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Impact of abundance data errors on the uncertainty of an ecological water quality assessment index

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ABSTRACT

Increased awareness about the uncertainty of ecological water quality (EWQ) assessment tools in river management has led to the identification of the underlying uncertainty sources and the quantification of their effect on assessment. More specifically, with respect to macroinvertebrate-based EWQ assessment, use of erroneous abundance data has been identified as a (possible) source of uncertainty. In this paper, the effect of erroneous abundance data on the uncertainty of an EWQ assessment index was investigated. A model simulation based method, the virtual ecologist approach, was used to estimate the impact of abundance data errors on the uncertainty of the Multimetric Macroinvertebrate Index Flanders (MMIF). The results of this study show that the effects of relative small errors on the MMIF and assessment are limited. Additionally, it is observed that uncertainties due to abundance errors increase with decreasing EWQ (i.e. lower MMIF). This is important, since decision-makers typically formulate management actions for rivers with a low EWQ. In short, the innovative virtual ecologist approach proved to be very successful to research the index uncertainty and present a unique insight in the functioning of the assessment index.

1. Introduction

Ecological water quality (EWQ) assessment of freshwater ecosystems is subject to uncertainty and errors. Decision-makers are increasingly aware of the importance of including uncertainty in the assessment of the aquatic environment (Uusitalo et al., 2015). Consequently, it is a matter of concern that the sources of the uncertainty in the assessment are identified and effects are quantified (Clarke et al., 2002). For instance, macroinvertebrate-based EWQ assessment is often based on presence-absence and abundance data to calculate a multimetric index (Hering et al., 2003, 2004). As such, errors in these data will influence the precision of the multimetric index calculation, EWQ assessment and decisions in river management.

Clarke and Hering (2006) state that variations in macroinvertebrate field data are due to sampling variations, sampling method, natural temporal variation (i.e. variations caused by reasons other than stress or pollution), sample processing and errors in taxonomic identification. Several studies have researched the effect of these variations and errors on EWQ assessment (Clarke et al., 2002, 2006; Haase et al., 2006; Lorenz and Clarke, 2006; Šporka et al., 2006; Vlek et al., 2006; Johnson et al., 2012). Sampling variations are observed variations within one site, caused by a spatial heterogeneity in microhabitats and distribution of macroinvertebrate species in these habitats. Lorenz and Clarke (2006) introduced the term "sample coherence" with the aim to assess within site variability. They concluded that sample coherence, expressed in several similarity indices, between replicates in one site is high.

Clearly, the precision of the used sampling method will be influenced by the range of habitats (i.e. area) which are sampled and the number of sampling units (Barbour et al., 2003). With respect to number of sampling units, Vlek et al. (2006) investigated the effect of sample size (i.e. physical size, expressed as the length over which the river is sampled) on metric uncertainty by comparing the variance of several metrics for an increased sample size. As expected, the precision (uncertainty) of all metrics increased (decreased) as the sample size increased. The sample size needed to gain a certain degree of precision was, however, different for every metric.

Furthermore, with respect to natural variations, a high "seasonal coherence" was observed, indicating that samples taken in the same season show higher similarity than samples taken in different seasons (Lorenz and Clarke, 2006). This was confirmed by Šporka et al. (2006) and Johnson et al. (2012), who observed an effect of seasonality on the samples and calculated metrics. In a final example, Clarke et al. (2006) researched the uncertainty due to sample processing by quantifying the effect of sub-sampling on a number of metrics. Sub-sampling is carried out by selecting a representative part of the sample and is required according to the

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STAR-AQEM method (Clarke and Hering, 2006). Clarke et al. (2006) took replicates of sub-samples to assess the effect of this procedure on the metric uncertainty. They concluded that sub-sampling of the field sample can cause variations in several metrics up to 50%.

Apart from sampling variations and method, temporal variations and sample processing, errors in the taxonomic identification are a source of uncertainty in EWQ assessment (Clarke and Hering, 2006). The taxonomic identification covers the identification of species and the abundance of each unique species. The latter data are often used to calculate metrics which account for community evenness and/or diversity (for example, the Shannon Wiener Diversity index). As indicated by Haase et al. (2006) and Jones (2008), the errors in species identification will influence the assessment results. Additionally, the variations and errors in the identification of species abundance could also have an impact on the uncertainty of the EWQ assessment. However, to the authors' knowledge, this impact has yet to be quantified.

In this research, we investigated the impact of errors in species abundance data on a multimetric index and the coupled EWQ assessment. To do so, we used the virtual ecologist approach of Zurell et al. (2010) which has received increasing attention to assess the quality of sampling protocols, data collection and model evaluation. In a virtual experiment, data are simulated by an observer model and used as input for a simulation model, which, in our case, is the multimetric index. We used an observer model to simulate errors on abundance data and researched the effect of these errors on the multimetric index. The paper is structured as follows: in Section 2, we present the set-up of the virtual experiment, the used data and multimetric index. In Section 3, we present the results of the experiment. Finally, in Section 4, we discuss and summarise the findings of the experiment and the implications for EWQ assessment.

2. Materials and methods

A schematic representation of the virtual experiment is presented in Fig. 1. In the top panel of the figure, the methodology of a field experiment is shown. A sample of the river's macroinvertebrate community is taken, the sample is processed and the present taxa and abundance are identified. The taxa and abundance data (Section 2.1) are used as input for the multimetric index (Section 2.2), so that the EWQ of the river can be assessed. In the lower panel of Fig. 1, simulated data are generated with an observer model and the original data (Section 2.3). In this experiment, the observer model accounts for errors in the abundance data due to miscounts, misidentification and erroneous estimates. The simulated data are used to calculate the multimetric index and to assess the EWQ. Monte Carlo (MC) simulations are used to estimate the uncertainty of the multimetric index (Section 2.4). In order to estimate the effect of the abundance error on the assessment, the true metric results are compared with the MC simulations (Section 2.5).

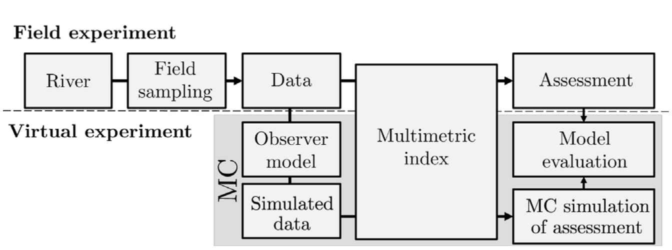

Fig. 1. Illustration of the virtual experiment. In the top panel, the procedure of a typical field experiment is shown, in which data are collected by sampling the river's macroinvertebrate community. The data are used to calculate the multimetric index and assess the EWQ of the river. In the virtual experiment (lower panel), simulated data are generated with an observer model. This model simulates data by perturbing the original dataset with an error rate (see also Section 2.3). Monte Carlo (MC) simulations are used to estimate the uncertainty of the multimetric index. The MC simulations are evaluated by comparing the simulations with the true metric values.

2.1. Data

The dataset consists of samples of macroinvertebrates collected by the Flemish Environment Agency (VMM). The macroinvertebrate samples were collected by the VMM over a period of 20 years. Throughout this period, the VMM has monitored the EWQ at more than 2500 locations in Flanders spread over different water bodies (Boets et al., 2013). All data were collected using the sampling methodology described by De Pauw and Vanhooren (1983) and Gabriels et al. (2010). The macroinvertebrate community was sampled using kick sampling with hand nets (De Pauw and Vanhooren, 1983) or artificial substrates (De Pauw et al., 1986, 1994). In the laboratory, the macroinvertebrate species were picked and identified based upon the determination key of De Pauw and Vannevel (1991) and the reference taxa list of Gabriels et al. (2010). The abundance of all present taxa was counted or estimated in a tray. An estimate of the abundance was done when more than 10 instances of the species were present. Typically, this was done by dividing the tray in a number of subsections and counting the species abundance in one subsection of the tray. Finally, the count in this one subsection was multiplied by the number of equal subsections in the tray (internal communication and VMM (2014)). In this study, abundance data between 2000 and 2012 of the VMM data base were used. The dataset comprises 7260 unique samples collected in 2682 sampling locations.

2.2. Multimetric index

The multimetric index used in this study was the Multimetric Macroinvertebrate Index Flanders (MMIF) (Gabriels et al., 2010). The MMIF is a multimetric index that aggregates five metrics accounting for evenness, species richness and sensitivity properties of the macroinvertebrate community. The included metrics are the taxa richness (TAX), the number of Ephemeroptera, Plecoptera and Trichoptera (EPT), Number of other (i.e. non-EPT) Sensitive Taxa (NST), the Shannon-Wiener Diversity (SWD) index and the Mean Tolerance Score (MTS). A scoring system is appointed to each metric based on defined reference values. These score values range from zero to four with four being assigned to the metric values nearest to the reference value. The five scores are summed and subsequently divided by 20 to obtain a discrete value for the MMIF between 0 and 1, representing an ecologically unfavourable and favourable status of the water body, respectively. These values are then classified in 5 classes – Bad, Poor, Moderate, Good and High – based on quality class ranges which are defined for every type of water body through an intercalibration exercise (Buffagni and Furse, 2006; Gabriels et al., 2010). Since abundance data are only used to calculate the SWD, we only analysed the SWD metric and its related score (SWD_s), as well as the effect of this metric on the numerical MMIF value and MMIF class ($MMIF_c$).

2.3. Observer model

The observer model simulates data from the original abundance data (Section 2.1). It is assumed that abundance errors increase with increasing values of the abundance. The simulated data are generated from the original dataset by adding a multiplicative normal distributed (**N**) error model:

$$\mathbf{A}' = \mathbf{A} + \mathbf{A} * \mathbf{N}(0, \epsilon^2) \quad (1)$$