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RESEARCH ARTICLE

Inferring community properties of benthic macroinvertebrates in streams using Shannon index and exergy

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Abstract Definition of ecological integrity based on community analysis has long been a critical issue in risk assessment for sustainable ecosystem management. In this work, two indices (i.e., Shannon index and exergy) were selected for the analysis of community properties of benthic macroinvertebrate community in streams in Korea. For this purpose, the means and variances of both indices were analyzed. The results found an extra scope of structural and functional properties in communities in response to environmental variabilities and anthropogenic disturbances. The combination of these two parameters (four indices) was feasible in identification of disturbance agents (e.g., industrial pollution or organic pollution) and specifying states of communities. The four-aforementioned parameters (means and variances of Shannon index and exergy) were further used as input data in a self-organizing map for the characterization of water quality. Our results suggested that Shannon index and exergy in combination could be utilized as a suitable reference system and would be an efficient tool for assessment of the health of aquatic ecosystems exposed to environmental disturbances.

Keywords benthic macroinvertebrates, ecological integrity, anthropogenic pollution, self-organizing map

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1 Introduction

Characterization of community properties has long been a critical issue in ecological science for the sustainable management of ecosystems exposed to natural and anthropogenic disturbances since the late 1970s (Mejer and Jørgensen, 1979; Jørgensen, 1992; Magurran, 2004). Indicators presenting ecological integrity such as Shannon index (Shannon, 1948), emergy (Odum, 1988) and exergy (Mejer and Jørgensen, 1979; Jørgensen, 1992) have always been chosen for the analysis of information embedded in ecosystems by measurements of energy.

The Shannon index indicates the structure of communities (i.e., species richness and evenness in species), whereas exergy reflects the function of communities according to energy required to maintain the system equilibrium. The Shannon index was originally proposed to understand the community structure (Shannon, 1948), and take the relative abundances of different species into account (Magurran, 2004). This index has been widely used as a ecological indicator for several decades (Hellawell, 1986; Niemi and McDonald, 2004). Exergy (or eco-exergy) has also been considered as a indicator mainly for energy analysis at ecosystem level (Mejer and Jørgensen, 1979; Jørgensen et al., 1995; Svirezhev, 2000; Jørgensen et al., 2005a; Li et al., 2013). Exergy could be analyzed based on thermodynamic principles with a focus on the development of an open ecosystem from its reference state (Jørgensen and Fath, 2004; Jørgensen and Nors Nielsen, 2007), in other words, how much energy is needed to decompose a biological system into inorganic matter or destroy it completely (Svirezhev, 2000; Jørgensen and Nors Nielsen, 2007). For practical and monitoring purposes, exergy has been measured to detect the information level of ecosystem dynamics (Bendoricchio and Jørgensen, 1997; Silow and Mokry, 2010), including social-economic ecosystems (Dai et al., 2012), eutrophication in lakes (Suzuki et al., 2000; Xu et al., 2011; Marchi et al., 2012), conservation (e.g., marine and coast) (Libralato et al., 2006; Pusceddu and Danovaro, 2009), benthic macroinvertebrates (Xu et al., 1999; Silow and In-Hye, 2004; Bae et al., 2013), the biogeochemical cycle (Svirezhev et al., 2003), and genetic information (Jørgensen et al., 2004).

We focus on the concurrent use of means and variances of the Shannon index and exergy to characterize community properties in response to natural and anthropogenic disturbances. Although numerous studies have been conducted to evaluate ecological water quality in streams, the measurements have primarily relied on mean values including diversity indices, biological indices or metrics (Hellawell, 1986; Park et al., 2001; Jørgensen et al., 2005a; Qu et al., 2008). The mean and variance of exergy in combination, for instance, have not been concurrently examined across different levels of water pollution. Benedetti-Cecchi (2003) reported that the variance should be checked explicitly in experimental designs with respects to biological and ecological processes. Since community data are highly variable due to high species richness and different responses to natural variabilities and anthropogenic disturbances, variances (i.e., second moment) residing in communities would be suitable for the analysis of the states of ecosystems in addition to the mean value (i.e., first moment). Consequently, analysis of variances could serve as a powerful tool to test those ecological hypotheses that may advance our current knowledge (Link and Nichols, 1994; Inouye, 2005).

In this study, two indices (i.e., Shannon index and exergy) were chosen to analyze the ecological integrity of benthic macroinvertebrates communities in streams in Korea across different levels of water pollution. The variances of both two indices were presented for point sampling (i.e., one-time sampling) and then for the analysis of benthic macroinvertebrate communities. Finally, we report how means and variances of these two indices in combination could effectively address structural and functional properties in stream communities as an in-depth reference system for water quality indicators, when presenting the ecological integrity in aquatic ecosystems.

2 Materials and methods

2.1 Shannon index and exergy

The Shannon index, which is a well-known parameter to express the diversity of communities (Shannon, 1948), is defined as

$$H = -\sum_{i=1}^{S} p_i \ln p_i, \tag{1}$$

where S is the total number of species, $p_i = n_i/N$ represents the proportion or density of the i^{th} species to the total density in the community, n_i is the abundance of the i^{th} species, and $N = \sum_{i=1}^{S} n_i$ is the total abundance.

Based on the second law of thermodynamics applied to an open system, the energy required to decompose the system or destroy it completely is expressed as exergy (Ex) (Mejer and Jørgensen, 1979; Svirezhev, 2000):

$$Ex = RT\sum_{i=1}^{S}\left[p_i \ln\frac{p_i}{p_i^0} - (p_i - p_i^0)\right], \tag{2}$$

where R (= 8.31 J/(mol·K)) is the gas constant and T is the absolute temperature in Kelvin. As indicated above, p_i is concentration or occurrence probability of the i^{th} components in suitable units, and p_i^0 is the concentration of the i^{th} components at the thermodynamic equilibrium or at any reference equilibrium state. The term component is used in a broad sense, and includes simple inorganic and organic compounds, macro-molecular aggregates such as detritus, and organisms. Arbitrary reference states have been defined, particularly in the case of biological components (Herendeen, 1989).

2.2 Variances of Shannon index and exergy

Using the Delta method (Greene, 2003), variance of a function $g(X_1,\ldots,X_s)$ was estimated and could be approximated according to the first order term of Taylor's expansion, which contains the covariance term (Cov) between two variables:

$$V[g(X_1,\ldots,X_S)] \approx \sum_{i=1}^{S}\sum_{j=1}^{S}\mathrm{Cov}(X_i,X_j)\frac{\partial g}{\partial X_i}\frac{\partial g}{\partial X_j}. \tag{3}$$

A theoretical formula of variance of the Shannon index was reported for simple random sampling (Nayak, 1985; Chao and Shen, 2003; Ramezani et al., 2010):

$$V(H) \approx \frac{1}{N}\left[\sum_{i=1}^{S} p_i(\ln p_i)^2 - \left(\sum_{i=1}^{S} p_i \ln p_i\right)^2\right]. \tag{4}$$

For estimation of the variance of the two indices, X_i was replaced by p_i in Eq. (3). The variance (V) and covariance (Cov) for a random sample could be determined as $V(p_i)= p_i(1-p_i)/N$ for $(i=j)$ and $\mathrm{Cov}(p_i, p_j)=-p_ip_j/N$ for $(i\neq j)$ (N is the total abundance as indicated above). According to Eq. (3) and similar reasoning to obtain the variance of the Shannon index (Eq. (4)), the variance of exergy was derived in this study. While the partial derivatives are

$\partial H/\partial p_i = -(1 + \ln p_i)$ for the Shannon index, the partial derivatives of exergy are given by $\partial Ex/\partial p_i = RT\ln(p_i/p_i^0 + p_i^0 - 1)$. It should be noted that $\sum_{i=1}^{S} p_i = 1$. Inserting these expressions into Eq. (3) gives the variance for exergy:

$$V(Ex) \approx \frac{R^2T^2}{N}\left[\sum_{i=1}^{S} p_i\left(\ln\frac{p_i}{p_i^0} + p_i^0\right)^2 - \left[\sum_{i=1}^{S} p_i\left(\ln\frac{p_i}{p_i^0} + p_i^0\right)\right]^2\right]. \tag{5}$$

Eqs. (4) and (5) enable calculation of the variances of the Shannon index and exergy for the macroinvertebrate data, respectively. It is worth noting that variance could be obtained from point sampling data. The reference values (p_i^0) are needed and must be different from 0. In this study, the data collected at the first time at each sampling site were selected as the reference values. For example, data collected in November 2004 in DUK were selected as reference values (p_i^0) for the i^{th} species for calculating exergy of the data in February 2005 (p_i) and so on (see Fig. 2). Some species had 0 individual in the reference state, which will cause the problem of division by zero when calculating exergy and its variance according to Eqs. (2) and (5). To avoid this problem, 1 individual/m^2 was added to the density for those species. The number of all other species remained unchanged since their densities were sufficiently larger than 1 individual/m^2.

2.3 Field data

The samplings of benthic macroinvertebrates (n_i) and environmental factors (e.g., temperature and biochemical oxygen demand (BOD_5)) were collected and measured at 11 field sites in different streams in the Suyong and Nakdong River Basins, Korea. There are two groups of sampling: monthly sampling over the periods 1992–1995 and seasonal sampling from 2005 to 2007 (Park et al., 2006a,b; Qu et al., 2008; Tang et al., 2010; Chon et al., 2013). These 11 field sites were classified into three kinds of water pollution: least pollution (DUK, OCU, TSD), intermediate pollution (DDK, DKS, DAG, ONS, and TKC) and severe pollution (HJD, THP and TCL) (Tang et al., 2010). Other information regarding the sampling method, site locations, biological indices are provided in detail by Qu et al. (2008) and Tang et al. (2010).

2.4 Self-organizing map

The means and variances of the Shannon index and exergy were normalized by their own ranges and then patterned using a self-organizing map (SOM) based on the method by Kohonen network (Kohonen, 1988). SOM has been utilized to pattern community data and find the impact of environmental variability for ecological risk assessment (Park et al., 2003; Song et al., 2007; Chon, 2011; Chon et al., 2013). In this respects, an array of artificial neurons (i.e., computational nodes (10×7)) was arranged in a two dimensional space. The input data contain N_0 observations, with one observation representing one node, and the parameters (e.g., means and variances of the Shannon index and exergy) of the i^{th} observation were expressed as a vector x_i. In the network, each neuron j is connected to each node i. The connectivity is represented by weighting factors, $w_{ij}(t)$, which adaptively changed at each iteration of calculations, t. Initially, the weights were randomly assigned. When the input vector was sent through the network, the summed distance for each neuron j was calculated by

$$d_j(t) = \sum_{i=0}^{N_0-1}\left(x_i - w_{ij}(t)^2\right).$$

The neuron responding maximally to a given input vector was selected as the winning neuron, the weight vector of which had the shortest distance to the input vector. The winning neuron and possibly its neighboring neurons were allowed to learn by changing their weights in a manner that further reduced the distance between the weight and the input vector as

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)\left(x_i - w_{ij}(t)\right)Z_j,$$

where Z_j was assigned a value of 1 for the winning (and its neighboring) neuron(s) through training, while it was assigned values of 0 for the rest of neurons. The symbol η (t) denoted the fractional increment of the correction and was initially assigned to a larger value and then gradually reduced during the training process. Detailed information describing the training procedures and application of SOM to ecological data was described in detail by Park et al. (2006b), Chon (2011), and Chon et al. (2013).

3 Results

The Shannon index generally increased with decrease in water pollution (Fig. 1), which shows a negative correlation with BOD_5 values (Fig. 1). Regarding BOD_5, the values from least to intermediately polluted sites were generally less than 7.0 mg/L (Fig. 1), where the values in some sites (i.e., HJD, THP, and TCL) where were characteristic by severely polluted water range from 32 mg/L to 47 mg/L. Overall, variance of the Shannon index was less variable, opposite to what we observed in the mean values (Figs. 2 and 3). The means and variances of the Shannon index were generally higher in the least

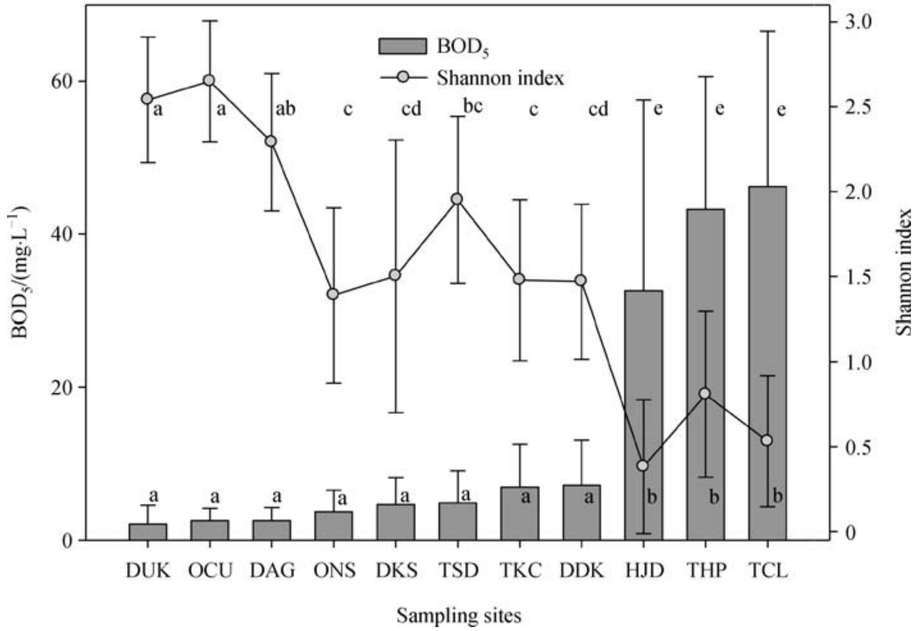

Fig. 1 Average values of BOD_5 and Shannon index. Different alphabets listed near the bars in the figure indicate statistical difference according to Tukey's test.

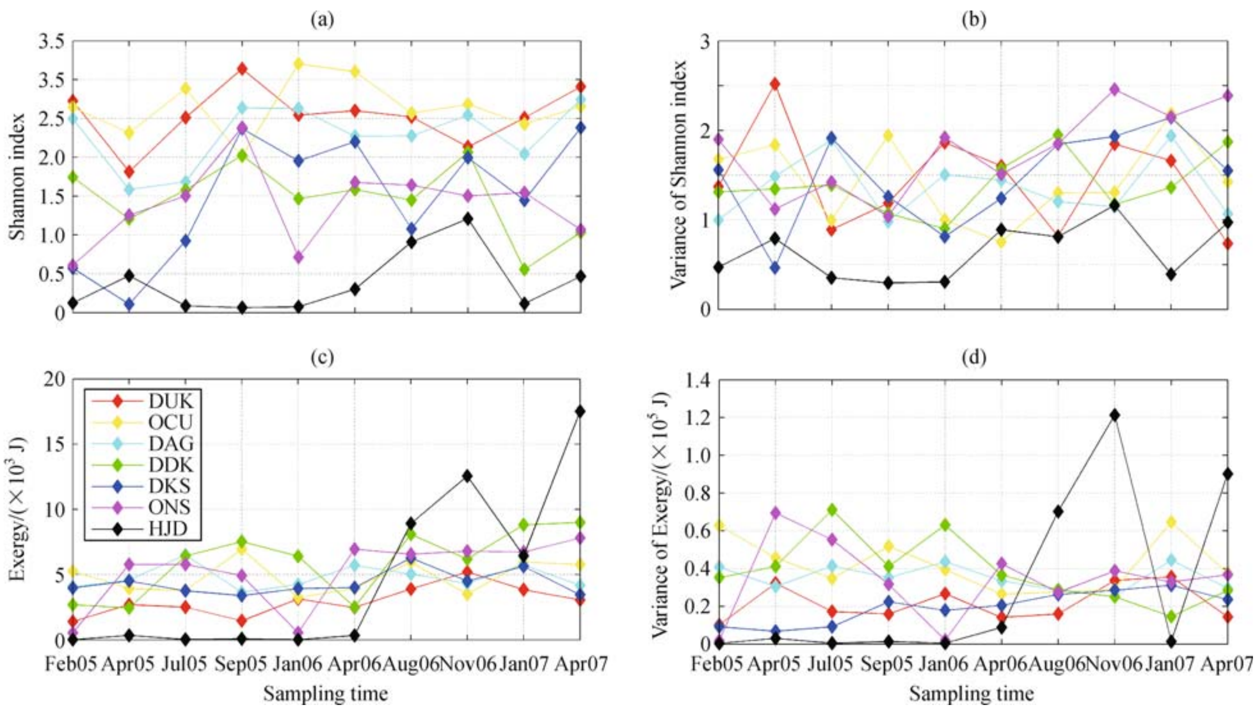

Fig. 2 Shannon index, exergy and their variances across different level of pollution based on seasonal samplings of benthic macroinvertebrates in streams in Korea from February 2005 to April 2007. Different lines indicating sample sites. (a) Shannon index, (b) Variance of Shannon index, (c) Exergy, and (d) Variance of exergy. The numbers on the *x*-axis represent the timing of sampling (e.g., 05 indicating 2005). The results were calculated based on Eqs. (1), (2), (4), and (5).

polluted sites (Fig. 1); however, this is not the case for some sites (i.e., DUK and TSD) (Fig. 2), where the mean values of the Shannon index ranged from 1.5 to 2.0, whereas the variance increased markedly when values were higher than 2.5 (e.g., April 2005 at DUK (Fig. 2(b)), March 1993 and January and February 1994 (Fig. 3(b))). In

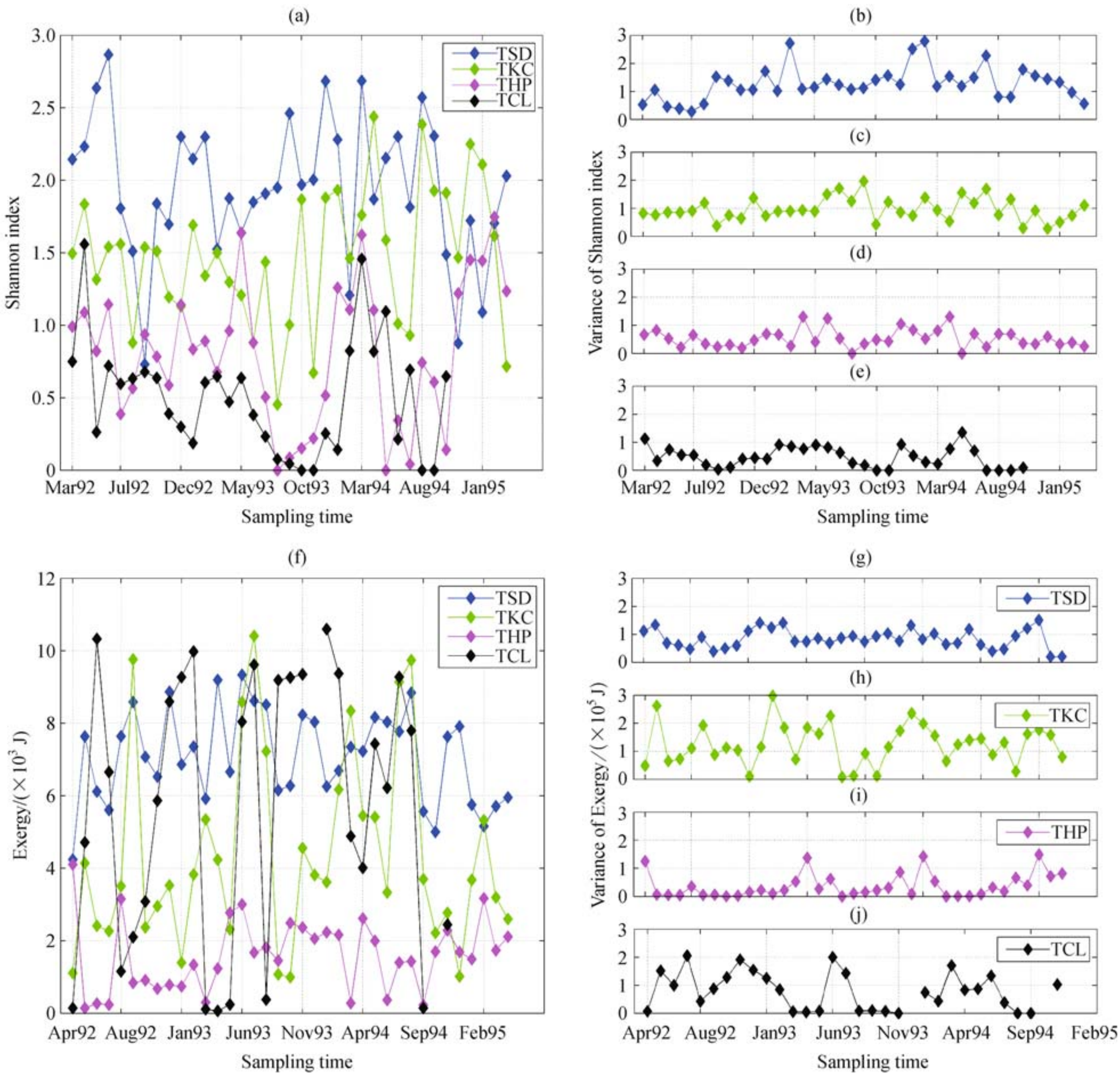

Fig. 3 Shannon index, exergy and their variances across different level of pollution based on monthly sampling of benthic macroinvertebrates in streams in Korea from February 1992 to March 1995. (a) Shannon index, (b–e) Variance of Shannon index, (f) Exergy, (g–j) Variance of exergy. The results were calculated based on Eqs. (1), (2), (4), and (5). The numbers on the *x*-axis indicate the year of data collection (e.g., 92 equivalents to 1992).

this case, the decrease in densities of some dominant species (e.g., Ephemerellidae sp.) was observed that the number was 729 individuals/m^2 in February 1993 and then decreased to 115 individuals/m^2 (March 1993). Low values of abundance affected evenness, although species richness was high in the same sample, Shannon index might be low since it consists of two components: species richness and evenness (Pielou, 1977).

It should also be noted that the variances of the Shannon index appeared to be relatively stable at different level of pollution compared with those mean values (Fig. 2(b)). Variances of the intermediately and least polluted sites range from 1.0 to 2.0, whereas these values were around 0.5 in severely polluted sites (Fig. 2(b)). The variance of the Shannon index ranged from 1.0 to 2.0 in the intermediately and least polluted sites (TSD and TKC in Figs. 3(b) and 3(c)), while the value was around 0.5 in the severely polluted sites (HJD, THP and TCL) (Figs. 3(d) and 3(e)). Overall, the values of variance appeared to stabilize, although the ranges were broad compared with the mean values of the Shannon index (Figs. 2 and 3).

Exergy also showed different patterns in response to different levels of pollution, although some points were same as the Shannon index (Figs. 2–4). The mean values of exergy were generally higher in the least polluted sites (Figs. 2(c) and 3(f)), which are similar to the mean values of the Shannon index. However, in the severely polluted sites, the mean values showed a high degree of fluctuation. For instance, the severely polluted site (e.g., HJD), showed strong variation in the mean values of exergy (Fig. 2(c)). This was also the case for THP and TCL (Fig. 3(f)). This was because exergy was mainly controlled by the contribution of abundant species. If the abundance of dominant species was highly fluctuating, exergy would be variable (Park et al., 2006a). This indicates that exergy could better represent the dynamics of community, whereas the Shannon index would generally represent the overall structural properties of communities (i.e., species richness and evenness).

The variance of exergy showed less fluctuation than its mean values (Figs. 2(d) and 3(g)–3(j)), which was similar to the Shannon index. However, variance was sufficiently variable to such an extent that the values could still represent dynamics in stream communities and address community property pertaining to sampling sites. The increase in exergy and its variance was due to strong variability observed in the abundance of the dominant taxa, mainly Chironomidae, in the severely polluted sites ranging between several hundred individuals/m^2 to several thousand individuals/m^2 in the field data. According to Eqs. (2) and (5), exergy and its variance depend on the ratio (p_i/p_i^0) and the difference $(p_i - p_i^0)$, and the changes in the dominant species in the polluted sites would primarily contribute to the increase in the mean and variance of exergy in such a case.

The values of variance could consequently represent the functioning of community compositions through exergy dynamics. This type of variability was demonstrated in TKC with intermediate level of pollution. Although TKC showed lower Shannon index (Fig. 3), the mean and variance of exergy were highly variable at this site (Figs. 3 (f) and 3(h)). The peak values of exergy variance in TKC were frequently over 2×10^5 J, whereas the maximum of variance in the least polluted site (TSD) never reached 2×10^5 J (Figs. 3(g) and 3(h)). This was due to high variability in dominant taxa as indicated above. In TKC, species tolerant to organic pollution were observed in high abundance intermittently (e.g., *Basommatophora* sp., Physidae sp. with maximum density of 1,635 individuals/m^2) since the site was intermediately polluted with organic enrichment.

It should also be noted that exergy could be used to differentiate pollution sources based on its mean and variance. Two sites, THP and TCL, were both severely polluted (Figs. 3(f), 3(i), and 3(j)), however the exergy values clearly differentiated. Specifically, the mean values of exergy were invariably minimal at THP, whereas the exergy values were highly variable at low levels at TCL (Fig. 3(f)). Furthermore, variance of exergy was minimal in THP, while the value showed substantial variation in TCL (Figs. 3(i) and 3(j)). More precisely, species with higher differences in abundance of dominant taxa, were present in TCL, whereas the densities were invariably low in THP. TCL was highly polluted with organic material; however, THP was affected by industrial pollutants that were produced from small-scale companies located in the river basin around the sampling sites, showing extremely low species richness and abundance (Song et al., 2007). Overall, these findings demonstrate that exergy and its variance enable an in-depth scope of community functioning, and that it is feasible to use the variables to differentiate communities affected by different disturbing agents.

The correlation matrices were shown in Fig. 4 to illustrate the relationships between the means and variances of the Shannon index and exergy. Overall, the means and variances of the two indices were not closely associated, spreading over the scattergrams. Some linearity was observed between the mean and variance within each Shannon index and exergy, but only in the lower range, and the values were otherwise spread broadly in both the seasonal (left panels) and monthly (right panels) data (Fig. 4). Correlations of the two parameters across Shannon index and exergy were even further minimal. These findings indicated that the parameters of the two indices were not closely related; accordingly, information describing the mean and variance could serve as an independent source of community compositions. It should also be noted that two values (both maximum and minimum) of mean exergy matched one value of mean Shannon index in the low range (see the subplot with circles in Fig. 4), suggesting that both the maximum and minimum values of exergy could occur in the polluted sites concurrently.

Using the means and variances of the Shannon index and exergy as input data, a self-organizing map was trained to show overall community patterns (Fig. 5). The clusters effectively reflected different combination of these parameters. When the profiles of four parameters were superimposed on the SOM, the vertical gradient was mainly observed along with increases in the mean and variance of the Shannon index (upper: lower, and bottom: higher) (Fig. 6). Exergy also showed a similar gradient, being higher in clusters Ⅲ and Ⅳ at the bottom area of the map. However, the mean and variance of the Shannon index were located in different positions. Mean values were higher in cluster Ⅳ at in the bottom right corner, whereas variance values were higher at the bottom left corner (Fig. 6). It is also worth noting that the variance and mean of the Shannon index was markedly low in a certain area in the top of the SOM.

Overall, clusters Ⅲ and Ⅳ at the bottom of the map

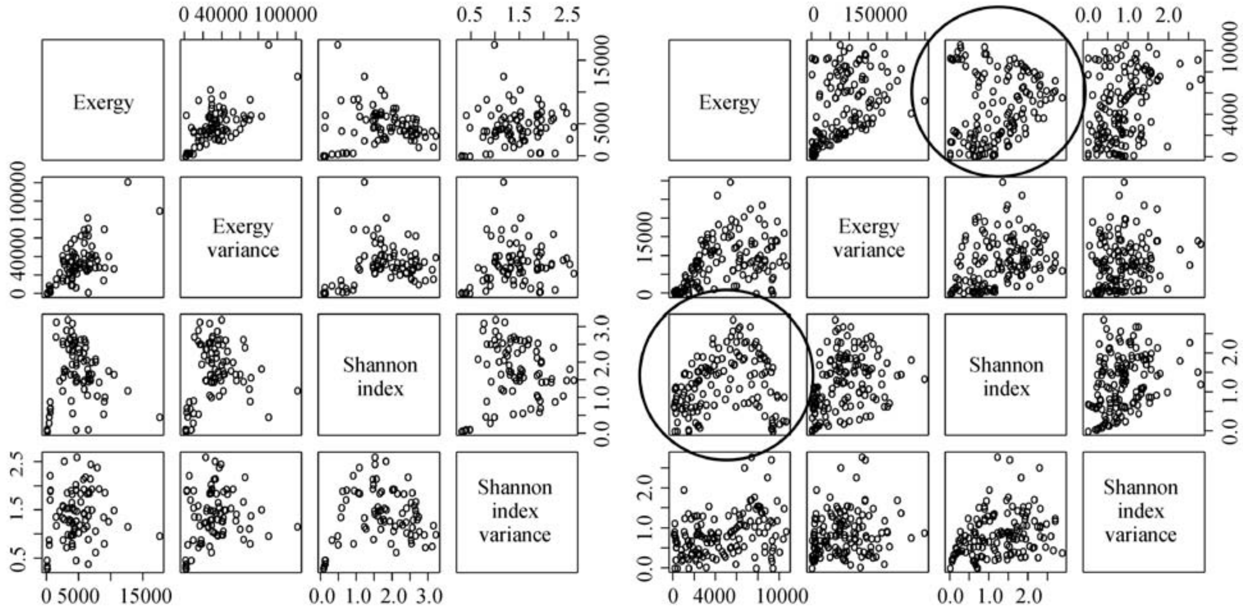

Fig. 4 Correlation matrices between the Shannon index, exergy and their variances for seasonal (84 points, left panel) and monthly (144 points, right panel) data for benthic macroinvertebrates. The circles in the subfigure in the right panel presenting the correlation between exergy and Shannon index show both maximum and minimum values of exergy corresponding to low values of the Shannon index.

mainly represented the least polluted state with relatively high mean Shannon index values, and a majority of communities collected in TSD, DUK, and OCU belonged to these clusters (Fig. 5). Clusters Ⅲ and Ⅳ, however, differentiated according to combinations of parameters although they belonged to the same level of the least polluted state. The differences in parameters were accordingly observable in subpanels in Fig. 6. Cluster Ⅳ appeared to be a typical community frequently observed in the least polluted sites with high mean and relatively lower variance of the Shannon index (Figs. 5 and 6). Communities belonging to Cluster Ⅲ, however, showed somewhat different parameter compositions, with lower mean but with higher variance of the Shannon index. Exergy levels, both mean and variance, were higher in cluster Ⅲ. These findings indicated that more variability of community abundance (e.g., fluctuation of dominant species) could be characterized by combination of the four parameters.

Species abundance patterns were also confirmed with field data according to clusters on the SOM as shown in Fig. 7. In this figure, abundances of the top 20 species were presented except the clusters Ⅰ, Ⅵ, and Ⅶ presenting severe pollution with a limited number of species, and less abundant species were omitted for the purpose of simplicity in illustration. The list of top 20 species and the total number of species in each cluster were presented in the Appendix. Overall trends of species abundance patterns were accordingly observable according to different clusters. Typical species composition in the least polluted sites with maximum mean of the Shannon index was illustrated by cluster Ⅳ (Figs. 5 and 7). Species richness was in the maximal range, and the abundances of dominant species were appeared to be evenly proportioned in this case. Comparing with cluster Ⅳ, however, cluster Ⅲ, showed communities with lower mean but higher variance of the Shannon index (i.e., the sampled communities at TSD and DUK as mentioned earlier (Fig. 5)). In this case, evenness decreased due to enhanced difference in abundance of dominant species as shown in the bar graph in Fig. 7.

Clusters Ⅰ, Ⅵ and Ⅶ presenting polluted sites also clearly differentiated according to combination of parameters (Fig. 5). Cluster Ⅵ represents typical communities observed in the sites severely polluted with organic matter; with relatively low mean values of the Shannon index and relatively high mean values of exergy due to abundance of the selected species tolerant to organic pollution (Fig. 5). Cluster Ⅶ, however, was different from cluster Ⅵ by presenting all the parameters in the minimal values, indicating severe industrial pollution in THP as stated above (Figs. 3(e) and 3(f)). Cluster Ⅳ, on the other hand, presented the communities with less stress of organic pollution, showing higher mean values of the Shannon index and lower mean values of exergy (i.e., decrease in abundance of tolerant species) (Fig. 5). Differentiation of communities was further illustrated in field data (Fig. 7). Cluster Ⅶ, showing minimal values of all parameters, was overwhelmed by the first dominant species. In cluster Ⅵ, however, abundance of the first dominance somewhat decreased whereas abundance of other species increased correspondingly (Fig. 7).

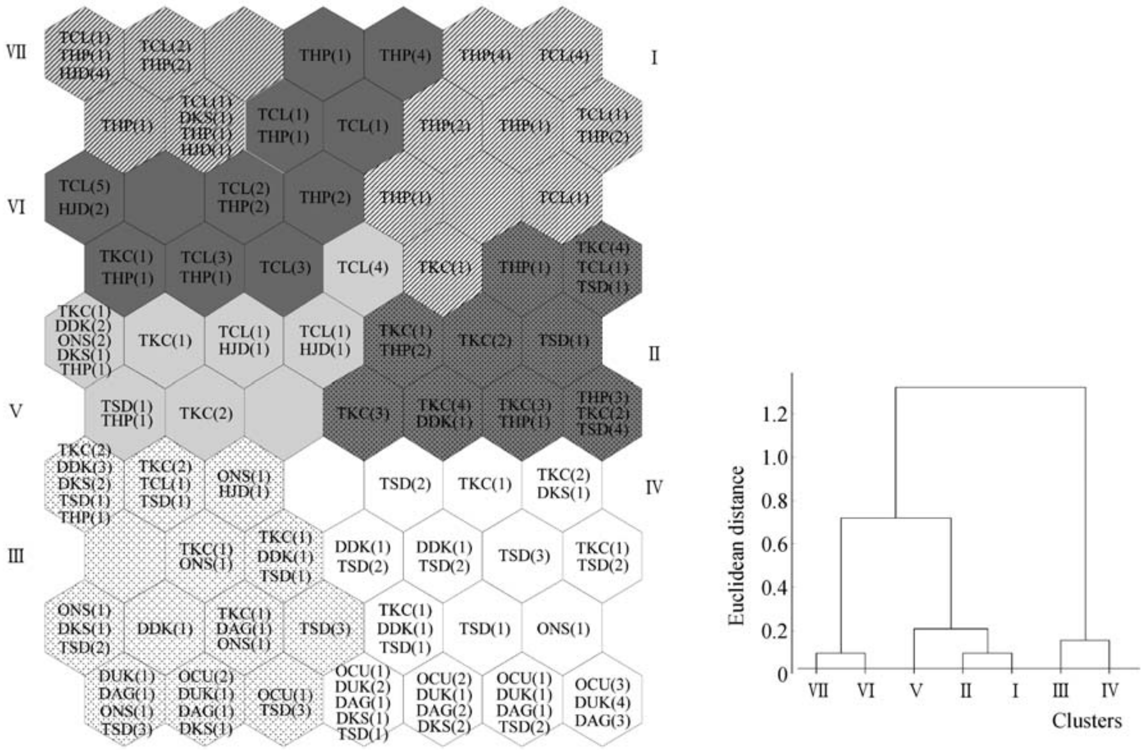

Fig. 5 Clustering by SOM based on the four parameters (means and variances of the Shannon index and exergy) as input data. Seven clusters were observed in relation to different level of pollution (see Results for more explanation). The right subfigure presents dendrogram according to Ward's method (Ward, 1963). The numbers in parentheses following the name of sample sites within the node of SOM indicate the number of samples belonging to the cluster.

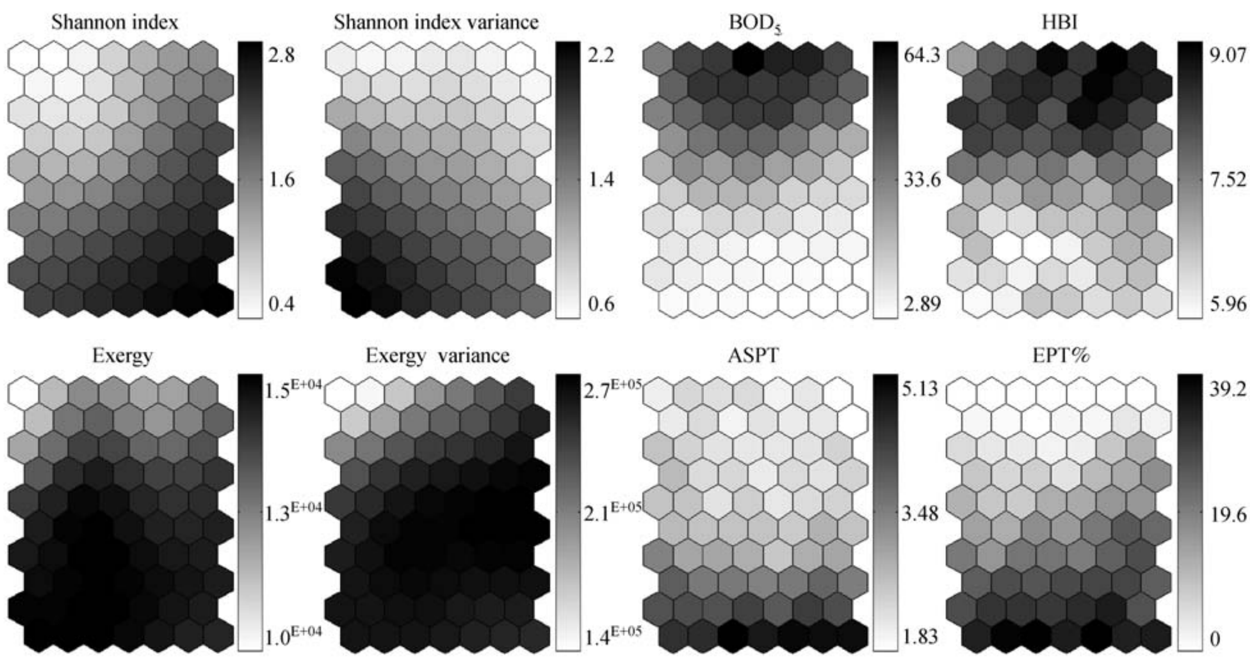

Fig. 6 Profiles of mean and variances of the Shannon index and exergy, BOD_5 and biological indices when the variables were visualized on the SOM (Fig. 5).

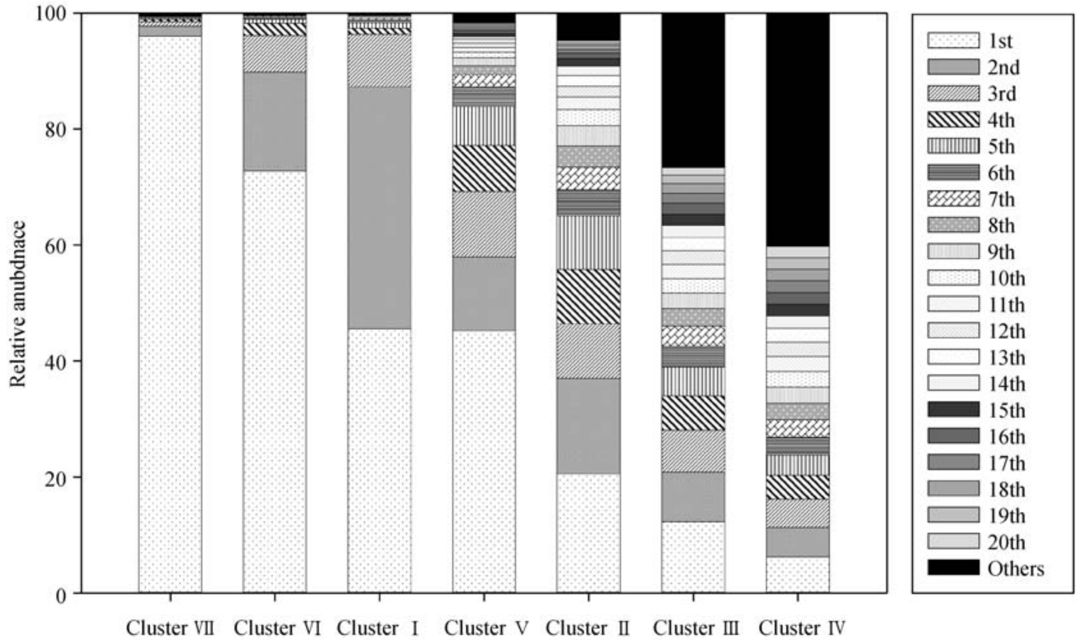

Fig. 7 Relative abundance (%) of benthic macroinvertebrate in each cluster presented on the SOM (Fig. 5). The top 20 dominant species were listed for clusters Ⅱ, Ⅲ, Ⅳ, and Ⅴ, and the top five dominant species listed in clusters Ⅰ, Ⅵ and Ⅶ (See Appendix for the number of total species and names of dominant species.)

Clusters Ⅱ and Ⅴ similarly differentiated communities in the intermediately polluted sites (Figs. 5 and 6). Parameter compositions in these clusters were opposite. Cluster Ⅴ showed high mean of the Shannon index and low mean of exergy along with low variance of the Shannon index and higher variance of exergy. In Cluster Ⅱ, the reversed situation occurred with higher mean of exergy and lower mean of the Shannon index (Figs. 5 and 6). Similarly, differences in parameters were also reflected in species abundance (Fig. 7).

Widely known biochemical (BOD_5) and biological (ASPT, HBI, and EPT%) indices were compared with four parameters based on the profiles of the SOM (Fig. 6). After training with SOM as shown in Fig. 5, the four parameters were initially superimposed on the map by moving average smoothing method based on two nearest neighbor nodes. Subsequently the profiles of four indices were also visualized on the map (Fig. 6). Since each index only presents one aspect, the single value was not able to present the community state in a full scope. BOD_5 presenting the biochemical property of oxygen demand showed a gradient in the upper, polluted part of the SOM (Fig. 6). Nevertheless, the gradient was not precise in the lower, polluted part on the SOM (Fig. 5). Thus, detailed differentiation was not measurable in the zone of least polluted sites. Similarly, profiles of biological indices were also addressed differently according to profiles based on the four parameters. HBI showed the similar gradient observed by BOD_5 (Fig. 6). The profile was relatively broader than the profile of BOD_5. Profiles of EPT% and ASPT, which showed high levels in least polluted area, however, were different from the profile of HBI, being limitedly higher at the bottom area of the SOM since the values would be higher at clean sites. Nevertheless, profiles of EPT% and ASPT were further different in some degree. EPT% appeared to be the highest range at the bottom area of the SOM whereas ASPT showed the maximum level more specifically at the bottom right corner of the map (Fig. 6). This indicated that the biological indices could be differently characterized according to profiles of the parameters. ASTP matched the maximum mean values of Shannon index and lower values of other three parameters, especially variance of Shannon index, comparing with EPT% (Fig. 6). Considering ASPT would be represented by the number and abundance of taxa at the family level, which was less tolerant to pollution (Armitage et al., 1983), maximum mean values of the Shannon index would indicate the possibility of a higher number of species that are less tolerant to pollution. Consequently cluster Ⅳ, matching high Shannon index values at the bottom right corner of the SOM, would show higher levels of ASPT. HBI, on the other hand, mainly presented the similar impact observed by BOD_5 as stated above. Overall, four parameters could effectively diagnose the classification system by water quality indices according to community properties based on information concepts.

4 Discussion

In this study, analyses of community properties were performed based on the means and variances of the Shannon index and exergy, and the parameters were feasible in expressing in-depth ecological integrity across different levels of pollution. With further addition of variances, community properties could be more specifically identified regarding structural and functional aspects. At least polluted sites, communities with relatively higher variance but with lower mean values of the Shannon index were identified from communities with lower variance but with maximal mean values of the Shannon index (clusters Ⅲ and Ⅳ in Fig. 5). In addition, communities collected in the severely polluted sites THP and TCL accordingly differentiated (clusters Ⅰ, Ⅵ, and Ⅶ in Fig. 5) according to mean and variance of exergy.

The conventional physicochemical (BOD_5) and biological (HBT, ASPT, and EPT%) indices were effectively mapped on the SOM based on the profiles of the four parameters (Fig. 6). Since the parameters are determined based on information levels, changes in water quality indices were identifiable and can be efficiently tractable in terms of structural and functional change in community properties. The Shannon index was derived by ensuring two conditions that the measure of diversity will be a maximum when all the species are presented in equal proportions (i.e., maximum evenness) and that the population with larger number of species will have the higher diversity, given equal evenness (Pielou, 1977). The Shannon index could reflect structural property of communities, evenness and richness in species compositions. Exergy, on the other hand, addresses dynamics of dissipation energy by defining the amount of work that a system can perform as it is brought into thermodynamic equilibrium with its environment (Straškraba et al., 1999). Consequently, the two indices in combination were feasible in illustrating change in community states in both structural and functional properties based on information concepts when exposed to natural variability and pollution.

There are numerous biological indices (e.g., BOD_5, HBT, ASTP, and EPT%) to evaluate quality of aquatic ecosystems (Jørgensen et al., 2005a). It was agreeable that development of single parameter would be desirable in order to express overall integrity of the sampled data with a general index. However, parameters have only partially been much successful in solely illustrating the overall gradient of water quality under the constraint of complex environmental impact (Hering et al., 2006). Although multi-metrics have been proposed based on community abundance data and development of single index based on multi-metrics, screening is still ongoing (Barbour et al., 1996; Reynoldson et al., 1997; Blocksom et al., 2002; Chon, 2011). These indices were mostly based on empirical results. Consequently, the parameters based on information concepts would be suitable in objectively diagnosing community variability (Fig. 6) and could serve as an efficient reference system for the proposed index.

Regarding illustration of community properties, it was worth noting that variances of the Shannon index and exergy were effective in expressing community variation. Although theoretical formula of Shannon index variance was first reported in the 1980s (Nayak, 1985), it has not been utilized extensively when evaluating ecological integrity and neither with exergy. To the best of authors' knowledge, this is the first report focusing on concurrent utilization of the means and variances of the Shannon index and exergy for expression of ecological integrity. It should also be noted that the Shannon index and exergy (Eqs. (4) and (5)) could be calculated from point sampling as proposed in this study, which would not require additional samples and therefore reduce time and effort required in surveys.

Beside exergy, emergy has been proposed to account for the quality of energy by the use of transformity factor (Odum, 1988). While exergy analysis focused on the first step (i.e., reference state) of the inputs, emergy analysis considered all direct and indirect inputs to be on the same level (Bastianoni et al., 2007). Emergy would be often more easy to compute if the ecological network is known. However, exergy may have a better theoretical basis since it was developed by thermodynamic theory and seems to be a proper measure of survival and growth of the organisms, especially in life systems (Jørgensen et al., 1995). In benthic macroinvertebrate communities, the reference state was considered as an important factor regarding maintenance of system equilibrium. Moreover species in the same consumer level have different weight to express the proper amount of information level in communities (Jørgensen et al., 2005b). Consequently, exergy was chosen in our study instead of emergy in this regard.

Further study is necessary to reveal how the four parameters could sensitively reveal the impact of environmental disturbances along with more field data in diverse situations. These findings should also facilitate development of hypotheses by ecologists and ecosystem managers regarding whether ecological integrity management could be expressed for resource conservation and sustainable management of aquatic ecosystems.

5 Conclusions

The means and variances of the Shannon index and exergy based on information concepts could be suitable in revealing new scopes in defining ecological integrity, reflecting changes in structural and functional properties of communities in response to pollution. Along with variance, the Shannon index could be used to more clearly identify communities in the least polluted sites with relatively low mean values of diversity, such as communities with high richness but low evenness. In addition, mean and variance of exergy accordingly reflected the dynamics of dominant species across different levels of pollution. When the parameters were trained with the SOM, the conventional physicochemical and biological indices were effectively mapped on the SOM. In-depth illustration was possible by diagnosing the index classification with combination of the parameters in responding to environmental impact. Considering that objective expression of ecosystems is an urgent concern in sustainable ecosystem management, use of the means and variances of the two parameters in combination would be an efficient tool for assessing of ecological integrity and could be utilized as a suitable reference system for assessment of the health of aquatic ecosystems exposed to environmental disturbances.

Appendix

Table A1 List of top 20 species (density; individual/m^2) and the total number of species observed in different clusters based on SOM

Rank	Cluster Ⅰ	Cluster Ⅱ	Cluster Ⅲ	Cluster Ⅳ	Cluster Ⅴ	Cluster Ⅵ	Cluster Ⅶ
1st	*Chironomus flaviplumus* (5,067)	*Limnodrilus hoffmeisteri* (3,913)	*Orthocladius suspensus* (6,303)	*Baetis fuscatus* (2,528)	*Chironomus flaviplumus* (4,739)	*Chironomus flaviplumus* (5,067)	*Chironomus flaviplumus* (9,354)
2nd	*Limnodrilus hoffmeisteri* (4,637)	*Physa acuta* (3,138)	*Baetis fuscatus* (4,384)	*Cheumatopsyche* sp. (2,062)	*Orthocladius suspensus* (1,336)	*Limnodrilus hoffmeisteri* (4,637)	*Conchapelopia unzenalba* (163)
3rd	*Psychoda* sp. (1,004)	*Orthocladius suspensus* (1,792)	*Cheumatopsyche* Kua (3,709)	*Parametriocnemus stylatus* (1,989)	*Cricotopus* sp. (1,184)	*Psychoda* sp. (1,004)	*Limnodrilus hoffmeisteri* (81)
4th	*Erpobdella* sp. (115)	*Baetis fuscatus* (1,787)	*Chironomus flaviplumus* (3,008)	*Synorthocladius semivirens* (1,653)	*Limnodrilus hoffmeisteri* (829)	*Orthocladius suspensus* (115)	*Psychoda* sp. (36)
5th	*Enchytraeus* sp. (107)	*Chironomus flaviplumus* (1,756)	*Orthocladius yugashimaensis* (2,529)	*Simulium* sp. (1,436)	*Baetis fuscatus* (709)	*Tvetenia tamafalva* (107)	*Physa acuta* (22)
6th	*Orthocladius suspensus* (54)	*Conchapelopia japonica* (860)	*Serratella setigera* (1,842)	*Hydroptila* sp. (1,242)	*Erpobdella* sp. (355)	*Paratrichocladius rufiventris* (54)	*Cricotopus* sp. (19)
7th	Glossiphonidae sp. (40)	*Micropsectra atrofasciatus* (738)	*Cricotopus* sp.3 (1,791)	*Orthocladius suspensus* (1,226)	*Conchapelopia japonica* (225)	*Tubifex tubifex* (40)	*Orthocladius yugashimaensis* (9)
8th	*Tvetenia tamafalva* (36)	*Cricotopus* sp.3 (691)	*Tanytarsus* sp. (1,559)	*Eukiefferiella ilkleyensis* (1,150)	*Micropsectra atrofasciatus* (151)	*Conchapelopia japonica* (36)	*Erpobdella lineata* (8)
9th	*Tubifex tubifex* (11)	*Erpobdella* sp. (674)	*Limnodrilus hoffmeisteri* (1,367)	*Tanytarsus* sp. (1,133)	*Psychoda* sp. (149)	*Glyptotendipes* sp. (11)	*Orthocladius* sp. (7)
10th	*Orthocladius* sp. (11)	*Bithynia Kiusiuensis* (525)	*Diamesa plumicornis* (1,268)	*Orthocladius* sp. (1,104)	*Polypedilum unifascium* (96)	*Eukiefferiella* sp. (11)	*Cricotopus* sp.2 (7)
11th	*Conchapelopia japonica* (11)	*Psychoda* sp. (412)	*Synorthocladius semivirens* (1,255)	*Conchapelopia japonica* (1,038)	*Paratrichocladius rufiventris* (87)	*Enchytraeus* sp. (11)	*Glyptotendipes* sp. (6)
12th	*Tipula* sp. (8)	Hirudinae sp. (360)	*Micropsectra atrofasciatus* (1,230)	*Tvetenia tamafalva* (1,014)	*Tvetenia tamafalva* (86)	*Tanytarsus* sp. (8)	*Conchapelopia japonica* (5)
13th	*Cricotopus* sp. (7)	*Orthocladius* sp. (344)	*Hydroptila* sp. (1,150)	*Chironomus flaviplumus* (977)	Glossiphonidae sp. (63)	*Orthocladius* sp. (7)	*Tanytarsus* sp. (4)
14th	*Polypedilum unifascium* (4)	*Tanytarsus* sp. (304)	*Conchapelopia japonica* (1,057)	*Rheopelopia toyamazea* (841)	*Orthocladius* sp. (53)	*Cheumatopsyche* sp. (4)	*Pseudoorthocladius* sp. (4)
15th	*Baetis fuscatus* (4)	*Tubifex tubifex* (247)	*Cheumatopsyche* sp. (995)	*Brillia* sp. (827)	*Lamprortus orientalis* (48)	Hirudinae sp. (4)	*Saetheria tylus* sp. (2)
16th		Glossiphonidae sp. (181)	*Tvetenia tamafalva* (963)	*Ecdyonurus kibunesis* (826)	*Tubifex tubifex* (48)		*Tvetenia tamafalva* (2)
17th		*Sympotthastia takatensis* (129)	*Sympotthastia takatensis* (894)	*Polypedilum unifascium* (822)	*Eukiefferiella ilkleyensis* (41)		*Eukiefferiella ilkleyensis* (2)
18th		*Cheumatopsyche* sp. (121)	*Parametriocnemus stylatus* (842)	*Serratella setigera* (819)	Hirudinae sp. (37)		*Brillia* sp. (1)
19th		*Cricotopus* sp. (85)	*Stenochironomus nelumbus* (749)	*Gammarus fasciatus* (818)	*Cheumatopsyche* sp. (33)		*Gammmmmarus fasciatus* (1)

(*Continued*)

Rank	Cluster Ⅰ	Cluster Ⅱ	Cluster Ⅲ	Cluster Ⅳ	Cluster Ⅴ	Cluster Ⅵ	Cluster Ⅶ
20th		*Polypedilum unifascium* (74)	*Polypedilum aviceps/su* (673)	*Micropsectra atrofasciatus* (779)	*Brillia* sp. (29)		*Hirudo nipponica* (1)
Total no. of species	11,116	19,051	51,208	40,639	10,487	11,119	9,741

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