadis, G.; Voutsa, D.; Anthemidis, A.; Sofoniou, M.; Kouimtzis, T. 2003. Assessment of the surface water quality in Northern Greece, *Water Research* 37: 4119–4124. http://dx.doi.org/10.1016/S0043-1354(03)00398-1

Singh, K. P.; Malik, A.; Singh, V. K. 2006. Chemometric analysis of hydro-chemical data of an alluvial river - a case study, *Water, Air, and Soil Pollution* 170: 383–404. http://dx.doi.org/10.1007/s11270-005-9010-0

Sojka, M.; Siepak, M.; Ziola, A.; Frankowski, M.; Murat-Blazewska, S.; Siepak, J. 2008. Application of multivariate statistical techniques to evaluation of water quality in the Mala Welna River (Western Poland), *Environ. Monit. Assess.* 147: 159–170. http://dx.doi.org/10.1007/s10661-007-0107-3

Spanos, T.; Simeonov, V.; Stratis, J.; Xristina, X. 2003. Assessment of water quality for human consumption, *Microchim Acta* 141: 35–40. http://dx.doi.org/10.1007/s00604-002-0921-9

Tarrado, M.; Barcelo, D.; Tauler, R. 2006. Identification and distribution of contamination sources in the Erbo river basin by chemometrics modeling coupled to geographical information systems, *Talanta* 70: 691–704. http://dx.doi.org/10.1016/j.talanta.2006.05.041

Vaikasas, S. 2010. Mathematical modelling of sediment dynamics and their deposition in Lithuanian rivers and their deltas (case studies), *Journal of Environmental Engineering and Landscape Management* 18(3): 207–216. http://dx.doi.org/10.3846/jeelm.2010.24

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 Research* 32: 3581–3592. http://dx.doi.org/10.1016/S0043-1354(98)00138-9

Vidal, M.; Lopez, A.; Santoalla, M. C.; Valles, V. 2000. Factor analysis for the study of water resources contamination due to the use of livestock slurries as fertilizer, *Agricultural Water Management* 45: 1–15. http://dx.doi.org/10.1016/S0378-3774(99)00073-6

Voutsa, D.; Manoli, E.; Samara, C.; Sofoniou, M.; Stratis, I. 2001. A study of surface water quality in Macedonia, Greece: speciation of nitrogen and phosphorus, *Wat., Air. Soil. Poll.* 129: 13–32. http://dx.doi.org/10.1023/A:1010315608905

Zhang, Y.; Guo, F.; Meng, W.; Wang, X. 2009. Water quality assessment and source identification of Daliao river basin using multivariate statistical methods, *Environmental Monitoring and Assessment* 152: 105–121. http://dx.doi.org/10.1007/s10661-008-0300-z

Zhou, F.; Guo, H.; Liu, Y.; Jiang, Y. 2007. Chemometrics data analysis of marine water quality and source identification in Southern Hong Kong, *Marine Pollution Bulletin* 54: 745–756. http://dx.doi.org/10.1016/j.marpolbul.2007.01.006

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