Supplementary Information 1: Global Aquatic Biodiversity Impact of Nitrogen and Phosphorus Fertiliser Use of Major Crops:

Table of Contents

1 Supplementary Introductory Material

1.1 Handling of Fate Factors for Soils between LCIA methodologies

Table 1: Spatially explicit LCIA methodology handling of nutrient emissions from soils of Phosphorus and Nitrogen fate and transportation (Fate Factors) to fresh and marine water environments, respectively. An additional comparison is made with the Fate factor methodology developed for this study.

		ReCiPe 2016	LC Impact	IMPACT World+	This Study
	Geographic Scope	Global	Global	Global	Global
	Nutrients Assessed	N & P	N & P	N & P	N & P
P - Freshwater	**FF Considered**	+	+	+	+
	Spatially-Explicit FFs	+	+	+	+
	FF Developer	Helmes et al. (2012)[1] for point sources	Helmes et al. (2012)[1] for point sources Scherer and Pfister (2015)[2] for diffusive sources	Helmes et al. (2012) [1] for point sources	This study for point sources
	FF Model Scale	Grid Cell 30-arc min	Grid Cell 30-arc min	Grid Cell 30-arc min	Grid Cell 5-arc min
	Soil Nutrient Model that FF is based on		SCALA Model (Prasuhn, 2006)		IMAGE-GNM Model (Beusen et al., 2015)
	Assumptions for Soils	10% FF reduction made for diffusive sources	Updates FFs from Helmes et al (2012) with SCALA Model results for diffusive sources	No reductions made for diffusive sources	
	Soil Nutrient Model Scope		Switzerland		Global
N - Marine	**FF Considered**	+	+	+	+
	Spatially-Explicit FFs	+	+		+
	FF Developer	Cosme et al (2018)[3]	Cosme et al (2018)[3]		This study for point sources based on Cosme et al (2018)[3] method
	FF Model Scale	Basin	Basin		Grid Cell 5-arc min
	Soil Nutrient Models	GLOBAL NEWS 2 Model (Mayorga et al, 2010)	GLOBAL NEWS 2 Model (Mayorga et al, 2010)	CARMEN Model	IMAGE-GNM Model (Beusen et al., 2015)
	Assumptions for Soils			Assumes 70% of N discharged to freshwater reaches marine water.	
	Nutrient Model Scope	Global	Global	Europe	Global

2 Supplementary Methodology Material

2.1 Quantifying Nutrient Emission Inventory

To identify eutrophication impact through LCIA, it is important to quantify and identify the main pathways and major contributing regions of N and P emissions through the emission inventory. Previous global studies have typically quantified nutrient emissions to the environment using the soil nutrient budget. Liu et al., (2010)[4] identified around half of global total N inputs to croplands were lost to the environment. Bouwman et al., (2013)[5] estimated 93 Tg N yr^{-1} was lost from arable lands and 45 Tg N yr^{-1} from grasslands. Lasseletta et al., (2014)[6] showed 53% of N added to croplands is lost to the environment through an analysis between crop yields and N inputs based on FAO data from 124 countries. Zhang et al., (2015)[7] built a global N budget database identifying the N losses to the environment were around 100 Tg N yr^{-1} in 2010. Most of these studies focus on total N fluxes aggregated from different crops (and grasses) with less attention on crop-specific disparity, reducing their ability to guide fertilisation management.

Biophysical crop growth models designed for assessing crop yields, crop water consumption and agricultural climate change have also been used to assess nutrient losses[8–12]. Biophysical crop growth models have the advantage over mass balance approaches by being spatially variable by considering site-, climate- and management-specific differences. However, currently biophysical models lack global spatial abilities (EPIC; Van der Velde et al., 2009[8]), have coarse resolutions (DAYCENT; Del Grosso et al., 2009[9]) or are not crop-specific (DNDC; Qiu et al., 2011[10]). Globally spatialised models of the EPIC model have been developed. GEPIC, the GIS-based EPIC model, initially developed by Liu et al., (2007)[13], provides scope to spatially identify nutrient losses for site and crop-specific analysis. However, GEPIC is no longer supported by the ArcGIS platform. The PEPIC model created by Liu et al., (2016)[11] is the EPIC model developed in Python programming however it lacks suitability for individual users in its current form.

Biophysical crop models may provide more robust on-field results, but data limitations at the global scale (including, nutrient type applied, application schedules, management practices and technology used) means differences in nutrient losses are insignificant[11]. Liu et al., (2016)[11] identified three commonly used fertilisation schedules predicting similar nutrient losses, only minor differences in yield output and similar losses to annual mass balance approaches. Hence, mass balance approaches at the annual scale are suitable to conform with data limitations and LCIA methodologies.

The **soil nutrient budget** is well-recognised as a fundamental indicator to analysis environmental impact from fertilisers at any scale[14–16]. The soil nutrient budget analyses the nutrient inputs and outputs, identifying either a surplus (positive) or deficient (negative) budget. For example, the agronomic soil nutrient budget for nitrogen inputs (comprising of biological fixation (N_{fix}), atmospheric

N deposition (N_{dep}), application of synthetic N fertiliser (N_{fert}) and animal manure fertiliser (N_{man})) and outputs (Crop Harvesting (N_{withdr}) and Nitrogen volatilisation (N_{vol})) form the following mass balance:

$$N_{budget} = N_{fix} + N_{dep} + N_{fert} + N_{man} - N_{withdr} - N_{vol}$$

As P does not have any fluxes with the atmosphere, only synthetic fertiliser (P_{fert}) and manure (P_{man}) are applied on the field. Phosphorus uptake (P_{withdr}) through the crop is the only output included within the budget:

$$P_{budget} = P_{fert} + P_{man} - P_{withdr}$$

Negative balances indicate depletion of the soil stocks, while a positive balance can accumulate in the soil or be lost to atmospheric, terrestrial, and aquatic environments. Different agricultural practices lead to positive, or negative imbalances. In Europe, positive soil nutrient balances lead to pollution of ground and surface waters, whereas agricultural practices with negative nutrient imbalances (generally found in developing countries) may result in the depletion of soil nutrient stocks, seriously threatening future agricultural production, as in many African countries[17].

The ratio of nutrient applied compared to the crop uptake of nutrient, commonly known as the **Nutrient Use Efficiency** (NUE), is a well-documented indicator of sustainability[7,18,19]:

$$NUE(\%) = \frac{N_{crp}}{N_{fix} + N_{dep} + N_{fert} + N_{man}} \times 100$$

Nitrogen outputs include nutrient withdrawn by the crop (N_{withdr}, Kg ha^{-1}) and is given by:

$$N_{withdr} = G_{yield} \times NCon_{Av.} \times W_{Dry}$$

where G_{yield} (kg ha^{-1}) is grain yield per hectare, $NCon_{Av.}$ is the average nutrient content per specific crop (%) and W_{Dry} is the dry weight percentage. NUE values greater than 100% suggest a lower N application rate compared to the nutrient being taken up by the crop product. Such a situation lends itself to land degradation through nutrient soil mining, suggesting loss of soil fertility and crop yield decline, such as in central Africa[18]. Such systems are not suitable and should be avoided to maintain agricultural productivity and soil fertility. NUE values between 90% and 100% still represent a risk of soil mining due to additional N inputs not met by N outputs and losses to the environment are not compensated. Well balanced nutrient use efficiencies are ranged at 80-90%. N application rates with NUE values below 70%, as in China and Europe, include an increased risk of nitrogen loss and should be avoided to protect the environment[18]. Improving the nitrogen use efficiency has been documented as having the most effective means of increasing crop productivity while decreasing environmental degradation[7,20]. However, lack of information within the indicator does not allow quantification of environmental impact.

The above definitions of the soil nutrient budget and the nutrient use efficiency are interconnected through their mathematical definitions[7]:

$$N_{budget} = N_{withdr}\left(\frac{1}{NUE} - 1\right)$$

Formulating each part of the soil budget involves a number of uncertainties, particularly at the global scale[4,5,7,21]. For each element of the soil budget, the following sub-sections identify current methods of data collection, analyses and where current research gaps exist:

2.1.1 Fertiliser Input (N_{fert} and N_{man})

Most nutrient modelling studies have used national datasets to compile rough estimates of fertiliser rates into global spatially explicit grid cell models, obtained from FAOSTAT (FAO 2015) and subnational data for the USA (USDA – National Agricultural Statistics Service, 2015), China (National Bureau of Statistics of China, 2014; China livestock Yearbook Editing Committee, 2014) and Europe (European Commission, 2015). Some publications have devised average applications rates (Kg/ha) per grid cell per country for aggregated crop groups[15]. Whilst others have used linear relationships between fertiliser consumption and food production to devise average grid cell datasets[4]. Few studies have been conducted to develop geographically spatially explicit global datasets, on synthetic and manure fertiliser rates on a 5 by 5 arc min grid cell, using spatial disaggregation approaches[22–24]. However, these spatially explicit datasets have not been fully utilised to analyse environmental impact of fertiliser use; particularly eutrophication potential. Here we use spatial disaggregated mineral fertiliser and manure input datasets at the 5 arcmin resolution taken from earthstat.com, which has been devised through the work by Mueller et al., (2012)[24] and West et al., (2014)[23].

2.1.2 Nitrogen Fixation (N_{fix})

Biological N_2 Fixation (N_{fix}) occurs symbiotically by leguminous crops and non-symbiotically by Cyanobacteria. Most studies have globally adapted the fixation rates initially taken from Smil (1999)[25] who estimated 5 Kg of N per hectare for non-leguminous crops and 20-30Kg of N per hectare in wetland rice fields during the growing season (Table 2)[4,15,23,26].

For leguminous crops, such as pulses and soybean, studies have assumed N fixation by its relationship to the crop harvest product, by multiplying the N in the harvested product by a factor of 2[15,23]. This factor accounts for all above – and below-ground plant parts, as per Mosier et al., (1998)[27].

2.1.3 Nitrogen Deposition (N_{dep})

The majority of global studies[4,15,23,26] take nitrogen deposition results obtained from an ensemble of atmospheric chemistry-transport models[28] overlaid onto crop distribution maps[29]. To date no improved global deposition maps have been formulated. Global deposition rates were taken from earthstat.com, which uses atmospheric deposition rates taken from global estimates for the IPCC AR[30].

2.1.4 Crop Nutrient Withdrawal (N_{withdr})

Nitrogen withdrawal within crops has previously been analysed according to the yield level and the nitrogen or phosphorus content for different crops[7,15,21,23]. The values of nitrogen content of crops vary between studies. Some studies only take nitrogen contents from crops grown solely in North America[23] and OECD Countries[31]. Few studies have used Lassaletta et al., (2014)[6] comprehensive dataset of N content from various sources (Table 2).

Table 2: List of 17 crops and their dry fraction, N and P content on a dry matter basis, taken from Bouwman et al., (2017) and Lassaletta et al., (2014). Biological fixation rates taken from West et al., (2014).

Crop	N Content (-)	P Content (-)	Dry Fraction (-)	Bio Fix Rate (kg/ha)
Barley	0.0170	0.0036	0.8800	5
Cassava	0.0020	0.0004	0.3260	5
Cotton	0.0290	0.0053	0.9200	5
Ground Nuts	0.0570	0.0042	0.9420	5
Maize	0.0140	0.0029	0.8800	5
Millet	0.0150	0.003	0.85	5
Oil Palm	0.015	0.0031	0.94	5
Potatoes	0.003	0.0005	0.212	5
Rapeseed	0.035	0.0056	0.91	5
Rice	0.013	0.0025	0.88	25
Rye	0.0176	0.0038	0.9400	5
Sorghum	0.015	0.003	0.85	5
Soybeans	0.062	0.005	0.85	-*
Sugarbeet	0.002	0.0004	0.26	5
SugarCane	0.002	0.0004	0.232	5
Sunflower	0.034	0.0045	0.92	5
Wheat	0.019	0.0034	0.88	5

* Soybean bio fixation quantity devised from multiplying the N in the harvested product by a factor of 2

2.1.5 Nitrous Oxide (N_2O), Nitric Oxide (NO) Emissions and Ammonia (NH_3) volatilisation

Direct N_2O and NO emissions from fertiliser application and spreading of manure are calculated with residual maximum likelihood (REML) regression models. The nitrous oxide emissions (N_2O) REML model is based on 846 series of measurements in agricultural fields[31]. The model takes into consideration environmental (climate, soil organic carbon content, texture, drainage, and soil pH) and management-related factors (N application rate, fertiliser type and crop type). The NO REML model considers the N application rate per fertiliser type, soil organic carbon content and soil drainage.

Nitrogen volatilisation from the spreading of animal manure is calculated with an empirical model that considers crop type, fertiliser type, manure and fertilisation application mode, soil cation exchange capacity, soil PH and climate[32]. We assumed all manure applied to cropland is incorporated as per Bouwman et al., (2013)[33].

2.2 Effect Factor for Freshwater and Marine Environments

The Effect Factor (EF) describes the environmental impact (fraction of potentially not occurring or disappearing fraction of species) following the increase of pollutant concentration in a particular water body. Azevedo et al., (2013)[34] focuses on stream and lake waterbody compartments to develop EFs for phosphorus within freshwater bodies, whilst Cosme et al., (2014, 2015)[35,36] has focussed on the development of oxygen depletion (exposure factor, XF) and ecosystem damage levels (effect factor, EF) within Large marine Ecosystems (LME) for nitrogen emissions.

In freshwater environments, the effect models to describe EFs are based on log-logistic relationships between the potentially not occurring fraction (PNOF, dimensionless) of species (autotrophs and heterotrophs) and total P (TP) concentration. Azevedo et al., (2013)[34] used data from peer-reviewed articles reporting the occurrence of freshwater species at specific TP concentrations to determine the species richness along a TP gradient. Three different EF models are identified for LCIA methods; marginal increase, linear change and average change[34]. These models differ with respect to their assumption of linearity/nonlinearity of responses and data input requirements. For freshwater eutrophication, linear effect factor models (LEF) are primarily used within spatially-explicit LCIA methodologies (LC IMPACT, 2016[37]; ReCiPe, 2016[38]) because the ambient concentration of pollutant is unknown. LEF describes the change from a preferred state (a target state, with "zero" effect), where the concentration of pollutant is zero to the concentration where the effect is 50% of the maximum.

$$LEF = \frac{0.5}{10^{\alpha}}$$

Where α is the total P level (log m^3/kg) in a water type relating to either streams or lakes within a climate region (cold, temperate, sub-tropical, tropical or xeric)[34]. LEFs are given below (Table 3) and used in both LC IMPACT 2016 and ReCiPE 2016:

Table 3: Linear Effect Factors for different water types and climates

	Lake PDF·m³/kg	Stream PDF·m³/kg
Sub-Tropical	13457.67	777.98
Tropical	13457.67	777.98
Temperate	1253.05	674.48
Cold	18279.74	674.48
Xeric	13457.67	777.98

The LEF is multiplied by a species richness density to calculate the total disappearing fraction of species. LC IMPACT 2016 uses solely fish species richness within particular ecoregions, whilst ReCiPe (2016) uses a total species density parameter which approximates to 7.89×10^{-10} species/m³ [39]. A benefit of the LC IMPACT 2016 method is the improved spatial variability in relation to fish species densities per ecoregion, obtained from Abell et al., (2008)[40].

The EF within freshwater bodies for a specific water type, *w*, for a specific ecoregion, *r*, via LC IMPACT 2016 is:

$$EF_{w,r} = \frac{FRD_{w,r} \times LEF_{w,r}}{FR_{global}}$$

Where FRD is the fish richness density (species/m^3), LEF is the Linear Effect Factor (PDF·m^3/kg) and FR is the total fish species richness in the global pool taken from IUNC, (2014).

The LEF is employed within ReCipE 2016 and LC IMPACT 2016 (ReCiPE, 2016; LC IMPACT, 2016). ReCiPe 2016 provides a single parameter for the species richness density taken from Goedkoop et al., (2009)[39]. Whilst the LC IMPACT 2016 methodology provides improved spatial resolution through fish species richness density (FRD) per ecoregion, *r* (determined from fish species richness (FSR) in ecoregion, *r*, taken from Abell et al., (2008)[40] and freshwater volumes, *V*, from rivers and lakes from Helmes et al., (2012)[1]). This study used the LC IMPACT 2016 methodology using freshwater volumes taken from PCR-GLOBWB 2 (Sutanudjaja et al., 2018):

$$FRD_{w,r} = \frac{FSR_r}{V_{w,r}}$$

The resulting EF for freshwater bodies is the Potentially Disappeared Fraction of Fish Species per Kg of Phosphorus (PDF·yr kg_P^{-1}). The EF combined with the Fate Factor (years) produces the CF measured as the resulting disappearing fraction of fish species during a year; commonly written as PDF·yr ·kg_P^{-1} [39].

For marine environments, Cosme et al., (2017)[41] provides effect factors based on marine ecosystem response to N-inputs. The sensitivity to hypoxia of 91 demersal marine species (including fishes, crustaceans, molluscs, echinoderms, annelids, and cnidarians) is used to model the effect factors (EF, PAF·m^3 ·kgO_2^{-1}). Species sensitivity distributions are applied to estimate the average effect of hypoxia on demersal communities as an HC_{50} indicator. The HC_{50} indicator represents the stressor intensity of dissolved oxygen depletion that affects 50% of the exposed population above their individual sensitivity thresholds. Dissolved oxygen depletion is by consumption through aerobic respiration of organic material by heterotrophic bacteria. Organic material increases due to organic carbon cycles fuelled by phytoplankton growth (primary producers), due to N input in the euphotic zone of coastal waters. Dissolved oxygen consumption has been estimated by Cosme et al., (2015)[36] and incorporated within the exposure factor (XF) for 66 LMEs worldwide, varying from 0.45 kgO2·kgN-1 in the central

Arctic Ocean to 15.9 $kgO2 \cdot kgN\text{-}1$ in the Baltic Sea. The EF ($PAF \cdot m^3 \cdot kgO_2^{-1}$) is calculated within Cosme et al., (2017)[41] as the average change of the effect on ecological communities occurring in demersal habitats, due to a change in the stressors intensity in a receiving ecosystem *l*:

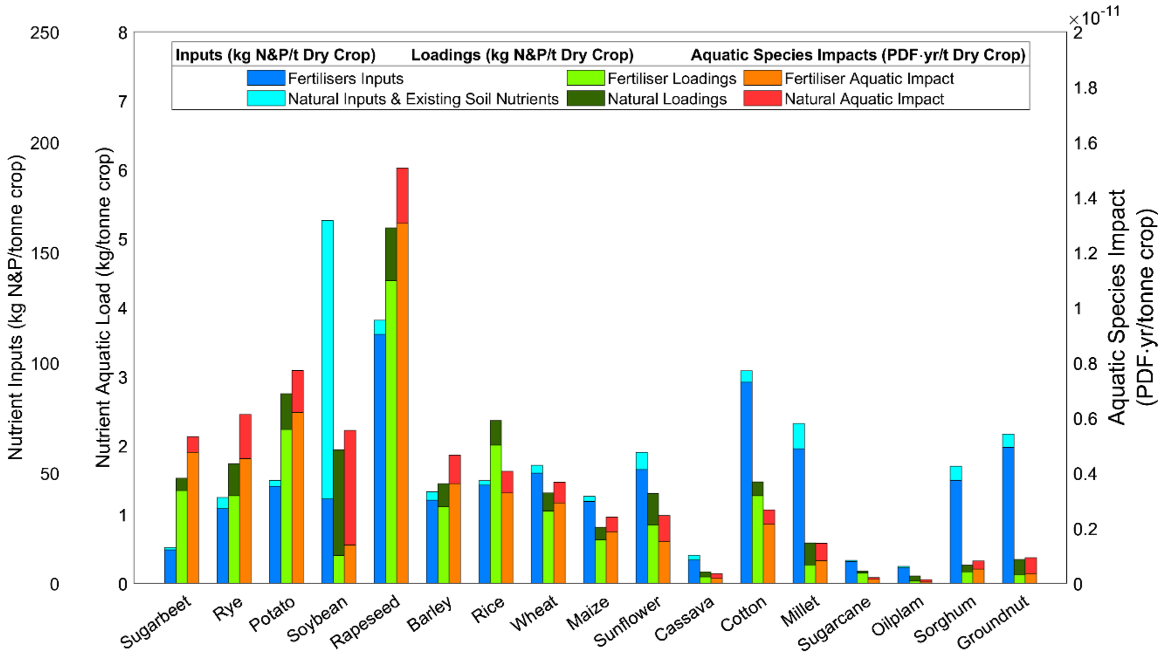
$$EF_l = \frac{\Delta PAF_l}{\Delta DO_l} = \frac{0.5}{HC_{50l}}$$

To harmonise the endpoint scores in the LCIA framework, a conversion of the marine eutrophication endpoint CF from PAF to a PDF is made using the conversion factor of 0.5[42] . The conversion factor assumes one half of the species affected above their sensitivity to the hypoxia threshold (PAF metric) would disappear (PDF metric). This value is assumed based on the seasonality of planktonic production and biological processes, water temperature and stratification as well as nutrient flows[42]. The relative PDF metric was translated to an absolute metric through multiplication of the PDF by species density distributions, as per Cosme et al., (2017)[43]. We divided the demersal species densities by the global demersal species pool of 626, to obtain a global relative metric and harmonise our marine species impact results with our freshwater species result, as per LC IMPACT.

3 Supplementary Result Material

3.1 N and P Fertiliser Applications, loadings and Impacts to Marine and Freshwater Environments

a.



b.

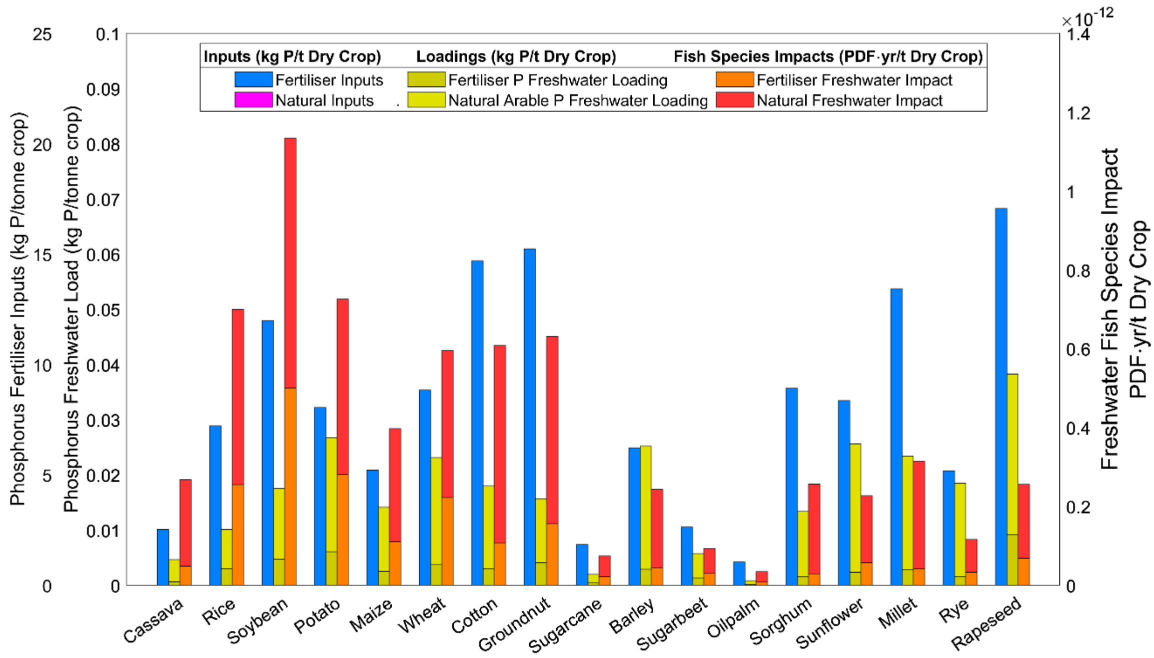
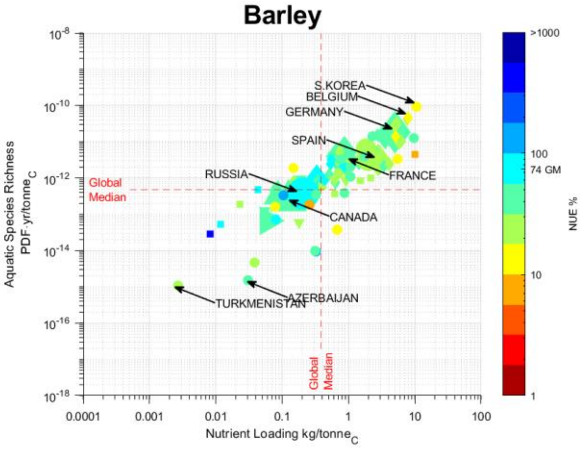
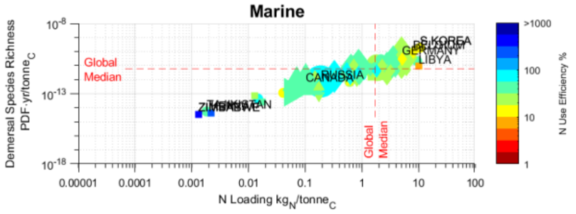
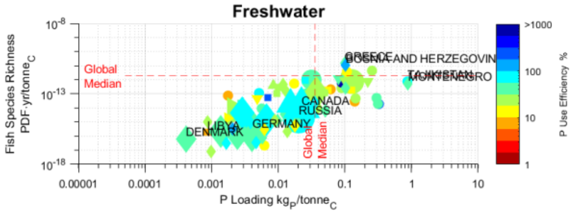


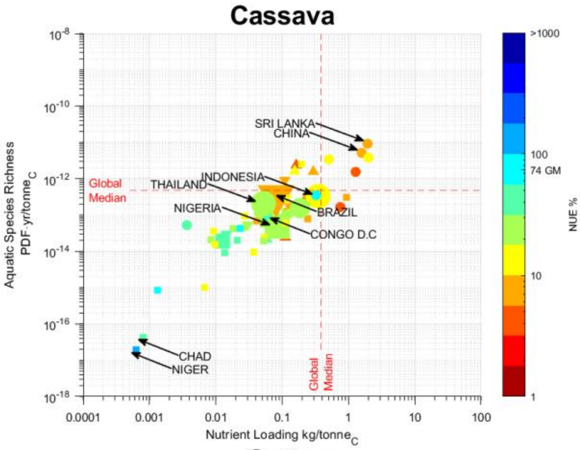
Figure 1: Global weighted averages of fertiliser field application (blue), aquatic receptor loadings (green) and aquatic impacts (red) per tonne of crop for seventeen different crops assessed for nitrogen in marine environments (a) and phosphorus in freshwater environments (b). Crops are order descending based on their ratio of nutrient inputs to receptor loading intensities; high ratios means better use of nutrients on the field for crop production and reduced nutrient transport to aquatic receptors, low ratios suggestions inefficient use of nutrients of the field and increased nutrient transport to receptors.

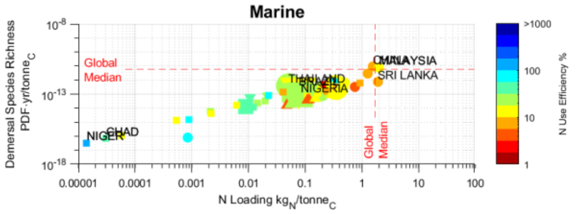
3.2 Crop Fertiliser Impact Performance Assessment Country Level

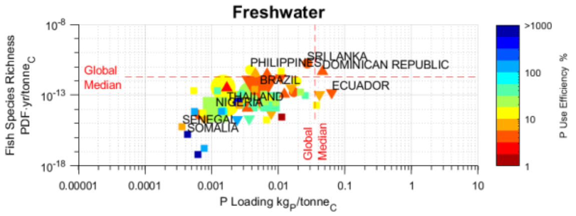


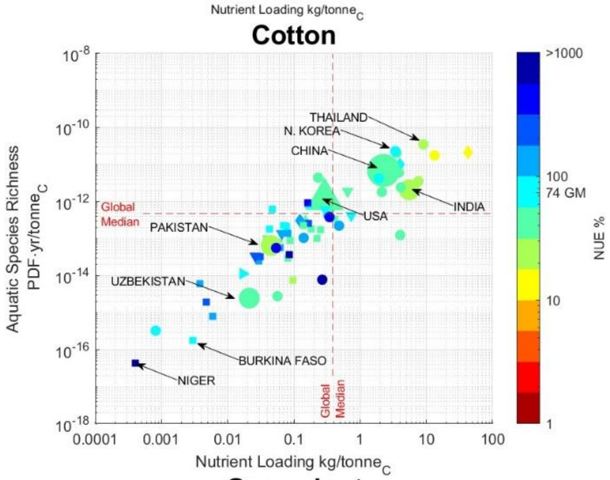


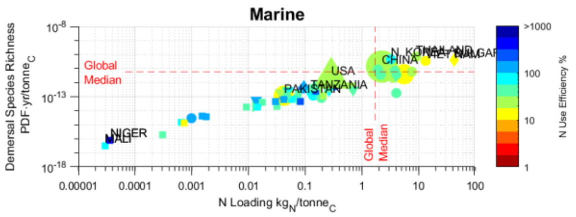


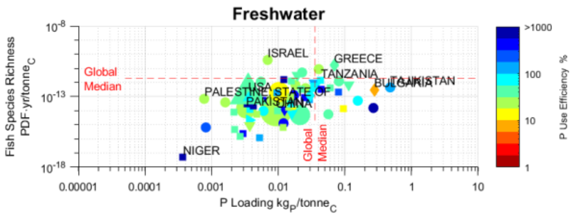


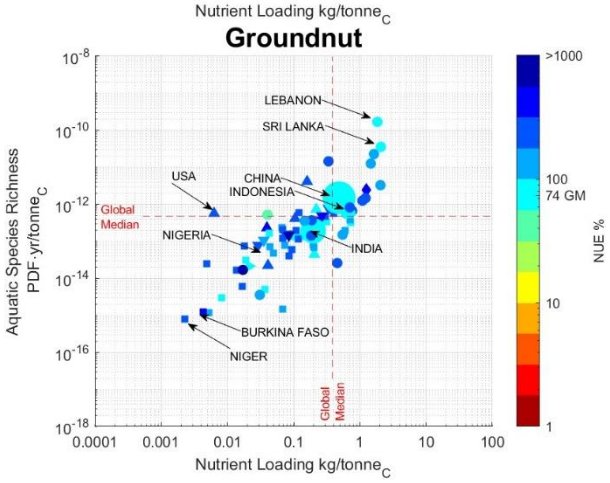


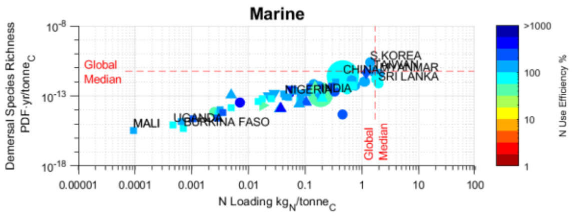


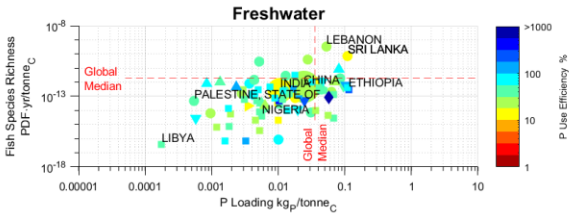


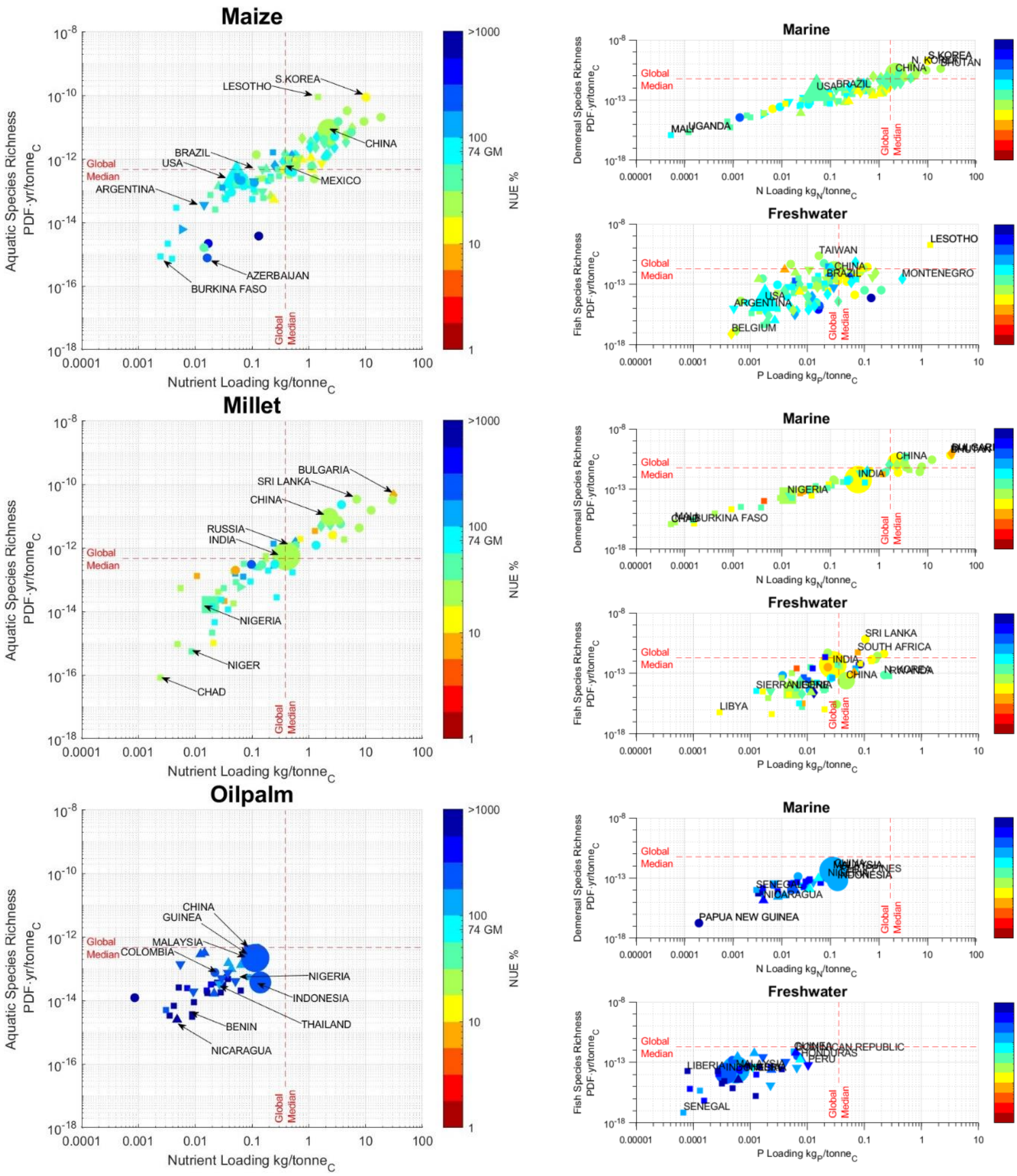


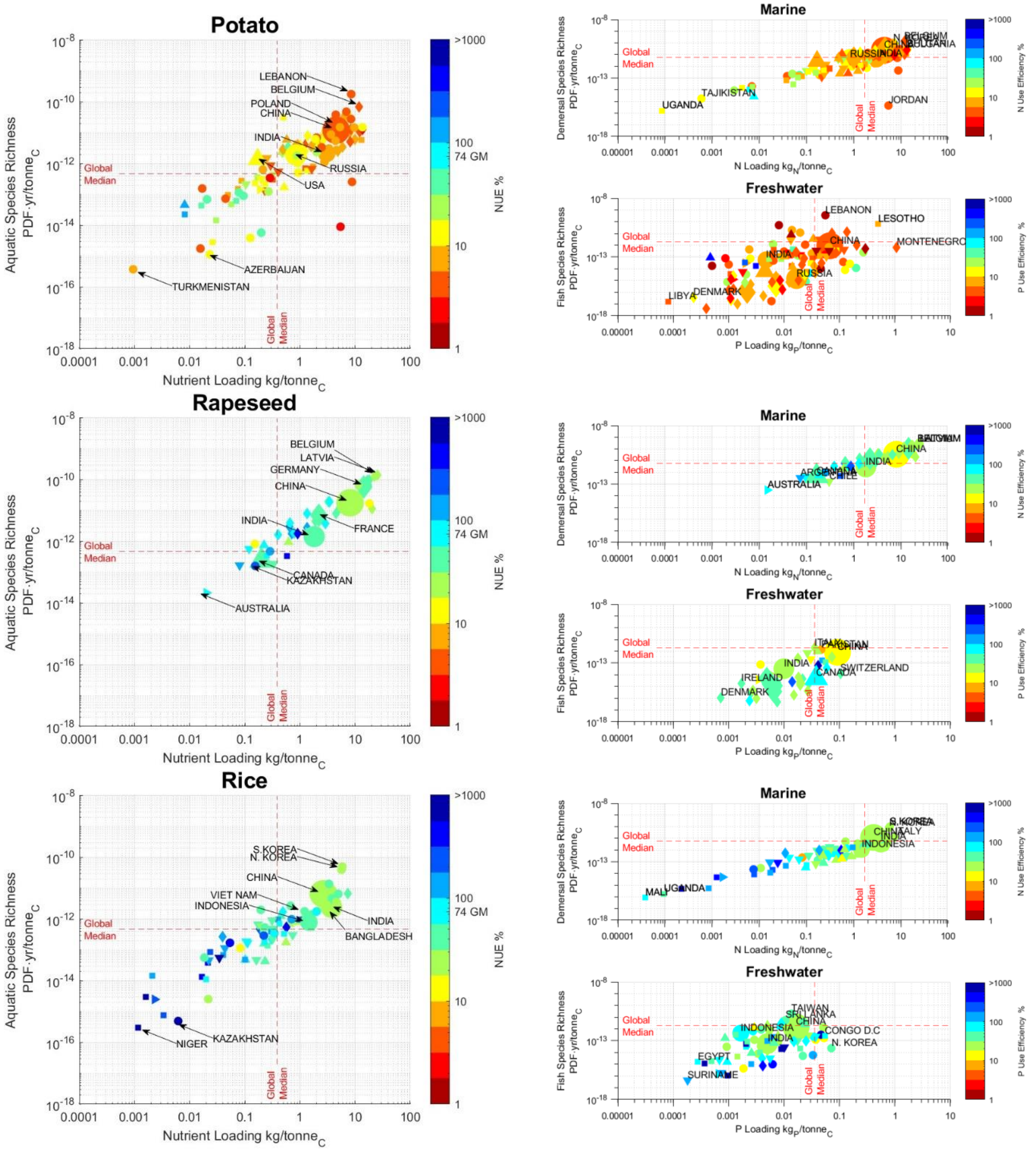




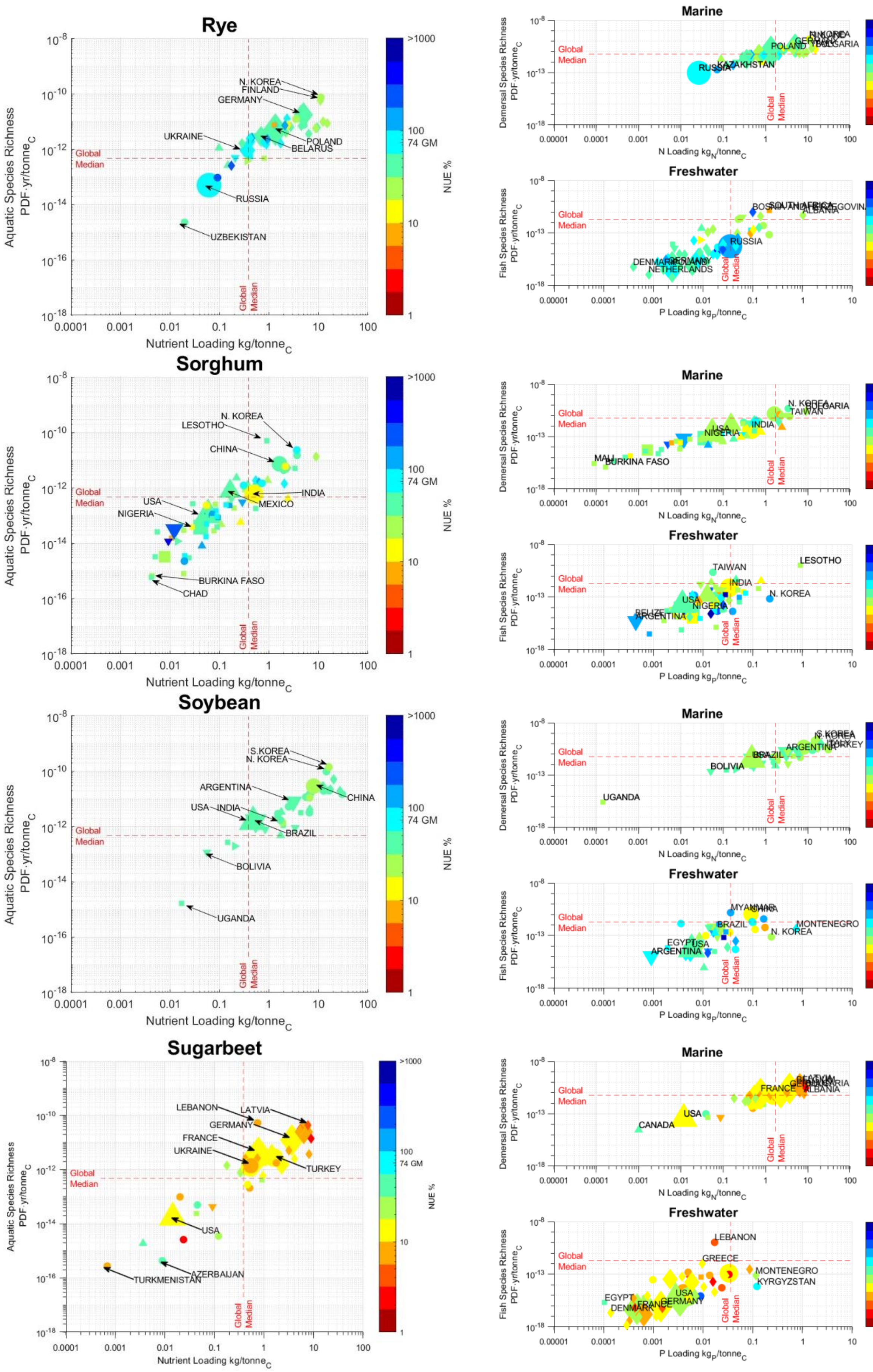





Maize
Millet
Oilpalm
Aquatic Species Richness PDF·yr/tonne$_C$
Nutrient Loading kg/tonne$_C$
NUE %
>1000
100
74 GM
10
1
Global Median
LESOTHO
S.KOREA
CHINA
BRAZIL
USA
MEXICO
ARGENTINA
AZERBAIJAN
BURKINA FASO
BULGARIA
SRI LANKA
RUSSIA
INDIA
NIGERIA
NIGER
CHAD
GUINEA
MALAYSIA
COLOMBIA
INDONESIA
THAILAND
BENIN
NICARAGUA
Marine
Freshwater
Demersal Species Richness PDF·yr/tonne$_C$
Fish Species Richness PDF·yr/tonne$_C$
N Loading kg$_N$/tonne$_C$
P Loading kg$_P$/tonne$_C$
N Use Efficiency %
P Use Efficiency %
N. KOREA
BHUTAN
MALI
UGANDA
TAIWAN
MONTENEGRO
BELGIUM
SOUTH AFRICA
LIBYA
SIERRA LEONE
PAPUA NEW GUINEA
SENEGAL
PHILIPPINES
LIBERIA
PERU
HONDURAS
CENTRAL AFRICAN REPUBLIC



Potato
Aquatic Species Richness PDF·yr/tonne_C
Nutrient Loading kg/tonne_C
NUE %
Global Median
LEBANON
BELGIUM
POLAND
CHINA
INDIA
RUSSIA
USA
AZERBAIJAN
TURKMENISTAN
Rapeseed
BELGIUM
LATVIA
GERMANY
CHINA
INDIA
FRANCE
CANADA
KAZAKHSTAN
AUSTRALIA
Rice
S.KOREA
N. KOREA
CHINA
VIET NAM
INDONESIA
INDIA
BANGLADESH
KAZAKHSTAN
NIGER
74 GM
Marine
Demersal Species Richness PDF·yr/tonne_C
N Loading kg_N/tonne_C
N Use Efficiency %
RUSSIA
JORDAN
TAJIKISTAN
UGANDA
BULGARIA
Freshwater
Fish Species Richness PDF·yr/tonne_C
P Loading kg_P/tonne_C
P Use Efficiency %
LEBANON
LESOTHO
MONTENEGRO
INDIA
CHINA
RUSSIA
LIBYA
DENMARK
AUSTRALIA
IRELAND
SWITZERLAND
CANADA
INDONESIA
MALI
UGANDA
TAIWAN
SRI LANKA
CONGO D.C
N. KOREA
EGYPT
SURINAME



Rye
Aquatic Species Richness
PDF·yr/tonne$_C$
Nutrient Loading kg/tonne$_C$
Global Median
NUE %
>1000
100
74 GM
10
1
N. KOREA
FINLAND
GERMANY
UKRAINE
POLAND
BELARUS
RUSSIA
UZBEKISTAN
Marine
Demersal Species Richness
N Loading kg$_N$/tonne$_C$
N Use Efficiency %
POLAND
KAZAKHSTAN
RUSSIA
Freshwater
Fish Species Richness
P Loading kg$_P$/tonne$_C$
P Use Efficiency %
RUSSIA
ALBANIA
NETHERLANDS
Sorghum
N. KOREA
LESOTHO
CHINA
INDIA
MEXICO
USA
NIGERIA
BURKINA FASO
CHAD
MALI
TAIWAN
Soybean
S.KOREA
N. KOREA
ARGENTINA
CHINA
USA
INDIA
BRAZIL
BOLIVIA
UGANDA
MONTENEGRO
MYANMAR
EGYPT
Sugarbeet
LEBANON
LATVIA
GERMANY
FRANCE
UKRAINE
TURKEY
USA
AZERBAIJAN
TURKMENISTAN
ALBANIA
CANADA
GREECE
KYRGYZSTAN
DENMARK

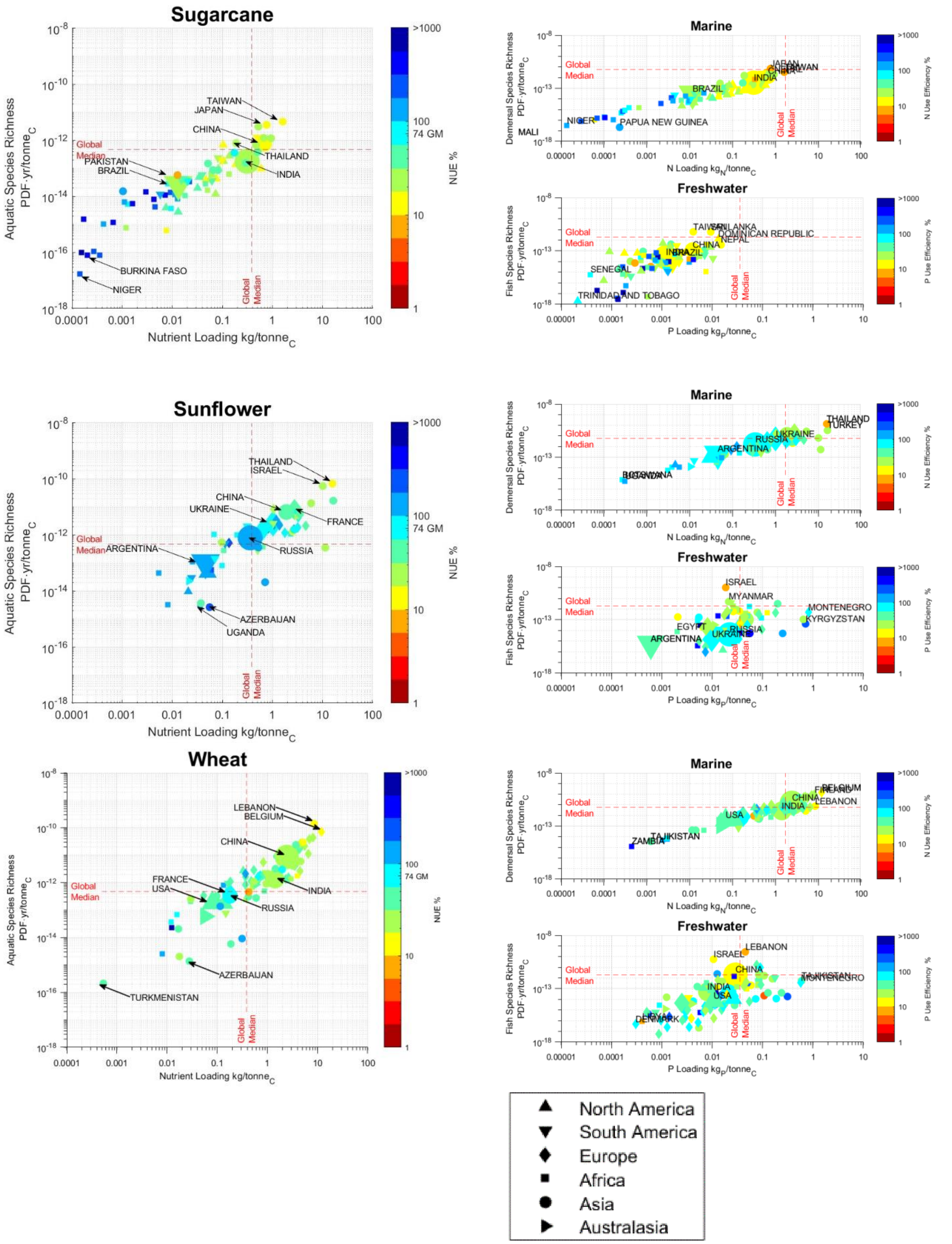


Figure 2: Intensities of Nitrogen and Phosphorus loadings to waterbody receptors per unit ton of yield at the country level. Countries with the smallest production (for a total of 0.01% of global total production of each crop) are discarded; shapes represent different continents; sizes represent production of each country; colour represents species richness impact (PDF·yr/tonne$_c$); Dashed red line represents the global mean of loadings and impacts; numbers represent country code according to the FAO UNI Country Codes http://www.fao.org/countryprofiles/iso3list/en/ and are listed with country name within the supplementary excel data spreadsheet under specific crop-country outputs.

3.3 Nutrient Transport, Receptor Vulnerability and Overall Characterisation Factor Maps

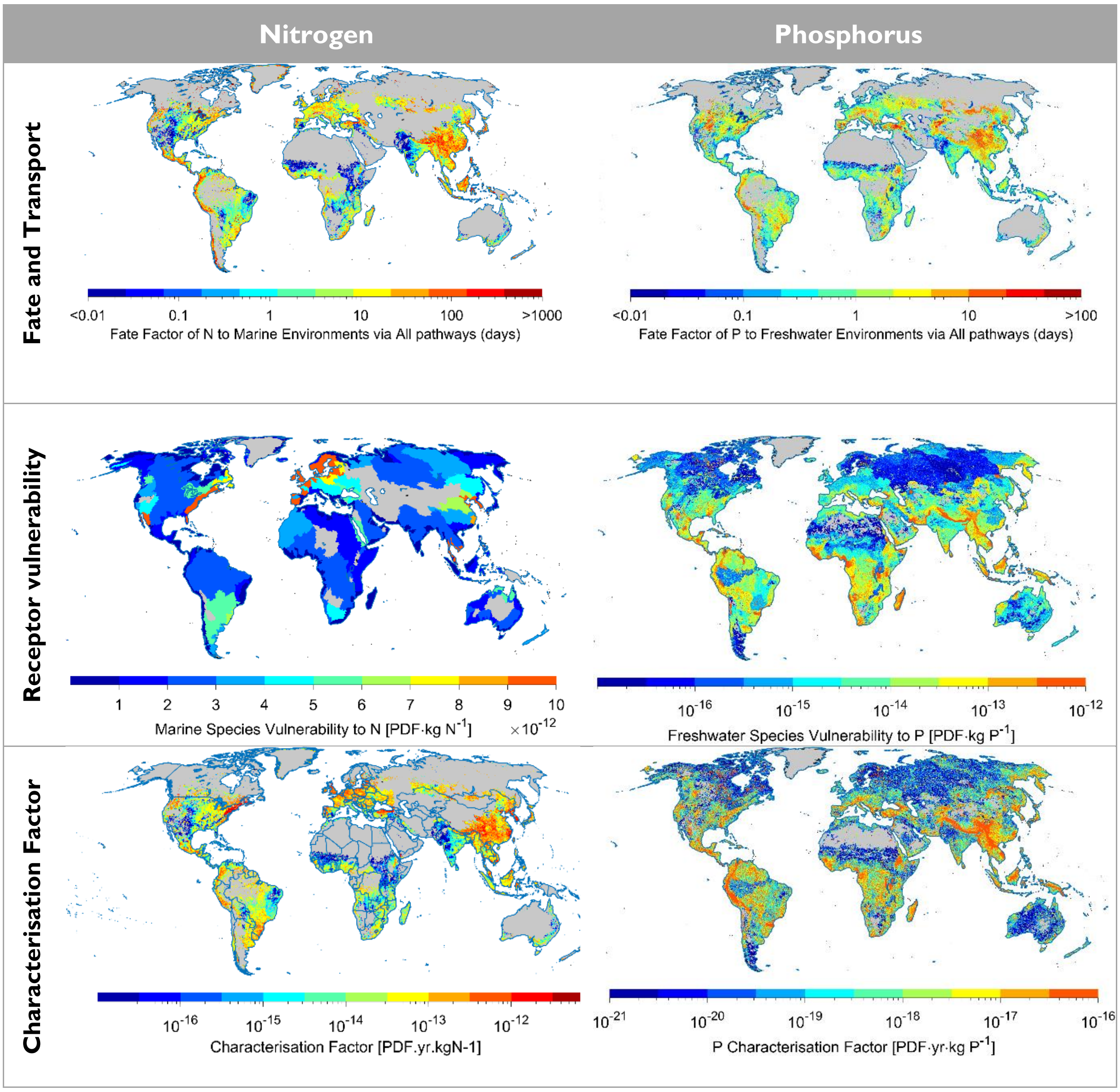


Figure 3: LCIA mapping of the Fate Factor, Exposure Factor and Effect Factor. The Fate Factor is identified through the Fate and Transport mapping of Nitrogen and Phosphorus showing key regions where transport of nutrients to receptors is more susceptible. The exposure and Effect Factors are combined within the Receptor Vulnerability mapping. For marine environments we used data from Cosme and Hauschild (2017)[41] whilst for freshwater environments we followed the LC Impact methodology[37] whilst using improved hydrological data from PCR-GLOBWB 2[44]. The overall susceptibility to nutrient transport and receptor vulnerability is shown within the final characterisation factor.

3.4 Global Fate Factor Statistics specific for Agricultural Soils

Table 4: Global FF Statistics for Agricultural Soils. Global weighted averages were calculated using diffusive emissions taking from IMAGE-GNM and cropland cover from Earthstat.

Fate Factor per soil emission pathway and receptor		**Minimum (Seconds)**	**5th percentile (seconds)**	**Mean (days)**	**95th percentile (days)**	**Maximum (years)**	**Standard Deviation (days)**	**Global Weighted Average (days)**
P Freshwater	All Pathways	1.24E-16	2847.63	10.35	21.49	51.74	238.05	7.01
	Surface Runoff	8.67E-18	199.80	0.73	1.93	8.06	16.19	0.62
	Erosion	1.15E-16	5674.50	10.03	20.15	45.00	229.02	6.39
N Freshwater	All Pathways	2.09E-16	2952.76	26.01	74.50	695.53	796.21	19.76
	Surface Runoff	8.67E-18	140.74	0.67	1.62	8.06	16.18	0.47
	Erosion	1.15E-16	4027.12	24.46	74.77	682.56	785.68	18.79
	Leach	1.25E-16	5833.67	8.67	11.13	29.18	191.46	3.48
N Marine	All Pathways	4.42E-38	77.22	225.58	390.74	118.70	1805.70	67.40
	Surface Runoff	4.42E-38	1.49	1.07	5.10	0.07	2.33	1.02
	Erosion	4.42E-38	15.82	42.23	217.93	5.54	131.29	39.32
	Leach	4.42E-38	12.93	9.42	31.33	0.23	10.77	8.24

3.5 Linear Regression Analysis

Table 5: Simple Linear Regression Analysis for spatial variability of the characterisation factor for wheat. $I_{N/P\ Marine/Freshwater}$ is the biodviersity impact caused by Nitrogen/Phosphorus Fertiliser Use in Marine and Freshwater Environments; $E_{N/P}$ is the emission inventory on fields for nitrogen or phosphorus; $FF_{N/P}$ is the fate and transport of nitrogen/phosphorus from fields to marine/freshwater environments; XF_N is the exposure factor of nitrogen on oxygen concentration levels in marine environments; EF_N is the effect factor representing the marine species richness impact due top oxygen concentration levels; EF_P is the effect factor representing the freshwater fish species impact due to an increase in phosphorus concentrations in freshwater. Spatial variability is measured via high coefficients of determination (R^2), relatively low sum of squares (SS), mean square (MS) and standard error (SE).

	Equation of linear regression	R^2	SS	MS	SE
Log(E_N)vs. log($I_{N\ Marine}$)	$\log(I_N) = -7.02\times\log(E_N) - 39.96$	0.09	28767016	56.53	0.0407
logFF_N vs. log($I_{N\ Marine}$)					
Surface Runoff	$\log(I_N) = 2.28\times\log(FF_{NfQrso}) - 20.13$	0.82	19844320	47.75	0.0086
Erosion	$\log(I_N) = 2.66\times\log(FF_{Nsoilloss}) - 25.14$	0.85	28417012	57.16	0.0053
Leaching	$\log(I_N) = 2.85\times\log(FF_{Nleach}) - 23.79$	0.84	20247534	45.49	0.0058
Log(XF_N) vs. log($I_{N\ Marine}$)	$\log(I_N) = -16.69\times\log(XF_{Nsoil}) - 38.86$	0.051	28767016	56.16	0.037
Log(EF_N) vs. log($I_{N\ Marine}$)	$\log(I_N) = 1.14\times\log(EF_{Nsoil}) - 13.99$	0.0056	28767016	46.16	0.41
Log(E_P)vs. log($I_{P\ Freshwater}$)	$\log(I_P) = -10.50\times\log(E_P) - 39.18$	0.013	15764128	24.18	0.0087
logFF_P vs. log($I_{P\ Freshwater}$)					
Surface Runoff	$\log(I_P) = 3.38\times lo(FF_{PfQrso}) - 24.88$	0.62	12075399	22.916471	0.016
Erosion	$\log(I_P) = 4.19\times\log(FF_{Psoiloss}) - 30.62$	0.62	15963728	24.28	0.0088
Existing Erosion	$\log(I_P) = 4.22\times\log(FF_{P\ Existing\ soiloss}) - 28.21$	0.62	15963728	24.28	0.011
logEF_P *vs. log*($I_{P\ Freshwater}$)	$\log(I_P) = 1.20\times\log(EF_{Psoil}) - 1.20$	0.59	15973864	24.29	0.039

3.6 Sensitivity Analysis – Sensitivity Ratios

Table 4: Sensitivity Ratios (SR) on primary parameters that build the FF, EF and XF. FFs model sensitivity ratios to temperature, nitrogen load in rivers and phosphorus content in soils

Variable	Parameter	Influence on parameter	Average SR	Range	Source
Primary Parameters to Impact (I)					
Emission Inventory	E	I Marine Impact I Freshwater Impact	1 1	~ ~	This Study
Fate Factor	*FF*	I N Marine Impact I N Freshwater Impact I P Freshwater Impact	1 1 1	~ ~ ~	This Study
Exposure Factor	XF	I N Marine Impact	1	~	This Study
Effect factor	EF	I N Marine Impact P Freshwater Impact	1 1	~ ~	This Study
P Content in Soils	*P Content*	FF P Impact	1.00	0.91 – 3.18	This Study
Primary Parameters to FF, XF and EF					
Soil Emission Fraction	$f_{zE(i,j)}$	FF N Marine FF N Freshwater FF P Freshwater	1 1 1	~ ~ ~	This Study
River FF	$\mathrm{FF}_{\mathrm{River\ E(fw)(i,j)}}$	FF N Marine FF N Freshwater FF P Freshwater	1 1 1	~ ~ ~	This Study
Retention Fraction	$\mathrm{f}_{\mathrm{E(i,j)}}$	FF N Marine FF N Freshwater FF P Freshwater	9.31 5.47 5.88	1.9 – 10 0 – 10 0 - 10	This Study
Rate of Persistence	$(\lambda_{E(j)})$	FF N Marine FF N Freshwater FF P Freshwater	-1.1	~	This Study
Volume Water in Ecoregion	$V_{w,r}$	EF P	-0.91	~	This Study (LC IMPACT Methodology)
Fish Species Richness in Ecoregion	FSR_r	EF P	1	~	This Study (LC IMPACT Methodology)
LME – dependent primary production rates	$\mathrm{PP}_{\mathrm{LME}}$	XF N	0.92	~	Cosme et al (2015)
Secondary producer assimilation fraction	$f_{SPassimil}$	XF N	-0.59	~	Cosme et al (2015)
Primary producer sinking fraction	f_{PPsink}	XF N	0.51	~	Cosme et al (2015)
Species Sensitivity to hypoxia (lowest-observed effect concentration)	LOEC	EF N	0.001-0.027	~	Cosme et al (2017)
Secondary Parameters for FF					
Surface Water Fraction	f_{qrso}	FF N Marine FF N Freshwater FF P Freshwater	0.001 0.01 0.02	-0.04 - 0.079 0 - 0.079 0.003 - 0.1	This Study
Erodibility Fraction	f_{ero}	FF N Marine FF N Freshwater FF P Freshwater	0.57 0.72 0.99	0 - 2 0.014 -1 0.89 - 1	This Study
Leach Fraction	$f_{leach,soil}$	FF N Marine FF N Freshwater FF P Freshwater	0.54 0.37 ~	0 - 1.33 0 - -1.00 ~	This Study
Riparian Fraction	$f_{den,rip}$	FF N Marine FF N Freshwater FF P Freshwater	-0.09 -0.12 ~	-0.68 - 0 -0.07 - 0 ~	This Study

Deep Groundwater Delivery Fraction	$fQgwb$	FF N Marine FF N Freshwater FF P Freshwater	0.0053 0.01 ~	-0.0071 – 0.843 -0.11 – 0.97 ~	This Study
TS/SS Fraction	$f_{N,TS/SS}$	FF N Marine FF N Freshwater FF P Freshwater	0.29 0.37 ~	0 – 1.00 0 – 1.00 ~	This Study
Tertiary Parameters to FF					
		Soil Compartment of FF			
Arable Landcover	$Landuse$	FF N Marine FF N Freshwater FF P Freshwater	0.15 0.12 0.01	-0.22 – 1.00 0 – 1.00 0 – 0.26	This Study
Precipitation	pnet	FF N Marine FF N Freshwater FF P Freshwater	0.03 0.02 -	-0.24 – 0.63 -0.022 – 0.53 -	This Study
Temp	t	FF N Marine FF N Freshwater FF P Freshwater	0.016 0.13 -	0 – 0.26 0 – 1.14 -	This Study
Groundwater Depth	D_{sgrw}, D_{dgrw}	FF N Marine FF N Freshwater FF P Freshwater	-0.02 -0.03 ~	-0.80 – 0 -0.97 – 0 ~	This Study
		Water Compartment of FF			
Hydraulic Load	H_L	FF N Marine FF N Freshwater FF P Freshwater	2.72 0.84 0.67	-3.23 – 10 -1.05 – 4.39 0 – 4.11	This Study
Residence Time Marine	τ	FF N Marine	0.64	0.49 – 1.1	This Study
Residence Time freshwater	R	FF N Marine FF N Freshwater FF P Freshwater	-2.9 0.16 0.35	-92.03 – 7.06 -4.26 - 2.55 -4 - 1	This Study
N Load reaching Rivers	C_N	FF N Marine FF N Freshwater	-0.52 0.11	-2.14 - 10 -1.84 - 0.83	This Study
Temperature	t	FF N Marine FF N Freshwater FF P Freshwater	-3.97 -1.22 -0.83	-62.74 – 19.67 -7.98 – 1.88 -6.05 – 1.41	This Study
Discharge	Q	FF N Marine FF N Freshwater FF P Freshwater	57.99 -0.19 -0.21	-20.80 – 7.63e5 -2.66 – 2.69 -3.02 - 3.96	This Study

3.7 Ranked Cumulative Distribution and Inflection Point

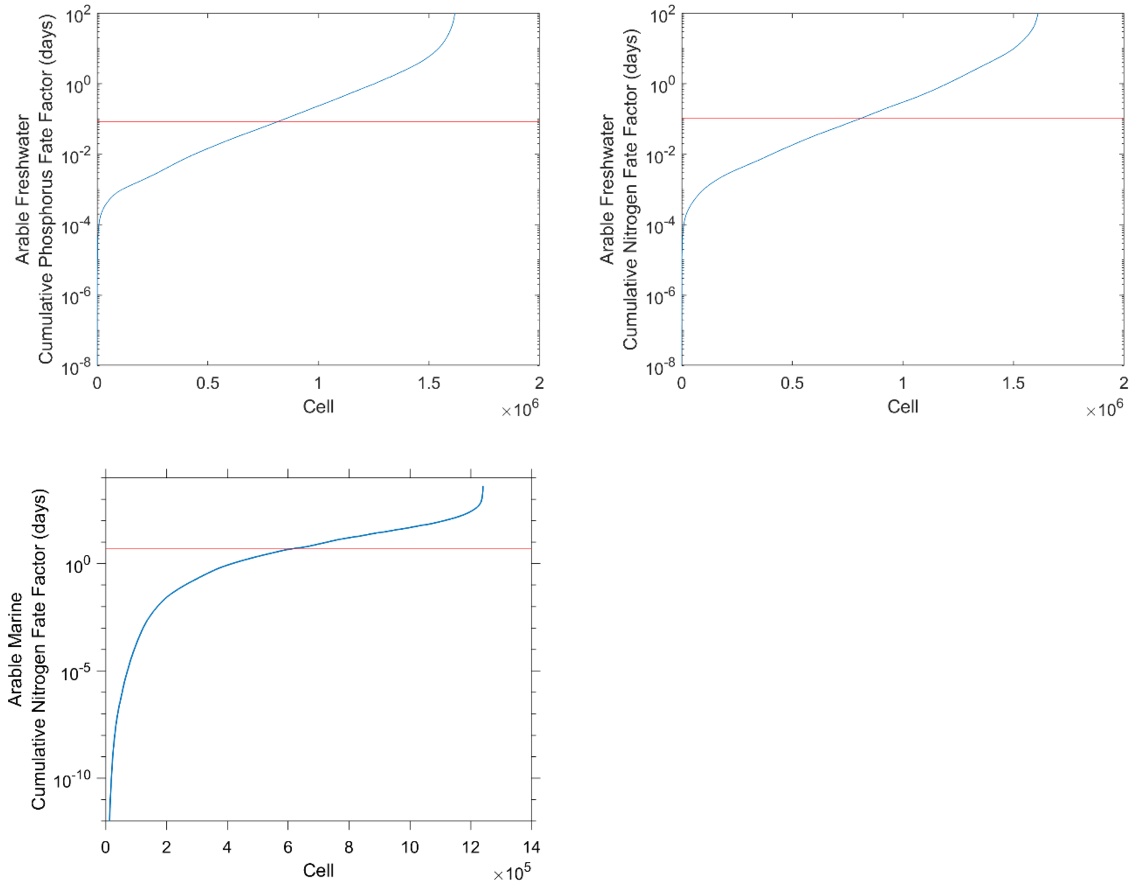
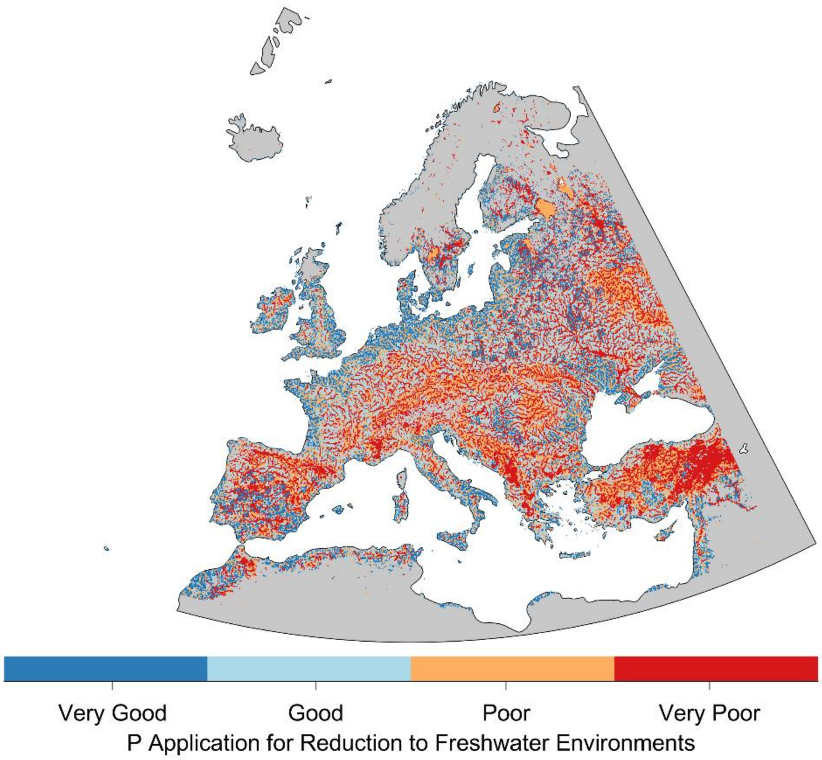


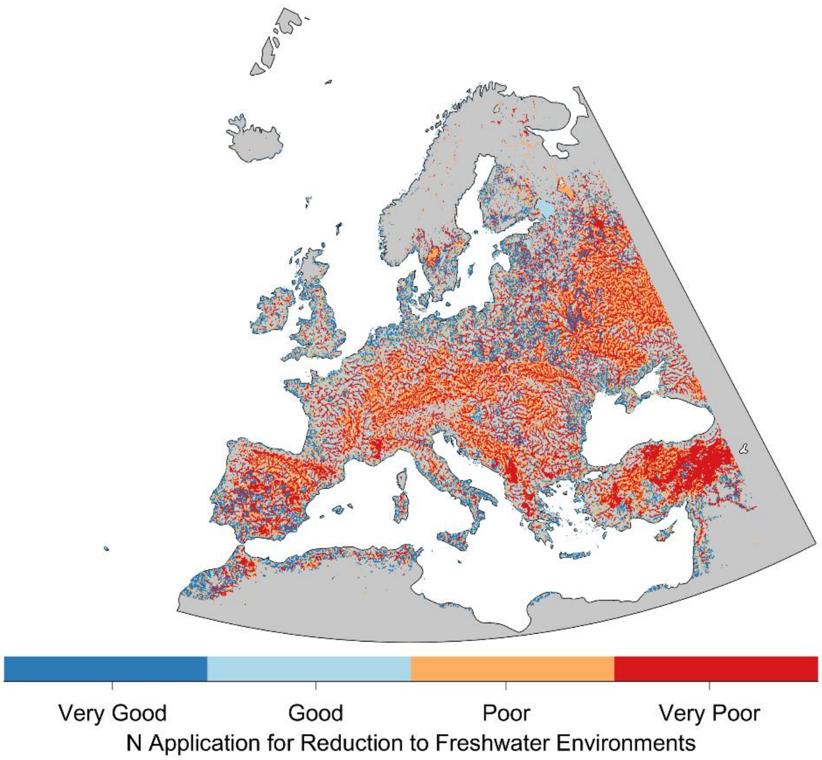
Figure 5: Ranked cumulative fate factors for (a.) Phosphorus and (b.) Nitrogen in Freshwater. Ranked fate factors for (c) Nitrogen in marine Environments. The Inflection line (red line) identifies emissions with short and long travel times to the river mouth or near marine ecosystem. Inflection for Phosphorus and Nitrogen in freshwater is 0.08 days and 0.12 days, respectively. For marine environments, nitrogen inflection increases to 5.07 days.

3.8 Nutrient Strategic Management Europe Example

a.



b.



c.

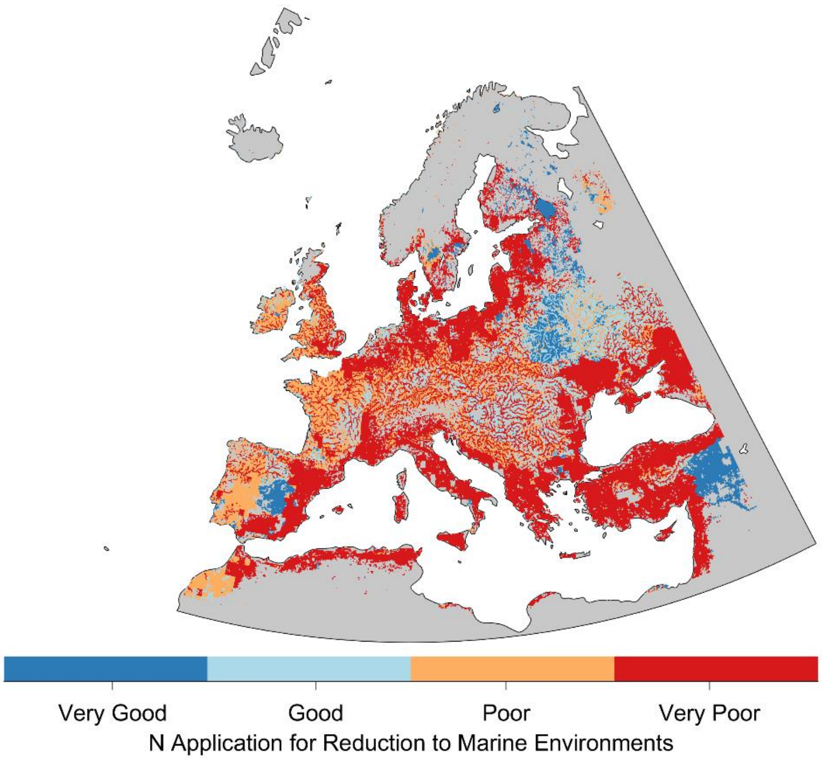
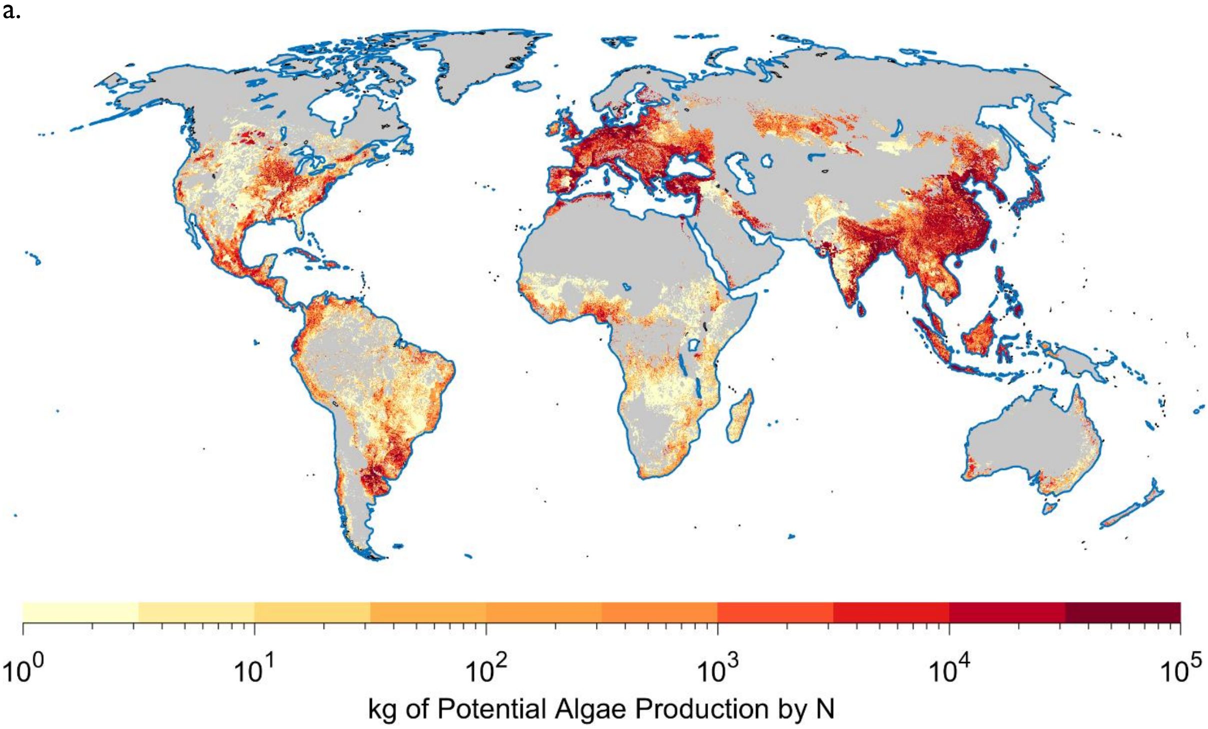


Figure 6: European spatial nutrient management plans for (a) P in freshwater, (b) Nitrogen in freshwater and (c) nitrogen in marine environments. The scale represents the best and worst location to apply fertilisers relative to their transportation within the receptor environment and over agricultural emissions.

3.9 Algae Production Freshwater

a.



b.

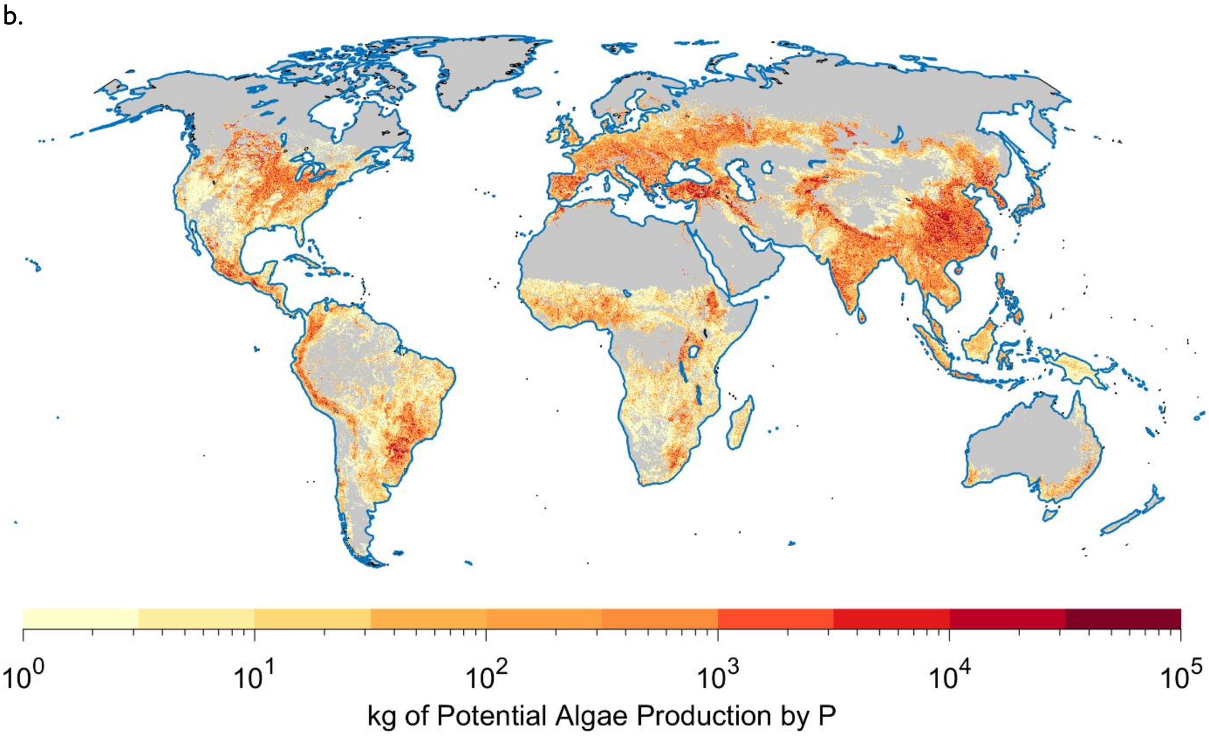


Figure 6: Potential algae growth caused by Nitrogen (a) and Phosphorus (b) loading under co-limitation assumptions

4 References

1. Helmes, R. J. K., Huijbregts, M. A. J., Henderson, A. D. & Jolliet, O. Spatially explicit fate factors of phosphorous emissions to freshwater at the global scale. *Int. J. Life Cycle Assess.* **17**, 646–654 (2012).
2. Scherer, L. & Pfister, S. Modelling spatially explicit impacts from phosphorus emissions in agriculture. *Int. J. Life Cycle Assess.* **20**, 785–795 (2015).
3. Cosme, N. M. D. Spatially explicit fate factors of waterborne nitrogen emissions at the global scale. *Int. J. Life Cycle Assess.* **23**, 1286–1296 (2018).
4. Liu, J. *et al.* A high-resolution assessment on global nitrogen flows in cropland. *Proc. Natl. Acad. Sci.* **107**, 8035–8040 (2010).
5. Sciences, N. A. of. Correction for Bouwman et al., Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900-2050 period. *Proc. Natl. Acad. Sci.* **110**, 21195–21195 (2013).
6. Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J. & Garnier, J. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. *Environ. Res. Lett.* **9**, 105011 (2014).
7. Zhang, X. *et al.* Managing nitrogen for sustainable development. *Nature* **528**, 51–59 (2015).
8. Velde, M. V. D., Bouraoui, F. & Aloe, A. Pan-European regional-scale modelling of water and N efficiencies of rapeseed cultivation for biodiesel production. *Glob. Change Biol.* **15**, 24–37 (2009).
9. Del Grosso, S. J. *et al.* Global scale DAYCENT model analysis of greenhouse gas emissions and mitigation strategies for cropped soils. *Glob. Planet. Change* **67**, 44–50 (2009).
10. Qiu, J. *et al.* GIS-model based estimation of nitrogen leaching from croplands of China. *Nutr. Cycl. Agroecosystems* **90**, 243–252 (2011).
11. Liu, W. *et al.* Global assessment of nitrogen losses and trade-offs with yields from major crop cultivations. *Sci. Total Environ.* **572**, 526–537 (2016).
12. Liu, W. *et al.* Integrative Crop-Soil-Management Modeling to Assess Global Phosphorus Losses from Major Crop Cultivations. *Glob. Biogeochem. Cycles* **32**, 1074–1086 (2018).

13. Liu, J., Williams, J. R., Zehnder, A. J. B. & Yang, H. GEPIC – modelling wheat yield and crop water productivity with high resolution on a global scale. *Agric. Syst.* **94**, 478–493 (2007).
14. OECD. *Environmental Performance of Agriculture in OECD Countries Since 1990*. (OECD, 2008). doi:10.1787/9789264040854-en.
15. Bouwman, A. F. *et al.* Lessons from temporal and spatial patterns in global use of N and P fertilizer on cropland. *Sci. Rep.* **7**, 1–11 (2017).
16. Turner, M. D., Hiernaux, P. & Schlecht, E. The Distribution of Grazing Pressure in Relation to Vegetation Resources in Semi-arid West Africa: The Role of Herding. *Ecosystems* **8**, 668–681 (2005).
17. Tully, K., Sullivan, C., Weil, R. & Sanchez, P. The State of Soil Degradation in Sub-Saharan Africa: Baselines, Trajectories, and Solutions. *Sustainability* **7**, 6523–6552 (2015).
18. Brentrup, F. & Lammel, J. Nitrogen Use Efficiency, Nitrogen balance, and Nitrogen productivity – a combined indicator system to evaluate Nitrogen use in crop production systems. 4 (2016).
19. Brentrup, F. & Lammel, J. Nitrogen Use Efficiency, Nitrogen balance, and Nitrogen productivity – a combined indicator system to evaluate Nitrogen use in crop production systems. in (2016).
20. Cassman, K. G., Dobermann, A., Walters, D. T. & Yang, H. Meeting Cereal Demand While Protecting Natural Resources and Improving Environmental Quality. *Annu. Rev. Environ. Resour.* **28**, 315–358 (2003).
21. Zhang, X. *et al.* Quantifying Nutrient Budgets for Sustainable Nutrient Management. *Glob. Biogeochem. Cycles* **34**, e2018GB006060 (2020).
22. Potter, P., Ramankutty, N., Bennett, E. M. & Donner, S. D. Characterizing the Spatial Patterns of Global Fertilizer Application and Manure Production. *Earth Interact.* **14**, 1–22 (2010).
23. West, P. C. *et al.* Leverage points for improving global food security and the environment. *Science* **345**, 325–328 (2014).
24. Mueller, N. D. *et al.* Closing yield gaps through nutrient and water management. *Nature* **490**, 254–257 (2012).

25. Smil, V. Nitrogen in crop production: An account of global flows. *Glob. Biogeochem. Cycles* **13**, 647–662 (1999).

26. Beusen, A. H. W., Van Beek, L. P. H., Bouwman, A. F., Mogollón, J. M. & Middelburg, J. J. Coupling global models for hydrology and nutrient loading to simulate nitrogen and phosphorus retention in surface water – description of IMAGE–GNM and analysis of performance. *Geosci. Model Dev.* **8**, 4045–4067 (2015).

27. Mosier, A. *et al.* Closing the global N2O budget: nitrous oxide emissions through the agricultural nitrogen cycle. *Nutr. Cycl. Agroecosystems* **52**, 225–248 (1998).

28. Reay, D. S., Dentener, F., Smith, P., Grace, J. & Feely, R. A. Global nitrogen deposition and carbon sinks. *Nat. Geosci.* **1**, 430–437 (2008).

29. Monfreda, C., Ramankutty, N. & Foley, J. A. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Glob. Biogeochem. Cycles* **22**, (2008).

30. Dentener, F. *et al.* Nitrogen and sulfur deposition on regional and global scales: A multimodel evaluation. *Glob. Biogeochem. Cycles* **20**, (2006).

31. Bouwman, A. F., Boumans, L. J. M. & Batjes, N. H. Modeling global annual N2O and NO emissions from fertilized fields. *Glob. Biogeochem. Cycles* **16**, 28-1-28–9 (2002).

32. Bouwman, A. F., Boumans, L. J. M. & Batjes, N. H. Estimation of global NH3 volatilization loss from synthetic fertilizers and animal manure applied to arable lands and grasslands. *Glob. Biogeochem. Cycles* **16**, 8-1-8–14 (2002).

33. Bouwman, L. *et al.* Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900–2050 period. *Proc. Natl. Acad. Sci.* **110**, 20882–20887 (2013).

34. Azevedo, L. B. *et al.* Species richness–phosphorus relationships for lakes and streams worldwide. *Glob. Ecol. Biogeogr.* **22**, 1304–1314 (2013).

35. Cosme, N. M. D. & Hauschild, M. Z. Estimation of Effect Factors for application to marine eutrophication in LCIA. in *Abstract book - SETAC Europe 24th Annual Meeting* (SETAC Europe, 2014).
36. Cosme, N., Koski, M. & Hauschild, M. Z. Exposure factors for marine eutrophication impacts assessment based on a mechanistic biological model. *Ecol. Model.* **317**, 50–63 (2015).
37. Life cycle impact assessment methodology. https://lc-impact.eu/.
38. ReCiPe2016v1.1. | RIVM. https://www.rivm.nl/documenten/recipe2016v11.
39. Goedkoop, M., Heijungs, R. & Huijbregts, M. Report I: Characterisation. 132.
40. Abell, R. *et al.* Freshwater Ecoregions of the World: A New Map of Biogeographic Units for Freshwater Biodiversity Conservation. *BioScience* **58**, 403–414 (2008).
41. Cosme, N. & Hauschild, M. Z. Characterization of waterborne nitrogen emissions for marine eutrophication modelling in life cycle impact assessment at the damage level and global scale. *Int. J. Life Cycle Assess.* **22**, 1558–1570 (2017).
42. Cosme, N. M. D. & Hauschild, M. Z. Effect factors for marine eutrophication in LCIA based on species sensitivity to hypoxia. *Ecol. Indic.* **69**, 453–462 (2016).
43. Cosme, N., Jones, M. C., Cheung, W. W. L. & Larsen, H. F. Spatial differentiation of marine eutrophication damage indicators based on species density. *Ecol. Indic.* **73**, 676–685 (2017).
44. Sutanudjaja, E. H. *et al.* PCR-GLOBWB 2: a 5 arcmin global hydrological and water resources model. *Geosci. Model Dev.* **11**, 2429–2453 (2018).