Do we have to incorporate ecological interactions in the sensitivity assessment of ecosystems? An examination of a theoretical assumption underlying species sensitivity distribution models

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Abstract

Species sensitivity distributions (SSDs) are statistical distributions which extrapolate single-species toxicity test results to ecosystem effects. This SSD approach assumes that ecological interactions between populations, such as grazing and competition, do not influence the sensitivity of ecosystems. The validity of this assumption in a simple freshwater pelagic ecosystem was tested using ecosystem modelling. For each of a 1000 hypothetical toxicants, a lognormal SSD was fitted to chronic single-species EC10s of the species present. As such, these distributions did not account for ecological interactions and were therefore termed ‘conventional SSDs’ (cSSDs). Next, sensitivity distributions that did take into account ecological interactions were constructed (eco-SSD) for the same 1000 toxicants, using an ecosystem model. For 254 of the 1000 hypothetical toxicants, mean and/or variance of the cSSD were significantly higher than mean and/or variance of the eco-SSD, as such rejecting the general validity of the tested assumption. A classification tree approach indicated that especially toxicants which directly affect phytoplankton (i.e. herbicides) may have a higher mean for cSSD than for eco-SSD. Conversely, means of eco-SSD and cSSD tend to be equal for toxicants directly affecting zooplankton and fish, e.g. insecticides. For the 254 hypothetical toxicants for which the tested assumption was false, a predicted no effect concentration (PNEC) calculated as the lowest single-species EC10 divided by an application factor of 10 was on average a factor 10 lower than the corresponding ecosystem-NOEC calculated by the ecosystem model.
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1. Introduction

Ecological effect assessments aim at evaluating or predicting the effects of a chemical substance on the structure and function of ecosystems. In environmental risk assessments, these “higher-level effects” are usually estimated by extrapolation of single-species effect data. Statistical models are used to perform such extrapolation and are known as ‘species sensitivity distributions’ (SSDs). A set of assumptions is associated with both the underlying theory and the application of SSDs (Forbes and Calow, 2002). These assumptions can be divided into (1) T-assumptions, i.e. related to the theory underlying the SSD methodology, and (2) P-assumptions, i.e. related to the way the SSD methodology is applied in practice (Forbes and Calow, 2002). Several authors have examined these assumptions experimentally (e.g., Duboudin et al., 2004a; Hose and van den Brink, 2004, Versteeg et al., 1999). However, it has been more common to investigate the implications of a violation of an assumption for water quality standard derivation (e.g., Duboudin et al., 2004a; Forbes et al., 2001; Hose and van den Brink, 2004).
Brink, 2004; Maltby et al., 2005) than to test the validity of the assumption itself (e.g. Newman et al., 2000; Selck et al., 2002). Also, efforts are skewed towards the testing of ‘P-assumptions’ (e.g., Kefferd et al., 2005; Maltby et al., 2005; Duboudin et al., 2004a; Forbes et al., 2001; Hose and van den Brink, 2004). Studies on assumptions related to the theoretical background of SSDs, i.e. ‘T-assumptions’ are scarce. Until now only assumption T3, i.e. that ecosystem structure is equally or more sensitive than ecosystem function, has been tested (Selck et al., 2002; Baleczon and Pratt, 1994).

In this paper, the assumption T1 will be tested, i.e. that ecological interactions between species do not influence the parameters of the sensitivity distribution. A “conventional” SSD is based on single-species toxicity test results (hereafter termed ‘cSSD’) and considers species as isolated entities without taking into account possible ecological interactions between populations. If ecological interactions between species do not influence the sensitivity distribution (i.e. if T1 is valid), a sensitivity distribution that does take into account ecological interactions should be the same as the cSSD, i.e. parameters describing both distributions should be the same.

In the present study we constructed cSSDs for 1000 hypothetical toxicants. Each cSSD was based on single-species toxicity test results of phytoplankton, zooplankton, and fish. In parallel, sensitivity distributions taking into account ecological interactions between species, here termed “eco-species sensitivity distributions” (eco-SSDs) were constructed for the same 1000 toxicants. Eco-SSDs were based on no observed effect concentrations (NOECs) for the populations present in the ecosystem, as such taking into account ecological interactions. These population-NOECs were calculated by an ecosystem modelling approach. A comparison between the parameters of eco-SSDs and cSSDs was performed to test assumption T1. Statistical analyses were used to examine the relationship between validity of T1 and toxicant type.

2. Materials and methods

2.1. Considered ecosystem

The ecosystem for which hypothesis T1 was tested is a simple lentic pelagic system consisting of populations of one fish species, three zooplankton species (two are slow growing, one is fast growing) and two phytoplankton species (one is slow growing, one is fast growing).

2.2. Ecosystem model

A mechanistic dynamic ecosystem model was constructed using an object oriented framework. The model consists of a set of objects, where each object describes the growth of a population in terms of its total biomass using differential equations based on USEPA (2002). By connecting different objects (rotifers: fast growing; large cladocerans: slow growing; large copepods: slow growing), and one planktivorous fish object. Ecological interactions were set according to Sommer et al. (1986). Large-bodied zooplankton (most copepods and cladocerans) graze on both small and large phytoplankton, while small-bodied zooplankton can only ingest small phytoplankton. Planktivorous fish preferred large-bodied over small-bodied zooplankton as food source (Werner and Hall, 1974; Chang et al., 2004). The resulting customized food web is shown in Fig. 1.

The ecosystem model was calibrated to obtain a realistic succession of seasonal events for this type of system, as described in Sommer et al. (1986). These events are, (1) bloom of spring phytoplankton, (2) bloom of small zooplankton, resulting in a ‘clear water phase’, (3) a bloom of summer phytoplankton, followed by (4) a bloom of larger zooplankton, and (5) a small peak of fish. Parameter values resulting in population dynamics reflecting those events are given in the supporting document.

The toxic effect sub-models embedded in the ecosystem model, consist of logistic concentration–effect functions describing the effects of the toxicants on the parameters of the ecosystem model. Modelling the dynamics of an exposed ecosystem is performed by adjusting these parameters according to the concentration–effect functions and the exposure concentration. Parameters in the ecosystem model, that vary as a function of toxicant concentration are (1) the mortality rate of zooplankton and fish, and (2) the photosynthesis rate of phytoplankton. An overview of the equations of the toxic effect sub-models and the values assigned to their parameters is given in Table 1.

2.3. cSSD vs. eco-SSD for one hypothetical toxicant

Assume that for a toxicant $t_x$, all chronic $EC_{10\%}$ of all possible aquatic species, are represented by a lognormal species sensitivity distribution $SSD_1$ with a mean $\mu_1$ and a standard deviation $\sigma_1$: $SSD_1 \sim (\mu_1, \sigma_1)$.

As for any toxicant, the parameters of $SSD_1$ are not known, as it is impossible to subject each and every species to toxicity testing. Instead, these parameters have to be estimated experimentally by testing the sensitivity of only a small fraction of all possible species. It was thus assumed that for $t_x$, chronic $EC_{10\%}$ had been experimentally derived for standard test species which are representative for the populations in the considered ecosystem. As too little is known about the sensitivity of standard test species relative to that of untested species, $6 EC_{10\%}$ were sampled randomly from $SSD_1$. To estimate the parameters

![Food web diagram of the considered ecosystem](image)
Phytoplankton: effect on photosynthesis

\[
P_{\text{max}} = \frac{P_{\text{max}}}{(\text{e}^{\text{max}})}
\]

EC10 = \text{lethal concentration for 10% of the organisms, as determined in the acute toxicity assay; LCR= Ratio of photosynthetic rate (d) for zooplankton and 9.5 for fish) were found in Lange et al. (1998). Values for slope (1.8 for all populations) were found in Smit et al. (2001).}

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Zooplankton and fish: effect on mortality rate

Knorr = \text{mortality rate (1.1); br= natural logarithm; time= duration of toxicity assay (d), set to two days for all zooplankton and fish; LC50= lethal concentration for 50% of the organisms, as determined in the acute toxicity assay; LCR= Ratio of "lethal effect concentration" to "chronic effect concentration"

Next, the same 6 EC10s were used in the toxic effect sub-models of the 6 populations in the ecosystem model (Table 1). With the as such parameterized ecosystem model, the dynamics of these populations at different exposure concentrations of txi were predicted. Exposure concentrations ranged from the 1st to the 95th percentile of SSDi. The exposure period was from late spring to late summer, i.e. comparable to many large-scale studies. To compare the biomass status of a population in the unexposed (reference) situation with its status at the different exposure concentrations, relative differences (RDs) were calculated:

\[
RD_{tx} = \frac{X_{tx,p}}{X_{ref,p}}
\]

with:

\[
X_{tx,p} = \text{the time-averaged biomass concentration of population 'p', when exposed to a toxicant concentration 'tx';}
\]

\[
X_{ref,p} = \text{the time-averaged biomass concentration of population 'p' in the unexposed case, i.e. the reference value}
\]

Because 20% is the minimum detectable difference for most population characteristics in the field (Suter, 1993), RD-values of 0.2 or lower were considered as detectable decreases of biomass. Similarly, RD-values of 0.2 or higher were considered as detectable increases of biomass. In the context of ecological effect assessments, both increases and decreases of phytoplankton biomass were considered undesirable: the former because of an increased eutrophication risk, the latter because of a loss of primary production, a key process in pelagic aquatic ecosystems. For fish and zooplankton, biomass decreases were considered as undesirable. The NOEC of a population, hereafter termed 'population-NOEC', was defined as the highest concentration at which no observable undesired effect was predicted for that population. Note that these population-NOECs were determined using an ecosystem model, as such taking into account ecological interactions in this NOEC calculation. A cumulative plot of those 6 population-NOECs was defined as the eco-Species Sensitivity Distribution for tx1 (eco-SSD):

\[
\text{eco-SSD} = (\mu_{tx}, \sigma_{tx}).
\]

Using these definitions, the hypothesis T1 was rephrased as:

\[
\mu_{tx} = \mu_{tx,\text{eco}} + \sigma_{tx,\text{eco}}.
\]

Consequently, the validity of T1 was tested for tx1 using two-sided t and F-tests and a p-level of 0.05.

2.4. Extension to 1000 hypothetical toxicants

The methodology described in the previous paragraph was followed for toxicants tx from tx1 to tx100. SSDi to SSD100 differed in mean but had the same standard deviation (\(\sigma_{tx}=\sigma_{tx,\text{eco}}=\sigma_{tx,\text{NOEC}}=1\)). A standard deviation of one order of magnitude is representative for SSDs of many chemicals (e.g. examples in Duboudin et al., 2004b). The means of the 1000 toxicants were sampled from a lognormal distribution with mean −0.43 and standard deviation 0.92. These variability settings were calculated from Gonzalez-Doncel et al. (2006) from means and standard deviations of NOEC values of fish (n=343), crustaceans (n=414), and algae (n=186) for all toxicants included in different toxicity databases.

2.5. Comparing 'safe concentrations' derived from cSSD with ecosystem-NOECs derived from the ecosystem model

We tested if 'safe concentrations' derived from a cSSD, i.e. not accounting for ecological interactions, were different from their corresponding ecosystem-NOECs, i.e. accounting for ecological interactions.

A predicted no effect concentration (PNEC) based on SSD was established by means of two frequently used methods: (1) using the lowest of the 6 chronic single-species EC10s (which represent three trophic levels), divided by an application factor of 10 (AF – PNEC) and (2) the left side 50% confidence limit of the hazardous concentration for 5% of the species (HC5 – PNEC), as in Wagner and Lokke (1991). Note that the AF – PNEC was derived based on EC10 data, in the absence of single-species NOEC data, as proposed by the TGD (EU, 2003). The ecosystem-NOEC was defined as the lowest population-NOEC in the eco-SSD: when exposed to this ecosystem-NOEC, no population will experience an undesirable effect.

2.6. Relationship between toxicant type and validity of T1

Here, we examined whether the validity of T1 is related to the type of toxicant. Toxicant type was arbitrarily defined here on the basis of the relative sensitivity of the considered species for the toxicant. In this context, the relative sensitivity is defined by the following two quantities:

\[
\text{r}_{\text{P}} = \log(\text{EC}_{10,\text{phytoplankton}}) - \log(\text{EC}_{10,\text{zooplankton}})
\]

\[
\text{r}_{\text{F}} = \log(\text{EC}_{10,\text{zooplankton}}) - \log(\text{EC}_{10,\text{fish}})
\]

with log(\text{EC}_{10,\text{phytoplankton}}) and log(\text{EC}_{10,\text{zooplankton}}) equal to the logarithm of the geometric mean of the EC10 values of the two phytoplankton and three zooplankton species, respectively. These quantities are an indication of which species are directly targeted by the toxicant. For example, a toxicant with a value of -2 for \text{r}_{\text{PZ}} (EC10phytoplankton is two orders of magnitude smaller than EC10zooplankton) primarily targets phytoplankton, e.g. a herbicide. We examined if the validity or violation of T1 was related to toxicant type, i.e. to \text{r}_{\text{PZ}} and \text{r}_{\text{F}}. This was performed using two associated statistical approaches: discriminant analysis and classification trees.

Stepwise discriminant function analyses (Jennrich, 1977) were used to determine which variable (\text{r}_{\text{PZ}} or \text{r}_{\text{F}}) discriminates best between two or more
were toxicants into groups 0 and 1 (Breiman et al., 1984). The same was done to discriminate power, and 1 indicates no discriminative power at all. Partial lambda values were calculated for \( r_{PZ} \) and \( r_{ZF} \) to indicate the discriminating power of these two variables. A partial lambda value of 0 indicates a perfect discriminative power, and 1 indicates no discriminative power at all.

Next, a classification tree based on \( r_{PZ} \) and \( r_{ZF} \) was built in order to classify toxicants into groups 0 and 1 (Breiman et al., 1984). The same was done to classify toxicants into groups 2 and 3. A classification tree is a data mining technique to classify cases, in this case toxicants, into groups based on a set of variables, in this case \( r_{PZ} \) and \( r_{ZF} \). A classification tree consists of a set of split conditions which are connected by branches (Fig. 3). To classify a toxicant into a group, one starts at the top split condition and runs through the tree until an end node is reached. This end node shows the group into which the toxicant is located. Partial lambda values were calculated for \( r_{PZ} \) and \( r_{ZF} \) to indicate the power to discriminate between group 0 toxicants vs. group 1 toxicants. Split conditions are based on the variables considered in the analysis, in this case \( r_{PZ} \) and \( r_{ZF} \) and determine how the tree should be run through. The \( r_{PZ} \) and \( r_{ZF} \) values of two-third of the 1000 toxicants together with their group membership (e.g. group 0 or 1) were used to construct the tree. This two-third is called the training-set. Split conditions were calibrated to maximize the amount of correctly classified training-set toxicants. Afterwards, the remaining one-third of the 1000 toxicants (test-set), i.e. not used in the tree development, was used as a cross validation of these split conditions. The results of this cross validation reflect the predictive capacity of the constructed trees. Note that the ratio of group 0 toxicants vs. group 1 toxicants was equal between training-set and test-set, as demanded by the classification tree-methodology. This was also the case for the ratio of group 2 toxicants vs. group 3 toxicants.

3. Results and discussion

3.1. Mean and variance of cSSD and eco-SSD

For 254 of the 1000 toxicants, the mean and/or variance of the eco-SSD were significantly different from those of the corresponding cSSD. In 190 cases, the mean of the cSSD was significantly different from that of the eco-SSD. In 94 cases, the variance of the cSSD was found to be significantly different from that of the eco-SSD. In 30 cases, both mean and variance of the cSSD were found to be significantly different from those of the corresponding eco-SSD. In 30 cases, both mean and variance of the cSSD were found to be significantly different from those of the corresponding cSSD.

3.2. Comparing ‘safe concentrations’ derived from cSSD with ecosystem-NOECs derived from the ecosystem model

PNECs derived as the lowest single-species EC\(_{10}\) divided by an application factor of 10 (AF-PNECs) were, on average, 10 times lower than the corresponding ecosystem-NOECs. For 769 of the 1000 considered toxicants, HC\(_5\)-PNECs were found to be, on average, a factor 3 lower than the corresponding ecosystem-NOECs. For 95 of the 190 toxicants for which only the \( \mu_{cSSD} \) or \( \mu_{eco} \) was derived, the HC\(_5\) was larger than the ecosystem-NOEC. For all toxicants for which only \( \sigma_{cSSD} \) or \( \sigma_{eco} \) was derived, the HC\(_5\) was found to be smaller than the ecosystem-NOEC. For 28 of the 30 toxicants for which both \( \mu_{cSSD} \); \( \mu_{eco} \) and \( \sigma_{cSSD} \); \( \sigma_{eco} \) were derived, the HC\(_5\) was larger than the ecosystem-NOEC.

In a comparison of HC\(_5\)s derived from SSSDs with experimentally derived ecosystem-NOECs, Versteeg et al. (1999) found the former to be consistently lower than the latter, a finding which is also observed by Hose et al. (2003) and Selck et al. (2002). However, in a comparison of HC\(_5\)s with ecosystem-NOECs for 6 insecticides, Malby et al. (2005) found the latter to be lower than the former for continuous exposure to lindane and fenvalerate. Thus, literature indicates that, although cases exist in which the HC\(_5\) is higher than an experimentally derived ecosystem-NOEC, these cases are scarce. The probability that this will occur is probably lower than what the results in this paper suggest. A reason for this might be that in the cited studies, cSSDs were constructed using more species than those present in the experimental ecosystem study. For example, Selck et al. (2005) included single-species fish-EC\(_5\)s to construct cSSDs for LAS and TBT. A subsequent comparison with NOEC data obtained in ecosystem-level studies without fish revealed a highly protective HC\(_5\)s. For that reason, Posthuma et al. (2002) have suggested to carefully consider the composition of the ecosystem to be protected when constructing a cSSD. In our work, EC\(_{10}\) in the cSSD were assumed to be representative for the sensitivity of the species in the considered ecosystem model. As such, it was possible to test T1, and exclude possible effects of species composition of the cSSD.

3.3. For which toxicants is T1 valid? Discriminant analysis approach

When \( r_{PZ} \) and \( r_{ZF} \) values of the 1000 considered toxicants are plotted (Fig. 2), it appears that the power to discriminate between group 0 toxicants (i.e. for which \( \mu_{cSSD} > \mu_{eco} \)) and group 1 toxicants (i.e. for which \( \mu_{cSSD} < \mu_{eco} \)) is larger for \( r_{PZ} \) than for \( r_{ZF} \). Group 1 toxicants are primarily located left from \( r_{PZ} = 0 \), while group 0 toxicants are located slightly higher.
more to the right of $r_{PZ}=0$ (Fig. 2A). Indeed, the partial Lambda values of $r_{ZF}$ (0.89) and $r_{PZ}$ (0.68 (<0.89)) indicate that $r_{PZ}$ has more power to discriminate between both groups of toxicants than $r_{ZF}$. This means that one can a priori classify a toxicant in group 0 or 1, based on the $r_{PZ}$ value of that toxicant. Since the $r_{PZ}$ value is simply $\log(EC_{10,phytoplankton})−log(EC_{10,zooplankton})$, two single-species toxicity test results are sufficient to classify a toxicant in group 0 or group 1.

In contrast, $r_{PZ}$ and $r_{ZF}$ have no power at all to discriminate between group 2 (i.e. for which $\tilde{\sigma}_b = \sigma_{eco}$) and group 3 toxicants (i.e. for which $\tilde{\sigma}_p > \sigma_{eco}$), as reflected by partial Lambda values of 0.99 ($\approx 1$) for both $r_{PZ}$ and $r_{ZF}$ and Fig. 2B.

3.4. For which toxicants is T1 valid? Classification tree approach

In Fig. 3 the resulting classification tree predicting if $\tilde{\mu} > \mu_{eco}$ (coded class “1”) or if $\tilde{\mu} > \mu_{zooplankton}$ (coded class “0”) based on $r_{PZ}$ and $r_{ZF}$ is shown. The tree consists of split conditions (ellipses) and end nodes (boxes). One has to start at the top of the tree and let the split conditions decide which way to proceed. If a split condition is fulfilled, this results in a continuation via the left branch. The tree is followed until an end node is reached. This end node gives the resulting classification (underlined). For example, the dashed line indicates the pathway for a toxicant for which $r_{PZ}=2$. Since the first split condition ($r_{PZ} \leq -0.3861$) is not fulfilled (if $r_{PZ}=2$), one has to continue to the left branch of the tree. As such, a second split condition is reached ($r_{PZ} \leq -0.9385$) which is also not fulfilled in this example. As a result, a toxicant with $r_{PZ}=2$ is classified as class “0”, i.e. $\tilde{\mu} = \mu_{zooplankton}$, for that toxicant. In a similar way, a toxicant for which $r_{PZ}=2$ and $r_{ZF}=0$ will be classified as class “1”, i.e. $\tilde{\mu} \neq \mu_{eco}$, for that toxicant, as indicated by the dotted line in Fig. 3.

The number of training-set toxicants which were correctly and erroneously classified using these split conditions is also given in these end nodes. For example, in the box situated in the left side of the tree, 35 toxicants were classified correctly (i.e. in class 1), while 2 were classified erroneously. Toxicants classified in end nodes marked with an asterisk, have a probability of $\approx 90\%$ of being classified correctly.

The importance of $r_{PZ}$ in distinguishing group 0 from group 1 toxicants, as suggested by the discriminant analysis, is confirmed by this classification tree, where $r_{PZ}$ determines the first split, and hence has the most influence on the resulting classification of a toxicant.

The subsequent cross validation of this classification tree indicates that the tree also has some predictive power for the test-set toxicants. Within the test-set, 63% of the group 1 toxicants were classified correctly by the tree. Also, 93% of the group 0 toxicants within the test-set were classified correctly by the tree. Note that these test-set toxicants were not used in the construction of the classification tree.

Van den Brink et al. (2006) found that the $HC_{50}$ of chronic invertebrate-SSDs for herbicides are on average two orders of magnitude higher than those of chronic phytoplankton-SSDs for herbicides, i.e. that...
In the same study, the difference between invertebrate and fish-HC50 was found to be 1 order of magnitude, i.e. corresponding to $r_{PZ} \approx 0$. Hence, it can be safely hypothesised that toxicants primarily targeting phytoplankton have $r_{PZ} = -2$ (EC10so of zooplankton are two orders of magnitude higher than those of phytoplankton), and $r_{ZF} = 0$ (EC10 of zooplankton and fish are equal). From the classification tree, it becomes apparent that those toxicants may have $\hat{\mu}_i > \mu_{eco,i}$, as indicated by the dotted line in Fig. 3. Thus, for these toxicants, T1 is not valid: when accounting for ecological interactions, the mean ecosystem sensitivity for herbicides ($\mu_{eco,i}$) is predicted to be different from the mean ecosystem sensitivity when ecological interactions are not accounted for ($\hat{\mu}_i$). Hence, the applications of the cSSD approach for herbicides may lead to inaccuracies caused by differences between cSSD and eco-SSD. Conversely, toxicants primarily targeting zooplankton and fish, have $\hat{\mu}_i = \mu_{eco,i}$, as indicated by the dashed line in Fig. 3. This suggests that the mean of eco-SSD and cSSD is comparable for these toxicants. An explanation for the different results obtained for both toxicant types may be found in the number of populations experiencing food web-mediated indirect effects. Toxicants primarily targeting phytoplankton, can give rise to a reduction of zooplankton resulting from a decrease in available phytoplankton biomass. A reduction in fish biomass can be observed as a second-order indirect effect. Because a cSSD approach would categorize the phytoplankton as the trophic level being mostly affected by the toxicant, it ignores possible (indirect) effects on two trophic levels. Conversely, in case of toxicants targeting zooplankton and fish, a cSSD approach categorizes both zooplankton and fish as being affected, thereby only ignoring possible (indirect) effects on one trophic level, i.e. on phytoplankton. These considerations seem to justify earlier suggestions to only incorporate organisms from sensitive trophic levels in the cSSD (e.g. Posthuma et al., 2002). However, while these earlier suggestions have mainly been based on statistical considerations (i.e. the violation of the assumption of (log) normality of SSDs that include both sensitive and insensitive species), our present simulation study seems to justify these suggestions from an ecological point of view. Indeed, incorporating species in an SSD which are not directly targeted by the toxicant (e.g. zooplankton in the case of herbicides), reflects the erroneous idea that those species are also not affected in an ecosystem context. Consequently, the mean of such a cSSD
will be higher than a cSSD only consisting of sensitive species. Schmitt-Jansen and Altenburger (2005) have shown that the mean of a cSSD for a herbicide containing only phytoplankton species (i.e., sensitive for the herbicide) agreed well with the mean sensitivity of those species within an ecosystem.

A similar classification tree approach for σ did not result in any classifying nor predictiv power, because of the limited fraction of toxicants in group 3. The difference between standard deviations of cSSD and eco-SSD does not necessarily make the eco-SSD more conservative than the cSSD. The lower percentiles of the cSSD will still be lower than the lower percentiles of the eco-SSD (Fig. 4B). In contrast, the opposite may hold when the mean of the eco-SSD is lower than the mean of the cSSD (Fig. 4A). However, this will depend on the chosen percentile of a cSSD (i.e., what “σ” is in “HC_y”).


Appendix A. Supplementary data


References


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