Ecological Informatics 5 (2010) 79–88

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Phytoplankton assemblages, environmental influences and trophic status using canonical correspondence analysis, fuzzy relations, and linguistic translation

Janice L. Pappas *

Museum of Paleontology, University of Michigan, 1109 Geddes Ave., Ann Arbor, MI 48109-1079, United States

ARTICLE INFO

Article history:
Received 15 May 2009
Received in revised form 26 August 2009
Accepted 27 August 2009

Keywords:
Diatoms
Environmental indicator
Fuzzy relation
Linguistic modifiers
Great Lakes
Seasonal succession

ABSTRACT

In a global assessment, canonical correspondence analysis (CCA) and partial CCA were used to ordinate Lake Huron phytoplankton abundances from June and August 1991 and environmental variables. June taxa were associated with NO_3 and chloride, while August taxa were associated with SiO_2 and temperature, and to some degree, with TSP and NH_3. Dominant taxa were *Asterionella formosa*, *Fragilaria capucina*, *Fragilaria crotonensis*, *Tabellaria fenestrata*, and *Urosolenia eriensis* in June, and *Achnanthidium minutissimum*, *Cyclotella* #6, *Cyclotella comensis*, *Cyclotella michiganiana*, and *Cyclotella pseudostelligera* in August reflecting seasonal change. From local analysis using results from CCA and partial CCA in fuzzy relational analysis, *A. minutissimum* and *C. comensis* were influential in June, while *F. crotonensis* was influential in August. From linguistic translation and trophic status assignment, *F. capucina* and *T. fenestrata* indicated eutrophy, *A. formosa* indicated mesotrophy, *C. pseudostelligera* indicated mesotrophy–eutrophy, *F. crotonensis* and *U. eriensis* indicated oligotrophy–eutrophy, *Cyclotella* #6 indicated oligotrophy–mesotrophy, and *C. michiganiana* indicated oligotrophy. A linguistic solution with respect to trophic status is useful for policy makers and others interested in understanding water quality and ways to develop decisions about remediation.

1. Introduction

Phytoplankton are a major part of the aquatic food web and are important for relational and predictive schema for ecological assessment of the Great Lakes. Phytoplankton assemblages have been used for some time as water quality bioindicators in the Great Lakes (Stoermer, 1978). Of the phytoplankton, diatoms are recognized as bioindicators by governmental agencies and used in water quality assessment in North America (e.g., USEPA Environmental Monitoring and Assessment Program; USGS National Water-Quality Assessment Program; Great Lakes Environmental Indicators Project; Great Lakes Water Quality (Canada)) and Europe (e.g., Water Framework Directive; Biological Diatom Index). Their importance as such is evident in many studies on topics including eutrophication (e.g., Hall and Smol, 1999), lake acidification (e.g., Battarbee et al., 1999), hydrologic and climatic change in lakes (e.g., Fritz et al., 1999), and in oceans (e.g., Sancetta, 1999). Diatoms are widely distributed (Harwood and Nikolaev, 1995) and account for a significant portion of the total worldwide primary production (van den Hoek et al., 1995; Mann, 1994, 1999). They are found in seawater, freshwater, brackish water, and soil (Round et al., 1990). Not only are they found in the plankton, but also on a variety of substrates, including rocks, sand, plants, and animals (Round et al., 1990). Individual species are adapted to a wide range of environmental conditions, including 83 °C geyser pools and −2 °C polar sea ice in Iceland (Harwood and Nikolaev, 1995), hot springs in Iceland (Villeneuve and Pienitz, 1998), the Arctic (Hamilton et al., 1994), and in the Antarctic (Spaulding and McKnight, 2000).

In ecological studies, temporal variability, spatial scaling, qualitative, and quantitative measures are characteristic of data used in assessment. Because of their siliceous frustules, diatoms are preserved in the sediments (e.g., Wolin et al., 1988), and along with availability in water, provide a long temporal record in aquatic systems such as the Great Lakes. Diatoms occur nearshore and offshore, at the surface and throughout the water column, so they also provide a spatial record.

To model complexities of ecosystems, multivariate statistics have been used. These methods are widely accepted and proven ways to transform raw data into a biplot picture of variation (Gower and Hand, 1996). For example, the variation may be a gradient (ter Braak, 1986) or separation of groups as a result of using canonical correspondence analysis (CCA) (ter Braak, 1988a; Jongman et al., 1995). If the raw data do not produce an interpretable picture, data transformation or standardization may be used (Noy-Meir, 1973; Noy-Meir et al., 1975). The picture that emerges from using these techniques is relational in interpretation, but geometric as a result of actual numerical analysis. The exploratory or explanatory results reflect the complexity of ecological data, but these results have limited use in ecosystem modeling over temporal and spatial scales, especially for predictive purposes.

In general, there are at least three matters that are relevant for consideration in ecological assessment research. First, there is a great

* Tel.: +1 734 764 7207; fax: +1 734 936 1380.
E-mail address: jlpappas@umich.edu.

1574-9541/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.ecoinf.2009.08.005

need to integrate ecological data across temporal and spatial scales. Existing data gleaned from disparate sources might represent brief, short events during a single time period or at a particular stratum in a lake. Using such data to develop a realistic picture of the complexities of an ecosystem is a challenge. Second, there is a need to combine qualitative and quantitative data to make the best use of all the available information. Theoretical models determine the kind of data that are informative, while the data collected provide the constraints to construct a model. There is a challenge in combining numerical and non-numerical measures that mesh within a realistic model. Finally, in using data and models, stochasticity and observational limitations manifested as uncertainty are separate but important determinants in devising a realistic picture of an ecosystem. Moreover, randomness is not necessarily representative of all the various types of uncertainties inherent in an ecosystem. This point is important in devising mathematical procedures for use in assessment models that clarify which underlying biological principles are at work in an ecosystem, and to what degree non-random uncertainty is not accounted for by such a model.

Sometimes, data sets used in ecological analysis are deficient in one way or another. For example, abundance data may not have a sufficient level of specificity of taxon names or identifications. Chemical data may contain some but not all concentrations for nutrients or trace elements or organics. These deficiencies are a kind of inherent uncertainty. Even relatively complete data sets may contain uncertainties.

Over the years, much data has been collected with regard to the ecological status of the Great Lakes. Theoretical models can be devised to model non-random uncertainty using fuzzy set theory (Zadeh, 1965). In ecology, the methods used to analyze data are second only to the data themselves. Despite uncertainty inherent in data, many methods do not reflect this. Conceptualizing ecological data as relational, using fuzzy set theory (Roberts, 1986, 1987, 1989) or fuzzy coding (Pappas and Stoermer, 1995), has been increasingly recognized for its potential in modeling the inherent uncertainty in such data.

By using results from multivariate analysis as an exploratory or explanatory phase in assessing a region of the Great Lakes, fuzzy relational analysis (e.g., Zimmermann, 2001), as an extension of fuzzy set theory, can be used to make water quality assessments based on groups of taxa and the effects of individual inputs into the ecosystem as well as the degree of effects with respect to interaction among taxa. Linguistic translation of results would make such results accessible to policy makers.

We are interested in applying fuzzy set theory and fuzzy relational analysis to assess the status of one area of the Great Lakes, including modeling the uncertainty that is inherent in analyzing such data. Fuzzy set theory and fuzzy relational analysis provide a way to model the complexities of ecosystems and make assessments in both a quantitative and linguistic fashion. This is important not only in making a realistic scientific assessment, but also in making scientific results understandable to policy makers and the public. Developing quantitative methods for use in ecological studies of complex problems is useful in advancing the understanding of ecosystems, and translating quantitative results into understandable language promotes the possibility of enacting effective remediation.

Our study involves developing a comparative fuzzy relational and pictorial presentation of seasonal changes between phytoplankton assemblages in Lake Huron and determines which taxa are environmental indicators (or bioindicators) of trophic status at different times of the year. Moreover, we aggregate the results from each month to be used as a basis for linguistic translation with respect to degree of truth in the results. Linguistic solution of numerical results facilitates usage of results by any individual interested in understanding environmental conditions of Lake Huron, including the public and policy makers. In addition, we provide an environmental assessment of changes over a period of years by comparing our results to previous studies.

2. Methods

2.1. Data collection and statistical analysis

Phytoplankton were collected from surface samples in Lake Huron near Port Huron, MI in June and August 1991, and data from this collection was used as the basis for study. (Although the data used in this study are seemingly dated, when available, more recent data may be used with the methods herein described. That is, the methods given are applicable, regardless of the content of the data used.) In the field, temperature was measured at the time of sample collection. For chemical analyses, a 750 ml subsample was measured colorimetrically using a Technicon Autoanalyzer in the laboratory (Schelske et al., 1974). Chemical constituents measured were silica (SiO_2), total soluble phosphorus (TSP), nitrate (NO_3), ammonia (NH_3), and chloride (Cl^-). From the phytoplankton assemblages, 50 ml subsamples were fixed with glutaraldehyde and filtered (Stoermer et al., 1978). Identification and enumeration of phytoplankton were accomplished using a Leitz Ortholux microscope furnished with oil immersion objective with numerical aperture of 1.3 with a magnification of 1250×. From our study, 121 taxa were identified and enumerated. For more on the methods of slide preparation and species enumeration, see Stoermer et al. (1978). For taxa not identifiable to species level, the numbering system used is that of Stoermer and Yang (1969).

Multivariate statistical data analysis was accomplished using canonical correspondence analysis (CCA) and partial CCA (ter Braak, 1988b, 1990) to recover global information about the taxa and their environment. Using CCA, phytoplankton relative abundances constrained by environmental variables were converted to approximate weighted averages per canonical vector (ter Braak, 1988a,b). Each canonical vector may be defined as the relative importance of each taxon, since each canonical vector is a composite gradient of those environmental variables that have the most influence. Intraset correlation coefficients represent relative importance of environmental variables per canonical axis. Both weighted averages and intraset correlation coefficients per canonical axis form the basis of importance matrices for use in local analysis.

For such an analysis on a local scale, fuzzy set theory and fuzzy relations (Zimmermann, 2001) were used to analyze dominant taxa whose influence is largest in terms of environmental variables with respect to the assemblage as a whole. Taxon weighted averages and environmental intraset correlation coefficients per canonical axis were fuzzified as

$$\mu_{\tilde{A}}(x) = \left(\frac{f(x) - \inf(x)}{\sup(x) - \inf(x)}\right) \tag{1}$$

where $\mu_{\tilde{A}}(x)$ is a fuzzy membership function of fuzzy set $\tilde{A}$, $\mu_{\tilde{A}}(x)$: $X \rightarrow [0, 1]$, $\forall\ x \in X$ for fuzzy weighted averages or fuzzy intraset correlation coefficients, $f(x)$, per canonical axis, *inf* is the infimum or greatest lower bound, and *sup* is the supremum or least upper bound.

From fuzzification, a comparison is made between June and August taxa. Degree of influence of environmental variables on taxa as well as the degree to which taxa was indicative of environmental conditions was examined using fuzzy relational analysis. These results were translated into ordinary language for use by individuals such as policy makers and depicted in diagrammatic or graphical form.

2.2. Fuzzy set theory and fuzzy relational analysis

In fuzzy set theory, let X be a non-empty set that is defined as the universe of discourse where the elements of X are x_1, x_2, …, x_n. A subset of X is defined as fuzzy set, $\tilde{A}$, where

$$\tilde{A} = \left\{(x, \mu_{\tilde{A}}(x)) \mid x \in X\right\}, \tag{2}$$

and let universe of discourse Y with elements $y_1, y_2, \ldots, y_n$ be a non-empty set with a subset of Y defined as a second fuzzy set, $\tilde{B}$, where

$$\tilde{B} = \left\{(y, \mu_{\tilde{B}}(y)) \,|\, y \in Y\right\}. \tag{3}$$

The fuzzy set is a grade of membership on the interval [0, 1], or μ: $\tilde{A} \to [0, 1]$ and μ: $\tilde{B} \to [0, 1]$ are mappings where each element x or y is assigned a degree of membership $0 \leq \mu_{\tilde{A}}(x) \leq 1$ or $0 \leq \mu_{\tilde{B}}(y) \leq 1$, respectively. For aggregation purposes, fuzzy set-theoretic operators *max* is used as the union and *min* is used as the intersection (e.g., Dubois and Prade, 1980). They are defined as

$$\forall x \in X, \mu_{\tilde{A} \cap \tilde{B}}(x) = \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)) \tag{4}$$

and

$$\forall x \in X, \mu_{\tilde{A} \cup \tilde{B}}(x) = \max(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)) \tag{5}$$

(Dubois and Prade, 1980; Zimmermann, 2001).

Similarly, fuzzy relations can be defined and are fuzzy sets in product or Cartesian spaces (Zimmermann, 2001). Let a fuzzy relation for X and Y be defined as

$$R = \left\{[(x, y), \mu_R(x, y)] \,|\, (x, y) \in X \times Y\right\}, \tag{6}$$

where the fuzzy relation, R, is in the Cartesian product space $X \times Y$. The fuzzy relation is a grade of membership of ordered pairs on the interval [0, 1], or $\mu_{\tilde{R}}$: $X \times Y \to [0, 1]$ is a mapping where elements x and y are assigned a degree of membership $0 \leq \mu_{\tilde{R}}(x, y) \leq 1$. For n-ary fuzzy relations,

$$R_1(x, y), (x, y) \in X \times Y \text{ and } R_2(y, z), (y, z) \in Y \times Z. \tag{7}$$

Fuzzy relations in different product spaces can be combined using the composition of relations. The *max–min* composition is defined as

$$\tilde{R}_1 \circ \tilde{R}_2 = \left\{\left[(x, z), \max_y\{\min\{\mu_{\tilde{R}_1}(x, y), \mu_{\tilde{R}_2}(y, z)\}\}\right] | x \in X, y \in Y, z \in Z\right\}. \tag{8}$$

Aggregation operations are defined as

$$R^{(1)} = \left\{\left(x, \max_y \mu_{\tilde{R}}(x, y)\right) \middle| (x, y) \in X \times Y\right\} \tag{9}$$

for the first projection,

$$R^{(2)} = \left\{(y, \max_x \mu_{\tilde{R}}(x, y)) \middle| (x, y) \in X \times Y\right\} \tag{10}$$

for the second projection, and

$$R^{(T)} = \max_x \max_y \left\{\mu_{\tilde{R}}(x, y) \,|\, (x, y) \in X \times Y\right\} \tag{11}$$

for the total projection. The cylindrical extension of the projection relation is the largest fuzzy relation (Zimmermann, 2001).

To depict fuzzy relations, fuzzy diagrams will be constructed. These diagrams will be useful in showing the degree of influence with respect to environmental variables. Moreover, from fuzzy relational operations and diagrams of the results, the degree to which taxa are useful as environmental indicators is determined. Using results from fuzzy relational analysis, seasonal succession from June to August may be given numerically and depicted in graphical form. From fuzzy relational analysis, normalized results may be used in linguistic translation.

2.3. Linguistic translation and fuzzy decision-making

Linguistic solutions (Zadeh, 1975; Tong and Bonissone, 1984; Pappas, 2006) reflecting degree of truth (Bellman and Zadeh, 1977; Baldwin, 1979) is used to make results accessible to the public and policy makers. From fuzzy relational results, a linguistic solution is devised using the second projection (Eq. (10)) of degree of environmental influence from fuzzy relational analysis. The second projection is used since this represents the degree of influence that environmental variables have with respect to change in community structure. Moreover, the second projection is a summary value of the degree to which each taxon is an indicator of environmental conditions, and these values may form the basis for linguistic translation.

Linguistic modifiers (or hedges) are used with regard to the conditions associated with water quality. Typically, trophic status is an important determinant in decision-making in terms of environmental remediation. The second projection (Eq. (10)) from fuzzy relational analysis is normalized and evaluated with reference to what is known about trophic indicator species from the scientific literature.

A fuzzy trophy set is devised and meaningful labels are determined by linguistic approximation using a semantic equivalence (Zadeh, 1975, 1978). The equivalent set, L, is inclusively L (*Trophy*) = {*mostly eutrophic, more eutrophic than oligotrophic* (=*mesotrophic*), *more oligotrophic than eutrophic, mostly oligotrophic*} and is defined as

$$\textit{Mostly eutrophic} = \{0.75 < x \leq 1\}$$

$$\textit{More eutrophic than oligotrophic (or mesotrophic)} = \{0.50 < x \leq 0.75\}$$

$$\textit{More oligotrophic than eutrophic} = \{0.25 < x \leq 0.50\}$$

$$\textit{Mostly oligotrophic} = \{0 < x \leq 0.25\}$$

where x is the normalized second projection value of a taxon. For $x = 1$, total eutrophy is defined, and for $x = 0$, totally pristine conditions exist. With published information on the environmental tolerances of each taxon to trophic level, assignment of trophic indicator status to each taxon is accomplished via the *max* function of aggregation.

For fuzzy decision-making, the *max* function (Zimmermann, 2001) is used to aggregate normalized second projection values and represent linguistic truth-values for each taxon as an indicator of trophic conditions. From the fuzzy trophy set, each taxon is assigned a label, and these labels are then evaluated with respect to published information on trophic status for each taxon. Evaluation is accomplished via construction of a fuzzy truth table where T is "true", F is "false", and $T+F$ is "undecided" (Zimmermann, 2001). That is, each taxon is identified to the degree to which it is a true indicator of environmental conditions.

3. Results

3.1. Canonical correspondence analysis

CCA was used to explore the relation between abundance and environmental variables. In CCA, a biplot of species scores, site scores, and environmental variables was devised and depicted as an ordination (Fig. 1). Species scores are approximate weighted averages that indicate optimal response to environmental variables, and intraset correlation coefficients indicate the strength of environmental influences (ter Braak, 1986; Jongman et al., 1995). Partial CCAs were conducted to determine particular environmental influences by partialling out the effects of all but those environmental variables that are highly correlated with each canonical axis.

From CCA, the first four eigenvalues were 0.57, 0.18, 0.16, and 0.09, and 89% of the species variation was explained. A Monte Carlo permutation test of the null model using 99 permutations produced a F-ratio of 1.04 with a P-value of 0.04 for the first canonical axis and a F-ratio of 1.96 and a

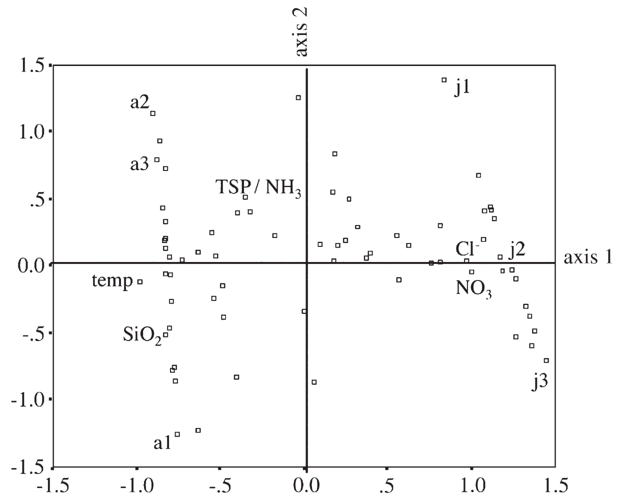

Fig. 1. CCA ordination of June and August, 1991 Lake Huron assemblages. Site scores for June are j1, j2, and j3, and for August are a1, a2, and a3. Environmental variables are also indicated. See text for description of environmental variables.

P-value of 0.08 for the trace. Intraset correlation coefficients showed that SiO_2 and temperature were highly negatively correlated (−0.83 and −0.98, respectively), while NO_3 and Cl^- were highly positively correlated (0.99 and 0.97, respectively) with the first constrained eigenvector. On that same eigenvector, June and August samples were separated in constrained environmental space (Fig. 1).

From the first partial CCA that tested for the effects of NO_3 and Cl^-, the eigenvalues were 0.176 and 0.129 for the first and second canonical axes. Intraset correlation coefficients for the first constrained eigenvector were −0.958 for NO_3 and −0.932 for Cl^-. The eigenvalues for the first and second canonical axes for the second partial CCA that tested for the effects of SiO_2 and temperature were 0.180 and 0.107, respectively. On the first constrained axis, SiO_2 and temperature had intraset correlation coefficients of −0.966 and −0.553, respectively.

Based on abundances and results from CCA and partial CCA, the dominant taxa that represent phytoplankton assemblages for June were *Asterionella formosa*, *Fragilaria capucina*, *Fragilaria crotonensis*, *Urosolenia eriensis*, and *Tabellaria fenestrata*. For August, the dominant taxa were *Achnanthidium minutissimum*, *Cyclotella* #6, *Cyclotella comensis*, *Cyclotella michiganiana*, and *Cyclotella pseudostelligera*. These taxa formed the basis of fuzzy relational analysis.

3.2. Fuzzy relational analysis

Using taxon weighted averages means representing taxa that are influenced by environmental variables to varying degrees. That is, taxa weighted averages represent optimal abundances constrained by the presence of particular environmental influences (ter Braak, 1996). Intraset correlation coefficients indicate degree of strength of environmental influence. To determine particular effects that particular environmental variables have on each taxon, fuzzy set theory and fuzzy relations were used to analyze a subsample of the ten dominant taxa previously mentioned—five from June and five from August. Fuzzification of species scores or intraset correlation coefficients was accomplished via normalization per canonical axis and produced fuzzy importance matrices (Table 1).

June taxon abundances are more highly influenced by NO_3 and Cl^-, and August taxon abundances are more highly influenced by SiO_2 and temperature (Table 2). This result is more succinctly indicated in the first projection (Table 3). The second projection indicates that NO_3 and Cl^- influenced taxa to a higher degree than other environmental variables (Table 3).

Results from *max–min* composition of fuzzified CCA weighted averages and fuzzified partial CCA weighted averages for NO_3 and Cl^- are presented in Table 4 and also represented by a fuzzy graph (Fig. 2). In Table 4, reading down columns gives the degree of influence of taxa as proxies for NO_3 and Cl^-, and reading across rows gives the degree of influence for all environmental variables. The first projection reflects taxon proxies for all environmental variables, while the second projection reflects June and August taxon proxies for NO_3 and Cl^- influence.

For SiO_2 and temperature, results of *max–min* composition of fuzzified CCA weighted averages and fuzzified partial CCA weighted averages are presented in Table 5. The results are also presented in a fuzzy graph (Fig. 3). Degree of influence of taxa as proxies for SiO_2 and temperature is found in columns, and degree of influence for al environmental variables

Table 1
Fuzzy importance matrices from CCA results.

	Species axis 1	Species axis 2	Species axis 3	Species axis 4
Temperature	0.00	0.43	0.48	0.17
SiO_2	0.08	0.00	1.00	0.27
TSP	0.33	1.00	0.00	1.00
NH_3	0.33	1.00	0.00	1.00
Cl^-	0.99	0.59	0.97	0.00
NO_3	1.00	0.51	0.60	0.13
Achnanthidium minutissimum	0.31	0.56	0.50	0.40
Asterionella formosa	0.89	0.46	0.31	0.40
Cyclotella #6	0.07	0.49	0.31	0.31
Cyclotella comensis	0.16	0.50	0.40	0.41
Cyclotella michiganiana	0.12	0.51	0.29	0.41
Cyclotella pseudostelligera	0.03	0.52	0.29	0.51
Fragilaria capucina	0.84	0.63	0.55	0.43
Fragilaria crotonensis	0.96	0.25	0.08	0.40
Tabellaria fenestrata	0.84	0.55	0.44	0.41
Urosolenia eriensis	0.88	0.50	0.37	0.42

Table 2
Max–min composition of fuzzy relations between fuzzified taxon weighted averages by fuzzified intraset correlation coefficients for all environmental variables, June and August 1991 data.

Taxon	Temperature	SiO_2	TSP	NH_3	Cl^-	NO_3
Achnanthidium minutissimum	0.48	0.50	0.56	0.56	0.56	0.51
Asterionella formosa	0.43	0.31	0.46	0.46	0.89	0.89
Cyclotella #6	0.43	0.31	0.49	0.49	0.49	0.49
Cyclotella comensis	0.43	0.40	0.50	0.50	0.50	0.50
Cyclotella michiganiana	0.43	0.29	0.51	0.51	0.51	0.51
Cyclotella pseudostelligera	0.43	0.29	0.52	0.52	0.52	0.51
Fragilaria capucina	0.48	0.55	0.63	0.63	0.84	0.84
Fragilaria crotonensis	0.25	0.27	0.40	0.40	0.96	0.96
Tabellaria fenestrata	0.44	0.44	0.55	0.55	0.84	0.84
Urosolenia eriensis	0.43	0.37	0.50	0.50	0.88	0.88

Table 3
From Table 1 results, projections of effects of all environmental variables across rows.

Taxon	1st projection	Environmental variable	2nd projection
Achnanthidium minutissimum	0.56	Temperature	0.48
Asterionella formosa	0.89	SiO_2	0.55
Cyclotella #6	0.49	TSP	0.63
Cyclotella comensis	0.50	NH_3	0.63
Cyclotella michiganiana	0.51	Cl^-	0.96
Cyclotella pseudostelligera	0.52	NO_3	0.96
Fragilaria capucina	0.84		
Fragilaria crotonensis	0.96		
Urosolenia eriensis	0.88		
Tabellaria fenestrata	0.84		

First projection—the higher the value, the more influence the environmental variable has on the taxon. Second projection indicates degree of influence by the environmental variable.

Table 4
Max–min composition of fuzzy relations of taxon fuzzified weighted averages of all environmental variables (rows) by NO_3 and Cl^- influence (columns), June and August 1991 data.

	Achnanthidium minutissimum	*Asterionella formosa*	*Cyclotella* #6	*Cyclotella comensis*	*Cyclotella michiganiana*	*Cyclotella pseudostelligera*	*Fragilaria capucina*	*Fragilaria crotonensis*	*Tabellaria fenestrata*	*Urosolenia eriensis*
Achnanthidium minutissimum	0.36	0.49	0.38	0.37	0.40	0.38	0.56	0.19	0.56	0.45
Asterionella formosa	0.53	0.46	0.40	0.46	0.40	0.41	0.55	0.19	0.46	0.45
Cyclotella #6	0.36	0.49	0.38	0.37	0.40	0.38	0.49	0.19	0.49	0.45
Cyclotella comensis	0.36	0.49	0.38	0.37	0.40	0.38	0.50	0.19	0.50	0.45
Cyclotella michiganiana	0.36	0.49	0.38	0.37	0.40	0.38	0.51	0.19	0.51	0.45
Cyclotella pseudostelligera	0.36	0.49	0.38	0.37	0.40	0.38	0.52	0.19	0.52	0.45
Fragilaria capucina	0.53	0.49	0.40	0.46	0.40	0.41	0.60	0.19	0.57	0.45
Fragilaria crotonensis	0.53	0.32	0.40	0.46	0.40	0.41	0.55	0.19	0.44	0.37
Tabellaria fenestrata	0.53	0.49	0.40	0.46	0.40	0.41	0.55	0.19	0.50	0.45
Urosolenia eriensis	0.53	0.49	0.40	0.46	0.40	0.41	0.55	0.19	0.55	0.45

are given in rows. The first projection is taxon proxies for all environmental variables, and the second projection is SiO_2 and temperature influence of June and August taxon proxies.

For June and August taxa as proxies for NO_3 and Cl^- as well as SiO_2 and temperature, respectively, the second projection (Eq. (10)) is given in numerical form in Table 6 with the degree of difference listed, and is depicted in fuzzy graphical form (Fig. 4). For the fuzzy graph, the darker the block, the more influence the taxon has on other individual taxa. For example, at the 0.5 or greater level, *Achnanthidium minutissimum*, *F. capucina* and *T. fenestrata* had greater influence with respect to all other taxa in June, and *Cyclotella* #6, *C. michiganiana*, *F. capucina*, and *T. fenestrata* had greater influence with respect to all other taxa in August (Fig. 4). Using Fig. 4, taxa are ranked with respect to how well they represent environmental conditions during either June or August. In June, the order of taxa from least influential to most influential are *F. crotonensis*, *Cyclotella* #6, *C. michiganiana*, *C. pseudostelligera*, *U. eriensis*, *C. comensis*, *Asterionella formosa*, *Achnanthidium minutissimum*, *T. fenestrata*, and *F. capucina*. In August, the least to most influential taxa are *Achnanthidium minutissimum*, *C. comensis*, *C. pseudostelligera*, *U. eriensis*, *F. crotonensis*, *Asterionella formosa*, *C. michiganiana*, *C.* #6, *T. fenestrata*, and *F. capucina*.

From the same figure (Fig. 4), taxa are identified as an indicator of environmental conditions to a degree for a particular month. Depending on the degree of darkness of the block (or higher maximum value), taxa that were better indicators of conditions in June were *Achnanthidium minutissimum* and *C. comensis*. In August, *F. crotonensis* was a better indicator of conditions as was *Cyclotella* #6, *C. michiganiana*, and *C. pseudostelligera*, albeit to a much lesser degree. *Asterionella formosa*, *F. capucina*, *U. eriensis*, and *T. fenestrata* had the same value for June and August, indicating that they were equally suited as environmental indicators for each month.

3.3. Linguistic translation and fuzzy decision-making

From the normalized second projections for June and August (Table 6), linguistic translation was devised for each dominant taxa with respect to indicator status for each month and in the aggregate via the *max* function (Table 7). For June, the taxa that were the most representative of the presence of NO_3 and Cl^- were *Achnanthidium minutissimum*, *F. capucina*, and *T. fenestrata*. For August with respect to SiO_2 and temperature, the most representative taxa were *Cyclotella* #6, *F. capucina*, and *T. fenestrata* (Table 7).

Many taxa were more truly representative of NO_3 and Cl^- conditions than not. For June, these taxa were *Asterionella formosa*, *Cyclotella* #6, *C. comensis C. michiganiana*, *C. pseudostelligera*, and *U. eriensis*. For August,

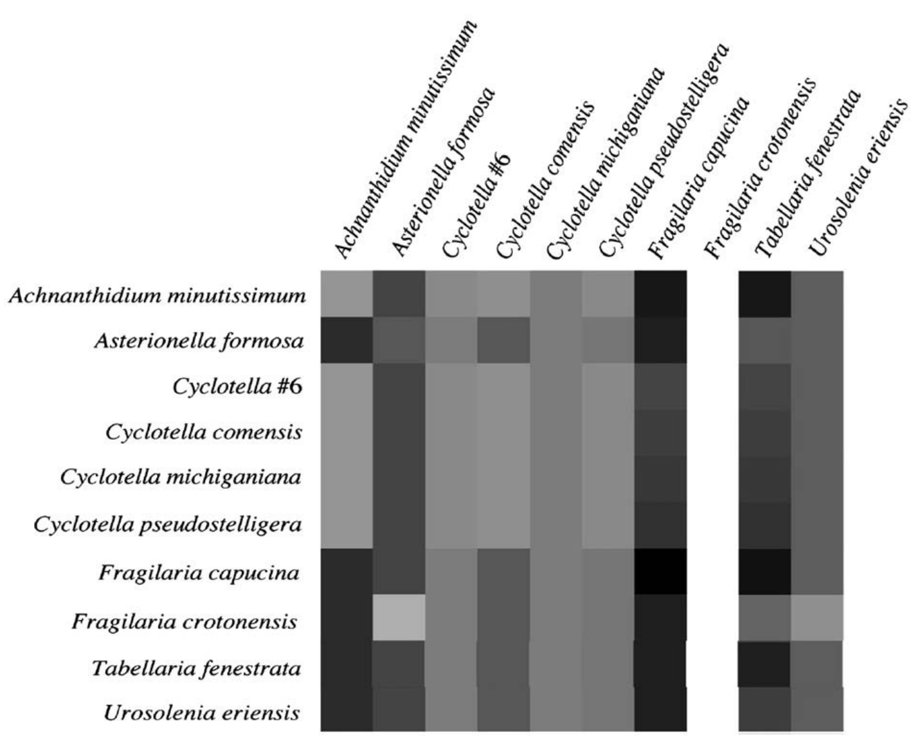

Fig. 2. Fuzzy graph of taxon–taxon influences with respect to NO_3 and Cl^- as given in Table 4.

Table 5
Max–min composition of fuzzy relations of taxon fuzzified weighted averages of all environmental variables (rows) by SiO_3 and temperature influence (columns), June and August 1991 data.

	Achnanthidium minutissimum	*Asterionella formosa*	*Cyclotella #6*	*Cyclotella comensis*	*Cyclotella michiganiana*	*Cyclotella pseudostelligera*	*Fragilaria capucina*	*Fragilaria crotonensis*	*Tabellaria fenestrata*	*Urosolenia eriensis*
Achnanthidium minutissimum	0.35	0.49	0.38	0.37	0.40	0.38	0.56	0.19	0.56	0.45
Asterionella formosa	0.40	0.46	0.55	0.43	0.50	0.43	0.46	0.48	0.46	0.45
Cyclotella #6	0.35	0.49	0.38	0.37	0.40	0.38	0.49	0.19	0.49	0.45
Cyclotella comensis	0.35	0.49	0.38	0.37	0.40	0.38	0.50	0.19	0.50	0.45
Cyclotella michiganiana	0.35	0.49	0.38	0.37	0.40	0.38	0.51	0.19	0.51	0.45
Cyclotella pseudostelligera	0.35	0.49	0.38	0.37	0.40	0.38	0.52	0.19	0.52	0.45
Fragilaria capucina	0.40	0.49	0.55	0.43	0.50	0.43	0.60	0.48	0.57	0.45
Fragilaria crotonensis	0.40	0.44	0.55	0.43	0.50	0.43	0.36	0.48	0.41	0.41
Tabellaria fenestrata	0.40	0.49	0.55	0.43	0.50	0.43	0.50	0.48	0.50	0.45
Urosolenia eriensis	0.40	0.49	0.55	0.43	0.50	0.43	0.55	0.48	0.55	0.45

only *C. michiganiana* was more truly representative than not of conditions with respect to SiO_2 and temperature. By contrast, in June, only *F. crotonensis* was not representative of NO_3 and Cl^- conditions, while many taxa were either mostly unrepresentative or not at all representative of August environmental conditions with respect to SiO_2 and temperature. The most unrepresentative taxa were *Asterionella formosa*, *F. crotonensis*, *U. eriensis*, *C. comensis*, and *C. pseudostelligera* with *Achnanthidium minutissimum* being completely unrepresentative (Table 7).

From the fuzzy trophy set and published information on indicator status for each taxon, linguistic truth-values were determined according to a fuzzy truth table (Table 8) (Zimmermann, 2001). For *Asterionella formosa*, *Cyclotella* #6, *C. michiganiana*, *C. pseudostelligera*, *F. capucina*, *F. crotonensis*, *T. fenestrata*, and *U. eriensis*, linguistic truth-value was “true” (Table 9). For *Achnanthidium minutissimum* and *C. comensis*, linguistic truth-value was “undecided” (Table 9). Linguistic truth-values form the basis of fuzzy decision-making (Zimmermann et al., 1984).

4. Discussion

4.1. Global and local analyses

In our study, global and local analyses were achieved to determine the status of the environment and seasonal succession of phytoplankton. In global analysis, CCA was used to show the change in dominant taxa from June and August (Fig. 1). June dominant taxa included those diatom species normally found in spring assemblages in the Great Lakes (e.g., Stoermer and Yang, 1969). Dominant diatom taxa for August mostly consisted of *Cyclotella* spp. and *Achnanthidium minutissimum*. With the exception of *C. comensis*, the other taxa are not necessarily known as summer dominant taxa in the Great Lakes (e.g., Stoermer and Yang, 1969). Taxon abundances are evaluated with regard to their “ability” to be an indicator of the environmental conditions in which they were found. As a result, global analysis did not provide a complete picture of seasonal

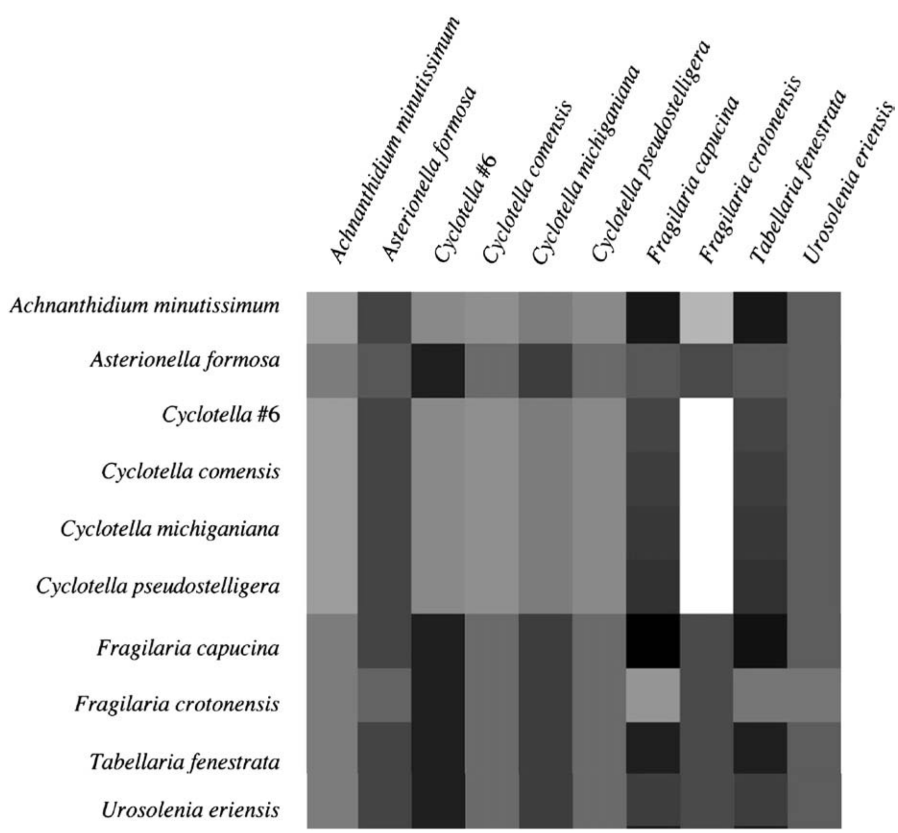

Fig. 3. Fuzzy graph of taxon–taxon influences with respect to SiO_2 and temperature as given in Table 5.

Table 6
Second projections (Eq. (10)) of taxa for June and August, 1991.

Taxon	June	August	Degree of change
Achnanthidium minutissimum	0.53	0.40	Decrease
Asterionella formosa	0.49	0.49	No change
Cyclotella #6	0.40	0.55	Increase
Cyclotella comensis	0.46	0.43	Slight decrease
Cyclotella michiganiana	0.40	0.50	Increase
Cyclotella pseudostelligera	0.41	0.43	Slight increase
Fragilaria capucina	0.60	0.60	No change
Fragilaria crotonensis	0.19	0.48	Increase
Tabellaria fenestrata	0.57	0.57	No change
Urosolenia eriensis	0.45	0.45	No change

Degree of change from June to August is also reported.

succession, at least insofar as matching change in dominant taxa to particular environmental variables governing the state of Lake Huron near Port Huron, Michigan in 1991.

From local analysis using fuzzy relations, the degree of influence that environmental conditions had on the dominant taxa from June and August and the degree to which the dominant taxa are environmental indicators of trophic status were determined, and these results show that specific taxon abundances are not the whole picture with respect to defining the environment. In spite of being a June dominant taxon, *F. crotonensis* had less influence than it did in August. All other June dominant taxa had the same influence in June and August. This indicated that although a different environmental regime was present in August, June dominant taxa persisted. Degree of influence remained approximately the same (*C. comensis*) or increased in August for those identified as dominant taxa. The exception is *Achnanthidium minutissimum*, which decreased in degree of influence in August despite being a dominant taxon.

For *F. crotonensis* and *Achnanthidium minutissimum*, each taxon was a better indicator of environmental conditions for the season rather than being indicators based only on abundance. *F. crotonensis* is an indicator of complete biodegradation of organic compounds and weak NH_3 pollution being present (Lowe, 1974). *Achnanthidium minutissimum* is an indicator of pollution in the form of nitrogenous compounds (Lowe, 1974). In global analysis, NH_3 was indicated secondarily as influential in environmental conditions in August, and

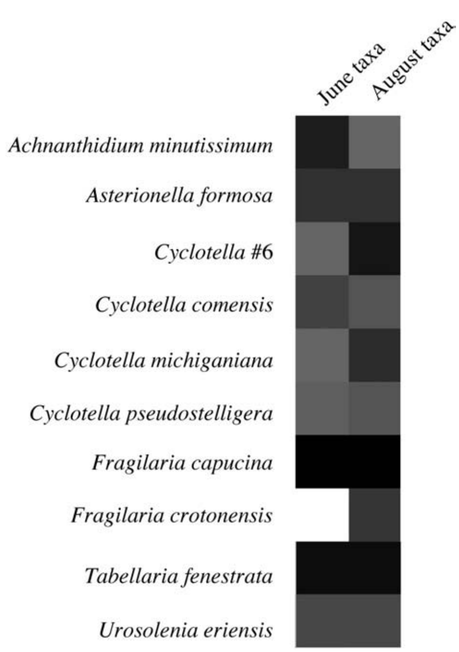

Fig. 4. Second projections (Eq. (10)) for June and August taxa as a fuzzy graph.

Table 7
Normalized second projections for taxon indicators and *max* function for logical "OR".

Taxa	June (NO_3 and Cl^-)	August (SiO_2 and temperature)	*Max* function $\vee$
Achnanthidium minutissimum	0.83	0	0.83
Asterionella formosa	0.73	0.45	0.73
Cyclotella #6	0.51	0.75	0.75
Cyclotella comensis	0.66	0.15	0.66
Cyclotella michiganiana	0.51	0.50	0.51
Cyclotella pseudostelligera	0.54	0.15	0.54
Fragilaria capucina	1	1	1
Fragilaria crotonensis	0	0.40	0.40
Tabellaria fenestrata	0.93	0.85	0.93
Urosolenia eriensis	0.63	0.25	0.63

Information about taxon representation of trophic status and other properties is given.

locally *F. crotonensis* and *A. minutissimum* were found to corroborate this.

From global and local analyses, degree of each taxon's "ability" to indicate the environmental conditions present was shown to be a useful tool in determining the environment's trophic status from season to season (Table 7). In June, the overall condition of the environment was eutrophy, given the presence of dominant taxa usually found in such conditions (e.g., Stoermer and Yang, 1969). In particular, *F. capucina* is highly correlated with Cl^- (Stoermer and Kreis, 1980), and is an indicator of eutrophy (Lowe, 1974). *T. fenestrata* is indicative of eutrophic conditions (Lowe, 1974). *U. eriensis* has been found to be present in eutrophic conditions as well (Edlund and Stoermer, 1993). *Asterionella formosa* and *F. crotonensis* are found in mesotrophic to eutrophic conditions (Lowe, 1974). The total projection for June taxa indicated eutrophy to degree 0.60.

In August, dominant taxa of *Cyclotella* species indicated oligotrophy (Lowe, 1974). In August, conditions did not improve greatly from June since the total projection indicated eutrophy to degree 0.60.

In global analysis, one taxon that was found to be dominant in August, but not in June was *C. comensis*. This taxon is an indicator of nitrogenous pollution and has been increasing in abundance later in the season (Stoermer and Kreis, 1980; Stoermer et al., 1983; Pappas and Stoermer, 1995). However, in local analysis, *C. comensis* was approximately equally influential in June and August, not indicating much change between seasons.

4.2. Linguistic translation and fuzzy decision-making

Using linguistic approximation and fuzzy decision-making by evaluating degree of truth with respect to trophic status, our results provide a more detailed picture of the contribution each dominant taxon made toward assessing the environment. For June with regard to NO_3, *Achnanthidium minutissimum* (Lowe, 1974), *C. comensis* (e.g., Pappas and Stoermer, 1995), and to some degree, *U. eriensis* (Edlund and Stoermer, 1993) are indicators of nitrogenous pollution. This type of pollution is considered to be secondarily an indicator of eutrophy, in contrast to pollution from phosphate inputs (e.g., Stoermer et al., 1978; Pappas and Stoermer, 1995). Our results on trophic status of *A. minutissimum* and *C. comensis* are interpreted to

Table 8
Fuzzy truth tables for logical "OR", where $\vee$ is the *max* function, "*T*" is "true", "*F*" is "false", and "$T+F$" is "undecided" (Zimmermann, 2001).

$\vee$	T	F	$T+F$
T	T	T	T
F	T	F	$T+F$
$T+F$	T	$T+F$	$T+F$

Table 9
Fuzzy decision-making using linguistic translation of *max* function values and fuzzy truth table labels with respect to trophic indicator status.

Taxa	*Max* function ∨	Fuzzy decision	Environmental tolerance identifier	Linguistic truth-value
Achnanthidium minutissimum	0.83	Eutrophy	Oligotrophy; tolerates NO_3[a]	$T+F$
Asterionella formosa	0.73	Mesotrophy	Mesotrophy[b] to Eutrophy[c,d,e]	T
Cyclotella #6	0.75	Mesotrophy	Oligotrophy[e,f]	T
Cyclotella comensis	0.66	Mesotrophy	Oligotrophy; tolerates NO_3[c,d,e,f]	$T+F$
Cyclotella michiganiana	0.51	More oligotrophy	Oligotrophy[c,e,f]	T
Cyclotella pseudostelligera	0.54	Mesotrophy	Eutrophy[c,d,f]	T
Fragilaria capucina	1	Eutrophy	Eutrophy; tolerates high Cl^-[c,e]	T
Fragilaria crotonensis	0.40	More oligotrophy	Mesotrophy[f] to Eutrophy[c,d,e]	T
Tabellaria fenestrata	0.93	Eutrophy	Eutrophy[c,d,e]	T
Urosolenia eriensis	0.63	Mesotrophy	Oligotrophy to eutrophy; tolerates NO_3[a,e]	T

[a] Lowe (1974).
[b] Edlund and Stoermer (1993).
[c] Pappas and Stoermer (1995).
[d] Stoermer and Kreis (1980).
[e] Stoermer et al. (1983).
[f] Stoermer and Yang (1969).

reflect this since they were found to have the linguistic truth-value of "undecided" (Table 9).

From our results, some taxa are interpreted to be indicative of a broader spectrum of trophic conditions since *Cyclotella* #6, *C. pseudostelligera*, *F. crotonensis*, and *U. eriensis* covered multiple categories of trophic status with linguistic truth-values of "true" (Table 9). Those taxa that were found to be indicative of a particular category of trophy were *Asterionella formosa* for mesotrophy, *C. michiganiana* for oligotrophy, and both *F. capucina* and *T. fenestrata* for eutrophy. A taxon such as *A. formosa* occurred under mesotrophic conditions (e.g., Stoermer and Yang, 1969; Pappas and Stoermer, 1995). *C. michiganiana* as an indicator of oligotrophy, has been substantiated to be so according to published accounts (Stoermer and Yang, 1969; Stoermer et al., 1983). In June with regard to Cl^-, *F. capucina* was found to be an indicator of eutrophy, and this taxon has been found to tolerate slight increases in salt concentration (Stoermer and Kreis, 1980). *T. fenestrata* has also been documented to be tolerant of eutrophy (Stoermer and Kreis, 1980; Stoermer et al., 1983; Pappas and Stoermer, 1995).

Linguistic translation of the results was particularly useful in amalgamating fuzzy relational results and what is known about taxon indicators from the scientific literature. More specifically, trophic status of the environment on a taxon-by-taxon basis was made and translated into ordinary language to make results of this environmental study accessible to anyone with an interest in the results, including policy makers and members of the public.

4.3. Seasonal succession

To examine seasonal succession, results from second projections (Eq. (10)) of June and August taxa are plotted in a single diagram (Fig. 5). Dominant taxa in June and August gave an overall indication of environmental conditions that was somewhat different from the second projections for these months. This shows that only looking at dominant taxa may not give an entire picture of change in environmental conditions. In general, eutrophy was present in June and oligotrophy in August based on dominant taxa only. However, two taxa that were August dominants were important indicators of an increase in nitrogenous compounds in June, namely, *Achnanthidium minutissimum* and *C. comensis*. *F. crotonensis*, a June dominant, was an important indicator of at least mesotrophic conditions emerging (Table 9). All other taxa exhibited the same value for June and August, indicating persistence in the environment, regardless of the conditions. With global and local analyses, a combination diagram is made to represent a timeline of changes in the environment (Fig. 5).

4.4. Seasonal changes from year to year

The shift in taxon dominants among the seasons from year to year is examined (Table 10). In a comparison of data from 1974, 1980, and

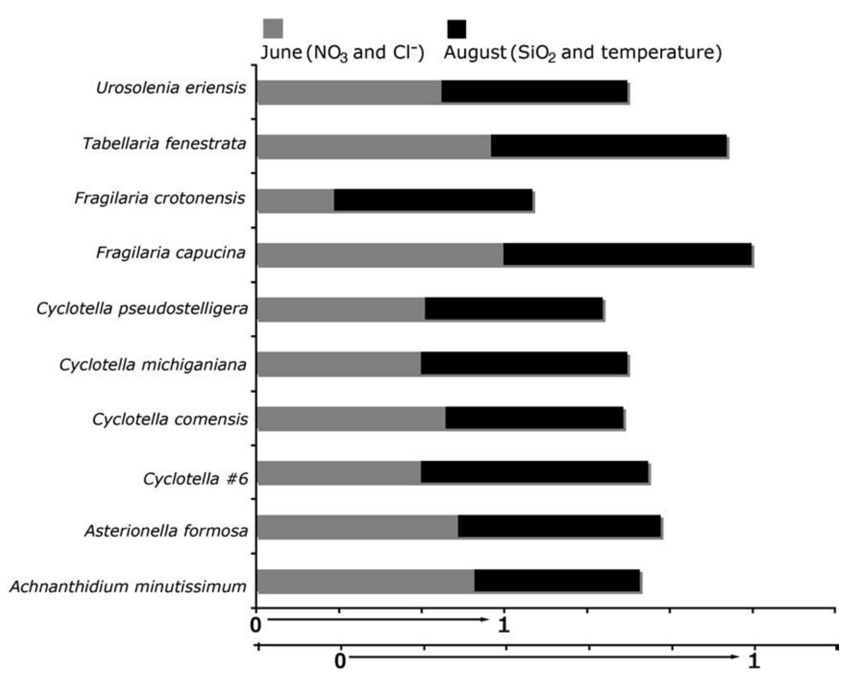

Fig. 5. Timeline of succession from June to August, 1991 for dominant taxa determined globally and particular outcomes for taxa from local analysis.

Table 10
Yearly and seasonal succession of dominant Lake Huron taxa common to and reported in Stoermer and Kreis (1980) for 1974, Stoermer et al. (1983) for 1980, Pappas and Stoermer (1995) for 1991, and results from the current study.*

1974	1980	1991
Fragilaria capucina *Fragilaria crotonensis* *Cyclotella comensis*	*Fragilaria crotonensis* *Cyclotella comensis*	*Fragilaria capucina* *Cyclotella comensis* *Tabellaria fenestrata*
Spring	Spring	Spring
Fragilaria capucina *Fragilaria crotonensis* *Tabellaria fenestrata*	*Fragilaria capucina*	*Fragilaria capucina** *Fragilaria crotonensis** *Tabellaria fenestrata**
Summer	Summer	Summer
	Cyclotella comensis *Fragilaria crotonensis*	*Cyclotella comensis**
Fall *Fragilaria capucina* *Cyclotella comensis*	Fall *Fragilaria capucina* *Cyclotella comensis*	

1991, *C. comensis* was found to be a dominant taxon. In 1974, it was a dominant in the fall, while in 1980 it was a dominant in the summer and fall. Our local analysis indicated that *C. comensis* is a dominant in the fall, but is influential in the spring to late summer as well. *F. capucina* was a dominant in the spring and fall in 1974, 1980, and spring of 1991, while *F. crotonensis* was a dominant in spring, 1974 and summer, 1980. We found *F. capucina* to be a dominant taxon in spring as well as a persistent taxon into the summer. With *F. crotonensis*, our finding of dominance in spring is the same as that for 1974, but in particular, we found that the taxon is influential in summer as well.

4.5. Additional analyses for fuzzy decision-making

Our analyses showed that there are different facets to determining the status of environmental conditions in Lake Huron near Port Huron, Michigan. To make comparisons to the latest status of Lake Huron near Port Huron, Michigan, additional analyses using the methods described herein could be conducted when more recent data become available. The details of the results lend themselves to other means of amalgamating the information into a usable format, such as linguistic translation. Further, decision-making may be added to our analysis by devising fuzzy rules and including expert opinion (e.g., Marsili-Libelli, 2004; Tzionas et al., 2004; Uricchio et al., 2004; Pappas, 2006). Fuzzy rules are based on baseline or "ideal" conditions for comparison to actual data. For example, weighting (Dubois and Prade, 1984) of particular taxa or physical and chemical parameters in terms of importance in trophic (or other ecological identifier) status could be incorporated into baseline schema for comparison to actual conditions to produce a more refined version of linguistic translation. Fuzzy decision-making on the status of Lake Huron near Port Huron could be instituted based on a weighted schema and include information from experts as well as other kinds of information in order to develop environmental policy. Additionally, fuzzy regression (e.g., Savic and Pedrycz, 1991) may be used to develop predictive models of uncertainties in outcomes of environmental analysis when the uncertainty is not due to randomness.

Another kind of decision-making instrument involves using fuzzy evaluation by classification (Celmins, 2000). Degree of truth that the rules are adhered to produces numerical results that are sorted in a fuzzy classification level. The outcome at each level determines the degree of water quality remediation to be implemented. Fuzzy classification can be used for temporal changes using fuzzy clustering (e.g., Equihua, 1990; Salski, 2007) or spatial distributions of taxa using fuzzy kriging (e.g., Salski, 1999; Hengl et al., 2002). Knowledge-based modeling has been used as well (e.g., Salski, 1992). Algal bloom prediction in a lagoon was the basis for a study implementing fuzzy rules of daily patterns of chemical and physical parameters (Marsili-Libelli, 2004). Fuzzy logic modeling was used to predict algal biomass concentrations in a lake that was already deemed to be eutrophic (Chen and Mynett, 2003).

Tran et al. (2002) used fuzzy decision analysis to integrate ecological indicators. Fuzzy ranking of ecosystems with respect to environmental conditions was determined, and this was used to suggest cumulative impacts over a wide region, the mid-Atlantic part of the United States. Ioannidou et al. (2003) used fuzzy inference and expert judgment to determine impact and interactions of various kinds of pollutants and water level changes in a lake in Greece. Fuzzy decision analysis (e.g., Zimmermann, 1987) can be used as a basis for environmental policy assessment.

Natural resource inventories based on methods such as geographic information systems (GIS) (USEPA (GLNPO)) were used in multiple fuzzy membership maps that were devised based on pixel and color mixture methods to classify inventories that are continuous or have fuzzy boundaries (Hengl et al., 2002). Pixel and color mixture maps used with GIS were found to be useful in visualization of uncertainty in spatial prediction (Hengl et al., 2002).

Ecosystem assessment and remediation recommendations in decision-making were accomplished using a fuzzy cognitive map approach to model Lake Erie (Hobbs et al., 2002). This integrated model used multivariate statistics and fuzzy cognitive maps not only to characterize the ecological status of Lake Erie, but also to promote interaction among experts to facilitate successful management of the lake (Hobbs et al., 2002). More generally, Tan and Özesmi (2006) used fuzzy cognitive maps with application to all shallow lake systems.

In an automated case-based reasoning system using a Takagi-Sugeno-Kang fuzzy model, a biological forecasting system was devised (Fernández-Riverola and Díaz, 2004; Fernández-Riverola et al., 2007). In this system, diatoms were counted but not identified. Rather, the predictive value was viewed to be concentration of numbers of diatoms with respect to nutrients. In this case, the amount of diatom cells was used as a global bioindicator of the general assessment of a water mass.

These and other ways of using fuzzy decision-making will enhance the realistic outcome of environmental assessment. Modeling uncertainty in ecological systems and evaluation of environmental conditions can only improve with the usage of fuzzy analytical tools.

5. Conclusions

From fuzzy relational analysis, *F. capucina* and *T. fenestrata* are indicators of eutrophy, *Asterionella formosa* is an indicator of mesotrophy, *C. pseudostelligera* is an indicator of mesotropy to eutrophy, *F. crotonensis* and *U. eriensis* are indicators of oligotrophy to mesotrophy, and *C. michiganiana* is an indicator of oligotrophy.

From a season-to-season comparison, fuzzy relational analysis indicates that most of the dominant taxa persisted from June to August, regardless of trophic conditions. The exceptions to this were *Achnanthidium minutissimum* and *C. comensis*, which are indicators of an increase in nitrogenous compounds, and were influential in August. Since dominant taxa in August were indicators of oligotrophic conditions, fuzzy relational analysis revealed that potentially, a nitrogenous pollution problem may actually be present.

From year to year, there was an overall shift in dominant taxa. In 1991, *F. crotonensis* was no longer considered to be a dominant taxon as it was in 1974 and 1980. Instead, *T. fenestrata* was the dominant taxon in 1991.

References

Baldwin, J.F., 1979. A new approach to approximate reasoning using a fuzzy logic. Fuzzy Sets and Systems 2, 309–325.
Battarbee, R.W., Charles, D.F., Dixit, S.S., Renberg, I., 1999. Diatoms as indicators of surface water acidity. In: Stoermer, E.F., Smol, J.P. (Eds.), The Diatoms: Applications for the Environmental and Earth Sciences. Cambridge University Press, Cambridge, pp. 85–127.

Bellman, R.E., Zadeh, L.A., 1977. Local and fuzzy logics. In: Dunn, J.M., Epstein, G. (Eds.), Modern Uses of Multiple-valued Logic. D. Reidel Publishing, Dordrecht, pp. 105–165.

Biological Diatom Index (On-line), Cemagref, France, "More information on diatoms as water quality indicators," <http://www.cemagref.fr/English/ex/hydrosystem/Diatoms/diatoms03.htm>.

Celmins, A., 2000. Classification by attribute evaluation. Proceedings of the 19th International Conference of the North American Fuzzy Information Processing Society, NAFIPS'2000, Atlanta, Georgia, pp. 123–127.

Chen, Q., Mynett, A.E., 2003. Integration of data mining techniques and heuristic knowledge in fuzzy logic modeling of eutrophication in Taihu Lake. Ecological Modelling 162, 55–67.

Dubois, D., Prade, H., 1980. Fuzzy Sets and Systems: Theory and Applications. Academic Press, New York. 393 pp.

Dubois, D., Prade, H., 1984. Criteria aggregation and ranking of alternatives in the framework of fuzzy set theory. In: Zimmermannn, H.-J., Zadeh, L.A., Gaines, B.R. (Eds.), Fuzzy Sets and Decision Analysis. Elsevier Science Publishing, Amsterdam, pp. 209–240.

Edlund, M.B., Stoermer, E.F., 1993. Resting spores of the freshwater diatoms *Acanthoceras* and *Urosolenia*. Journal of Paleolimnology 9, 55–61.

Equihua, M., 1990. Fuzzy clustering of ecological data. Journal of Ecology 78, 519–534.

Fernández-Riverola, F., Díaz, F., 2004. Employing TSK fuzzy models to automate the revision stage of a CBR system. In: Conejo, R., Urretavizcaya, M., Pérez-de-la-Cruz, J.-L. (Eds.), Current Topics in Artificial Intelligence, 10th Conference of the Spanish Association for Artificial Intelligence (CAEPIA) and 5th Conference on Technology Transfer (TTIA) 2003, San Sebastian, Spain, Lecture Notes in Artificial Intelligence (LNAI), 3040. Springer-Verlag, Berlin Heidelberg, pp. 302–311.

Fernández-Riverola, F., Díaz, F., Corchado, J.M., 2007. Reducing the memory size of a fuzzy case-based reasoning system applying rough set techniques. IEEE Transactions on Systems, Man, and Cybernetics—Part C: Applications and Reviews 37, 138–146.

Fritz, S.C., Cumming, B.F., Gasse, F., Laird, K.R., 1999. Diatoms as indicators of hydrologic and climatic change in saline lakes. In: Stoermer, E.F., Smol, J.P. (Eds.), The Diatoms: Applications for the Environmental and Earth Sciences. Cambridge University Press, Cambridge, pp. 41–72.

Gower, J.C., Hand, D.J., 1996. Biplots. Chapman & Hall, London. 277 pp.

Great Lakes Environmental Indicators Project (GLEIP) (On-line), University of Minnesota Duluth, <http://glei.nrri.umn.edu/default/default.htm>.

Great Lakes Water Quality, Ecosystem Health Division, Environment Canada (On-line), <http://www.on.ec.gc.ca/monitoring/water-quality/greatlakes-e.html>.

Hall, R.I., Smol, J.P., 1999. Diatoms as indicators of lake eutrophication. In: Stoermer, E.F., Smol, J.P. (Eds.), The Diatoms: Applications for the Environmental and Earth Sciences. Cambridge University Press, Cambridge, pp. 128–168.

Hamilton, P.B., Douglas, M.S.V., Fritz, S.C., Pienitz, R., Smol, J.P., Wolfe, A.P., 1994. A compiled freshwater diatom taxa list for the arctic and subarctic regions of North America. Canadian Technical Report of Fisheries and Aquatic Sciences 1957, 85–102.

Harwood D.M. and Nikolaev, V.A., 1995. Cretaceous diatoms: morphology, taxonomy, biostratigraphy. In: C. D. Blome, P.M. Whalen and K.M. Reed (Convenors), L.E. Babcock and W.I. Ausich (Series Editors), Siliceous Microfossils: Short Courses in Paleontology, Number 8. The Paleontological Society, pp. 81–106.

Hengl, T., Walvoort, D.J.J., Brown, A., 2002. Pixel and colour mixture: GIS techniques for visualization of fuzziness and uncertainty of natural resource inventories. In: Hunter, GaryJ., Lowell, Kim (Eds.), Proceedings of the 5th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences (Accuracy 2002), Melbourne, Australia, pp. 300–309.

Hobbs, B.F., Ludsin, S.A., Knight, R.L., Ryan, P.A., Biberhofer, J., Ciborowski, J.J.H., 2002. Fuzzy cognitive mapping as a tool to define management objectives for complex ecosystems. Ecological Applications 12, 1548–1565.

Ioannidou, I.A., Paraskevopoulos, S., Tzionas, P., 2003. Fuzzy modeling of interactions among environmental stressors in the ecosystem of Lake Koronia, Greece. Environmental Management 32, 624–638.

Jongman, R.H.G., ter Braak, C.J.F., van Tongeren, O.F.R., 1995. Data Analysis in Community and Landscape Ecology. Pudoc, Wageningen. 299 pp.

Lowe, R., 1974. Environmental requirements and pollution tolerance of freshwater diatoms. United States Environmental Protection Agency, National Environmental Research Center, Office of Research and Development, Cincinnati, Ohio. EPA-670/4-74-005.

Mann, D.G., 1994. The origins of shape and form in diatoms: the interplay between morphogenetic studies and systematics. In: Ingram, D.S., Hudson, A.J. (Eds.), Shape and Form in Plants and Fungi. Academic Press, London, pp. 17–38.

Mann, D.G., 1999. The species concept in diatoms. Phycologia 38, 437–495.

Marsili-Libelli, S., 2004. Fuzzy prediction of the algal blooms in the Orbetello lagoon. Environmental Modelling and Software 19, 799–808.

Noy-Meir, I., 1973. Data transformations in ecological ordination: I. Some advantages of non-centering. Journal of Ecology 61, 329–341.

Noy-Meir, I., Walker, D., Williams, W.T., 1975. Data transformations in ecological ordination. II. On the meaning of data standardization. Journal of Ecology 63, 779–800.

Pappas, J.L., 2006. Biological taxonomic problem solving using fuzzy decision-making analytical tools. Fuzzy Sets and Systems 157, 1687–1703.

Pappas, J.L., Stoermer, E.F., 1995. Multidimensional analysis of diatom morphologic and morphometric phenotypic variation and relation to niche. Ecoscience 2, 357–367.

Roberts, D.W., 1986. Ordination on the basis of fuzzy set theory. Vegetatio 66, 123–131.

Roberts, D.W., 1987. A dynamical systems perspective on vegetation theory. Vegetatio 69, 27–33.

Roberts, D.W., 1989. Fuzzy systems vegetation theory. Vegetatio 83, 71–80.

Round, F.E., Crawford, R.M., Mann, D.G., 1990. The Diatoms. Biology and Morphology of the Genera. Cambridge University Press, Cambridge, United Kingdom. 747 pp.

Salski, A., 1992. Fuzzy knowledge-based models in ecological research. Ecological Modelling 63, 103–112.

Salski, A., 1999. Ecological modelling and data analysis. In: H.-J. Zimmermannn (Editor), Practical Applications of Fuzzy Technologies, D. Dubois and H. Prade (Series Editors), The Handbooks of Fuzzy Sets Series, Vol. 7; 247–266. Kluwer Academic Publisher, Boston, Massachusetts.

Salski, A., 2007. Fuzzy clustering of fuzzy ecological data. Ecological Informatics 2/3, 262–269.

Sancetta, C., 1999. Diatoms and marine paleoceanography. In: Stoermer, E.F., Smol, J.P. (Eds.), The Diatoms: Applications for the Environmental and Earth Sciences. Cambridge University Press, Cambridge, pp. 374–386.

Savic, D., Pedrycz, W., 1991. Evaluation of fuzzy regression models. Fuzzy Sets and Systems 39, 51–63.

Schelske, C.L., Rothman, E.D., Stoermer, E.F., Santiago, M.A., 1974. Responses of phosphorus limited Lake Michigan phytoplankton to factorial enrichments with nitrogen and phosphorus. Limnology and Oceanography 19, 409–419.

Spaulding, S.A., McKnight, D.M., 2000. Diatoms as indicators of environmental change in Antarctic freshwaters. In: Stoermer, E.F., Smol, J.P. (Eds.), The Diatoms: Applications for the Environmental and Earth Sciences. Cambridge University Press, Cambridge, pp. 245–263.

Stoermer, E.F., 1978. Phytoplankton assemblages as indictors of water quality in the Laurentian Great Lakes. Transactions of the American Microscopical Society 97, 1–16.

Stoermer, E.F. and Kreis, R.G., Jr., 1980. Phytoplankton composition and abundance in southern Lake Huron. University of Michigan, Great Lakes Research Division Special Report No. 65, EPA-600/3-80-061, United States Environmental Protection Agency, Duluth, Minnesota.

Stoermer, E.F., Yang, J.J., 1969. Plankton diatom assemblages in Lake Michigan, Great Lakes Research Division Special Report No. 47. University of Michigan, Ann Arbor, Michigan. 168 pp.

Stoermer, E.F., Ladewski, B.G., Schelske, C.L., 1978. Population responses of Lake Michigan phytoplankton to nitrogen and phosphorus enrichment. Hydrobiologia 57, 249–265.

Stoermer, E.F., Kreis Jr., R.G., Theriot, E.C., Ladewski, T.B., 1983. Phytoplankton abundance, species distribution, and community structure in Saginaw Bay and southern Lake Huron in 1980. United States Environmental Protection Agency, Environmental Research Laboratory, Duluth, Minnesota. EPA-600/S3-83-091.

Tan, C.O., Özesmi, U., 2006. A generic shallow lake ecosystem model based on collective expert knowledge. Hydrobiologia 563, 125–142.

ter Braak, C.J.F., 1986. Canonical correspondence analysis: a new eigenvector technique for multivariate direct gradient analysis. Ecology 67, 1167–1179.

ter Braak, C.J.F., 1988a. CANOCO: A FORTRAN program for canonical community ordination by [partial] [detrended] [canonical] correspondence analysis, principal components analysis and redundancy analysis (version 2.1). TNO Institute of Applied Computer Science, Wageningen, The Netherlands. 95 pp.

ter Braak, C.J.F., 1988b. Partial canonical correspondence analysis. In: Bock, H.H. (Ed.), Classification and Related Methods of Data Analysis. Elsevier Science Publishers, Amsterdam, pp. 551–558.

ter Braak, C.J.F., 1990. Update notes: CANOCO version 3.10. Agricultural Mathematics Group, Wageningen, The Netherlands.

ter Braak, C.J.F., 1996. Unimodal models to relate species to environment. Agricultural Mathematics Group, Wageningen, The Netherlands. 266 pp.

Tong, R.M., Bonissone, P.P., 1984. Linguistic solutions to fuzzy decision problems. In: Zimmermannn, H.-J., Zadeh, L.A., Gaines, B.R. (Eds.), Fuzzy Sets and Decision Analysis. Elsevier Science Publishing, Amsterdam, pp. 323–334.

Tran, L.T., Knight, C.G., O'Neil, R.V., Smith, E.R., Ritters, K.H., Wickham, J., 2002. Environmental assessment: fuzzy decision analysis for integrated environmental vulnerability assessment of the mid-Atlantic region. Environmental Management 29, 845–859.

Tzionas, P., Ioannidou, I.A., Paraskevopoulos, S., 2004. A hierarchical fuzzy decision support system for the environmental rehabilitation of Lake Koronia, Greece. Environmental Management 34, 24–260.

United States Environmental Protection Agency (US EPA) Environmental Monitoring and Assessment Program (EMAP) (On-line), http://www.epa.gov/emap/.

United States Environmental Protection Agency (US EPA) Great Lakes National Program Office (GLNPO) (On-line), <http://www.epa.gov/glnpo/>.

United States Geological Service (USGS) National Water-Quality Assessment Program (NAWQA) (On-line), <http://water.usgs.gov/nawqa/>.

Uricchio, V.F., Giodano, R., Lopez, N., 2004. A fuzzy knowledge-based decision support system for groundwater pollution risk evaluation. Journal of Environmental Management 73, 189–197.

van den Hoek, C., Mann, D.G., Jahns, H.M., 1995. Algae: An Introduction to Phycology. Cambridge University Press, Cambridge. 623 pp.

Villeneuve, V., Pienitz, R., 1998. Composition diatomfère de quatre sources thermales au Canada, en Islande et au Japon. Diatom Research 13, 149–175.

Water Framework Directive, European Union (On-line), <http://www.wfdireland.ie/>.

Wolin, J.A., Stoermer, E.F., Schelske, C.L., Conley, D.J., 1988. Siliceous microfossil succession in recent Lake Huron sediments. Archiv für Hydrobiologie 144, 17–198.

Zadeh, L., 1965. Fuzzy sets. Information and Control 8, 338–353.

Zadeh, L.A., 1975. The concept of a linguistic variable and its application to approximate reasoning. Parts 1, 2, and 3. Information Science 8, 199–249 8, 301–357; 9, 43–80.

Zadeh, L.A., 1978. PRUF—a meaning representation language for natural language. International Journal of Man–Machine Studies 10, 395–460.

Zimmermann, H.-J., 1987. Fuzzy Sets, Decision Making, and Expert Systems. Kluwer, Boston. 335 pp.

Zimmermann, H.-J., 2001. Fuzzy Set Theory and Its Applications, 4th Revised Edition. Kluwer, Boston. 399 pp.

Zimmermann, H.-J., Zadeh, L.A., Gaines, B.R., 1984. Fuzzy Sets and Decision Analysis. North-Holland, Amsterdam. 477 pp.