Accounting for bioavailability of aluminum in Dutch surface waters; towards environmental quality standards for ecotoxicological effects

Final report, October 2022.

written in the context of the project : "Inhaalslag bezien watervergunningen" Commissioned by: RIVM, National Institute for Public Health and the Environment.

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Abstract

Aluminum (Al) is the most abundant metal on earth, usually tightly captured in the mineral structure of rocks and clay minerals. Caused by soil acidification (by air pollution), mining and anthropogenic uses, aluminum is mobilized and can enter surface waters. Effects of aluminum on aquatic ecosystems show huge differences between water types, as dependent on three factors which jointly determine the bioavailability of Al: pH, dissolved organic carbon concentrations and hardness. In the past five years calculation methods have been developed in the US to calculate critical values for the protection of ecosystems that account for these differences in bioavailability. The goal of this report is to evaluate the compliance of these methodologies with EU-guidance and (if possible) to propose an environmental quality standard for Dutch fresh surface waters.

The US-EPA methodology and data have been well described, but the existing EPA-tools do not comply with the European Technical guidance for deriving environmental quality standards. However, with the existing data it was possible to adjust the US-EPA methodology to comply with EU-guidance. The adjustments were implemented in an Excel tool and an R-script was generated to compute water type-specific HC₅ values (Hazard Concentration for 5% of the species) according to European guidelines. An assessment factor of 5, reflecting remaining uncertainties in the toxicity data, is recommended on the HC₅.

Environmental quality standards (EQS) are values set by policy makers, ideally based on a sound scientific assessment of potential environmental impacts. In the case of aluminum however, calculated HC₅ values for Dutch fresh surface waters differed by six orders of magnitude depending on the water type (range: <0.003-3000 μ g/L). The US-EPA observed a similar variation, and has therefore decided not to set a specific EQS, but always demand a site-specific risk assessment by the use of a calculation tool. It is not in the competence of the contractor to decide upon the desired level of protection and the practical implications of certain choices. In order to offer options for Dutch policy makers, different EQS values are presented, obviously with different levels of protection.

For future compliance testing it is important that the analytical method for aluminum in water samples quantifies a bioavailable fraction of aluminum that is representative for the bioavailability of aluminum in the toxicity experiments that were used to derive the EQS. This is currently not the case. Instead of the common strong acidification of water samples a mild acidification to pH 4 is recommended.

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1 Introduction

In the context of the project "Inhaalslag bezien watervergunningen", Rijkswaterstaat has commissioned RIVM to draft a proposal for revised environmental quality standards (EQS) for aluminum (AI) in surface water. It should be noted that the responsibility for standard setting lies with the Ministry for Infrastructure and Water Management. The present report serves as scientific background document.

The current Dutch environmental quality standard for aluminum in Dutch surface waters is in place since 2002. It concerns an indicative maximum permissible addition (MPA) of 12 μ g/L. This concentration may be corrected for the natural background concentration to yield a maximum permissible concentration (MPC). The Dutch natural background concentration in fresh water has been set at 36 μ g/L (van de Plassche, 2002; RIVM, 2022). It should be noted that this background concentration was derived in a different way than more recently used for other metals by Osté (2013).

Various comments were made about the derived MPA. The main points were that the behaviour, bioavailability and ecotoxicity of aluminum are highly dependent on pH and that the MPA was derived from studies that are not representative for the Dutch situation. In more recent years, water quality standards have been derived for aluminum in a number of countries, that could be useful for substantiating a revised Dutch Al-EQS. In Table 1 fresh water quality criteria from several countries are listed. The actual legal aquatic EQS values are often difficult to find, and the status of some values is uncertain. Some values may be outdated, whereas others may still have the status of a proposed value. Several derivation approaches have been employed in different countries. These include approaches that focus on different forms of bioavailable aluminum (Al³⁺, monomeric aluminum or dissolved aluminum) and pH-dependent approaches.

Country	year	Al-form	Standard	μg/L	condition	Ref.
Canada	1987	Total Al	AQL	5 ¹	pH<6.5	Canada 2007
				100 ²	pH≥6.5	
	2021	Total Al	FWQG	variable	Site -specific	Canada 2021
Germany	2010	Al ³⁺	AA-EQS	50 ²		LAWA, 2010
			MAC-EQS	250 ³		
The Netherlands	2002	Dissolved Al	MPA (indicative)	12		RIVM, 2022
						Van de Plassche, 2002
United Kingdom	2007	Monomeric Al	PNEC (chronic)	0.05 ³		EA, 2007
			PNEC (acute)	0.25 ⁴		
	unknown	Total Al	MAC-EQS	1000 ⁴	pH≥6	UK, 2018
		Dissolved Al		1004	pH<6, soft	
		Dissolved Al		1000 ⁴	pH<6, hard	
USA	1988	Total Al	AWQC (acute)	750 ²		EPA, 1988
			AWQC (chronic)	87 ²		
	2018	Total Al	AWQC (acute)	1-4800	Site-specific	EPA, 2018a
			AWQC (chronic)	0.8-3200		

Table 1 Overview of existing water quality criteria for aluminum in freshwater in different countries.

AQL=Acceptable Quality Limit; FWQG=Federal Water Quality Guideline; AA-EQS= Annual Average – Environmental Quality Standard; MAC-EQS=Maximum Acceptable Concentration; MPA = Maximum Permissible Addition; PNEC=Predicted No Effect Concentration; AWQC=Ambient Water Quality Criteria

¹ Outdated

² Proposal, legal reference not found.

³ Not implemented due to absence of suitable analytical method.

⁴ Indirect reference (mentioned in document as EQS surface water to derive discharge limits for AI), legal source not found.

The most promising approach seems to be available from the United States Environmental Protection Agency. The US-EPA published an ecotoxicologically based guideline for aluminum in 2018 that used several Multiple Linear Regression models (MLR) to describe the bioavailability of aluminum based on pH, hardness and DOC for freshwater species of different trophic levels (EPA, 2018). The US-EPA did not set fixed risk limits but provided a tool for site-specific risk assessment. The US-EPA 's way of deriving EQS values differs from the European one, but the dataset and normalization show potential to be adjusted to comply with European guidance. Canada simplified the US-EPA method, and used one overall equation for all the aquatic species instead of several bioavailability equations for species from different trophic levels.

Commissioned by RIVM, this report assesses the usefulness of the US-EPA methodology for the Dutch situation. Questions were:

- 1) Is the US-EPA methodology well described and properly executed?
- 2) Are the MLR equations and the underlying toxicity data useful for derivation of an AA-EQS¹ and MAC-EQS² according to European guidelines? If yes, which EQS-value options could be derived?

This study assesses the possibility of inclusion of Al-MLRs in the site-specific risk assessment for metals in the Netherlands. A site-specific risk assessment tool called PNEC-pro is authorized to be used to account for differences in metal bioavailability when assessing the chemical quality of a waterbody (Rijkswaterstaat, 2020). MLRs for Zn, Cu, Ni and Pb already have been included in PNEC-pro.

¹ AA-EQS is an annual average concentration for the risk assessment of annual average concentrations of sites.

² MAC-EQS is a maximum acceptable concentration for the risk assessment of individual samples.

2 Sources, behaviour and ecotoxicology of aluminum

2.1 Sources of aluminum

Aluminum (Al) is a natural metal in the earth's crust, where it is tightly bound by oxygen and silicon. Aluminum is extremely abundant; after oxygen and silicon it is the third most abundant element in the earth's crust and the most abundant metal. Aluminum exists naturally in ores like bauxite and in common clay and sand. The estimated crustal (lithospheric) abundance of aluminum is 82.3 gram/kg (Pogue and Lukiw, 2014). Despite its high abundance in rocks and soils, the aluminum concentrations in surface water are low, generally in the microgram per liter range. Approximately 1.1×10^{12} tons of metallic aluminum have been extracted from geological deposits and exported into the biosphere since aluminum production began to grow in the beginning of the 20th century, and about two-thirds of this amount is estimated to be still in production, through recycling, re-use and intrinsic longevity (Pogue and Lukiw, 2014).

According to the Dutch national Pollutant Release and Transfer Register (PRTR), the annual release of aluminum to surface water between 2010 and 2020 was approximately 40-49 tonnes, caused by sewage treatment plants, traffic and industry (Rijksoverheid, 2022). Not included in the data of the PRTR is the natural weathering and leaching from soil, that also contribute to aluminum in surface water. This process of natural mobilization of aluminum is enhanced by soil acidification through air pollution (Lawrence et al., 2007, Li et al.2022). Due to atmospheric deposition of sulfur and nitrogencompounds (acid rain), aluminum is mobilized in areas where the soil has a low buffer capacity (such as sandy soils). Under natural conditions the solubility of aluminum at low pH is especially relevant. At neutral pH, the solubility is very low.

2.2 Ecotoxicology of aluminum

Aluminum has no biologically important functions or beneficial properties to aquatic life, and is therefore considered a non-essential metal (EPA 2018a and reference therein). Elevated levels of aluminum can affect the regulation of ions (like salts) and inhibit respiratory functions, like breathing (EPA, 2018b). Aluminum can accumulate on the surface of a fish's gill, leading to respiratory dysfunction and possibly death. In plants reduced root growth and reduced yields in acidic soils are associated with the presence of free aluminum (Rahman and Upadhyaya, 2021). In algae, aluminum interferes with intracellular phosphorus and glucose metabolism (EA, 2007).

The bioavailability of aluminum to aquatic organisms depends on several water chemistry parameters. For example, pH determines both aluminum solubility and speciation, and the level of competition between Al³⁺ and protons (H⁺) and other cations, such as calcium (Ca²⁺) for the uptake by aquatic biota. Organic aluminum complexes, such as those formed with humic and fulvic acids, tend to increase total aluminum concentrations in solution, but reduce the bioavailability of aluminum to aquatic organisms.

An ecotoxicological effect value such as EC_{10} , (or EC_{20} or EC_{50}) of a substance is supposed to be an intrinsic value for a biological species. Particularly for metals, it was shown however, that effects of total (dissolved) metal concentrations in various ecotoxicity tests could not always be explained by differences in metal concentrations. It was observed that species- EC_{xx} values can be highly variable, depending on the type of water that was used in the ecotoxicity test. Parameters like pH, DOC and hardness often appeared to have a substantial effect on the ecotoxicity. This is because these parameters determine chemical speciation reactions. Chemical speciation implies that metals can occur in different ionic forms that are not equally toxic, that metals can form complexes and

precipitates, and that hardness, for example, can mitigate the uptake of metals. Bioavailability has been widely studied, and the concept of bioavailability is translated into equations that reflect processes and reactions that play a role in predicting toxic effect levels. The most sophisticated models are the biotic ligand models (BLMs). An important aspect of the BLM-concept is competitive binding of the toxicant to ligands such as dissolved organic carbon and biological membranes (see Figure 1). Based on these concepts, tools for the prediction of bioavailability and ecotoxicity under various water chemistry variables are available for several metals (Zn, Cu, Ni, Pb, Cd) and authorized for regulatory use.

The concept of bioavailability is that toxicity only occurs when aluminum binds to or crosses biological membranes. There is a constant competition between the metal and other substances in the water for binding to the membrane. When the sites on the membrane are for example already occupied by Caor Mg-ions, binding of aluminum is reduced. When there is a high concentration of dissolved organic matter available, the binding of aluminum to the biological membranes is also reduced, and precipitated aluminum is not bioavailable either. The relative importance of these processes depends on the intrinsic binding coefficients, equilibrium partition coefficients and the actual chemical composition and concentrations of substances in the water.



Figure 1 Schematic overview of processes that determine the toxicity of metals (<u>www.pnec</u>-pro.nl).

Theoretically, BLMs are species-specific and metal-specific and different BLMs exist for acute and chronic effects. For pragmatic reasons, BLMs for species of three different trophic levels including algae, invertebrates and fish are generally considered sufficient to normalize the toxicity data of all test organisms or a whole ecosystem (EC, 2018). Using read-across, the species-specific BLMs are assigned to species within the same trophic level for which no BLM has been developed. This is justified by the assumption that there is a large similarity between species on the cellular level.

Normalization (Step 3 in Figure 1) means that effect concentrations obtained in an ecotoxicity test with certain water characteristics ($EC_{xx,test}$) are adjusted to reflect the bioavailability in a particular water body of interest; so the $EC_{xx,test}$ is adjusted to a concentration that in the field situation would lead to similar occupation of the biotic ligand (membrane) and thus to similar effects. Normalized values are also called water type-specific values.

BLMs are also sometimes referred to as 'full' BLMs to emphasize that advanced iterative chemical speciation calculations are involved. Besides the complexity of the full BLM calculations, a large number of monitoring parameters (pH, DOC, Na, Ca, Mg, K, Fe, carbonates, sulphates and chloride) are required, which are not always available and it would raise extensive costs for water authorities to collect these. In order to overcome these drawbacks, a simplified procedure is often employed, using Multiple Linear Regression models (MLR). MLRs are straightforward equations, that enable calculation of the normalized EC_{xx} with a common spreadsheet program. MLRs provide satisfactory results amongst others for Zn, Cu, Ni (Verschoor et al., 2012) and Pb (Vink and Broers, 2016) and have been included in the PNEC-pro tool that is offered by Deltares for site-specific water quality assessment (<u>www.pnec-pro.nl</u>).



2.3 Aluminum speciation and analysis

Figure 2 Results of aluminum speciation calculations at a total of 65 μ M aluminum (example) in the absence of ligands (Zhou et al., 2008).

The chemistry of aluminum in surface water is complex (see example in Figure 2) because of the following properties:

- aluminum is amphoteric, meaning that it can act as an acid or a base depending on the pH in the environment
- aluminum is more soluble in both acidic solutions and in basic solutions than in circumneutral solutions. The solubility limit of aluminum varies from 20 μ g/L at pH 6.5 to > 1000 μ g/L at pH 5 (Santore et al. 2018).
- specific ions such as chloride, fluoride, nitrate, phosphate and sulfate form soluble complexes with aluminum;
- Al³⁺ can form strong complexes with fulvic and humic acids;
- hydroxide ions can connect aluminum ions to form soluble and insoluble polymers (e.g. gibbsite, corundum);
- under at least some conditions, solutions of aluminum in water approach chemical equilibrium rather slowly, with monomeric species of aluminum transforming into insoluble polymers which precipitate out of solution over time;

For aluminum, the EC_{xx} is a function of pH, DOC and hardness. The MLRs have been derived for total recoverable aluminum in reconstituted water of laboratory tests, because in several chronic studies ecotoxic effects increased with increasing total aluminum concentrations, while measured concentrations of dissolved and monomeric aluminum changed very little with increasing total aluminum concentrations (Gensemer et al., 2018; Cardwell et al., 2018). It appeared that although the toxicity of aluminum could be explained by the dissolved Al³⁺ at pH 5.0 or lower, the toxicity of aluminum in circumneutral waters did not correlate with dissolved aluminum. Rodriguez et al.(2019) elaborated on this issue and explained this phenomenon by the two toxic mechanisms of aluminum: 1) at acidic pH the toxicity of aluminum appears to be attributable to iono-regulatory effects and 2) at neutral or alkaline pH conditions physical effects are often attributable to the coating of the respiratory membranes with Al-hydroxide precipitates.

Unlike laboratory test water, natural surface waters typically contain suspended solids that include aluminum in the forms of oxides or silicates. Common analytical methods using strong acid will dissolve most or all of the inert non-toxic aluminum present in solid particles, and will report these concentrations as "total or total recoverable" aluminum In natural surface waters with suspended solids, the aluminum mobilized from the suspended solids during analysis can result in "false" exceedances of the environmental quality criteria. Therefore, Rodriguez et al.(2019) recommended to use a method that could appropriately measure aluminum for regulatory purposes, concerning aluminum that is not associated with suspended solids, and including Al-hydroxide particulates that are present at circumneutral pH. This preferred method measures the fraction of aluminum responsible for toxicity and is described in Appendix 1 (see also paragraph 7.2).

3 Differences between US-EPA and EU approach

In this chapter it is explained to what extent the EPA derivation method of the Al-EQS deviates from the EU Technical guidance for deriving environmental quality standards (further referred to as EU-guidance no. 27) (EC, 2018).

3.1 Species sensitivity distribution

Water quality criteria are derived from a species sensitivity distribution (SSD) if there are sufficient ecotoxicity data available. From a distribution of ecotoxicity data a hazard concentration that is protective for aquatic ecosystems (HC_5) can be statistically derived. An assessment factor is eventually also applied to the HC_5 , amongst others depending on the reliability of the statistical outcome, the presence of particularly sensitive groups of species, the number and relevance of species in the distribution and the type of experiments (field or lab).

Key differences between the US and EU approaches include:

- 1) use of chronic NOEC or EC_{10} in the EU versus chronic EC_{20} in the US;
- 2) use of species-mean endpoints in an SSD by the EU versus genus-mean endpoints in Genus Sensitivity Distribution (GSD) the US;
- 3) inclusion of algae and higher plant data in the EU SSD versus exclusion of algae and plant data in the US GSD, see Figure 3;
- 4) use of different statistical models for calculating the HC₅; the US-EPA derives the HC₅ from four most sensitive species, in the EU the complete SSD is used.

In the US-EPA guidance, acute and chronic criteria were derived that are allowed to be exceeded only once in 3 years, whereas in Europe annual average concentrations need to comply with an Annual Average - EQS (AA-EQS) and individual samples may not exceed the maximum acceptable EQS (MAC-EQS).



Figure 3 Difference between US-EPA and EU approach for calculation of site-specific HC5. A. Genus sensitivity distribution for invertebrates and fish based on chronic total aluminum (AI) effect concentrations, 20% (EC20s; US Environmental Protection Agency [USEPA] approach) and (B) species sensitivity distributions for algae/plants, invertebrates, and fish based on chronic total aluminum EC10s (European Union [EU] approach) adjusted to a dissolved organic carbon (DOC) of 2 mg/L, a pH of 7, and hardness of 75 mg/. Figure B is generated with ssdtools in R using the dataset and models selected in this report.

Based on the differences mentioned above, it is concluded that the US-EPA tool (results visualized in Figure 3A) is not useful for application within the European and Dutch regulatory frameworks. However, Figure 3B shows an assessment following European guidelines, so EC₁₀ for algae and plants are available and the statistical derivation method can be adjusted to comply with the European guidelines.

3.2 Calculation of water type-specific quality criteria

The EPA developed a spreadsheet-tool called "Al-criteria calculator v2" for the calculation of sitespecific water quality standards (further referred to as the EPA-tool³). The EPA-tool provides an EC₂₀based chronic EQS and an EC₅₀-based acute EQS. The EPA-tool is based on publications of DeForest et al. (2018 and 2020). Slightly different spreadsheet-tools are also provided by these authors in the supplemental information to their publications, further referred to as DeForest-tools. DeForest et al. implemented both US and European approaches for the calculation of chronic water type-specific EQS. These tools use separate equations for algae, crustaceans and fish. Canada derived one overall equation based on the work of DeForest et al. (2018 and 2020). The Canadian work was outside the scope of this assignment.

Thus, the considered calculation tools for water type-specific aluminum criteria are:

- 1) EPA Al-criteria calculator v2 (2018)
- 2) DeForest et al. 2018, supplemental information
- 3) DeForest et al. 2020, supplemental information

The DeForest 2020 version is an update of the 2018 version with an applicability for a broader range of water types and a larger toxicity database. All the tools run in Microsoft Excel.

The following steps were taken by DeForest et al. (2018 and 2020) to create an aluminum calculation tool for chronic toxicity according to European methodology:

- 1) Chronic toxicity data of algae *Pseudokirchneriella subcapitata* were added to the SSD. Data are available from Gensemer et al. (2018), supplemental information.
- 2) EC_{10} values were selected instead of EC_{20} ;
- 3) An algae MLR was added to the present crustacean and fish MLRs. So, three MLRs are present to normalize all species mean EC_{10} values in the toxicity database;
- 4) An HC₅ calculation according to the EU statistical approach, i.e. the calculation of the 5th percentile of log-transformed (normalized) EC_{10} values by a Gaussian distribution function, including the 90% confidence interval around the 5th percentile. The HC₅ is the median of a distribution of SSD-curves, also referred to as HC₅-50⁴, with the HC₅-5 and HC₅-95 as lower and upper limit of the 90% confidence interval.

EPA also offers an R-script for normalization of toxicity data. Probably this tool is not suitable for the average water manager, but it can be used for research purposes. In order to make the R-script compliant with EU guidance no. 27 the same adjustments need to be made as in the US-spreadsheet.

PNEC-pro is a Dutch tool to calculate water type-specific quality criteria for Zn, Cu, Ni and Pb. PNECpro followed the European approach. Implementation of the DeForest-tool in PNEC-pro is feasible. The following chapters will go into more detail to the selected MLRs, the toxicity database and will show preliminary results for the Dutch situation.

³ https://www.epa.gov/sites/default/files/2018-12/aluminum-criteria-calculator-v20.xlsm

⁴ The HC₅-50 is generally slightly lower than a single-fit point estimate of the HC₅ (Aldenberg et al., 2002)

4 Multiple linear regression models (MLRs)

This chapter describes the EC_{10} -MLR models as presented in the most recent publication of DeForest et al. (2018 and 2020).

In paragraph 4.2 the differences between (simple) linear regression and multiple linear regression are briefly explained. In paragraph 4.3 it is described for which species the MLRs were developed and how they were derived. In paragraph 4.4 the level of validation is described.

The **development of MLRs** for regulatory purposes requires the collection or generation of many ecotoxicity data, and involves the following steps:

- 1) Performance of laboratory experiments to determine dose-response relationships for algae, crustaceans and fish at a variety of water chemistries (different pH, DOC and hardness);
- 2) Derivation of empirical relationships between EC_{xx} and pH, DOC and hardness for each of the three species;
- 3) Validation of the MLRs with tests in natural waters.

These steps were executed and described by DeForest et al. (2018; 2020); Gensemer et al. (2018); and EPA (2018).

The **application of MLRs** to derive EQS values requires data of a larger variety of species in order to create a SSD. This is described in Chapter 5.

4.1 Toxicity data for MLR development

Three sets of toxicity data were used for the derivation of Al-MLRs for the following species: the algae *Pseudokirchneriella subcapitata*⁵, the crustacean *Ceriodaphnia dubia* and the fish *Pimephales promelas* (see Appendix 2). The dataset provided by DeForest et al. (2020) is the most recent and most complete existing dataset. For MLR development DeForest et al. only used chronic toxicity data. Application to acute toxicity data assumes that the same toxic mechanisms are present.

The toxicity tests for MLR development were performed with reconstituted water, that means that the pH, DOC and hardness are adjusted to obtain a controlled range of water chemistry conditions. A combination of three DOC, three hardness and three (roughly) pH values was tested.

Chronic toxicity tests with *P. subcapitata* were performed according to OECD test guideline 201, a 72h static test. Short-term (7d), static renewal tests were done with *C. dubia* and *P. promelas* according to US guidelines. For *C. dubia*, which has a short life-cycle, a 7-days test duration represents chronic exposure, while for *P. promelas* this is an extended acute test. Reported endpoints were EC₁₀ and EC₂₀, as well as pH, DOC and hardness.

DeForest et al. (2020) added results of nine toxicity tests to the *C. dubia* dataset of 2018 and also nine additional test results to the *P. promelas* dataset, in order to extend the range of the water chemistry (see Table 2).

⁵ Currently the formal name is *Raphidocelis subcapitata*, but in this report we keep using the name *Pseudokirchneriella subcapitata* to avoid confusion because this name is used in all the underlying studies and databases as well.

MLR parameter	test range
рН	6.0-8.7
Hardness	9.8 – 428
DOC(mg/l)	0 08 - 12 3

Table 2 Water characteristics of the toxicity data which determines the applicability domain of the MLRs.

4.2 Single versus multiple regression and interactions

A variety of statistical regression options were employed by DeForest et al. (2018 and 2020). The main approaches are described in this paragraph.

A simple linear regression equation expresses the influence of one parameter x (for instance DOC) on a variable y (for instance an EC₁₀), which is mathematically described by the general equation:

 $y = a \cdot x + b$, where *a* is the slope of the line and *b* is the intercept with the y-axis. The equation is by definition visualized by a straight line in a x-y graph.

A multiple (log-)linear regression model contains more parameters, for instance in the case of bioavailability besides DOC also pH and hardness. This formula looks like:

 $lnEC_{xx} = a \cdot \ln(DOC) + a_2 \cdot pH + a_3 \cdot \ln(Hardness) + \cdots b$ where each parameter has its own slope a_1, a_2, a_3 which determines how sensitive the EC_{xx} is for changes in that particular parameter.

A MLR does not lead to a simple graph with one parameter on the x-axis, because there are several (ideally independent) parameters that determine the outcome; in fact it is a multidimensional case. The parameters DOC and hardness are transformed to the natural logarithms, because their values are usually not normally but log-normally distributed. The pH is not transformed because it is already expressed as the logarithm of the H⁺-concentration.

Besides the effect of each individual parameter, interactions between parameters may exert an effect on the EC_{xx}. By the introduction of interaction terms, the model loses its linear character. Because the significance of the interaction terms can be tested by multiple linear regression techniques we still refer to these models as MLRs. The following four interactions were tested as potential extra terms in the development of the MLR (DeForest et al., 2018 and 2020):

 $ln(DOC) \times pH$: a negative term would characterize the mitigating effect of DOC on aluminum bioavailability, which tends to decrease as pH increases;

 $\ln(Hard) \times pH$: a negative term would reflect that the mitigating effect of hardness on aluminum bioavailability tends to decrease as pH increases;

 $ln(Hard) \times ln(DOC)$: a negative term would reflect that the mitigating effect of DOC on aluminum bioavailability tends to decrease as hardness increases;

 pH^2 : a negative term would help account for decreasing aluminum bioavailability as pH increases from 6 to 7 and then increasing aluminum bioavailability as pH increases from pH 7 to pH 8.

In general, including more terms in the regression improves the accuracy of the model, but one has to be careful for over-parameterization. Some parameters may be correlated; including them both in the MLR introduces a pseudo-reliability. The selection of significant parameters and interactions by DeForest et al. (2018 and 2020) followed a stepwise approach. They tested the additional gain in accuracy after addition of an extra parameter or an extra interaction term. The accuracy was

evaluated based on adjusted R², predicted R², AIC and BIC⁶, similar to the procedures used to derive the MLRs for Cu, Ni and Zn in PNEC-pro (Verschoor et al., 2012). A substantially lower predicted R² is an indication that the model may be overfitted and/or is reliant on individual data points.

4.3 Derivation of MLRs

MLRs were derived from correlation of experimental EC₁₀ values with pH, DOC and hardness of the test media. DeForest et al. (2018) derived MLRs based on chronic toxicity tests for the algae *P. subcapitata,* which is required according to European guidelines. DeForest et al. (2020) updated the MLRs of *C. dubia* and *P. promelas* to expand the applicability range of the MLRs over a broader range of test conditions. In DeForest et al. (2020), different mathematical ways of MLR derivation were compared:

- 1) Development of MLRs for *C. dubia* and *P. promelas*; each MLR had its own intercept and slope;
- 2) Development of pooled MLRs for *C. dubia* and *P. promelas*. The MLRs of *C. dubia* and *P. promelas* had a common slope derived from the combined dataset, but species-specific intercepts⁷.

The first approach has the advantage of being more species-specific and fits better to the data of the individual species. The second approach has the advantage that the pooled dataset is larger, so the statistical power is enhanced. A pooled model also warrants that the normalization of EC_{10} is identical for all taxa, and so a shift in the ranking of species in the SSD cannot occur.

An overview of all of the EC_{10} and some EC_{20} models, and in which tools they were implemented, is given in Appendix 3. In Table 3 an overview of some MLRs for normalization of EC_{10} values is given. Three options are presented that illustrate the main differences between: 1) models without interactions, 2) species-specific models with statistically significant interactions, and 3) pooled models with statistically significant interactions.

In developing its final tool, the US-EPA decided to use the species-specific *C. dubia* and *P. promelas* models rather than the pooled *C. dubia* and *P. promelas* EC₂₀-models. This decision was based on patterns in the residuals of the pooled model that were not observed in the individual species models. For example, the US-EPA commented that the *C. dubia* pooled MLR model was over-predicting the EC₂₀ (predicted EC₂₀ higher than observed values) as pH increased, and under-predicting EC₂₀ as DOC and total hardness increased (lower predicted EC₂₀ than observed values). Conversely, the *C. dubia* individual-species MLR model showed no trends in the residuals over any of the test parameters. Likewise, there were similar trends in the residuals for the pooled *P. promelas* MLR model. Following this reasoning and previous approaches in application of BLMs in the PNEC-pro tool, we selected the species-specific MLRs for calculation of water type-specific quality criteria in the Netherlands.

⁶ The Akaike information criterion (AIC) and the Bayesian Information Criterion (BIC) are estimators of prediction error and thereby of the relative quality of statistical models for a given set of data. They provide a means for model selection. BIC and AIC differ in the "penalty terms" they use for additional parameters. ⁷ Note that intercepts are not used in the normalization procedure.

	a1	a2	a3	a4	a5	a6	Adj. R ²	Reference
	In (DOC)	pН	<i>ln</i> (Hard)	In (Hardness)	In (DOC)	pH ²	-	
				x pH	х рН			
P. subcapitata								
No interactions	+0.349	+0.346	-	-	-	-	0.312	De Forest et al 2018
With interactions	+2.342	+20.923	+4.560	-0.628	-0.288	-1.274	0.940	De Forest et al 2018
C. dubia								
No interactions	+0.536	+0.871	+0.375	-	-	-	0.658	De Forest et al 2018
With interactions	+0.700	+2.368	+3.030	-0.375	-	-	0.925	De Forest et al 2020
Pooled	+0.660	+1.969	+2.216	-0.278	-	-	0.916	De Forest et al 2020
P. promelas								
No interactions	+0.495	+0.966	+0.354	-	-	-	0.822	De Forest et al 2018
With interactions	+1.828	+1.932	+1.914	-0.248	-0.193	-	0.913	De Forest et al 2020
Pooled	+0.660	+1.969	+2.216	-0.278	-	-	0.875	De Forest et al 2020

Table 3 MLR-models for normalization of chronic EC10. For the Dutch approach models with the highest R^2 were selected.

Note that R^2 of the pooled models for *C.dubia* and *P. promelas* are different because they describe the correlation between the model prediction and the observed EC_{10} for each species separately. The intercept *b* is not included in the table because it is eliminated during the normalization process.

The EPA-tool was used to address all waters within a pH range of 5.0 to 10.5. This exceeds the boundaries of the applicability domain of the MLRs (see Table 2). The EPA took this approach so that the recommended criteria can be calculated for a broader range of natural waters found in the US. In the Netherlands pH values down to a value of 4 are sometimes encountered in natural waters and DOC values larger than 12.3 mg/L are quite common. In Chapter 0 the chemistry of Dutch waters is described in more detail. HC₅ values generated for water types outside of the applicability range should be considered carefully and used with caution. Also in PNEC-pro, it is possible to calculate a HC₅ for waters outside the applicability domain. The outcomes are flagged to draw attention on the fact that the HC₅ is more uncertain.

4.4 Validation and cross-species extrapolation of the MLRs

The validation of models is usually done by taking a new set of toxicity tests (so data not used for model development) preferably carried out with natural water samples to check if the predicted EC_{10} for those tests is within a factor of two of the observed value. The nine additional toxicity tests with *C. dubia* and *P. promelas* can be considered as a validation step. In this case, validation resulted in a slight adjustment of the MLR. This approach was similar to the validation of Cu-BLMs (De Schamphelaere and Jansen, 2004).

The MLR of *C. dubia* is used for a variety of other invertebrate species: snails, annelids, rotifers, insects, and bivalves. Likewise the *P. promelas* MLR is used for other fish and frog species and the *P. subcapitata* MLR is used for aquatic plants (*Lemna minor*). For Cu, Ni and Zn such a cross-species extrapolation is justified by additional studies. For Al, such studies were conducted with the rotifer and great pond snail at nominal pH 6.3, with various hardness and DOC levels. However, the results of this validation-study were not published, all EC₂₀ values are in the EPA-report, but only one (the lowest) EC₁₀ value of each species is available in the database of DeForest et al. (2020).

As a conclusion, one can state that the validation and justification for cross-species extrapolation of the available aluminum MLRs needs improvement.

5 Application of MLRs for Dutch EQS derivation

5.1 Data requirements and selection

Three MLRs were developed using ecotoxicity data of three species representing three different trophic levels. The **implementation of MLRs** requires additional toxicity data in order to create a species sensitivity distribution, from which an HC_5 can be derived.

According to the EU guidance no. 27, the HC_5 of an SSD is considered reliable if the database contains preferably more than 15, but at least 10 NOECs/EC₁₀ values, from different species covering at least eight specific taxonomic groups. An overview of data abundance is given in paragraphs 5.2 and 5.3.

Because quality criteria for data selection are approximately identical between the US-EPA (Stephan, 1986) and EU (EC, 2018) and many of the underlying test reports are not publicly available, we pragmatically adopted all studies that have been selected by US-EPA in their 2018 report. The chronic data in the EPA-tool are not directly suitable because they are expressed as EC_{20} -values. DeForest et al. collected EC_{10} -values from the same studies and extended the toxicity database with new studies. This database fulfils the requirements needed to derive water type-specific quality criteria according to the European methodology.

US-EPA (2018a) has set-up a list of criteria for quality control of toxicity data to decide upon including or not including particular studies in a database for aluminum EQS-derivation:

- US-EPA mentioned the importance of aging of the stock solution and pH control of the test as important factors for reliability checking;
- Only data from toxicity tests conducted using chloride, nitrate and sulfate salts (either anhydrous or hydrated) are used in this effects assessment;
- The assessment endpoints for aquatic life criteria are based on survival, growth and reproduction;
- A pH of the water tested of less than 5 was deemed too low to allow for the toxicity data to be used quantitatively;
- Because the chemical speciation and reactivity in seawater is very different from freshwater, only freshwater data for metals were selected;
- There were insufficient data with sea water to derive separate salt water MLRs.

The complete chronic and acute toxicity databases that may be used for implementation in a Dutch aluminum calculation tool are presented in Appendix 4 and Appendix 5. Each EC_{xx} value is normalized to water type-specific conditions with either the algae MLR, the crustacean MLR or the fish MLR. The assignment of a specific MLR to other species is also indicated in Table 4 and Table 5.

5.2 Chronic toxicity data

In Table 4, a comparison is made between the number of toxicity data in the EPA Aluminum criteria calculator v2, the calculation tools provided by DeForest (2020) and the database we derived from those sources. 'The most prominent difference between our selection and those of DeForest is that we do not consider the 7-days fish tests as true chronic tests and removed them from the database.

Requirement EU guidance	EPA (EC ₂₀)	DeForest 2020	Our selection		
Taxonomic group:	# EC ₂₀	# EC ₁₀	# EC ₁₀	species	MLR
					no.
Fish (species frequently tested include salmonids,	2	311	1	Fathead minnow, <i>Pimephales</i> promelas	1
minnows, bluegill sunfish, channel catfish, etc.);	1	-	-	Atlantic salmon, <i>Salmo salar</i> ²	1
A second family in the	2	1	1	Brook trout, Salvelinus fontinglis ³	1
amphibian, etc.);	1	1	1	Zebrafish, Danio rerio	1
	1	-	-	Wood frog, Rana sylvatica ⁴	1
A crustacean (e.g.	33	30	31	Cladoceran, Ceriodaphnia dubia*	1
cladoceran, copepod,	-	1	-	Cladoceran, Ceriodaphnia sp.	
ostracod, isopod,	1	2	1	Cladoceran, Daphnia magna ⁶	1
amphipod, crayfish, etc.);	2	1	2	Amphipod, Hyalella azteca ⁷	1
An insect (e.g. mayfly, dragonfly, damselfly, stonefly, caddisfly, mosquito, midge, etc.);	3	1	1	Midge, Chironomus riparius ⁸	2
A phylum other than Arthropoda or Chordata	6	1	1	Rotifer, Brachionus calyciflorus ⁹	2
(e.g. Rotifera, Annelida,	1	1	1	Fatmucket, Lampsilis siliquoidea	2
Mollusca, etc.);	4	1	1	Great pond snail <i>, Lymnaea</i> stagnalis ¹⁰	2
An order of insect or any phylum not already represented;	1	1	1	Oligochaete <i>, Aeolosoma</i> sp.	2
Algae or Cyanobacteria;	-	27	27	Pseudokirchnerielle subcapitata*11	3
Higher plants.	-	1	1	Lemna minor ¹¹	3
Total data	58	100	70		
#species	13	14	13		

Table 4 Overview of chronic data in EPA document, the DeForest (2020) and our database. Three MLRs were assigned to normalize the toxicity data: 1) the P.promelas MLR, 2) the C. dubia MLR and 3) the P. subcapitata MLR.

¹ This included tests used for BLM development. Because it concerned 7d (subchronic) test and not real chronic tests, these additional data were not selected in the "Dutch" database. We selected the 33-d study used by EPA also (Cardwell et al., 2018), that contained an EC₁₀. The other EPA datapoint (Kimball, 1978) was not available and an EC₁₀ of this study was not reported elsewhere.

 2 EPA-data concern tests with Al-sulphate, those were not selected by DeForest, a reason is not given. An EC₁₀ is not available.

³ EPA-data concern tests with aluminum sulphate, the study with the lowest EC_{10} was selected by DeForest. Since EPA did not provide EC_{10} , we adopted the EC_{10} used by DeForest et al.2020.

⁴ EPA considered test with *Rana sylvatica* not acceptable because test pH was too low. Still it was included in the aluminum criteria calculator.

⁵ EPA and DeForest have 28 tests in common. DeForest deselected four tests with aluminum chloride (ENSR 1992b) and one test of McCauley 1986 also with Al-chloride. They added two new records (CIMM 2009) that were not rejected by EPA, but not included by EPA either. These two data were part of the dataset for BLM development. We took the dataset of DeForest, and added one test of McCauly, but the four test EC_{10} of ENSR 1992 were not available to be included. Because there is no reason to believe that *Ceriodaphnia* sp. is different from *Ceriodaphnia dubia*, we combined the data.

⁶ DeForest included a *Daphnia magna* test of Kimball 1978 (with Al-sulphate) that was disqualified by EPA because the survival in the control was too low. We removed this datapoint.

⁷ DeForest removed the data of Wang et al.(2018); it is not clear why. EPA accepted the study. We included the data point of Wang et al.2018.

⁸ Two tests with Al- sulphate (Palawski et al.1989) were not selected from the EPA database by DeForest. It is not clear why. EC_{10} for these tests are not available, so we could not add them to our database.

 9 DeForest used the lowest EC20 of 431 µg/L from the EPA dataset, and the EC₁₀ from the same test. The other 5 EC₂₀-values in the EPA set were in the range 1604-4670 µg/L. EC₁₀ values for these missing tests are not available because the study (OSU 2018e) is not public.

 10 DeForest claims to have selected the test with the lowest EC₂₀ (out of 4 tests), This is true for the "raw" EC₂₀, but not for the normalized EC₂₀. The normalized EC₂₀ is the highest of aluminum 4 tests. Because EC₁₀ values are not available for the missing tests, we adopted the EC₁₀ that goes along with the high normalized EC₂₀.

¹¹ EPA did not use algae and plants in their Aluminum criteria calculator. So we adopted them from DeForest et al.2020.

5.3 Acute toxicity data

Acute toxicity tests were also collected by EPA in their EPA-tool. The EPA-tool contains EC₅₀ values for 22 species. The tools of DeForest (2018 and 2020) do not contain acute data. The dataset included in the EPA-tool does not contain algae or plants, so it is incomplete according to European methodology. An overview of the database composition is given in Table 5. Algae data are present to supplement the EPA-database.

Table 5 Overview of acute data requirements in EPA document and adopted in our database. Three MLRs were assigned to normalize the toxicity data: 1) the P. promelas MLR, 2) the C. dubia MLR and 3) the P. subcapitata MLR.

Requirement EU guidance				
Taxonomic group:	# EPA	# Our	species	MLR
	data	selection		No.
Fish (species frequently tested	2	2	Atlantic salmon, Salmo salar	1
include salmonids, minnows,	3	3	Brook trout, Salvelinus fontinalis	1
bluegill sunfish, channel catfish,	8	8	Fathead minnow, Pimephales promelas	1
etc.);	1	1	Green sunfish, Lepomis cyanellus	1
	1	1	Guppy, Poecilia reticulata	1
	14	14	Rainbow trout, Oncorhynchus mykiss	1
	1	1	Rio Grande silvery minnow,	1
			Hybognathus amarus	
	3	3	Smallmouth bass, Micropterus dolomieui	1
A second family in the phylum	1	1	Green tree frog, Hyla cinerea	1
Chordata (e.g. fish, amphibian,				
etc.);				
A crustacean (e.g. cladoceran,	1	1	Amphipod, Crangonyx pseudogracilis	2
copepod, ostracod, isopod,	1	1	Amphipod, Hyalella azteca	2
amphipod, crayfish, etc.);	54	54	Cladoceran, Ceriodaphnia dubia	2
	3	3	Cladoceran, Ceriodaphnia reticulata	2
	9	9	Cladoceran, Daphnia magna	2
	1	1	Cladoceran, Daphnia pulex	2
An insect (e.g. mayfly, dragonfly,	1	1	Midge, Paratanytarsus dissimilis	2
damselfly, stonefly, caddisfly,				
mosquito, midge, etc.);	1	1	Midge, Chironomus plumosus	2
A phylum other than Arthropoda	2	2	Fatmucket, Lampsilis siliquoidea	2
or Chordata (e.g. Rotifera,	1	1	Snail, Melanoides tuberculata	2
Annelida, Mollusca, etc.);	4	4	Snail, Physa sp.	2
An order of insect or any phylum	1	1	Ostracod, Stenocypris major	2
not already represented;	1	1	Worm, Nais elinguis	2
Algae or Cyanobacteria;	-	27	Pseudokirchneriella subcapitata	3
Higher plants.	-	-		
# Total data	114	141		
# Species	22	23		

5.4 Creation of tools

MRLs were implemented in Excel as well as in R-scripts. Different versions of the tools were used to cross-check the calculations. The latest versions of the tools were finally checked for 10 randomly selected samples. Resulting HC_5 values were identical, which implies that both tools (which are quite different in how they function) have identical underlying toxicity databases, and identical calculation procedures. The R-script for the calculation of HC_5 is included in Appendix 6.

In PNEC-pro, single transfer functions for Zn, Cu and Ni are used for the calculation of $QS_{bioavailable.}$. This is an approach that can be considered for aluminum also. Such a simplification introduces however additional uncertainties because the transfer function is not an exact simulation of the normalization procedure but an approximation of it. Transfer functions for acute and chronic HC₅ are derived by regression of predicted site-specific HC₅ values with DOC, pH and hardness of the water types.

The following transfer functions resulted in the best fits for chronic and acute HC₅:

 $log_{10}(HC_5) = Intercept + a_1 \cdot log_{10} (DOC) + a_2 \cdot pH + a_3 \cdot log_{10} (Hardness) + a_4 \cdot pH \cdot log_{10} (Hardness)$

Introduction of other interaction terms such as $pH \times log_{10}$ (DOC)·and $pH \times pH$ did not significantly improve the predictive power of the transfer functions. The parameters in the transfer functions are listed in Table 6, the graphs showing the statistical fit are shown in Figure 4.

Table 6 Parameters of the simplified equations for calculations of site-specific $HC_{5.}$

	Intercept	a1	a ₂	a ₃	a4	Adjusted r ²
chronic	-11.32348	0.40637	1.82928	6.74640	-0.89380	0.9210
acute	-9.13133	0.40176	1.61797	5.92374	-0.77501	0.8985



Figure 4 Goodness-of-fit between site-specific HC_5 values predicted with the normalization procedure with 3 MLRs and the HC_5 values estimated with the simplified transfer functions. Colored dots represent different water types, the pink dots refer to fens. The grey dotted lines represent uncertainty range of a factor 2, 5 and 10 above and below the best fitted line.

The simplified model is not used in the following chapters.

6 Calculation of water type-specific HC₅

6.1 General approach

For the Dutch water quality evaluation two consecutive steps may be applied; 1) generic and 2) sitespecific risk assessment (Rijkswaterstaat, 2020). To obtain insight in water types, the geographical distribution and surface areas involved, monitoring data were retrieved from Waterkwaliteitsportaal.nl, the most recent data were from 2020 (see paragraph 6.2, 6.3 and 6.4). Three approaches are described in the following paragraphs; a summary is provided in Chapter 7.

1) Assessment with monitoring data of Waterkwaliteitsportaal 2020

The EU guidance no. 27 states that: "The HC₅ selected should be protective of 95% of waters in the region (country) shown to have the highest bioavailability of that particular metal." Therefore normalizations are performed for as many natural samples that could be retrieved from Waterkwaliteitsportaal.nl for the most recent year (2020). When HC₅ endpoints are aggregated to water type, 5th percentiles are reported.

Two sets of HC_5 values are calculated (see paragraph 6.5) :

- a) HC₅ for all samples, regardless of the DOC, pH and hardness. This approach covers a maximum number of water types although it may contain less reliable HC₅ values if they were derived for samples that were outside the applicability domain of the MLRs.
- b) $\ \ HC_5$ only for samples within the applicability domain of the MLRs.

2) Assessment with a specific set of water chemistry conditions

In the EU guidance document no. 27 on Derivation of environmental quality standards it is stated that: "The EQS_{bioavailable} is a total dissolved metal concentration which is highly bioavailable and which does not make any allowance for background in its derivation. It is derived, initially, as the normalized, estimate of the HC_5 for a specific set of water chemistry conditions – one that is reflective of high bioavailability conditions.

An a priori selection of one specific set of parameter values that reflects a high bioavailability is not obvious, because the normalization of the toxicity data is affected by pH, DOC and hardness simultaneously and by interactions between these parameters. Different combinations of pH, DOC and hardness can lead to the same HC₅. The most vulnerable specific water chemistry conditions are determined from HC₅ values calculated with samples from Waterkwaliteitsportaal.nl (see paragraph 6.6).

3) Assessment with water types previously used for derivation of a EQS for copper

In 2012, a bioavailability based EQS for copper was adopted, based on the work of Vijver et al. (2008). This work included the establishment of six water types. For reasons of comparison, Al- HC_5 values are also calculated for these water types (see paragraph 6.7).

6.2 Selection of water types

Waterkwaliteitsportaal.nl contains more than 2.7 million chemical monitoring data of 2020. The database contains concentrations of 1046 chemical substances and more than 50 physico-chemical characteristics of the samples. The presence of monitoring data on pH, DOC and hardness is required to be able to normalize toxicity data of aluminum. The presence of Al-concentrations in the monitoring data is not required for derivation of EQS, but it would be nice to have them for a preliminary assessment of the consequences of a proposed HC₅ or EQS (see paragraph 7.2).

Following the Water Framework Directive, The Netherlands distinguishes approximately 50 water types, with different salinity, flow velocity, alkalinity, depth, width, surface area and soil type. For each water type biotic and abiotic characteristics have been identified and ecological targets described. The MLR models can only be applied to freshwaters; MLRs are not valid for saline water. Therefore samples from marine, coastal and transitional waters were not selected⁸. This concerns approximately 79% of the total surface water area of the Netherlands (Van Puijenbroek and Clement, 2010). The remaining 21% concerns freshwater types (including brackish waters⁹). Freshwater samples were grouped into 12 water types (see Table 7). A distribution of selected samples over WFD water types and a description of the WFD water types in Dutch is given in Appendix 7.

Because pH, DOC and hardness were not always determined in samples taken on exactly the same date, monthly average values were calculated in order to construct complete records for the calculation of water type-specific quality criteria. Sites with incomplete data or with missing water type were removed. On average approximately 7 monthly records could be retrieved per site. In this way, 5544 complete monthly records were obtained for 779 sites for the calculation of a site-specific HC₅.

Water type	Area		WFD types in selected dataset	Selecte	d sites	Monthly data
	ha	%		#	%	#
Brackish waters	27 205	8	M30, M31, M32	19	2	161
Brooks, fast flowing	172	< 0.1	R13, R14, R15, R17, R18	35	4	273
Brooks, slow flowing	2 097	1	R2, R3, R4, R5, R12,R19, R20	275	35	1926
Canals	18 733	5	M3, M6, M7, M10	138	18	1003
Ditches	15 630	4	M1, M2, M8	111	14	597
Fens	2 407	1	M12, M13, M26	34	4	140
Lakes, large	182 866	51	M21	11	1	118
Lakes, medium	47 195	13	M14, M20, M27	57	7	525
Lakes, small, peat	6 697	2	M25	3	0.4	13
Lakes, small, sand clay	19 803	6	M11, M16, M22	23	3	159
Rivers	23 369	7	R6, R7, R8, R16	71	9	623
Water in riverine area	10 569	3	M5	2	0.3	6
Total	329 538			779		5544

Table 7 Overview of Dutch water types in the selected dataset. Surface area figures were obtained from Van Puijenbroek and Clement (2010). Monthly data concerns complete datasets with mean concentrations of DOC, pH and hardness.

⁸ This concerned WFD water-types with codes K (coastal), O (transitional)

⁹ Brackish waters concern WFD water types M30 (0.3 to 3 g Cl/L), M31 (3-10 g Cl/L) and M32 (>10 g Cl/L).

6.3 Representativity of selected samples

The geographical distribution of the selected samples is given in Figure 5, which shows that the selected samples do not have a homogeneous coverage of The Netherlands. The main reason is that not all waterboards measured the hardness. A distribution of available data over sampling authorities is given in Appendix 8.



Figure 5 Geographical distribution of selected data. Provincial borders are indicated green.

Table 7 shows that the selected freshwater records represent all the major types of fresh waters: rivers, canals, ditches, fens and several types of lakes and brooks. However, the number of samples for each water type is not correlated with the relative surface area of the water types in The Netherlands. It appears that especially brooks are overrepresented in the data selection, whereas large lakes are underrepresented in the selected dataset. An overrepresentation of vulnerable, or highly diverse water types is however justifiable from an ecological point of view.

6.4 Water chemistry

The variation of water chemistry parameters used for the calculation of water type-specific quality criteria is shown in Box-Whisker plots in Figure 6. Probability distribution plots are provided in Appendix 8. The boxes represent the 25 to 75th percentile of the data and the bold lines represent the median values. The whisker represents the values within 3x the standard deviation, that is the 99.7 percentile interval assuming a Gaussian distribution. Data outside the whiskers are considered as outliers. The 5th percentiles of the water chemistry parameters, as well as the percentage of sites and samples with DOC, pH or hardness outside the applicability domain of the MLRs, are summarized in Table 8.



Figure 6 Box-Whisker plots that show the variation of water chemistry parameters used for calculation of water type-specific quality criteria of aluminum.

Figure 6 shows a few water types that are clearly distinct from the other water types, which implies that calculated HC_5 values for these waters will also likely be different from other water types. These concern:

- fens, which can be characterized by relatively low pH and low hardness;
- small peaty lakes, with relatively high DOC;
- brackish water, with relatively high hardness.

These water types also have a large proportion of samples with pH, DOC and/or hardness values outside the applicability domain of the MLRs. The boundaries of the applicability domain are most frequently exceeded by DOC (30% of the samples), followed by hardness and pH (each 4% of the samples). Overall 37% of the samples are outside the applicability domain of the MLRs (see Table 8).

Water type	DOC (mg/L)				рН			Hardness (mg CaCO₃/L)				Overall					
				Sites	Samples				Sites	Samples				Sites	Samples	Sites	Samples
	50p	5р	95p	OAD	OAD	50p	5р	95p	OAD	OAD	Median,	5р	95p	OAD	OAD	OAD	OAD
Brackish waters	9.2	5.2	22.3	21%	33%	8.0	7.8	8.5	5%	7%	552	360	3099	89%	75%	100%	89%
Brooks fast flowing	10.4	6.2	30.3	23%	26%	8.0	7.6	8.3	3%	0%	187	90	323	0%	1%	26%	28%
Brooks slow flowing	10.5	5.1	11.6	32%	32%	7.4	6.6	7.7	0%	1%	155	103	198	0%	0%	32%	33%
Canals	11.1	3.8	26.0	41%	37%	7.8	7.3	8.2	0%	1%	206	121	563	11%	17%	48%	48%
Ditches	11.0	5.1	28.1	44%	39%	7.6	6.7	7.1	2%	4%	209	103	836	19%	16%	53%	49%
Fens	14.7	4.6	31.1	65%	54%	5.8	4.3	7.8	59%	53%	13.2	4.0	112	44%	41%	85%	85%
Lakes large	11.7	6.0	12.7	27%	19%	8.3	8.3	8.6	0%	5%	204	204	262	0%	0%	27%	23%
Lakes medium	8.1	2.6	17.5	30%	19%	8.2	7.4	8.5	4%	9%	198	95	384	4%	7%	35%	32%
Lakes small peaty	19.2	8.7	37.8	67%	85%	7.9	7.2	8.1	0%	0%	194	75	226	0%	0%	67%	85%
Lakes small on sand or clay	9.1	5.3	19.9	17%	16%	7.8	7.2	8.4	4%	6%	166	69	281	4%	1%	26%	21%
Rivers	8.3	4.8	14.3	10%	12%	7.7	7.2	8.2	0%	1%	187	127	237	0%	0%	10%	13%
Water in riverine area	10.6	9.8	11.4	0%	33%	7.2	7.1	7.3	0%	0%	115	110	119	0%	0%	0%	33%
Overall (emperical)	10.2	4.1	23.2	33%	30%	7.6	6.5	8.3	4%	4%	181	49	525	9%	4%	40%	37%
Overall (area-weighted)	11.1	2.0	27.0			8.2	6.7	8.6			200	70	1615				

Table 8 .Overview of water chemistry conditions for different water types. (OAD = Outside of Applicability Domain of the MLRs). Parameter values are derived from annual mean values per sampling site.

6.5 HC₅ of water types in Waterkwaliteitsportaal 2020

An overview of the variation of acute and chronic HC_5 values is shown in Figure 7. In Appendix 10 the probability distributions of the HC_5 values are provided.



Figure 7 Variation of chronic and acute water type-specific HC5 values ($\mu g/L$).

Although the distributions of DOC and hardness tend to be log-normally distributed (see Appendix 9), the calculated HC_5 appears to be normally distributed in most of the water types. Therefore, the 5th percentile HC_5 for each water type was derived from the normal distribution curve, except for fens. In fens the distribution is skewed towards higher HC_5 values. Because neither a log-normal distribution nor a normal distribution seemed to be appropriate (see Appendix 10), an empirical 5th percentile was derived for fens.

In Table 9, the 5th-percentile HC_5 for each water type is listed. In Table 9A, the 5th percentile is derived from all data (from all water samples), whereas in Table 9B the 5th percentile is derived from samples with pH, DOC and hardness within the applicability domain of the MLRs.

Table 9 HC₅ values (fitted 5th percentile for each watertype) compared with the cumulative area the HC5 would protect. The HC_5 that protects 95% of the surface water area is estimated by interpolation of the two HC5 values that are closest to the 95% area.

Tuble 71. Dused off all sumples	Table A:	Based	on all	samples
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	5p-HC₅			5p-HC₅	
Chronic	(µg Al/L)	area%	Acute	(µg Al/L)	area%
Fens	0.04	100.0%	Fens	0.9	100%
Brackish waters	53	99%	Brackish waters	792	99%
Lakes, medium	92	92%	Lakes, medium	929	92%
Lakes, large	126	78%	Lakes, large	1234	78%
Lakes, small, sand clay	139	27%	Lakes, small, sand clay	1585	27%
Brooks, fast flowing	214	22%	Brooks, fast flowing	1854	22%
Canals	331	22%	Canals	1880	22%
Ditches	388	16%	Ditches	1921	16%
Rivers	452	12%	Rivers	2332	12%
Brooks, slow flowing	464	5%	Brooks, slow flowing	2324	5%
Lakes, small, peat	534	5%	Lakes, small, peat	2876	5%
Water in riverine area	605	3%	Water in riverine area	3874	3%
Area weighted 95 th percentile	75		Area weighted 95 th percentile	870	

Table B: Based on samples within the applicability domain of the MLRs

	5p-HC₅			5p-HC₅	
Chronic	(µg Al/L)	area%	Acute	(µg Al/L)	area%
Brackish waters	_1	100%	Fens	1005	100%
Lakes, medium	122	92%	Lakes, medium	1341	99%
Lakes, large	125	79%	Brackish waters	1548	86%
Fens	151	28%	Lakes, large	1753	78%
Lakes, small, sand clay	221	27%	Lakes, small, sand clay	1935	27%
Brooks, fast flowing	295	22%	Brooks, fast flowing	2062	22%
Canals	395	22%	Canals	2233	22%
Ditches	414	16%	Ditches	2470	16%
Rivers	446	12%	Brooks, slow flowing	2494	12%
Brooks, slow flowing	457	5%	Rivers	2503	11%
Water in riverine area	534	5%	Water in riverine area	2631	5%
Lakes, small, peat	605	3%	Lakes, small, peat	3283	2%
Area weighted 95 th percentile	98		Area weighted 95 th percentile	1408	

¹ Not enough data within the applicability domain, HC5 was adopted from Table A (All data).

Most striking are the low HC_5 values computed for fens (see Table 9). Note that the majority of the samples of these water types were outside the applicability domain of the MLR. The low pH in fens (53% of the samples has a pH<6) results in a high bioavailability of AI^{3+} and thus a higher predicted toxicity of aluminum in this water type. Because the MLRs were not validated to pH<6 the HC₅ values are more uncertain than HC₅ values at pH>6.

The relatively low HC_5 in brackish water is surprising at a first glance, because on average the samples have a high hardness and pH, which is thought to be a mitigating factor for metal toxicity. The low HC_5 values appear to correspond with those samples in the brackish water type with relatively low hardness values (<20 mg CaCO₃/L) and a pH<6.

Small peaty lakes also have a high percentage of samples outside the applicability domain, in this water type it concerns high DOC, leading to relatively high HC₅ values.

Removal of samples outside the applicability domain of the MLRs results in elimination of extremely low and extremely high HC_5 values. For Brackish water and Water in riverine area, the remaining dataset was too small to derive a 5th percentile. In those case the 5th percentile of the whole dataset (including samples outside the applicability domain was tentatively adopted).

6.6 HC₅ of a specific set of water chemistry conditions

The MLRs describe a combined effect of DOC, pH and hardness on the HC_5 . For the establishment of a specific set of water chemistry conditions the overall relation between each individual parameter and the HC_5 is visualized in Figure 8.



Figure 8 Relation between pH, DOC and hardness with the HC5. The range outside the applicability domain is shaded grey.

High toxicity (low HC_5) is observed particularly at relatively low and relatively high pH; at pH values outside the applicability domain. There is a general tendency of increasing HC_5 with increasing DOC, but occasionally low HC_5 also occur at high DOC. The effect of hardness is not very dominant, however, the lowest HC_5 values always coincide with lower hardness. These patterns do not necessarily imply a causal relationship, because a low hardness often coincides with a low pH (see Figure 9).



Figure 9 Correlation between pH, DOC and hardness.

A specific set of water chemistry conditions - one that is reflective of high bioavailability conditions, as EU guideline no. 27 suggests, could therefore be one with either a low or a high pH and relative low DOC and hardness. Several options are described:

- a) Worst case, based on the 5th percentile DOC and hardness and the 5th and 95th percentile pH of the most vulnerable water type (fens);
- b) Area-weighted 5th percentile DOC and hardness and the 5th and 95th percentile pH off all water types;
- c) Boundaries of the applicability domain.

In Table 10 the options are applied and corresponding HC_5 values are shown. It appears that at the upper boundaries of the pH-range, higher HC_5 values were calculated than at the lower boundaries. This implies that there is no need to define an upper boundary for the pH, because the low HC_5 values at the lower pH also protect water types with a higher pH.

Ontion		hardness	pH HC₅ (µ		ιg/L)
Option	(mg/L)	(mg CaCO₃/L)		HC₅ (µ chronic 0.002 478 202 281 3	acute
E th perceptile of the most vulnerable water type	4.6	4.0	4.3	0.002	0.07
5 percentile of the most vulnerable water type		4.0	7.8	478	3393
Area weighted E th perceptile of all water types	2.0	70	6.7	202	1455
Area weighted 5° percentile of all water types	2.0	70	8.6	281	2186
Applicability domain	0.09	0.9	6.0	3	17
	0.08	9.8	8.7	131	722

Table 10 Options for choosing a specific set of water chemistry parameters for derivation of an aluminum EQS.

6.7 HC_5 of water types previously used for the copper-EQS

EQS values for copper were set in 2012, based on bioavailability calculations in 6 Dutch water types: 1) large rivers, 2) canals, large and small lakes, 3) sandy springs, 4) streams and brooks, 5) ditches and 6) small acidic ponds. For each water type a range of pH and DOC and other parameters (Ca, Mg, Na, K, alkalinity, sulphate and chloride) were available. The data were assumed to be normally distributed, which enabled the calculation of a range of HC₅ values for each water type (Vijver et al., 2008). The 5th percentile HC₅ of the most sensitive national water type was adopted as first tier EQS in The Netherlands (RIVM, 2012). In the case of Cu, sandy springs appeared to be the most sensitive water type.

Monitoring data for the copper assessment originate from approximately 2006 or previous years. Since then, monitoring frequency and parameters have changed, DOC and hardness for example are nowadays more frequently measured and on more places than 15 years ago. Sets of simultaneously measured parameters can now be selected, which will provide a more precise insight in the variability of the corresponding HC_5 values. Moreover, the assignment of water types is nowadays recorded well for each individual sampling point in Waterkwaliteitsportaal.nl, which facilitates the selection and characterization of a larger variety of water types. Nevertheless, the water types used for copper, were used as a reference.

Average water chemistry of these water types were published and could be used to compute average HC_5 values for aluminum also. Vijver et al. (2008) determined that the data were normally distributed, so the 5th percentile for DOC and pH could be derived from the mean and the standard deviation (see Appendix 11). The 5th percentile hardness for these water types was not available and was estimated from data in Waterkwaliteitsportaal 2020. The results are shown in Table 11.

5 th percentile:	5p-DOC	5р-рН	5p-Hardness	HC ₅ (μg/L)
	mg/L	-	mg CaCO₃/L	chronic	acute
Large rivers	1.6	7.4	129	310	2002
Canals, large lakes, small lakes	1.2	7.4	95	256	1691
Streams, brooks	11.1	7.2	89	746	4486
Ditches	7.4	5.6	103	188	1074
Sandy springs	0.6	6.5	65	61	471
Small acid ponds	10.1	3.8	4	0.0003	0.02

Table 11 Calculated HC5 for water types previously used for the derivation of the Cu-EQS. The 5th percentiles DOC and pH were calculated from normally distributed DOC and pH data (Vijver et al., 2008), the 5th percentiles hardness was estimated from the data in Waterkwaliteitsportaal.

7 Options for aquatic environmental quality standards of aluminum

7.1 Assessment factor

For the translation of a HC_5 to a QS an assessment factor must be applied (see paragraph 3.1). A default assessment factor (AF) of 5 is recommended if HC_5 -values are derived from an SSD (EU technical guidance No. 27).

The environmental quality standard is then: QS= HC_5/AF

An AF of 5 is used by default, but may be reduced where substantial evidence removes residual uncertainty. The exact value of the AF depends on an evaluation of the uncertainties around the derivation of the HC_5 . As a minimum, the following points have to be considered when determining the size of the assessment factor (ECHA, 2008):

- 1. the overall quality of the database and the endpoints covered, e.g., if all the data are generated from "true" chronic studies (e.g., covering all sensitive life stages);
- 2. the diversity and representativity of the taxonomic groups covered by the database, and the extent to which differences in the life forms, feeding strategies and trophic levels of the organisms are represented;
- 3. the knowledge on presumed mode of action of the chemical (covering also long-term exposure); Details on justification could be referenced from structurally similar substances with established mode of action;
- 4. statistical uncertainties around the HC_5 estimate, e.g. reflected in the goodness of fit or the size of the confidence interval around the 5th percentile, and consideration of different levels of confidence (e.g., by a comparison between the median estimate of the HC_5 with the lower estimate (90% confidence interval) of the HC_5);
- 5. the comparisons between field and mesocosm studies, where available, and the HC_5 and mesocosm/field studies to evaluate the level of agreement between laboratory and field evidence.

The aluminum SSD contains plenty of data from eight different taxonomic groups for at least ten different species. However, many species are only present with one experimental data. Also, still there are some residual uncertainties that need to be accounted for, these uncertainties are described in Table 12. Based on the evaluation of the assessment factor criteria we recommend to keep the default assessment factor of 5.

1 True chronic studies were used for the SSD	No			
2 High diversity of species and taxonomic groups is present	Reasonable number of species			
	are available, but the cross-			
	species extrapolation is not			
	validated.			
3 Mode of action of the aluminum toxicity	Potential toxicity of Al-hydroxide			
	suspended particles not fully			
	understood.			
4 Uncertainty around HC₅	Relatively high uncertainty in			
	normalized EC_{10} , because many			
	samples were outside			
	applicability domain of MLR			
5 Presence of mesocosms or field studies	No			

Table 12 Evaluation of HC5 assessment factor criteria for aluminum.

7.2 Summary of options

The previous paragraphs offered an assessment of the variability of HC₅ values in Dutch fresh surface waters. The ultimate establishment of regulatory EQS values for aluminum should be made by policy makers. To support the decision making process this paragraph offers four options (see Table 13), based on choices and recommendations in other projects:

- 1) In the EU guidance document no 27 on Derivation of environmental quality standards it is stated that: "The HC_5 selected should be protective of 95% of waters in the region (country) shown to have the highest bioavailability of that particular metal. By definition, it will also be protective of almost all other waters in Europe within the validated range of the BLMs." Based on 5544 samples in Waterkwaliteitsportaal.nl, the highest bioavailability was found in fens.
- 2) In the EU guidance document no 27 on Derivation of environmental quality standards it is stated that: "The EQSbioavailable is a total dissolved metal concentration which is highly bioavailable and which does not make any allowance for background in its derivation. It is derived, initially, as the normalized, estimate of the HC₅ for a specific set of water chemistry conditions one that is reflective of high bioavailability conditions." Several potential reference sets are presented (see Table 13). Note that in the case of aluminum also a fraction of suspended Al-hydroxide particles are included in the EQS.
- 3) For comparison purposes the water types previously defined for derivation of a copper HC₅ in 2012 were used. The most vulnerable water type for copper was "sandy springs". For aluminum the most vulnerable water type is "small acid ponds" which is synonymous to "fens."
- 4) The US-EPA has recommended to always compute water type-specific quality standards for aluminum, that account for differences in bioavailability. Therefore they do not provide a QS. Given the high frequency of false exceedances when conservative Al-QS are used, the EPArecommendation of always applying a bioavailability correction could be considered in The Netherlands as well.

The four options for QS_{bioavailable} are presented in Table 13.

Table 13 Options for Environmental Quality standards of aluminum in freshwater, using an assessment factor of 5. Rounding of the QS_{bioavailable} is recommended, but not applied in this table. (DOC expressed in mg/L, hardness in mg CaCO₃/L). HC₅ are accompanied by the 90% confidence intervals (90% CI).

	ons for selection HC_5 : Chronic $HC5$ (µg/		nic HC5 (μg /L)	Acute HC5 (µg/L)		$QS_{bioavailable}$ (µg/L)	
		HC₅	(90% CI)	HC₅	(90% CI)	AA	MAC
1	most vulnerable water type (Waterkwaliteitsportaal, 2020)						
а	5 th percentile of all (Fen) samples	0.04	(0.002-0.2)	0.9	(0.1-3.4)	0.008	0.18
b	5 th percentile of (Lakes, medium) samples within applicability domain	122	(18-394)	1005	(440-1799)	24	201
2	specific set of water chemistry conditions (Waterkwaliteitsportaal, 2020)						
а	5 th percentiles of chemistry of most vulnerable water type	0.008	(0.005-0.05)	0.2	(0.03-0.7)	0.002	0.04
	(valid for DOC≥4.6, pH≥4.3, hardness≥4)		(,		()		
b	Area weighted 5 th percentiles of chemistry of all water-types	202	(54-457)	1455	(638-2599)	40	291
	(valid for DOC≥2.6, pH≥6.7, hardness≥70)	202		1100	(000 2000)	10	231
С	Boundaries of the applicability domain	2.8	(0.9-5.8)	17	(7.4-32)	0.6	35
	(valid for DOC>0.08, pH between 6-8.7, hardness>9.8)	2.0				0.0	5.5
3	water type from copper assessment, 2012						
	Most vulnerable water type for aluminum: small acid ponds	0.0003	(0.00001-0.03)	0.02	(0.002-0.1)	0.00006	0.004
4	case-by-case bioavailability correction	Use tools		Use tools		Use tools	

AA=Annual Average; MAC=Maximum Acceptable Concentration
7.3 Tentative implications for the risk assessment

7.3.1 A fixed QS_{bioavailable} for all watertypes (options 1, 2 and 3)

QS values were compared with total aluminum in filtered and unfiltered samples present in the database of Waterkwaliteitsportaal.nl. The assessment just provides a first impression of ranges of potential risks.

Aluminum concentrations were either determined in samples after filtration, or in unfiltered samples, that include suspended matter. The first method would underestimate potential risks, because bioavailable Al-hydroxide particulates are removed, whereas the second method could overestimate potential risks because tightly bound aluminum in natural suspended matter is included. The preferred method of analysis is described in Appendix 1. A summary of sample numbers, frequency of concentrations below the limit of detection (LOD) and concentration ranges is provided in Appendix 12. For range finding purposes, the best (filtered) and worst (unfiltered) case concentrations are compared with potential EQS-values. The AA-EQS values of option 1a, 2a and 3 are far below the lowest measured concentrations and could therefore not be shown in Figure 10. The EQS values of options 1b, 2b and 2c (all derived for samples within the applicability domain of the MLRs) are within the range of measured concentrations, drawn in Figure 10. Similar results are found for the preliminary assessment of exceedances of a potential MAC-EQS (see Figure 11).

Usually the LOD of aluminum in natural surface waters was 50 μ g Al/L, but LOD values of 1, 2, 10 or 20 μ g Al/L were also encountered. Concentrations <LOD were divided by 2, to combine these data in calculation with samples with concentrations larger than the LOD. Brooks (fast and slow flowing), canals, ditches, small peaty lakes and water in riverine have a median concentration below the LOD of 50 μ g/L. Some options for the QS are lower that the LOD, which means that analytical methods need improvement.

Chronic risk assessment



Figure 10 Variation of the aluminum concentration in filtered and unfiltered samples, compared with some options of **chronic** $QS_{bioavailable}$ values. The red lines are tentatively drawn as a preliminary comparison of current Al-concentrations with some options for $QS_{bioavailable}$ -values, the blue line shows the current MPC. MPC Options 1a, 2a and 3 are too small to show in the graphs. See text in this chapter for comments about the method for sampling and analysis of aluminum.

Acute risk assessment



Figure 11 Variation of the aluminum concentration in filtered and unfiltered samples, compared with some options of **acute** $QS_{bioavailable}$ values. The red lines are tentatively drawn as a preliminary comparison of current Al-concentrations with some options for $QS_{bioavailable}$ -values, the blue line shows the current MPC. MPC Options 1a, 2a and 3 are too small to show in the graphs. See text in this chapter for comments about the method for sampling and analysis of aluminum.

7.3.2 A site-specific QS_{bioavailable} (option 4)

In Figure 12 and Figure 13 the results of respectively a chronic and acute site-specific risk assessment are shown. Exact percentages of samples exceeding the QS are not reported because the current measurements are not done according to the preferred method of analysis, as mentioned above. The comparison is only presented as a preliminary impression of the range of predicted impact.

Application of a site-specific risk assessment on the currently available measurements confirms that mainly fens seem to be at risk; chronic as well as acute $QS_{bioavailable}$ are exceeded in the filtered samples. Not all watertypes have aluminum measurements in unfiltered samples. For the nine watertypes which do have unfiltered samples, the chronic risk ratio \approx 1, except for large lakes, where the risk seems to be a factor 10 higher. Acute risks for unfiltered samples are generally below 1, although data for the most vulnerable water type (fens) are missing.



Chronic risk ratios:



*Figure 12 Chronic risk ratios for aluminum in different water types based on measurements in filtered and unfiltered samples. * emphasizes the uncertainties related to the analytical method.*

Acute risk ratios:



*Figure 13 Acute risk ratios for aluminum in different water types based on measurements in filtered and unfiltered samples. * emphasizes the uncertainties related to the analytical method.*

8 Summary

Although aluminum is the most abundant metal on earth, their concentrations in surface water are usually low because aluminum is tightly captured in the mineral structure of rocks and clay minerals. Caused by soil acidification (by air pollution), mining activity and anthropogenic uses, aluminum is mobilized and can enter surface waters. Effects of aluminum on aquatic ecosystems show huge differences between water types. Differences in pH, dissolved organic carbon (DOC) and hardness determine whether aluminum occurs as toxic and bioavailable Al³⁺ or less toxic and less bioavailable Al-complexes or Al-hydroxide particulates. In the past five years, calculation tools have been developed in the US to calculate HC₅ values that account for differences of Al-toxicity amongst water types. The tools use multiple linear regression equations (MLR) derived from toxicity experiments with water types with pH between 6-8.7, DOC between 0.08 and 12.3 mg/L and hardness between 9.8 and 430 mg CaCO₃/L. The range in pH, DOC and hardness in the toxicity experiments determines the applicability domain of the MLRs. The goal of this report was to evaluate the compliance of the methodology with EU-guidance and if possible to calculate EQS for Dutch water types.

The US-EPA methodology and data (based on work of DeForest et al., 2018 and 2020) have been well described, but the existing EPA-tools do not comply with European methodology. The US-EPA chronic assessment is based on EC_{20} values, whereas in Europe EC_{10} or NOEC values are required. Furthermore, data and MLRs for algae are not included in the USE-EPA tool and the statistical methods to derive an HC_5 value from a species sensitivity distribution (SSD) are different. However, the EC_{10} values and algal data necessary to adjust the methodology in accordance with EU-guidance are available. We pragmatically relied on the EPA quality standards for the evaluation of toxicity studies; these are more or less compliant with European quality standards. An additional literature search to check the completeness of the data described in the EPA report was outside the scope of this study.

MLRs were used to extrapolate (normalize) the EC_{10} values obtained in test media with specific pH, DOC and hardness to conditions of an outdoor sample or water type of interest. MLRs are available for the algae *Pseudokirchneriella subcapitata*, crustacean *Ceriodaphnia dubia* and fish *Pimephales promelas*. Toxicity data for other 10 species are available to construct an SSD. These toxicity data were normalized with either one of the three MLRs depending of the trophic level of the test organism.

The adjustments were implemented in an Excel tool and an R-script to compute water type-specific HC_5 values according to European guidelines. The tools flag samples that fall outside the applicability domain of the MLRs. HC_5 values estimated for samples outside the applicability domain are not eliminated, but are considered less reliable.

Environmental quality criteria are values set by policy makers, ideally based on a sound scientific assessment of environmental vulnerabilities and risks. In the EU-guidance no. 27 it is stated that: "The HC_5 selected should be protective of 95% of waters in the region (country) shown to have the highest bioavailability of that particular metal." Often (but not necessarily) a specific set of water chemistry conditions reflecting a high bioavailability is used to derive HC_5 values. In this report HC_5 values were derived based on: 1) monitoring data of 5544 samples of 779 sites retrieved from archives of Waterkwaliteitsportaal.nl 2020, 2) a specific set of water chemistry conditions, and 3) water types previously used for derivation of a copper HC_5 in 2012.

In the case of aluminum, water type-specific HC₅ values may differ six orders of magnitude, and therefore, the US have decided not to set a specific EQS, but always demand a site-specific risk assessment by the use of their calculation tool. This report does not decide upon the desired level of protection and the feasibility of certain choices. In order to offer options for Dutch policy makers,

different EQS values are presented, obviously with different levels of protection. An assessment factor, reflecting remaining uncertainties in the toxicity data, needs to be considered when HC_5 is translated to EQS. There was no reason to lower the default assessment factor of 5 (recommended by EU guidance no 27), because: 1) some species only are represented by one experimental measurement; 2) there are no field or mesocosm studies available; 3) no validation to natural waters was described; 4) no cross-species validation of the used MLRs was described and 5) many water samples are outside the applicability domain of the MLRs.

For future compliance testing it is important that the analytical method for aluminum in the samples matches the bioavailability of aluminum that is reflected by the EQS. A mild acidification to pH4 prior to filtration over a 0.45 μ m filter is recommended. However, currently samples are acidified to pH1-2, either prior to or after filtration. The first method overestimates bioavailable Al, because it releases aluminum from natural suspended matter, whereas the second method removes Al-hydroxide particulates that are assumed to contribute to Al-toxicity. Despite these shortcomings, it is clear that HC₅ values derived for the most vulnerable water type (fens), as recommended by EU-guidance no.27 are exceeded by Al-concentrations on all water types, regardless of the analytical method. Application of a site-specific risk assessment tentatively shows that fens are at risk, due to a combination of relatively high Al-concentrations and low HC₅ values. The risks for other water types seem to be limited.

Acknowledgements

The author kindly acknowledges the scientific contribution of by experts of RIVM's Centre for Safety of Products and Substances at different stages of the project. Useful advice and feedback was received at three meetings and through comments on several drafts of this report. The feedback group consisted of dr. Charles Bodar, dr. Els Smit, dr. Eric Verbruggen, drs. Stan de Groot and prof. dr. Willie Peijnenburg.

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Appendix 1 Method to analyze bioavailable aluminum in natural surface water

The method of Rodriguez et al.(2019) consists of the preparation of a 1M sodium acetate buffer (2.449 g sodium acetate and 4.7 mL acetic acid, completed to 100 mL with deionized water in a volumetric flask) to achieve a pH of 4 in the buffer. If the prepared buffer is outside a range of 4.0 to 4.2, add acetic acid in μ L aliquots to bring the pH within the target range. Polypropylene cups with 25 mL of the test solution are titrated to pH 4 (pH 4.0–4.2) by addition of 1M buffer and poured into 50 - mL conical polypropylene tubes. The tubes are capped, agitated by hand, and mixed for 3 h at 22 °C at 100 rpm in an orbital shaker. After incubation, tubes are agitated again by hand, and 10 mL of the supernatant is filtered through a 0.45 - μ m PVDF membrane (Millex - HV; Merck - Millipore). Samples are acidified to 1% nitric acid (Merck Suprapur) and stored at 4 °C until analysis (by ICP - MS). Buffer reagents were Merck, pro analysis grade.

Appendix 2 Chronic toxicity data for MLR development

-			DOC		Hardness	EC10	EC10			
Dataset ¹	Endpoint	Duration	(mg/L)	рН	(mg/L)	(µg/L)	(95% CI)	(µg/L)	(95% CI)	Reference
Previous	Reproduction	7 d	0.1	6.92	9.8	66	(4-1211)	124	(12-1259)	CIMM 2009
Previous	Reproduction	7 d	0.1	7.84	9.8	312	(83-1174)	379	(141-1020)	CIMM 2009
Previous	Reproduction	7 d	0.1	6.34	25	20	(11-37)	37	(22-62)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.1	6.4	60	104	(74 - 146)	160	(123 - 209)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.1	6.38	121	143	(52 - 393)	222	(105 - 466)	Gensemer et al. 2018
Previous	Reproduction	7 d	2	6.34	25	284	(93 - 868)	377	(159 - 895)	Gensemer et al. 2018
Previous	Reproduction	7 d	2	6.38	61	504	(226 - 1126)	631	(362 - 1101)	Gensemer et al. 2018
Previous	Reproduction	7 d	2	6.37	121	924	(548 - 1558)	1012	(692 - 1479)	Gensemer et al. 2018
Previous	Reproduction	7 d	4	6.33	25	494	(396 - 616)	623	(532 - 729)	Gensemer et al. 2018
Previous	Reproduction	7 d	4	6.3	61	550	(436 - 694)	693	(618 - 777)	Gensemer et al. 2018
Previous	Reproduction	7 d	4	6.38	121	671	(603 - 747)	841	(773 - 914)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.3	7.15	50	1659	(na)	1780	(na)	McCauley et al. 1986 ²
Previous	Reproduction	7 d	0.3	7.61	51	306	(111-844)	426	(249-727)	McCauley et al. 1986 ²
Previous	Reproduction	7 d	2	6.37	25	281	(191 - 414)	353	(268 - 465)	Gensemer et al. 2018
Previous	Reproduction	7 d	2	6.34	25	411	(357 - 472)	452	(401 - 511)	Gensemer et al. 2018
Previous	Reproduction	7 d	2	6.35	25	348	(200 - 495)	440	(357 - 523)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	6.34	26	210	(80 - 250)	260	(170 - 310)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	6.36	122	300	(60 - 360)	390	(170 - 450)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	7	26	190	(90 - 320)	250	(150 - 340)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	7.1	123	620	(120 - 860)	860	(590 - 1090)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	8	25	630	(270 - 690)	700	(510 - 830)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	8	62	770	(450 - 1030)	1010	(740 - 1180)	Gensemer et al. 2018
Previous	Reproduction	7 d	0.5	8.1	123	680	(600 - 1020)	870	(710 - 1130)	Gensemer et al. 2018
New	Reproduction	7 d	1.87	6.42	64	679	(299-1542))	829	(437-1572)	Supplemental Data 1
New	Reproduction	7 d	8.71	6.33	133	3494	(na)	3829	(na)	Supplemental Data 1
New	Reproduction	7 d	12.30	6.40	138	5628	(3206-9880)	6224	(3866-10022)	Supplemental Data 1
New	Reproduction	7 d	1.64	6.30	428	1467	(969-2222)	2011	(1539-2628)	Supplemental Data 1
New	Reproduction	7 d	6.57	7.21	125	4909	(2695-8941)	6401	(4274-9588)	Supplemental Data 1
New	Reproduction	7 d	12.01	7.19	127	6106	(na)	6612	(na)	Supplemental Data 1
New	Reproduction	7 d	1.30	8.17	263	2297	(1575-3350)	3749	(2904-4838)	Supplemental Data 1
New	Reproduction	7 d	1.20	8.21	425	2045	(946-4422)	2852	(1647-4939)	Supplemental Data 1
New	Reproduction	7 d	1.04	8.70	125	1514	(na)	1693	(na)	Supplemental Data 1

CI = confidence interval; na = indeterminable ¹ "Previous" data were used to develop the *C. dubia* MLR models described in DeForest et al. (2018).. ² "Previous" and "New" data were combined to develop the *P. promelas* MLR models described in DeForest et al.(2020)..

			DOC		Hardness	EC10	EC10			
Dataset ¹	Endpoint	Duration	(mg/L)	рН	(mg/L)	(µg/L)	(95% CI)	(µg/L)	(95% CI)	Reference
Previous	Mean Dry Biomass	7 d	0.3	8	48	5117	(274-95679)	10,753	(1458-79301)	Parametrix 2009
Previous	Mean Dry Biomass	7 d	0.08	6	10.6	117	(na)	127	(na)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.19	6.1	25.8	93	(62-140)	136	(98-188)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.22	6	60.8	241	(156-372)	314	(200-495)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.09	6	123.9	481	(280-828)	624	(410-951)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.92	6.1	10.2	403	(372-436)	426	(402-451)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.86	6.1	61	582	(273-1240)	634	(338-1190)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.88	6.1	123.7	627	(433-907)	773	(559-1070)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	1.73	6.1	10.6	589	(436-797)	633	(497-805)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	1.74	6	59.9	1238	(999-1535)	1326	(1119-1571)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	1.56	6	118.2	1388	(997-1933)	1494	(1116-1999)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	3.35	6	11.8	726	(548-963)	829	(691-995)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	3.51	6	64.8	2164	(1841-2543)	2523	(1971-3230)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	3.27	6	119.6	2729	(2048-3636)	2938	(2288-3772)	Gensemer et al. 2018
Previous	Larval Survival	33 d	0.3	6	93.9	389	(na)	429	(na)	Cardwell et al. 2018
Previous	Mean Dry Biomass	7 d	0.7	6.1	25.9	562	(269-1173)	660	(364-1197)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.9	6	116	627	(228-1728)	824	(393-1729)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	2.9	6.1	122	1762	(1195-2596)	2210	(1640-2978)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.8	7.1	26.5	985	(516-1882)	1534	(932-2522)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	2.5	7	123	3979	(1994-7940)	5411	(3144-9313)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	0.7	8	28.8	4662	(2400-9057)	7262	(4714-11187)	Gensemer et al. 2018
Previous	Mean Dry Biomass	7 d	5	7.9	127	4672	(1552-14069)	6795	(3161-14607)	Gensemer et al. 2018
New	Mean Dry Biomass	7 d	7.0	6.04	134	3611	(2345-5560)	4618	(3281-6499)	Supplemental Data 2
New	Mean Dry Biomass	7 d	11.5	6.04	131	8375	(6074-11549)	9511	(7291-12408)	Supplemental Data 2
New	Mean Dry Biomass	7 d	1.1	6.82	422	1648	(947-2868)	2969	(2010-4386)	Supplemental Data 2
New	Mean Dry Biomass	7 d	7.2	7	135	6164	(4199-9049)	8047	(6273-10322)	Supplemental Data 2
New	Mean Dry Biomass	7 d	11.6	6.96	125	11064	(5057-24206)	12542	(6598-23842)	Supplemental Data 2
New	Mean Dry Biomass	7 d	1.1	8.06	288	3031	(642-14310)	5634	(1768-17957)	Supplemental Data 2
New	Mean Dry Biomass	7 d	1.6	8.12	396	7363	(2646-20489)	13274	(6674-26401)	Supplemental Data 2
New	Mean Dry Biomass	7 d	0.8	6.1	49	560	(322-974)	885	(574-1365)	Supplemental Data 3
New	Mean Dry Biomass	7 d	1.6	6	94	1424	(1028-1974)	1817	(1444-2287)	Supplemental Data 3

Table S2. Chronic aluminum toxicity data for *P. promelas*. (DeForest et al., 2020)

CI = confidence interval; na = indeterminable

¹ "Previous" data were used to develop the *P. promelas* MLR models described in DeForest et al. (2018). "Previous" and "New" data were combined to develop the *P. promelas* MLR models described in DeForest et al. (2020).

	EC ₁₀	,	EC ₂₀	•	EC ₅₀	•	Test	Test	Temp		Hardness	DOC	Measured
Endpoint	(µg Al/L)	(95% CI)	(µg Al/L)	(95% CI)	(µg Al/L)	(95% CI)	type	Duration	°C	рН	(mg/L)	(mg/L)	Al
Growth Rate	146.0	(92 - 231)	285.0	(224 - 362)	> 504		static	72 h	24	6.21	24.3	0.3	Х
Growth Rate	206.7	(121 - 353)	455.3	(298 - 696)	> 982		static	72 h	24	6.19	60	0.3	Х
Growth Rate	407.5	(194 - 856)	657.3	(381 - 1135)	1697.3	(1284 - 2243)	static	72 h	24	6.17	120	0.3	Х
Growth Rate	1263.1	(857 - 1862)	1474.4	(1213 - 1792)	2004.0	(1833 - 2191)	static	72 h	24	7.02	24.3	0.3	Х
Growth Rate	1036.0	(0.977 - 1.10)	1342.4	(1234 - 1460)	2244.0	(1857 - 2713)	static	72 h	24	6.99	60	0.3	Х
Growth Rate	1194.5	(944 - 1512)	1577.4	(1329 - 1873)	2739.0	(2463 - 3045)	static	72 h	24	6.97	120	0.3	Х
Growth Rate	1083.0	(631 - 1860)	1593.4	(1188 - 2138)	3428.0	(2456 - 4785)	static	72 h	24	8.05	24.3	0.3	Х
Growth Rate	950.1	(809 - 1115)	1345.0	(1190 - 1520)	2681.0	(2446 - 2938)	static	72 h	24	8.01	60	0.3	Х
Growth Rate	533.1	(331 - 860)	858.3	(613 - 1202)	2208.0	(1667 - 2924)	static	72 h	24	8.00	120	0.3	Х
Growth Rate	291.7	(78 - 1093)	496.0	(200 - 1229)	1422.1	(623 - 3248)	static	72 h	23	6.22	23	2	
Growth Rate	850.5	(673 - 1075)	1021.6	(852 - 1225)	1469.7	(1253 - 1725)	static	72 h	23	6.18	60	2	
Growth Rate	1397.1	(1118 - 1653)	1611.6	(1447 - 1795)	2140.0	(2002 - 2287)	static	72 h	23	6.14	120	2	
Growth Rate	2062.0	(1721 - 2471)	2336.0	(2014 - 2708)	2990.0	(2376 - 3764)	static	72 h	23	7	22	2	
Growth Rate	1970.6	(1765 - 2200	2459.0	(2209 - 2739)	> 3200		static	72 h	23	7.01	60	2	
Growth Rate	2429.0	(1833 - 3220)	2805.0	(2304 - 3417)	3733.0	(3524 - 3954)	static	72 h	23	7.03	120	2	
Growth Rate	1570.4	(1358 - 1816)	2308.0	(2080 - 2560)	4952.0	(4561 - 5377)	static	72 h	23	7.89	22	2	
Growth Rate	773.9	(582 - 1029)	1094.2	(909 - 1317)	2175.0	(1924 - 2460)	static	72 h	23	7.92	60	2	
Growth Rate	672.6	(601 - 752)	901.9	(847 - 960)	1614.4	(1502 - 1736)	static	72 h	23	7.96	120	2	
Growth Rate	583.6	(395 - 863)	836.1	(606 - 1154)	1706.6	(953 - 3057)	static	72 h	23	6.16	23	4	
Growth Rate	1100.7	(927 - 1307)	1356.6	(1191 - 1545)	2054.0	(1699 - 2483)	static	72 h	23	6.16	60	4	
Growth Rate	1239.8	(1119 - 1374)	1532.4	(1345 - 1746)	2333.0	(1852 - 2939)	static	72 h	23	6.18	120	4	
Growth Rate	2478	(2011 - 3053)	2865.0	(2452 - 3348)	3824.0	(3469 - 4214)	static	72 h	23	7.05	22	4	
Growth Rate	2655	(2277 - 3096)	3119.0	(2806 - 3468)	4295.0	(4123 - 4474)	static	72 h	23	7.03	60	4	
Growth Rate	3154	(2953 - 3369)	3633.0	(3478 - 3795)	4810.0	(4603 - 5026)	static	72 h	23	7.05	120	4	
Growth Rate	1342.9	(769 - 2344)	2108.0	(1453 - 3060)	> 5000		static	72 h	23	7.91	22	4	
Growth Rate	1508.7	(1355 - 1680)	1896.8	(1668 - 2157)	2987.0	(2105 - 4238)	static	72 h	23	7.83	60	4	
Growth Rate	1085.8	(1028 - 1147)	1472.4	(1256 - 1726)	2694.0	(1849 - 3927)	static	72 h	23	7.79	120	4	

Table S3. Chronic aluminum toxicity data for *P. kirchneriella*. (Gensemer et al., 2017)

CI = confidence interval; na = indeterminable

Appendix 3: MLR-models

In bold: Models used in Dutch tool. Ref 1 and DF2018 refer to DeForest et al., 2018, Ref 2 and DF2020 refer to DeForest et al., 2020.

	All EC10 n	nodels published												
Species	Endpoint Statistic	Model Variables	Model Statistic	Intercept	ln(DOC)	ln(Hard)	рН	pH ²	ln(DOC)× pH	ln(Hard)× pH	In(DOC)× In(Hard)	Adj. R2	Ref	
P. subcapitata	EC10	No interactions	AIC	4.372	0.349		0.346					0.312	1	
P. subcapitata	EC10		BIC	4.372	0.349		0.346					0.312	1	
P. subcapitata	EC10	With interactions	AIC	-77.283	2.342	4.560	20.923	-1.274	-0.288	-0.628		0.940	1,2	DF2018,
P. subcapitata	EC10		BIC	-77.283	2.342	4.560	20.923	-1.274	-0.288	-0.628		0.940	1	
P. subcapitata	EC10	Exclude DOC×pH	AIC	-72.032	0.313	4.435	19.564	-1.187		-0.610		0.830	1	
P. subcapitata	EC10		BIC	-72.032	0.313	4.435	19.564	-1.187		-0.610		0.830	1	
P. subcapitata	EC10	pooled	not publishe	ed								0.354	2	
C. dubia	EC10	No interactions	AIC	-1.311	0.536	0.375	0.871					0.658	1	
C. dubia	EC10		BIC	-1.311	0.536	0.375	0.871					0.658	1	
C. dubia	EC10	With interactions	AIC	-31.740	5.891	0.441	9.889	-0.674	-0.716		-0.183	0.731	1	
C. dubia	EC10		BIC	-31.740	5.891	0.441	9.889	-0.674	-0.716		-0.183	0.731	1	
C. dubia	EC10	Exclude DOC×pH	AIC	-51.420	1.208	3.639	13.338	-0.737	ex	-0.490	-0.155	0.719	1	DF2018
C. dubia	EC10		BIC	-11.054	0.571	2.900	2.282		ex	-0.365		0.685	1	
C. dubia (update)	EC10	With interactions	AIC	-32.273	0.697	2.768	6.089	-0.269		-0.335		0.929	2	
C. dubia (update)	EC10		BIC	-11.824	0.700	3.030	2.368			-0.375		0.925	2	
C. dubia (update)	EC20			?	0.597	2.089	8.802	-0.491		-0.230		?	3	EPA
C. dubia (update)	EC10	exclude pH ²	AIC	-11.824	0.700	3.030	2.368	ex		-0.375		0.925	2	
C. dubia (update)	EC10		BIC	-11.824	0.700	3.030	2.368	ex		-0.375		0.925	2	
C. dubia (update)	EC10	exclude pH ² , DOC×hardness	AIC	-11.824	0.700	3.030	2.368	ex		-0.375	ex	0.925	2	
C. dubia (update)	EC10		BIC	-11.824	0.700	3.030	2.368	ex		-0.375	ex	0.925	2	
C. dubia (update)	EC10	pooled	-	-8.474	0.660	2.216	1.969			-0.278		0.895	2	DF2020
P. promelas	EC10	No interactions	AIC	-0.696	0.495	0.354	0.966					0.822	1	
P. promelas	EC10		BIC	-0.696	0.495	0.354	0.966					0.822	1	
P. promelas	EC10	With interactions	AIC	-0.741	2.758	0.412	0.941		-0.360			0.889	1	
P. promelas	EC10		BIC	-0.741	2.758	0.412	0.941		-0.360			0.889	1	
P. promelas	EC10	Exclude DOC×pH	AIC	-12.009	0.545	3.201	2.794		ex	-0.460		0.850	1	DF2018
P. promelas	EC10		BIC	-12.009	0.545	3.201	2.794		ex	-0.460		0.850	1	
P. promelas (update)	EC10	With interactions	AIC and BIC	-6.700	1.828	1.914	1.932		-0.193	-0.248		0.898	2	
P. promelas (update)	EC20		AIC and BIC	-7.371	2.209	1.862	2.041		-0.261	-0.232		0.923	2	EPA
P. promelas (update)	EC10	pooled	-	-7.424	0.660	2.216	1.969			-0.278		0.833	2	DF2020

Additional notes on model selection:

In order to prevent overparameterization of the models, DeForest et al.(2018 and 2020) compared which parameters were retained or rejected in the MLRs following different statistical approaches.

For *P. subcapitata* they compared models with and without interaction terms and concluded that interaction terms are necessary. By inclusion of all four interaction terms, the pH² term, hardness × pH and DOC × pH were retained and the adjusted r^2 increased from 0.312 to 0.940. No clear pattern in the residuals was observed and all predicted EC₁₀ values were within a factor 2 of observed (DeForest et al.2018).

For *C. dubia* inclusion of an interaction hardness × DOC is probably not necessary. It appeared that this interaction term was selected in the EC_{20} models but not in the EC_{10} models, whereas consistency is expected between EC_{10} and EC_{20} models. Also there were doubts about the necessity to include the pH² term, because it was not consistently selected in both AIC and BIC-models. The inconsistency sµggests that it was an unnecessary term in the models where it was retained. Also the variance inflation factors suggested that there was (not surprisingly) severe collinearity between pH and pH². So, the only interaction term in the *C. dubia* is hardness × pH.

Whereas the interaction DOC × pH is not included in the *C. dubia* model, they were retained in the *P. promelas* models. DeForest et al.(2020) questioned the need to include this term because it appeared to have no substantial influence on the model performance (adjusted r^2 dropped from 0.923 to 0.903 in the *P. promelas* EC₂₀ models. Still, the model, including the DOC × pH was put forward as the final selected model, which was adopted for the Dutch approach too.

Appendix 4: Chronic toxicity database for calculation of water typespecific aluminum criteria.

species	endpoint	test	DOC	рН	Н	EC10	Reference
BLM: P. subcapitata_ With interact	ions						
Lemna minor (duckweed)	Total Dry Weight	7 d	0.3	6.05	52	2175	Cardwell et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	6.22	23	292	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	6.18	60	851	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	6.14	120	1397	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.00	22	2062	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.01	60	1971	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.03	120	2429	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.89	22	1570	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.92	60	774	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	2.0	7.96	120	673	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	6.16	23	584	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	6.16	60	1101	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	6.18	120	1240	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.05	22	2478	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.03	60	2655	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.05	120	3154	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.91	22	1343	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.83	60	1509	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	4.0	7.79	120	1086	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	6.21	24	146	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	6.19	61	207	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	6.17	121	408	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	7.00	22	1263	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	7.00	60	1036	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	7.00	120	1195	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	8.00	22.4	1083	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	8.00	60	950	Gensemer et al. 2018
Pseudokirchnerella subcapitata	Growth Rate	72 h	0.3	8.00	120	533	Gensemer et al. 2018
BLM: C. dubia (update)_ With inter	actions						
Aeolosoma sp	Population Size	17 d	0.3	6.00	50	988	Cardwell et al. 2018
Brachionus calyciflorus	# Individuals	48 h	0.3	6.30	100	304	Cardwell et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	0.1	6.92	9.8	66	CIMM 2009
Ceriodaphnia dubia	Reproduction	7 d	0.1	7.84	9.8	312	CIMM 2009
Ceriodaphnia dubia	Reproduction	7 d	0.1	6.34	25	20	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	0.1	6.40	60	104	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	0.1	6.38	121	143	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.34	25	284	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.38	61	504	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.37	121	924	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	4.0	6.33	25	494	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	4.0	6.30	61	550	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	4.0	6.38	121	671	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.37	25	281	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.34	25	411	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	2.0	6.35	25	348	Gensemer et al. 2018
Ceriodaphnia dubia	Reproduction	7 d	0.5	6.34	26	210	Gensemer et al. 2018
Ceriodaphnia dubia		7 d	0.5	6.36	122	300	Gensemer et al. 2018
	Reproduction	/ u	0.0				
Ceriodaphnia dubia	Reproduction	7 d	0.5	7.00	26	190	Gensemer et al. 2018
Ceriodaphnia dubia Ceriodaphnia dubia	Reproduction Reproduction Reproduction	7 d 7 d 7 d	0.5 0.5	7.00 7.10	26 123	190 620	Gensemer et al. 2018 Gensemer et al. 2018
Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia	Reproduction Reproduction Reproduction	7 d 7 d 7 d 7 d	0.5 0.5 0.5	7.00 7.10 8.00	26 123 25	190 620 630	Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018
Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia	Reproduction Reproduction Reproduction Reproduction	7 d 7 d 7 d 7 d 7 d	0.5 0.5 0.5 0.5	7.00 7.10 8.00 8.00	26 123 25 62	190 620 630 770	Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018
Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia	Reproduction Reproduction Reproduction Reproduction Reproduction	7 d 7 d 7 d 7 d 7 d 7 d	0.5 0.5 0.5 0.5 0.5	7.00 7.10 8.00 8.00 8.10	26 123 25 62 123	190 620 630 770 680	Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018
Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia Ceriodaphnia dubia	Reproduction Reproduction Reproduction Reproduction Reproduction Reproduction	7 d 7 d 7 d 7 d 7 d 7 d 7 d	0.5 0.5 0.5 0.5 0.5 0.5 1.9	7.00 7.10 8.00 8.00 8.10 6.42	26 123 25 62 123 64	190 620 630 770 680 679	Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 Gensemer et al. 2018 OSU 2018a

Ceriodaphnia dubia	Reproduction	7 d	12.3	6.40	138	5628	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	1.6	6.30	428	1467	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	6.6	7.21	125	4909	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	12.0	7.19	127	6106	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	1.3	8.17	263	2297	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	1.2	8.21	425	2045	OSU 2018a
Ceriodaphnia dubia	Reproduction	7 d	1.0	8.70	125	1514	OSU 2018a
Ceriodaphnia sp.	Reproduction	8 d	0.3	7.15	50	1659	Call et al. 1984
Chironomus riparius	Reproduction	28	0.5	6.60	95	1271	Cardwell et al. 2018
Daphnia magna	Reproduction	21 d	2.0	6.30	141	709	Gensemer et al. 2018
Daphnia magna	Reproduction	28 d	0.5	6.40	95	171	Kimball 1978
Hyalella azteca	Reproduction	42 d	0.3	6.04	106	272	Cardwell et al. 2018
Hyalella azteca	Reproduction	42 d	0.4	6.10	105	109	Wang et al. 2018
Lampsilis siliquoidea	Mean Dry Weight	28 d	0.3	6.10	113	861	Wang et al. In Review
Lymnaea stagnalis	Wet Weight	30 d	2.0	6.37	121	924	Cardwell et al. 2018
BLM: P. promelas (update)_ With in	nteractions						
Danio rerio (zebrafish)	Biomass	33 d	0.3	6.100	77	98	Cardwell et al. 2018
Pimephales promelas	Larval Survival	33 d	0.3	600	93.9	389	Cardwell et al. 2018
Salvelinus fontinalis	Weight	60 d	1.9	6.5	14.7	100	Cleveland et al. 1989

Comment:

1) It is arguable whether it was correct to treat *Ceriodaphnia dubia* (30 data) and *Ceriodaphnia sp.* (1 data) as separate species. We combined the two sets.

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Appendix 5. Acute toxicity database for calculation of water type-specific Al-criteria

species	endpoint	test	DOC	рН	Н	EC	250	Reference
BLM: P. subcapitata_ Wi	ith interactions	70.1	0.2	C 21	24.2		504	C
P. subcapitata (alga)	Growth Rate	72 h	0.3	6.21	24.3	>	504	Gensemer et al. 2018
P. subcapitata (aiga)	Growth Rate	72 n	0.3	6.19	60	>	982	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	5.17	120		1697.3	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	/2 h	0.3	7.02	24.3		2004	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	6.99	60		2244	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	6.97	120		2739	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	8.05	24.3		3428	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	8.01	60		2681	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	0.3	8	120		2208	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	6.22	23		1422.1	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	6.18	60		1469.7	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	6.14	120		2140	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7	22		2990	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7.01	60	>	200	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7.03	120		3733	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7.89	22		4952	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7.92	60		2175	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	2	7.96	120		1614.4	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	6.16	23		1706.6	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	6.16	60		2054	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	6.18	120		2333	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.05	22		3824	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.03	60		4295	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.05	120		4810	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.91	22	>	> 5000	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.83	60		2987	Gensemer et al. 2018
P. subcapitata (alga)	Growth Rate	72 h	4	7.79	120		2694	Gensemer et al. 2018
BLM: C. dubia (update)_	With interaction	าร						
Nais elinguis			3.2	6.51	17.89		3,874	Shuhaimi-Othman et al. 2012a, 2013
Snail, Physa sp.			1.1	6.59	47	>	23400	Call 1984; Call et al. 1984
Snail, Physa sp.			1.1	7.55	47		30600	Call 1984; Call et al. 1984
Snail, Physa sp.			1.1	8.17	47	>	24700	Call 1984; Call et al. 1984
Snail, Physa sp.			1.1	7.46	4/		55500	Call 1984; Call et al. 1984
Melanoides tuberculata			3.2	6.68	18.72		68230	Shuhaimi-Othman et al. 2012b, 2013
Lampsilis siliquoidea			0.5	8.19	107	>	54300	Ivey et al. 2014
Lampsilis siliquoiaea			0.48	6.1Z	106	>	6302 1000	Wang et al. 2016, 2018
Ceriodaphnia dubia			1.1	7.42	50 F 0 F		1500	McCauley et al. 1986
Ceriodaphnia dubia			1.1	7.80	50.5 FO		1500	McCauley et al. 1986
Ceriodaphnia dubia			1.1	8.13 7 E	50 25		2560	INICCAULEY EL AL. 1986
Ceriodaphnia dubia			0.5	7.5	25 40		1000	
Ceriodaphnia dubia			0.5	7.05	49		2450	
Ceriodaphnia dubia			0.5	7.5 Q 05	102		2430	
Ceriodanhnia dubia			0.5	7 15	100		2727	East and Stover 1995
Ceriodaphnia dubia			0.5	7.15	90		5673	Fort and Stover 1995
Ceriodanhnia duhia			0.5	8.2	89		2880	Sourcek et al. 2001
Ceriodaphnia duhia			1.6	8.2	142		153440	Griffitt et al. 2008
Ceriodaphnia duhia			0.5	6.01	10.6		71.12	European aluminum Association 2009
Ceriodaphnia duhia			2	6.05	10.6		686.5	European aluminum Association 2009
, Ceriodaphnia dubia			4	6.09	10.6		1558.1	European aluminum Association 2009
Ceriodaphnia dubia			0.5	6.01	10.6		68.1	European aluminum Association 2009

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European aluminum Association 2009

0.5 6.03 10.6

Ceriodaphnia dubia

species	endpoint t	est D	OC	рΗ	Н	EC	250	Reference
Ceriodaphnia dubia		0).5	5.97	10.6		193.5	European aluminum Association 2009
Ceriodaphnia dubia		0).5	5.92	10.6		141	European aluminum Association 2009
Ceriodaphnia dubia		0).5	6.99	10.6	>	1300	European aluminum Association 2009
Ceriodaphnia dubia		0).5	7.85	10.6	>	5000	European aluminum Association 2009
Ceriodaphnia dubia		2		6.8	10.6	>	10000	European aluminum Association 2009
Ceriodaphnia dubia		2	-	7.82	10.6	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		4	-	6.77	10.6	>	10000	European aluminum Association 2009
Ceriodaphnia dubia		4	-	7.66	10.6	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		0).5	7.9	10.6	>	2000	European aluminum Association 2009
Ceriodaphnia dubia		0).5	7.89	10.6	>	2000	European aluminum Association 2009
Ceriodaphnia dubia		0).5	6.04	60		111	European aluminum Association 2009
Ceriodaphnia dubia		2	-	5.98	60		1137	European aluminum Association 2009
Ceriodaphnia dubia		4	-	5.73	60		8047	European aluminum Association 2009
Ceriodaphnia dubia		0	0.5	6./1	60	>	10000	European aluminum Association 2009
Ceriodaphnia dubia		0).5	7.83	60	>	5000	European aluminum Association 2009
Ceriodaphnia dubia		2	-	6.79	60	>	10000	European aluminum Association 2009
Ceriodaphnia dubia		2	_	/.6/	60	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		4	-	6.68	60	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		4	-	7.62	60	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		2		6.06	120		3387	European aluminum Association 2009
Ceriodaphnia dubia		4		5.6	120		10484	European aluminum Association 2009
Ceriodaphnia dubia		0).5 	6.93	120	>	5000	European aluminum Association 2009
Ceriodaphnia dubia		0	0.5	7.88	120	>	5000	European aluminum Association 2009
Ceriodaphnia dubia		2	-	6./6	120	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		2	-	1./1	120	>	15000	European aluminum Association 2009
Ceriodaphnia dubia		4	-	0.0 7.0	120	~	15000	European aluminum Association 2009
Ceriodaphnia dubia		4		7.0	10.0	>	120	European aluminum Association 2009
Ceriodaphnia dubia		0	1.5	6.02	10.6		275	European aluminum Association 2010
Ceriodaphnia dubia		0	1.5	6.02	10.6		110.00	European aluminum Association 2010
Ceriodaphnia dubia		0	1.5	6.07	10.0		02 /05	European aluminum Association 2010
Ceriodanhnia dubia		0).J)5	6.09	10.0		32.435	European aluminum Association 2010
Ceriodanhnia duhia		0		6.1	10.0		222.27	European aluminum Association 2010
Ceriodaphnia dubia		0		7.08	10.0	~	996 A	European aluminum Association 2010
Ceriodanhnia duhia		0	7.J 15	7.00	10.0	Ś	1293 3	European aluminum Association 2010
Ceriodaphnia dubia		0	,.J) 5	7.53	10.0	-	132.04	European aluminum Association 2010
Ceriodaphnia dubia		0) 5	6.01	10.0 60		463	European aluminum Association 2010
Ceriodaphnia dubia		0	.5	5 99	60	>	859	European aluminum Association 2010
Ceriodaphnia reticulata		1	.1	7.25	45.1	-	2800	Shephard 1983
Ceriodaphnia reticulata		1	.1	6	45.1		304	Shephard 1983
Ceriodaphnia reticulata		1	.1	5.5	4		362	Shephard 1983
Daphnia maana		1	.1	7.8	48.5		3900	Biesinger and Christensen 1972
Daphnia maana		1	1	7.25	45.1		2800	Shephard 1983
, Daphnia magna		0).5	5.99	168	>	500	European aluminum Association 2009
Daphnia magna		0).5	6.98	168	>	500	European aluminum Association 2009
Daphnia magna		0).5	7.93	168	>	500	European aluminum Association 2009
Daphnia magna		0).5	7.92	168		795	European aluminum Association 2009
Daphnia magna		2		7.95	168	>	1200	European aluminum Association 2009
Daphnia magna		3		7.93	168	>	1200	European aluminum Association 2009
Daphnia magna		1	.6	7.6	220		38200	Kimball 1978
Daphnia pulex		1	.6	8.2	142		3650	Griffitt et al. 2008
Stenocypris major		3	.2	6.51	15.63		3102	Shuhaimi-Othman et al. 2011a
Crangonyx pseudogracilis		1	.6	6.75	50		9190	Martin and Holdich 1986
Hyalella azteca		0	.48	6.13	105	>	5997	Wang et al. 2016, 2017
Paratanytarsus dissimilis		2	.8	7.28	17.43	>	77700	Lamb and Bailey 1981, 1983
Chironomus plumosus		1	6	7	80		30000	Fargasova 2001, 2003
BLM: P. promelas (updat	e)_ With interact	ions		_			4.5-	
Oncorhynchus mykiss		0).4	5	14.3		160	Holtze 1983
Oncorhynchus mykiss		0).4	5.5	14.3		310	Holtze 1983
Oncorhynchus mykiss		1	1	6.59	47.4		7400	Call et al. 1984
Uncorhynchus mykiss		1	1	7.31	47.4		14600	Call et al. 1984

	and a state	4 4	DOC			FC	50	Defense
species	enapoint	test	DUC	рн	H	EC	.50	Reference
Oncorhynchus mykiss			1.1	8.17	47.4	>	24700	Call et al. 1984
Oncorhynchus mykiss			1.1	7.46	47.4		8600	Call et al. 1984
Oncorhynchus mykiss			0.5	7.61	26.35	>	9840	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	7.59	45.5	>	8070	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	7.6	88.05	>	8160	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	7.61	127.6	>	8200	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	8.28	23.25		6170	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	8.3	35.4		6170	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	8.31	83.6		7670	Gundersen et al. 1994
Oncorhynchus mykiss			0.5	8.31	128.5		6930	Gundersen et al. 1994
Salmo salar			0.5	5.5	6.8		584	Hamilton and Haines 1995
Salmo salar			0.5	6.5	6.8		599	Hamilton and Haines 1995
Salvelinus fontinalis			1.6	5.6	40		6530	Tandjung 1982
Salvelinus fontinalis			1.6	5.6	18		3400	Tandjung 1982
Salvelinus fontinalis			1.6	5.6	2		370	Tandjung 1982
Hybognathus amarus			0.5	8.1	140	>	59100	Buhl 2002
Pimephales promelas			1.1	7.61	47.4	>	48200	Call et al. 1984
Pimephales promelas			1.1	8.05	47.4	>	49800	Call et al. 1984
Pimephales promelas			0.9	6.5	21.6	>	400	Palmer et al. 1989
Pimephales promelas			0.9	7.5	21.6	>	400	Palmer et al. 1989
Pimephales promelas			0.9	7.5	21.6	>	400	Palmer et al. 1989
Pimephales promelas			0.9	6.5	21.6	>	400	Palmer et al. 1989
Pimephales promelas			0.9	7.5	21.6	>	400	Palmer et al. 1989
Pimephales promelas			0.5	8.1	140	>	59100	Buhl 2002
Micropterus dolomieui			1.6	5.05	12.15		130	Kane 1984; Kane and Rabeni 1987
Micropterus dolomieui			1.6	6.25	12.4	>	993.4	Kane 1984; Kane and Rabeni 1987
Micropterus dolomieui			1.6	7.5	12	>	216.8	Kane 1984; Kane and Rabeni 1987
Hyla cinerea (frog)			0.5	5.49	4.55	>	405.2	Jung and Jagoe 1995
Poecilia reticulata			3.2	6.68	18.72		6760	Shuhaimi-Othman et al. 2013
Lepomis cyanellus			1.1	7.55	47.4	>	50000	Call et al. 1984

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Appendix 6 R-script for calculation of Aluminum HC₅

```
# Water types
Samples<-read.csv("Monitoringset2020.csv")
attach(Samples)
# Toxicity data
Chronic.data<-read.csv("chronic data.csv", sep=';')
Acute.data<-read.csv("acute data.csv", sep=";")
# Applicability domain
# Flag samples outside domain
OoD1<-which(DOC>12.3|DOC<0.08)
OoD2<-which(pH>8.7|pH<6)
OoD3<-which(Hardness>430|Hardness<0.01)
table(table(OoD<-c(OoD1,OoD2,OoD3)))</pre>
Samples$OoD<-NA
Samples$OoD[OoD] <- "OoD"
# MLR functions
Alg.ECxx_norm<-function(Test=Tox.data) {</pre>
  log(Test$ECxx[i])-
    2.342*(log(Test$DOC[i])-log(DOC))-
    4.560*(log(Test$Hardness[i])-log(Hardness))-
   20.923*(Test$pH[i]-pH)-
   -1.274*(Test$pH[i]^2-pH^2)-
   -0.288*(log(Test$DOC[i])*Test$pH[i]-log(DOC)*pH)-
   -0.628*(log(Test$Hardness[i])*Test$pH[i]-log(Hardness)*pH)}
Crust.ECxx norm<-function(Test=Tox.data) {
  log(Test$ECxx[i])-
    0.697*(log(Test$DOC[i])-log(DOC))-
    2.768*(log(Test$Hardness[i])-log(Hardness))-
    6.089*(Test$pH[i]-pH)-
   -0.269*(Test$pH[i]^2-pH^2)-
    0*(log(Test$DOC[i])*Test$pH[i]-log(DOC)*pH)-
   -0.335*(log(Test$Hardness[i])*Test$pH[i]-log(Hardness)*pH)}
Fish.ECxx norm<-function(Test=Tox.data) {</pre>
  log(Test$ECxx[i])-
    1.828*(log(Test$DOC[i])-log(DOC))-
    1.914*(log(Test$Hardness[i])-log(Hardness))-
    1.932*(Test$pH[i]-pH)-
    0 *(Test$pH[i]^2-pH^2)-
   -0.193*(log(Test$DOC[i])*Test$pH[i]-log(DOC)*pH)-
   -0.248* (log(Test$Hardness[i])*Test$pH[i]-log(Hardness)*pH)}
# Execute MLR functions for all watertypes
logNorm.acute<-matrix(NA, nrow=dim(Acute.data) [1], ncol=dim(Samples) [1])</pre>
j<-which (Acute.data$MLR=="Algae");
        for (i in j){logNorm.acute[i,]<-Alg.ECxx norm(Acute.data)}</pre>
j<-which(Acute.data$MLR=="Crustaceans");
        for (i in j){logNorm.acute[i,]<-Crust.ECxx norm(Acute.data)}</pre>
j<-which (Acute.data$MLR=="Fish");
        for (i in j){logNorm.acute[i,]<-Fish.ECxx norm(Acute.data)}</pre>
logNorm.chronic<-matrix(NA,nrow=dim(Chronic.data)[1],ncol=dim(Samples)[1])
j<-which (Chronic.data$MLR=="Algae");
       for (i in j){logNorm.chronic[i,]<-Alg.ECxx_norm(Chronic.data)}</pre>
j<-which(Chronic.data$MLR=="Crustaceans");
        for (i in j) {logNorm.chronic[i,]<-Crust.ECxx norm(Chronic.data) }</pre>
j<-which (Chronic.data$MLR=="Fish");
       for (i in j){logNorm.chronic[i,]<-Fish.ECxx norm(Chronic.data)}</pre>
# Aggregate ECxx and calculate HC5
L<-dim(Samples)
Acute.summary<-as.data.frame(as.data.frame(logNorm.acute) %>%
      group by (Acute.data$Species) %>%
      summarize(across(1:L[1],mean,na.rm=T)))
      logMeans<-sapply(Acute.summary[,-1],mean)</pre>
      logStdevs<-sapply(Acute.summary[,-1],sd)</pre>
```

```
Samples$HC5.acute<-exp(qnorm(0.05,logMeans,logStdevs)) #point estimate
```

```
# Calculation of HC5-50 and its 90th percentile confidence interval:
# Constants k for n=23 (species) for calculation of 90th percentile around the HC5 are taken from SSD-book, Posthuma, Suter and Traas, 2002)
       Samples$HC5.acute_low<-exp(logMeans-2.32832*logStdevs)</pre>
       Samples$HC5.acute_median<-exp(logMeans-1.66752*logStdevs)
       Samples$HC5.acute high<-exp(logMeans-1.20181*logStdevs)</pre>
Chronic.summary<-as.data.frame(as.data.frame(logNorm.chronic) %>%
       group_by(Chronic.data$Species) %>%
       summarize(across(1:L[1],mean,na.rm=T)))
       logMeans<-sapply(Chronic.summary[,-1],mean)</pre>
       logStdevs<-sapply(Chronic.summary[,-1],sd)</pre>
       Samples$HC5.chronic<-exp(qnorm(0.05,logMeans,logStdevs)) # point estimate
\# Calculation of HC5-50 and its 90th percentile confidence interval:
\# Constants k for n=13 (species) for calculation of 90th percentile around the HC5
       Samples$HC5.chronic_nedian<-exp(logMeans-1.68700*logStdevs)
Samples$HC5.chronic_low<-exp(logMeans-2.6705*logStdevs)
Samples$HC5.chronic_high<-exp(logMeans-1.0814*logStdevs)
```

Appendix 7 Number of selected sampling sites per WFD water type

PBLcod	e and description (in Dutch)	WFD c	ode and description (in Dutch)	#
MBR	Brakke wateren	M30	Zwak brakke wateren	14
		M31	Kleine brakke tot zoute wateren	1
		M32	Grote brakke tot zoute wateren	4
MGD	Grote meren	M21	Grote diepe gebufferde meren	11
MKD	Kleine diepe plassen	M16	Diepe gebufferde meren	3
		M17	Diepe zwak gebufferde meren	_
		M18	Diepe zure meren	-
		M24	Diepe kalkrijke meren	-
		M28	Diepe laagveenmeren	-
MKO	Kleine ondiepe plassen (zand,	M11	Kleine ondiepe gebufferde plassen	18
	kalk)			
		M22	Kleine ondiepe kalkrijke plassen	3
MKV	Kleine ondiepe veenplassen	M25	Ondiepe laagveenplassen	3
MMO	Matig grote ondiepe meren	M14	Ondiepe gebufferde plassen	24
		M15	Ondiepe grote gebufferde plassen	-
		M23	Grote ondiepe kalkrijke plassen	-
		M27	Matig grote ondiepe laagveenplassen	5
MMD	Matig grote diepe meren	M20	Matig grote diepe gebufferde meren	28
		M29	Matig grote diepe laagveenmeren	-
MVN	Vennen	M12	Kleine, ondiepe zwak gebufferde plassen	22
		M13	Kleine, ondiepe zure plassen	5
		M26	Ondiepe, zwak gebufferde hoogveenplassen	7
MKA	Kanalen	M3	Gebufferde (regionale) kanalen	62
		M4	Zwak gebufferde (regionale) kanalen	-
		M6	Grote ondiepe kanalen	44
		M7	Grote diepe kanalen	16
		M10	Laagveen vaarten en kanalen	16
MSL	Sloten	M1	Gebufferde sloten (overgangssloten, sloten in rivierengebied)	104
		M2	Zwak gebufferde sloten (poldersloten)	4
		M8	Gebufferde laagveensloten	3
		M9	Zwak gebufferde hoogveen sloten	-
MWR	Wateren in het rivierengebied	M5	Ondiep lijnvormig water, open verbinding met	2
			rivier/geïnundeerd	
		M19	Diepe meren in open verbinding met rivier	-
RRV	Langzaam stromende rivier	R7	Langzaam stromende rivier/nevengeul op zand/klei	11
		R8	Zoet getijdenwater (uitloper rivier) op zand/klei	8
RRS	Snel stromende rivier	R16	Snelstromende rivier/nevengeul op zand of grind	1
RMB	Riviertje	R6	Langzaam stromend riviertje op zand/klei	51
RBL	Langzaam stromende wateren	R1	Droogvallende bron	-
		R2	Permanente bron	3
		R3	Droogvallende langzaam stromende bovenloop op zand	4
		R4	Permanent langzaam stromende bovenloop op zand	113
		R5	Langzaam stromende midden/benedenloop op zand	112
		R11	Langzaam stromende bovenloop op veen	-
		R12	Langzaam stromende midden/benedenloop op kalk	2
		R19*	Doorstroommoeras	9
		R20*	Moerasbeek	34
RSL	Snel stromende wateren	R9	Langzaam stromende bovenloop op kalk	-
		R10	Langzaam stromende middenloop op kalk	-
		R13	Snelstromende bovenloop op zand	5
		R14	Snelstromende midden/benedenloop op zand	4
		R15	Snelstromende riviertje op kiezelhouden bodem	2
		R17	Snelstromende bovenloop op kalkhoudende bodem	16
		R18	Snelstromende midden/benedenloop op kalk	8
OTY	Overgangswater	02	Estuarium met matig getijverschil	-
ZEE	Zee	K1	Polyhalien kustwater	-
		K2	Euhalien kustwater	-
KBS	Waddenzee, Oosterschelde	K3	Beschut polyhalien kustwater	-

*R19 en R20 komen in de PBL classificatie uit 2010 nog niet voor, toen werden deze wateren nog geclassificeerd als R4. In 2018 zijn ze toegevoegd als aparte KRW water types (Verdonschot, R en Verdonschot, P., 2018, Maatlatten voor doorstroommoerassen en moerasbeken, Notitie zoetwatersystemen, WUR, 84p., <u>link</u>

Further aggregation of water types in Table 7 was done as follows"

Water type	PBL code
Brackish waters	MBR
Brooks, fast flowing	RBS
Brooks, slow flowing	RBL
Canals	МКА
Ditches	MSL
Fens	MVN
Lakes, large	MGD
Lakes, medium	MMD+MMO
Lakes, small, peat	MKV
Lakes, small, sand clay	MKD+MKO
Rivers	RRV+RRS+RMB
Water in riverine area	MWR

Appendix 8 Sampling authorities

Table 14 Authorities involved in collection of the selected data.

	Compiled dataset			
	Monthly mean data	Annual mean data		
	(#samples)	(#sites)		
HHRS De Stichtse Rijnlanden	0	0		
HHRS Hollands Noorderkwartier	283	24		
HHRS van Delfland	0	0		
HHRS van Rijnland	0	0		
HHRS van Schieland en Krinpenerwaard	0	0		
Rijkswaterstaat	505	44		
Wetterskip Fryslân	82	20		
WS Aa en Maas	595	99		
WS Amstel Gooi en Vecht	0	0		
WS Brabantse Delta	1058	121		
WS De Dommel	875	82		
WS Drents Overijsselse Delta	354	95		
WS Hollandse Delta	237	27		
WS Hunze en AA's	0	0		
WS Limburg	971	132		
WS Noorderzijlvest	0	0		
WS Rijn en IJssel	37	9		
WS Rivierenland	0	0		
WS Scheldestromen	0	0		
WS Vallei en Veluwe	52	39		
WS Vechtstromen	156	31		
WS Zuiderzeeland	339	56		
Total	5544	779		

Appendix 9 Normal distributions of water characteristics

Dissolved organic carbon (mg/L)





Hardness (mf CaCO₃/L)



Appendix 10 Normal distributions calculated HC5

Acute HC5



Distribution of acute HC5 values fitted. Dotted lines represent the fitted 5th percentile and 50th percentile of each watertype, assuming a normal distribution. Based on 5544 monthly records.

Chronic HC5



Distribution of chronic HC5 values fitted. Dotted lines represent the fitted 5th percentile and 50th percentile of each watertype, assuming a normal distribution. Based on 779 annual records.

Appendix 11 Statistical data of water types used for copper EQS

Source: Vijver et al., 2008; RIVM,2012.

	DOC				рН					
	mean	±	sd	#samples/	#sites	mean	±	sd	#samples	#sites
Large rivers	3.1	±	0.9	926	12	7.7	±	0.2	4024	12
Canals, large lakes, small lakes	8.4	±	4.4	425	16	8.1	±	0.4	443	15
Streams, brooks	18.2	±	4.3	12	3	7.4	±	0.1	401	5
Ditches	27.5	±	12.2	7	4	6.9	±	0.8	7	4
Sandy springs	2.2	±	1.0	4	1	6.7	±	0.1	4	1
Small acid ponds	17.3	±	4.4	22	7	5.1	±	0.8	22	7

Appendix 12 Aluminum concentrations in filtered and unfiltered samples.

	Samples with aluminum (filtered) data				Samples with aluminum (total) data			
	#	<lod< td=""><td>Conc. range (µg/L)</td><td>Median (µg/L)</td><td>#</td><td><lod< td=""><td>Conc. range (µg/L)</td><td>Median (µg/L)</td></lod<></td></lod<>	Conc. range (µg/L)	Median (µg/L)	#	<lod< td=""><td>Conc. range (µg/L)</td><td>Median (µg/L)</td></lod<>	Conc. range (µg/L)	Median (µg/L)
Brackish waters	110	50%	<1 - 50	1.8	88	0%	2.0 - 934	50
Brooks fast flowing	273	99%	<50 - 350	25*	8	0%	67 - 290	155
Brooks slow flowing	1692	62%	2.4 - 760	25*	715	5%	<10 - 3400	98
Canals	905	60%	<1 - 1300	25*	167	7%	<10 - 1400	148
Ditches	673	71%	<10 - 1100	25*	368	25%	<10 - 4400	90
Fens	61	49%	<50 - 450	51	0			
Lakes large	50	20%	<1 - 11	1.5	51	0%	13.9 - 2480	319
Lakes medium	273	48%	<1 - 670	20	155	12%	<20 - 4300	74
Lakes small peaty	7	100%	<50 - 25	25*	0			
Lakes small on sand or clay	133	83%	<10 - 260	18	76	4%	<10 - 460	53
Rivers	612	31%	<1 - 190	13	504	5%	<10 - 4600	133
Water in riverine area	6	100%	<50	25*	0			
Overall	4795	60%	<1 - 1300		2132	9%	2.0 - 4600	

Concentration below the limit of detection were divided by 2 before they were combined with other data to calculate the median.

In most (81%) of the samples reported below the limit (LOD) of detection the LOD was 50 μ g Al/L. In the other 19% of the cases the LOD was smaller (either, 1,2,10 or 20 μ g Al/L).