Environment International 36 (2010) 514–520

Contents lists available at ScienceDirect

Environment International

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

Assessment of chemical screening outcomes based on different partitioning property estimation methods

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ARTICLE INFO

Article history:
Received 1 February 2010
Accepted 25 March 2010
Available online 6 May 2010

Keywords:
Partitioning property estimation
Chemical screening
Long range transport potential
Bioaccumulation potential
Quantitative structure–property relationship
Linear free energy relationship

ABSTRACT

Screening is widely used to prioritize chemicals according to their potential environmental hazard, as expressed in the attributes of persistence, bioaccumulation (B), toxicity and long range transport potential (LRTP). Many screening approaches for B and LRTP rely on the categorization of chemicals based on a comparison of their equilibrium partition coefficients between octanol and water (K_{OW}), air and water (K_{AW}) and octanol and air (K_{OA}) with a threshold value. As experimental values of the properties are mostly unavailable for the large number of chemicals being screened, the use of quantitative structure–property relationships (QSPRs) and other computational chemistry methods becomes indispensable. Predictions by different methods often deviate considerably, and flawed predictions may lead to false positive/negative categorizations. We predicted the partitioning properties of 529 chemicals, culled from previous prioritization efforts, using the four prediction methods EPI Suite, SPARC, COSMOtherm, and ABSOLV. The four sets of predictions were used to screen the chemicals against various LRTP and B criteria. Screening results based on the four methods were consistent for only ~70% of the chemicals. To further assess whether the means of estimating environmental phase partitioning has an impact, a subset of 110 chemicals was screened for elevated arctic contamination potential based on single-parameter and poly-parameter linear free energy relationships respectively. Different categorizations were observed for 5 out of 110 chemicals. Screening and categorization methods that rely on a decision whether a chemical's predicted property falls on either side of a threshold are likely to lead to a significant number of false positive/negative outcomes. We therefore suggest that screening should rather be based on numerical hazard or risk estimates that acknowledge and explicitly take into account the uncertainties of predicted properties.

1. Introduction

Persistence (P), bioaccumulation (B), toxicity (T) and long range transport potential (LRTP) are characteristics directly related to a chemical's environmental risk (Muir and Howard, 2006). Based on these four characteristics, 21 persistent organic pollutants, including nine new chemicals added in May 2009, are identified by the Stockholm Convention as requiring the control, reduction, or elimination of discharges, emissions, and losses to the global environment (UNEP, 2001; UNEP, 2009). P, B, T and LRTP are also criteria for prioritizing chemicals by other regulations such as the European Community Regulation REACH (European Commission, 2007). Regulatory agencies not only aim to reduce the levels and risk of existing high production volume chemicals with characteristics of P, B, T and LRTP, but also to adopt precautionary measures for new chemicals that are likely to be released into the environment. Often, few monitoring data are available for such chemicals, and the assessment of their environmental risk has to rely largely on environmental modeling (Fenner et al., 2005) and/or statistical approaches (Stenberg et al., 2009).

Various environmental models have been applied to assess P, B and LRTP of organic contaminants in the environment (Kelly et al., 2007; Czub et al., 2008; Klasmeier et al., 2006; Wania, 2003). Two approaches have been adopted: A specific chemical's fate in the environment is characterized by inputting its properties in a model calculating P, B and LRTP indicators (Mackintosh et al., 2004; Schenker et al., 2008; Wania and Dugani, 2003). This approach may be unacceptably time-consuming if the model calculation is complex and if the number of chemicals to be assessed is very large. Alternatively, P, B and LRTP are calculated for a multitude of hypothetical chemicals covering the partitioning property space, with the objective of identifying the partitioning property combinations that lead to high P, B, or LRTP (Brown and Wania, 2008; Czub et al., 2008; Kelly et al., 2007). The P, B, and LRTP attributes of real chemicals are then assessed by comparing their physicochemical properties with screening criteria (Brown and Wania, 2008). This approach is especially suited for screening a large number of chemicals.

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doi:10.1016/j.envint.2010.03.010

However, measured partitioning properties exist for only a small fraction of the multitude of organic chemicals in commerce. Thus, chemical screening efforts typically rely on partitioning properties predicted from quantitative structure–property relationships (QSPRs) or other chemical computation methods (Brown and Wania, 2008; Clausen et al., 2009).

Such methods are based on approaches of widely different complexity, and their application domain and prediction accuracy differ accordingly. EPI Suite (U.S. EPA, 2009) is one of the most widely used QSPR tools for physicochemical property prediction. The KOWWIN and HENRYWIN modules in EPI Suite are based on fragment contribution methods (Hine and Mookerjee, 1975; Meylan and Howard, 1995) that assign a factor for each identified fragment that is contributing to the predicted property. The contribution factors are determined by multiple linear regressions of measured properties using fragments present in the chemicals of a training set. The property for a chemical of interest is then predicted by multiplying the contribution factors with the number of fragments in the chemical. Because they rely on experimental properties of the chemicals in the training sets, the applicability domain of fragment-based QSPRs is restricted to the structural features present in the training sets. Predictions for chemicals outside the training set domain are of unknown uncertainty. Such limitation can be overcome by computational chemistry methods based on fundamental calculated molecular properties, such as SPARC and Cosmotherm (Hilal et al., 2007; Wittekindt and Goss, 2009). SPARC is believed to be able to estimate numerous physicochemical properties with great accuracy and be portable to any molecular structures (Hilal et al., 2007). Another calibration-independent computational method gaining wider application is COSMOtherm, a commercial software able to predict various physicochemical properties of organic molecules based on quantum chemistry and statistical thermodynamics (Eckert and Klamt, 2002; Klamt, 2005). In contrast to other methods, which only consider the two-dimensional molecular structure (SMILES string as input), COSMOtherm takes three-dimensional intermolecular interactions (MDL Mol files as input) into account and it is able to consider potential effects of conformers and intramolecular hydrogen bonds on the partitioning behavior (Arp et al., 2006; Niederer and Goss, 2008). Thus, COSMOtherm is expected to be more accurate than other prediction methods (Wittekindt and Goss, 2009).

Most of the models used in chemical screening estimate the environmentally relevant partitioning of organic chemicals from single-parameter linear free energy relationships (spLFERs) with the partition coefficients between gas, water and octanol (Cousins and Mackay, 2001; Seth et al., 1999). However, such spLFERs have been criticized because of their failure to appropriately describe the variability between substance classes that vary in polarity (Goss and Schwarzenbach, 2001) and between environmental phases that vary in sorption properties (Goss and Schwarzenbach, 2001; Niederer et al., 2006a). Poly-parameter linear free energy relationships (ppLFERs), which are able to account for multiple interactions between molecules and bulk phases, have been developed to better cope with both compound and phase variability (Goss, 1997; Goss and Eisenreich, 1996). By directly predicting the interactions between molecules and environmental phases, ppLFERs are expected to introduce less error than spLFERs. Recently, ppLFERs have been implemented in environmental fate models to directly link solute descriptors to chemical fate (Breivik and Wania, 2003; Brown and Wania, 2009). So far, ppLFER-based models have not been used in chemical screening and neither has there been an attempt to compare the result of screening using ppLFER and spLFER-based models.

Recent studies comparing predicted partitioning properties indicate that they are subject to large uncertainties (Wittekindt and Goss, 2009). How does this uncertainty affect the outcome of chemical screening that relies on the comparison of the predicted chemical partitioning properties with screening criteria? The objectives of this study are to evaluate discrepancies of chemical screening results that arise from the use of (i) different prediction methods for partitioning properties, and (ii) ppLFER and spLFER-based models. Whereas the predictions of four different methods are compared to a variety of B and LRTP screening criteria, a global model based on either ppLFERs or spLFERs is used to screen for chemicals of high LRTP.

2. Methods

2.1. Chemical screening based on different prediction methods

Partitioning between environmental phases and susceptibility to degradation are two major factors determining the fate and bioaccumulation of organic chemicals in the environment and thus screening outcomes (Brown and Wania, 2009; Wania, 2006). Several methods for the prediction of the environmental phase partitioning of organic chemicals exist, while the number of quantitative prediction methods for the degradation of organic chemicals in the environment and in organisms is quite limited, in particular methods with validity for a large number of chemicals. In this study, we thus confined our scope to prediction methods for phase partitioning.

2.1.1. Estimation of partitioning properties

Chemical partitioning properties were predicted using EPI Suite (v4.0), SPARC (v4.2), COSMOtherm (v2.1, COSMOlogic GmbH & Co. KG) and ABSOLV (ADMEBoxes v4.1, Pharma Algorithms, Inc). In the case of the first three methods, K_{OW} and K_{AW} were predicted and the K_{OA} was then derived from K_{OW} and K_{AW} through a thermodynamic triangle (Beyer et al., 2002). The ABSOLV module is based on a group contribution approach to predict the solute descriptors that appear in ppLFER equations (Clarke, 2009). These solute descriptors are then entered into ppLFERs (Brown and Wania, 2009; Goss, 2005) to predict K_{OW}, K_{AW} and K_{OA} of the target chemicals. For the second part of the study, the ABSOLV-predicted solute descriptors are used in conjunction with ppLFERs for aerosols and organic carbon to directly predict the particle-air partitioning coefficient (K_{PA}, unitless) (Arp et al., 2008) and the organic carbon–water partitioning coefficient (K_{OC}, unit: kg/L) (Niederer et al., 2006b).

2.1.2. Selection of screened chemicals

The chemicals in this study are selected from two lists of substances previously identified by Brown and Wania (2008) and Howard and Muir (2010) as potentially constituting a higher hazard. Based on structural resemblance to known persistent organic pollutants and on model results of the fate and human exposure of organic chemicals in the Arctic by Czub et al. (2008), Brown and Wania (2008) identified 120 potential arctic contaminants from five high production volume chemical lists. Those were combined with another 112 chemicals falling within one log-unit of the region in the chemical space identified as having an elevated arctic contamination and bioaccumulation potential (AC-BAP) (Brown and Wania, 2008). In the paper by Howard and Muir (2010), 610 chemicals with potentially persistent and bioaccumulative characteristics were identified by structure activity relationships and expert judgment (Howard and Muir, 2010). Combining the two sources yields a set of 740 chemicals, 529 of which can be handled by all four partition estimation methods and which therefore are used in this study.

2.1.3. Thresholds for chemical screening

Several criteria based on chemical partitioning properties have been used in the screening for B. In several cases, such as in the Stockholm Convention (UNEP, 2001) and the Canadian Environmental Protection Act (Government of Canada, 1999), K_{OW} serves to evaluate the bioaccumulation potential (BAP) of chemicals when no experimental bioconcentration/bioaccumulation factors (BCF/BAF) are available. Based on studies of bioaccumulation in aqueous organisms (Fisk et al., 1998; Kelly et al., 2007), chemicals with log $K_{OW} \geq 5$ are regarded as potentially bioaccumulative. However, studies on terrestrial food chains in northern Canada indicated that

organic chemicals with log K_{OW}<5 can biomagnify in air breathing organisms such as birds and mammals (Kelly and Gobas, 2001, 2003). Based on multimedia environmental model results, Kelly et al. (2007) suggested screening criteria for the potential bioaccumulation of organic chemicals in air breathing animals of log $K_{OW} \geq 2$ and log $K_{OA} \geq 6$. Meanwhile, Czub and McLachlan (2004) quantified bioaccumulation in the human chain and concluded that organic chemicals with $2 < \log K_{OW} < 11$ and $6 < \log K_{OA} < 12$ are likely to have the potential for bioaccumulation in humans. Whereas Czub and McLachlan (2004) assumed equilibrium partitioning in the physical environment, a more complex model calculation of human bioaccumulation in a temperate source environment that assumes neither equilibrium nor steady state (Undeman et al., submitted for publication) yields a slightly different set of thresholds for potential human bioaccumulation: {log $K_{AW} \geq -6$ and log K_{OA} + log $K_{AW} \leq 8.5$ and $8 \leq \log K_{OA} \leq 12$}.

The use of partitioning properties in the screening for an organic chemical's LRTP is much less common. Based on calculations with the global scale model Globo-POP (Wania and Mackay, 1995), organic chemicals with $-5 \leq \log K_{AW} \leq -1$ are flagged as having high LRTP (Fenner et al., 2005). Muir and Howard (2006, 2010) have applied this criterion when screening chemicals for LRTP. Recently, model calculations have been used to define partitioning property thresholds that allow for the simultaneous screening for chemicals with LRTP and the potential for bioaccumulation potential in the Arctic human food chain (Brown and Wania, 2008; Czub et al., 2008). The Arctic contamination and bioaccumulation potential (AC-BAP) is elevated for organic chemicals with: {log $K_{OW} \geq 3.5$ and log $K_{OA} \geq 6$ and $-7 \leq \log K_{AW} \leq 0.5$ and log $K_{AW} \leq -1.78 \times \log K_{OA} + 14.56$}. The areas of the chemical partitioning space flagged as having high BAP and LRTP by the different criteria discussed above are indicated by color shading in Fig. 1. We use all of these criteria to investigate the effect of the partitioning property prediction methods on the outcomes of chemical screening. In particular we try to quantify the potential number of false positive and false negative chemical screening results, which occur when the methods flag a chemicals as (not) hazardous while in reality it is not (it is).

2.2. Chemical screening using spLFER vs. ppLFER-based models

To evaluate the effect of the method used for estimating environmental phase equilibria on the results of chemical screening, we screened chemicals for an elevated Arctic Contamination Potential (ACP) (Wania, 2006) in two ways. We first compared the K_{OA} and K_{AW} of the screened chemicals, as obtained by ABSOLV-predicted solute descriptors and ppLFERs (Brown and Wania, 2008), against the area of elevated ACP ($eACP_{10} \geq 1\%$) with the threshold of {(log $K_{OA} \leq 10$ and log $K_{AW} \leq -0.5$) OR ($6.5 \leq \log K_{OA} \leq 10$ and log $K_{AW} > -0.5$)}, which was identified in the two-dimensional K_{OA}/K_{AW} chemical space by Wania (2003, 2006). We then calculated the area of elevated ACP as a function of the three-dimensional chemical partitioning space defined by K_{AW}, K_{OC} and K_{PA} using a version of the Globo-POP model which directly uses these three partition coefficients, rather than estimating them from K_{OA} and K_{OW}. Specifically, the $eACP_{10}$, as defined by Wania (2006), was calculated for hypothetical, perfectly persistent chemicals with all possible combinations of partition coefficients in the range of $-5 \leq \log K_{AW} \leq 3$, $-1 \leq \log K_{OC} \leq 11$ and $3 \leq \log K_{PA} \leq 12$ at a resolution of half a log-unit. These ranges were largely determined by the required computational effort. A three-dimensional chemical partitioning map displaying the $eACP_{10}$ as a function of K_{AW}, K_{OC} and K_{PA} is shown in Fig. 5. K_{OC}, K_{PA}, K_{AW} for the screened chemicals were predicted using ABSOLV-predicted solute descriptors and ppLFERs compiled by Brown and Wania (2009) and again compared against a threshold of $eACP_{10} \geq 1\%$. By using ABSOLV-predicted solute descriptors in both the spLFER and the ppLFER-based screening, we assure that any discrepancies in the screening result are truly caused by differences in the calculation of phase equilibria, rather than by differences in the accuracy of the model input parameters. Of the 529 chemicals mentioned above, only 110 have partitioning properties falling in the range of the three-dimensional ACP calculation. The evaluation of the difference in screening results from spLFER and ppLFER-based models is thus restricted to this subset of substances.

3. Results and discussion

3.1. Chemical screening outcomes based on different prediction methods

Partitioning properties predicted by EPI Suite, SPARC, Cosmotherm and ABSOLV (available as Supplementary data) were used to judge whether the 529 chemicals have the potential for bioaccumulation in aqueous organisms, in air breathing organism and in humans, for long range transport, and for accumulation in Arctic residents eating a traditional diet including marine mammals. Chemicals were flagged as potentially hazardous if the screening criteria are met. The 529 chemicals and the screening criteria are visualized using chemical partitioning maps (Fig. 1). On the partitioning maps, chemicals were flagged if they fall in the colored regions.

Fig. 2 illustrates screening results based on partitioning properties from different prediction methods. The thresholds of the screening criteria are represented by the red circles: the number within the circle indicates the number of chemicals meeting the hazard criterion. The number next to an arrow reflects the number of chemicals whose screening results

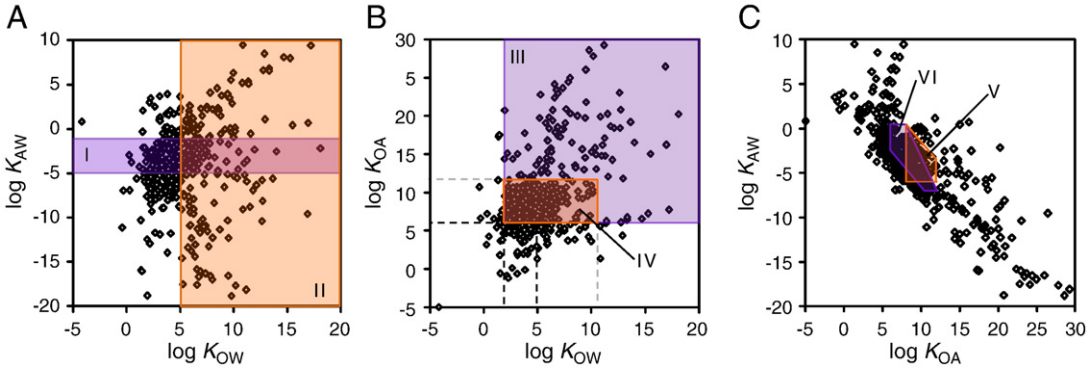

Fig. 1. Chemical partitioning space highlighting in color the screening criteria for (I) long range transport potential (LRTP); (II) bioaccumulation potential in the aqueous environment ($BAP_{aq.}$); (III) bioaccumulation in the terrestrial environment ($BAP_{terr.}$); (IV) bioaccumulation in humans using a level I model for the physical environment ($BAP_{hum.\ (Level\ I)}$); (V) bioaccumulation in humans using a level IV model for the physical environment ($BAP_{hum.\ (Level\ IV)}$) and; (VI) Arctic contamination and bioaccumulation potential (AC-BAP). Also indicated is the location of 529 chemicals in the partitioning space, using EPI Suite predicted partitioning properties for illustration.

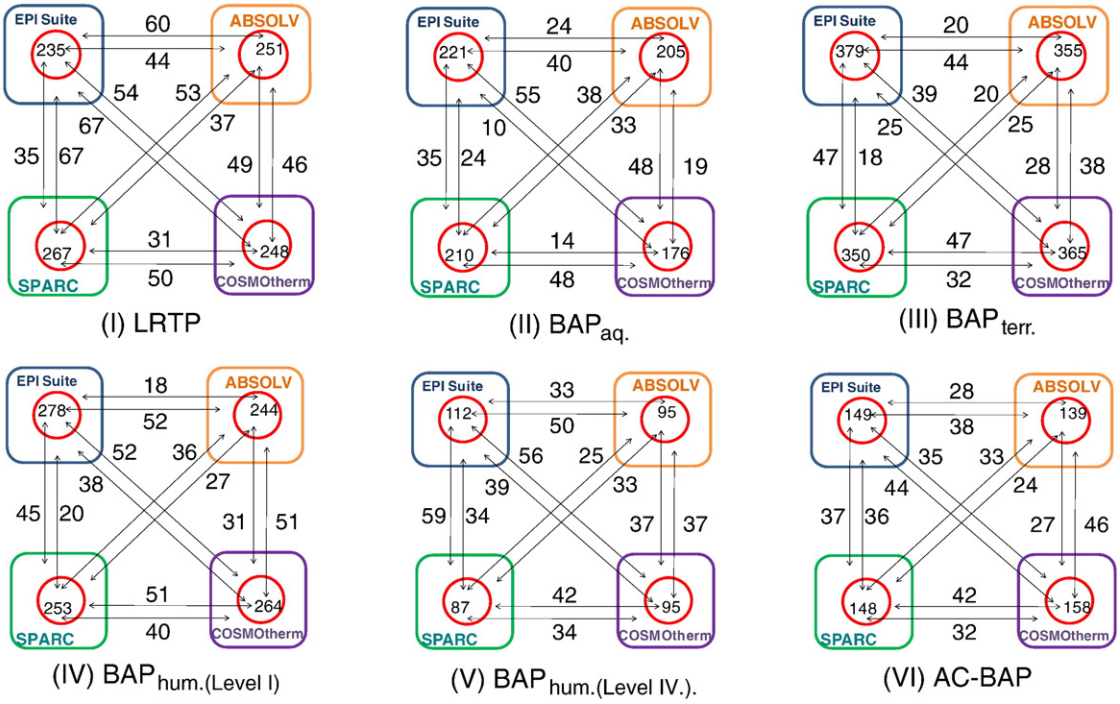

Fig. 2. Illustration for the changes of chemical screening results based on predicted partitioning properties from EPI Suite, SPARC, COSMOtherm and ABSOLV. The numbers within red circles indicate the number of chemicals flagged by the screening criteria. The numbers next to the arrows represent the number of chemicals whose screening results changes between the partitioning prediction methods.

changes based on different methods. For all of the criteria, screening outcomes are different depending on which prediction method was used. The number of chemicals with different screening results varies among the six screening criteria. That number is not only affected by the differences in the predicted partitioning properties, but also by the position of the chemicals on the partitioning maps. If a chemical falls close to the boundary of the colored regions, a small change of the partitioning properties is enough to change the screening result. Therefore, the extent of false positives/negatives in a threshold-based screening approach is affected not only by the uncertainties of the predicted partitioning properties, but also by the position of the chemicals on the chemical partitioning maps. It is noteworthy in this respect that the portion of false positives/negatives identified in this study is likely biased high because we focus on a set of pre-screened chemicals that are more likely to fulfill the screening criteria than a completely random set of substances.

Comparing each pair of prediction methods, the number of chemicals with different screening results can be as large as ~20% of the total 529 chemicals (Fig. 2-III). With EPI Suite, more chemicals are identified as bioaccumulative in the aqueous environment and in humans than with other prediction methods. However, when screening for elevated LRTP, fewer chemicals are identified with EPI Suite than with other methods. Meanwhile, SPARC flags more chemicals with elevated LRTP and less with elevated $BAP_{terr.}$ and $BAP_{hum.\ (Level\ IV)}$ than other methods.

For each of the five screening criteria, only ~70% of the total 529 chemicals have consistent screening results (Fig. 3). Among the chemicals

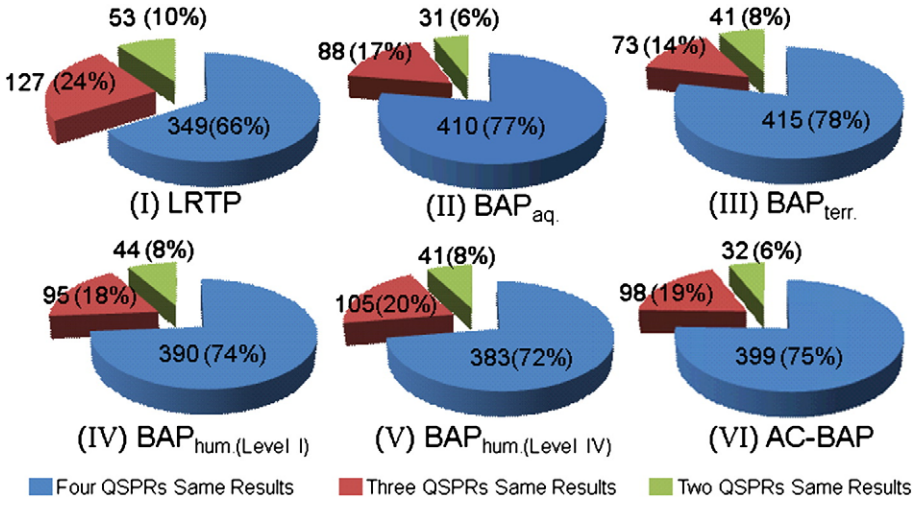

Fig. 3. Consistency of chemical screening results based on predicted partitioning properties from EPI Suite, SPARC, COSMOtherm and ABSOLV.

Table 1
Results of chemical screening for LRTP, $BAP_{aq.}$, $BAP_{terr.}$, $BAP_{hum.\ (Level\ I)}$, $BAP_{hum.\ (Level\ IV)}$ and AC-BAP based on EPI Suite, SPARC, COSMOtherm and ABSOLV.

	Number of chemicals out of 529									
	All four predictions same results (flagged)[a]	Three of the predictions same results	EPI suite false positive	EPI suite false negative	SPARC false positive	SPARC false negative	COSMOtherm false positive	COSMOtherm false negative	ABSOLV false positive	ABSOLV false negative
LRTP	349 (155)	127	15	32	14	6	13	19	11	17
$BAP_{aq.}$	410 (145)	88	15	4	16	5	2	20	14	12
$BAP_{terr.}$	415 (303)	73	15	4	5	12	10	17	2	8
$BAP_{hum.\ (Level\ I)}$	390 (188)	95	16	5	6	12	18	22	3	13
$BAP_{hum.\ (Level\ IV)}$	383 (146)	105	33	9	14	6	18	11	11	3
AC-BAP	399 (84)	98	14	14	11	10	19	13	6	11

[a] Flagged chemicals are those meet the screening criteria and being identified with potential hazard.

for which at least one pair of prediction methods gives different screening results, approximately two thirds have consistent screening results for three of the four methods. For the remaining third, two methods each give opposing results. We do not know which one of the methods, if any, correctly predicts the partitioning properties of the 529 chemicals. However, we may surmise that the one method leading to different screening results from the other three may have a higher probability of generating false positive (or negative) screening results. Accordingly, we assume that if one method flags a chemical as meeting a criterion and the other three methods do not, as giving a false positive result. Similarly, if only one of the four methods categorizes a chemical as not meeting a criterion, we assume this to be a false negative decision. The numbers of chemicals that are likely to have false positive/negative screening results are summarized for the four prediction methods and the six screening criteria in Table 1.

3.2. Chemical screening outcomes using ppLFER and spLFER-based models

As stated above, screening based on chemical partitioning maps often relies on partitioning coefficients in the air–water–octanol system (Czub et al., 2008; Wania, 2006), which may be poor predictors of partitioning between environmental phases. We therefore evaluated the effect of using a spLFER or a ppLFER-based model on the result of chemical screening for elevated ACP. Fig. 4 presents the traditional 2-dimensional chemical partitioning map, displaying the $eACP_{10}$, as calculated with the spLFER-based Globo-POP model, as a function of log K_{OA} and log K_{AW} (Wania, 2003). By placing 110 chemicals on the map using their ABSOLV-predicted K_{AW} and K_{OA}, we identify 88 as having elevated $eACP_{10}$ (>1%). Fig. 5 displays a 3-dimensional chemical partitioning map of $eACP_{10}$, again calculated with Globo-POP, but without the use of any spLFERs, as a function of log K_{AW}, log K_{OC}, and log K_{PA}. Placing the 110 chemicals on the maps in Fig. 5, using their ABSOLV-predicted K_{PA}, K_{OC} and K_{AW}, we identified 89 as having an elevated $eACP_{10}$. Although the number of chemicals being flagged using either an spLFER- or a ppLFER-based approach is very similar, five chemicals are classified differently. Of those five, four are flagged as having elevated $eACP_{10}$ using the 2-dimensional chemical space. All five chemicals have a log K_{OA} around 10, where the $eACP_{10}$ is highly sensitive to the gas-particle partitioning equilibrium. Nevertheless, only a small fraction (~5%) of chemicals has a different ACP screening results when using spLFER and ppLFER-based approaches, which is consistent with the study by Brown and Wania (2009) who also reported relatively small difference in the results of spLFER and ppLFER-based contaminant fate models. It appears that the uncertainty in the partitioning property values themselves is larger than the uncertainty introduced by the use of spLFERs.

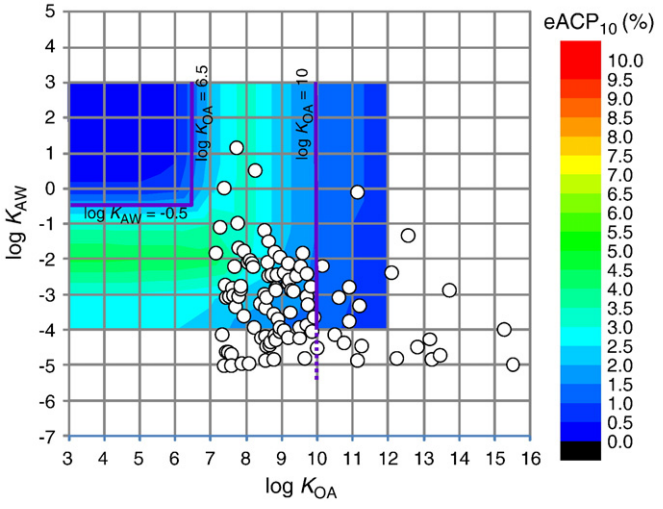

Fig. 4. Two-dimensional chemical partitioning map displaying the Arctic contamination potential ($eACP_{10}$) as a function of log K_{OA} and log K_{AW} as calculated by the Globo-POP model (Wania, 2003). The violet lines represent the boundary for elevated ACP ($eACP_{10}$>1%). 110 chemicals are placed on the map using their K_{OA} and K_{AW} obtained using ABSOLV-predicted solute descriptors and ppLFERs.

It is worthwhile to also directly compare the two and the three-dimensional partitioning maps of the $eACP_{10}$. The areas of elevated $eACP_{10}$ in Fig. 4 also appear in Fig. 5, but the partitioning combinations giving the highest $eACP_{10}$ in Fig. 5 do not exist in Fig. 4. These chemicals combine an intermediate K_{AW}, a low K_{OC} and a high K_{PA} (red area in the upper left of the panels in Fig. 5). Chemicals with a low K_{OC} and a high K_{PA} are water soluble but non-volatile, and therefore should have a very low K_{AW}. We therefore conclude that these hypothetical combinations of partitioning properties are not plausible, and indeed none of the 110 real chemicals falls into this region of the 3-dimensional partitioning space.

4. Conclusions

Computational chemistry methods, including LFERs, provide useful tools in performing screening assessment for a large number of chemicals with no or few measured physicochemical properties. However, as revealed in the present study, ~25% of the studied chemicals would have different screening results based on partitioning properties predicted by different methods. Therefore, caution should be taken when interpreting the results of screening exercises that are based on Yes/No decisions. The potential for ambiguous screening results and controversial, if not outright erroneous, decisions is obvious. The outcome of this study thus challenges the merit of screening exercises that rely on a comparison of predicted properties with threshold values and the validity of prioritized chemical lists that are generated by them. We therefore suggest that future effort should be directed towards developing screening approaches that are based on quantifying numerical hazard estimates

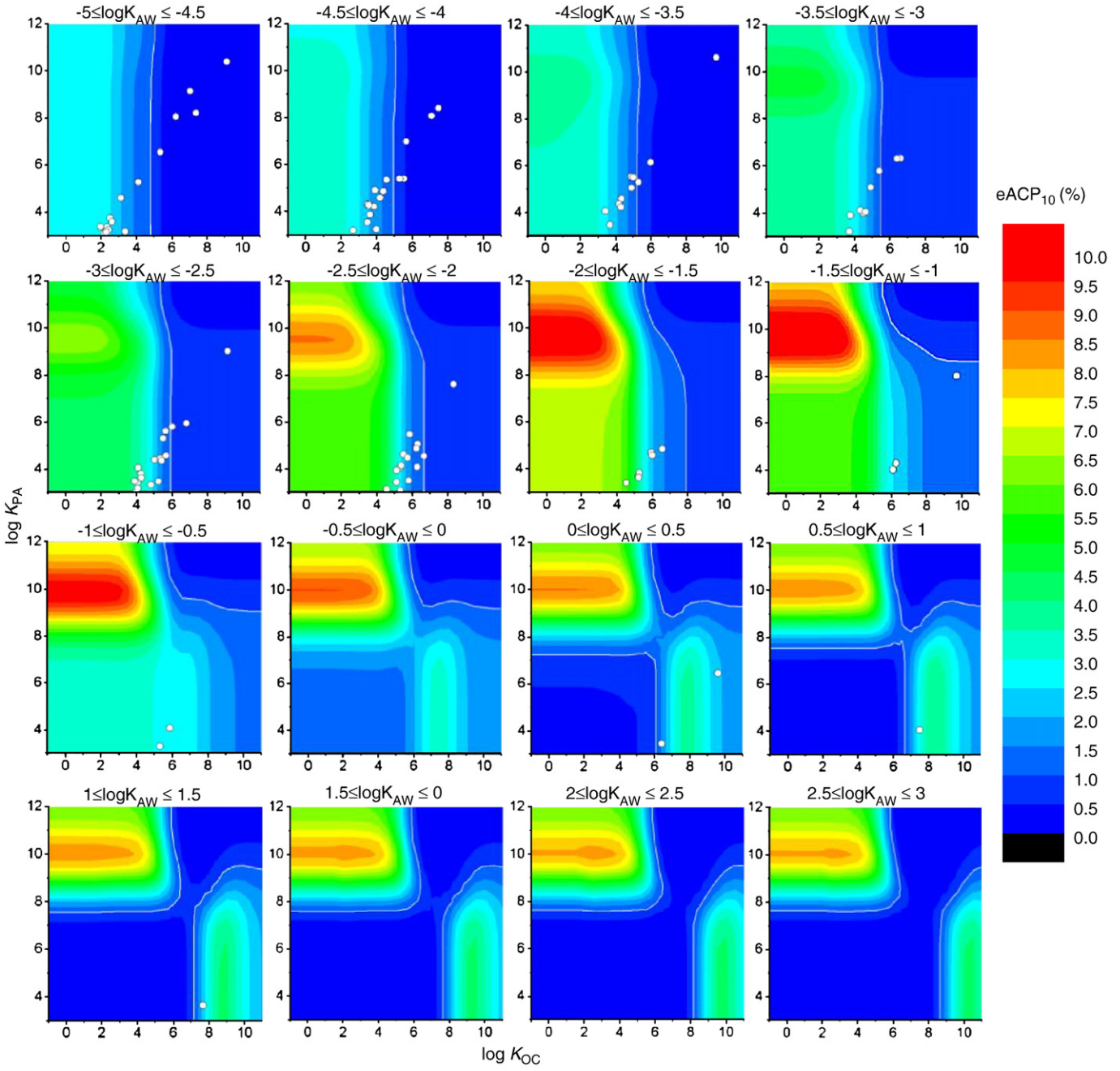

Fig. 5. Three-dimensional chemical partitioning map displaying the Arctic contamination potential ($eACP_{10}$) as a function of log K_{OC}, log K_{PA} and log K_{AW} as calculated by the Globo-POP model. The white curves represent the boundary for elevated ACP ($eACP_{10}$>1%). 110 chemicals are placed on the map using their K_{OC}, K_{PA} and K_{AW} obtained using ABSOLV-predicted solute descriptors and ppLFERs.

that take the uncertainty of the predicted properties into account (Arnot and Mackay, 2008). This could for example be achieved by explicitly predicting with fate models the exposure to each individual screened chemical using estimates of a chemical's properties and emissions and their uncertainties.

Acknowledgement

We are grateful to Lionel Carreira for assistance with SPARC and to the Long-range Research Initiative of the European Chemical Industry Association (CEFIC) and the Northern Contaminants Program of the Canadian Department of Indian Affairs and Northern Development for financial support.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.envint.2010.03.010.

References

Arnot JA, Mackay D. Policies for chemical hazard and risk priority setting: can persistence, bioaccumulation, toxicity, and quantity information be combined? Environ Sci Technol 2008;42:4648–54.

Arp HPH, Niederer C, Goss KU. Predicting the partitioning behavior of various highly fluorinated compounds. Environ Sci Technol 2006;40:7298–304.

Arp HPH, Schwarzenbach RP, Goss KU. Ambient gas/particle partitioning. 2: the influence of particle source and temperature on sorption to dry terrestrial aerosols. Environ Sci Technol 2008;42:5951–7.

Beyer A, Wania F, Gouin T, Mackay D, Matthies M. Selecting internally consistent physicochemical properties of organic compounds. Environ Toxicol Chem 2002;21:941–53.
Breivik K, Wania F. Expanding the applicability of multimedia fate models to polar organic chemicals. Environ Sci Technol 2003;37:4934–43.
Brown TN, Wania F. Screening chemicals for the potential to the persistent organic pollutants: a case study of Arctic contaminants. Environ Sci Technol 2008;42:5202–9.
Brown TN, Wania F. Development and exploration of an organic contaminant fate model using poly-parameter linear free energy relationships. Environ Sci Technol 2009;43:6676–83.
Clarke ED. Beyond physical properties — application of Abraham descriptors and LFER analysis in agrochemical research. Bioorg Med Chem 2009;17:4153–9.
Clausen J, Cramer R, Clough S, Gray M, Gwinn P. Assessing the sensitivity of quantitative structural activity analysis models for evaluating new military compounds. Water Air Soil Pollut 2009;202:141–7.
Cousins IT, Mackay D. Gas-particle partitioning of organic compounds and its interpretation using relative solubilities. Environ Sci Technol 2001;35:643–7.
Czub G, McLachlan MS. Bioaccumulation potential of persistent organic chemicals in humans. Environ Sci Technol 2004;38:2406–12.
Czub G, Wania F, Mclachlan MS. Combining long-range transport and bioaccumulation considerations to identify potential arctic contaminants. Environ Sci Technol 2008;42:3704–9.
Eckert F, Klamt A. Fast solvent screening via quantum chemistry: COSMO-RS approach. Aiche J 2002;48:369–85.
European Commission. Regulation for Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH). Available online http://guidance.echa.europa.eu/guidance_en.htm 2007 [Accessed Dec. 2009].
Fenner K, Scheringer M, MacLeod M, Matthies M, McKone T, Stroebe M, Beyer A, Bonnell M, Le Gall AC, Klasmeier J, Mackay D, Van De Meent D, Pennington D, Scharenberg B, Suzuki N, Wania F. Comparing estimates of persistence and long-range transport potential among multimedia models. Environ Sci Technol 2005;39:1932–42.
Fisk AT, Norstrom RJ, Cymbalisty CD, Muir DCG. Dietary accumulation and depuration of hydrophobic organochlorines: bioaccumulation parameters and their relationship with the octanol/water partition coefficient. Environ Toxicol Chem 1998;17:951–61.
Goss KU. Conceptual model for the adsorption of organic compounds from the gas phase to liquid and solid surfaces. Environ Sci Technol 1997;31:3600–5.
Goss KU. Predicting the equilibrium partitioning of organic compounds using just one linear solvation energy relationship (LSER). Fluid Phase Equilib 2005;233:19–22.
Goss KU, Eisenreich SJ. Adsorption of VOCs from the gas phase to different minerals and a mineral mixture. Environ Sci Technol 1996;30:2135–42.
Goss KU, Schwarzenbach RP. Linear free energy relationships used to evaluate equilibrium partitioning of organic compounds. Environ Sci Technol 2001;35:1–9.
Government of Canada. Canadian Environmental Protection Act (CEPA). Available onlinehttp://www.ec.gc.ca/CEPARegistry/1999 [Accessed Dec. 2009].
Hilal SH, Saravanaraj AN, Whiteside T, Carreira LA. Calculating physical properties of organic compounds for environmental modeling from molecular structure. J Comput-Aided Mol Des 2007;21:693–708.
Hine J, Mookerjee PK. Intrinsic hydrophilic character of organic compounds — correlations in terms of structural contributions. J Org Chem 1975;40:292–8.
Howard PH, Muir DCG. Identifying new persistent and bioaccumulative organics among chemicals in commerce. Environ Sci Technol 2010;44:2277–85.
Kelly BC, Gobas FAPC. Bioaccumulation of persistent organic pollutants in lichen–caribou–wolf food chains of Canada's Central and Western Arctic. Environ Sci Technol 2001;35:325–34.
Kelly BC, Gobas FAPC. An arctic terrestrial food-chain bioaccumulation model for persistent organic pollutants. Environ Sci Technol 2003;37:2966–74.
Kelly BC, Ikonomou MG, Blair JD, Morin AE, Gobas FAPC. Food web-specific biomagnification of persistent organic pollutants. Science 2007;317:236–9.
Klamt A. COSMO-RS: from quantum chemistry to fluid phase thermodynamics and drug design. Amsterdam: The Netherlands Elsevier Science Ltd; 2005.
Klasmeier J, Matthies M, Macleod M, Fenner K, Scheringer M, Stroebe M, Le Gall AC, Mckone T, Van De Meent D, Wania F. Application of multimedia models for screening assessment of long-range transport potential and overall persistence. Environ Sci Technol 2006;40:53–60.
Mackintosh CE, Maldonado J, Jing HW, Hoover N, Chong A, Ikonomou MG, Gobas FAPC. Distribution of phthalate esters in a marine aquatic food web: comparison to polychlorinated biphenyls. Environ Sci Technol 2004;38:2011–20.
Meylan WM, Howard PH. Atom fragment contribution method for estimating octanol–water partition-coefficients. J Pharm Sci 1995;84:83–92.
Muir DCG, Howard PH. Are there other persistent organic pollutants? A challenge for environmental chemists. Environ Sci Technol 2006;40:7157–66.
Niederer C, Goss KU. Effect of ortho-chlorine substitution on the partition behavior of chlorophenols. Chemosphere 2008;71:697–702.
Niederer C, Goss KU, Schwarzenbach RP. Sorption equilibrium of a wide spectrum of organic vapors in leonardite humic acid: experimental setup and experimental data. Environ Sci Technol 2006a;40:5368–73.
Niederer C, Goss KU, Schwarzenbach RP. Sorption equilibrium of a wide spectrum of organic vapors in leonardite humic acid: modeling of experimental data. Environ Sci Technol 2006b;40:5374–9.
Schenker U, Soltermann F, Scheringer M, Hungerbühler K. Modeling the environmental fate of polybrominated diphenyl ethers (PBDEs): the importance of photolysis for the formation of lighter PBDEs. Environ Sci Technol 2008;42:9244–9.
Seth R, Mackay D, Muncke J. Estimating the organic carbon partition coefficient and its variability for hydrophobic chemicals. Environ Sci Technol 1999;33:2390–4.
Stenberg M, Linusson A, Tysklind M, Andersson PL. A multivariate chemical map of industrial chemicals — assessment of various protocols for identification of chemicals of potential concern. Chemosphere 2009;76:878–84.
U.S. EPA. Estimation Programs Interface Suite™ for Microsoft Windows, v 4.00. United States Environmental Protection Agency, Washington, DC, USA. Available online http://www.epa.gov/oppt/exposure/pubs/episuite.htm 2009 [Accessed Feb. 2009].
UNEP. Stockholm convention on persistent organic pollutants. Available online http://chm.pops.int/Portals/0/download.aspx?d=UNEP-POPS-COP-CONVTEXT.English.pdf 2001 [accessed Dec. 2009].
UNEP. The Nine New POPs. An introduction to the nine chemicals added to the Stockholm Convention by the Conference of the Parties at its fourth meeting. Available online http://chm.pops.int/Programmes/NewPOPs/Publications/tabid/695/language/en-US/Default.aspx 2009 [accessed Mar. 2010].
Wania F, Mackay D. A global distribution model for persistent organic-chemicals. Sci Total Environ 1995;161:211–32.
Wania F. Assessing the potential of persistent organic chemicals for long-range transport and accumulation in polar regions. Environ Sci Technol 2003;37:1344–51.
Wania F. Potential of degradable organic chemicals for absolute and relative enrichment in the arctic. Environ Sci Technol 2006;40:569–77.
Wania F, Dugani CB. Assessing the long-range transport potential of polybrominated diphenyl ethers: a comparison of four multimedia models. Environ Toxicol Chem 2003;22:1252–61.
Undeman, E., T.N. Brown, Wania, F., M.S. McLachlan. The vulnerability of human populations to environmental exposure to organic contaminants. Submitted for publication.
Wittekindt C, Goss KU. Screening the partition behavior of a large number of chemicals with a quantum-chemical software. Chemosphere 2009;76:460–4.