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LCA FOR AGRICULTURE

Modelling spatially explicit impacts from phosphorus emissions in agriculture

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Abstract
Purpose Excess phosphorus from fertilizer application and mobilised soil phosphorus from erosion are partially lost to the aquatic environment where they might cause eutrophication. Phosphorus emissions vary spatially and it is the goal of this study to broaden the scope of the existing inventory to the global scale and to increase the spatial resolution by accounting for relevant environmental processes.
Methods Phosphorus emissions were estimated globally at a resolution of 5 arc-minutes for 169 crops. Two models were coupled for that purpose. First, the Universal Soil Loss Equation (USLE) model was used to determine soil erosion which is the dominant process inducing phosphorus emissions. Second, the Swiss Agricultural Life Cycle Analysis (SALCA) model was applied to estimate the phosphorus emissions from four different processes with erosion being one of them. The emissions as inventory were compared to the ecoinvent database and subsequently translated into environmental impacts on biodiversity via characterisation factors. Additionally, sensitivity and contribution to variance analyses were carried out.
Results and discussion Our results suggest that the data in the ecoinvent database, which is widely used for life cycle assessments, underestimate phosphorus emissions by up to an order of magnitude. Furthermore, the contribution to variance analysis highlighted the importance of regionalising both, inventory results and characterisation factors.
Conclusions Since the ecoinvent database provides a poor representation of global conditions, we highly recommend using regionalised estimates of phosphorus emissions provided in this study.

Keywords Agriculture · Erosion · Eutrophication · Life cycle assessment · Life cycle impact assessment · Phosphorus emissions · Regionalisation

1 Introduction

Phosphorus is a macronutrient for which no substitute exists. As a non-renewable resource, its overuse could lead to phosphorus scarcity and consequently threaten food security (Cordell and White 2011; Vaccari and Strigul 2011). At the same time, the global absolute and per capita demands of phosphorus are steadily increasing due to increased food production for a growing population, intensified fertilizer application, increased demand for non-food crops such as biofuels, and diets changing towards a more meat- and dairy-based nutrition requiring higher phosphorus inputs (Cordell et al. 2009). According to Metson et al. (2012), meat consumption has the highest share on the global average phosphorus footprint, accounting for 72 %.

Globally, the planetary boundary of biogeochemical flows including phosphorus was already transgressed, which emphasises the severity of the issue (Steffen et al. 2015). Not only food production but also ecosystems are endangered by our high phosphorus use. Globally, the most prevailing threat to freshwater quality is eutrophication (Björklund et al. 2009; Khan and Mohammad 2014) which is caused precisely by

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excessive emissions of phosphorus (P) into the aquatic environment. P is generally considered as the main driver for primary production in freshwater systems. Its over-enrichment leads to immense growth of algae and cyanobacteria which deplete dissolved oxygen with their high respiration rates. Consequently, faunal mortality increases and biodiversity decreases. In addition, pathogen growth is stimulated and the value of the water body for industrial or recreational uses is reduced (Ansari et al. 2011; Khan and Mohammad 2014).

Considering the large impact eutrophication has on the environment, it is commonly taken into account in life cycle assessment (LCA) frameworks. Various methods exist for this impact category (Hellweg and Milà i Canals 2014). The model implemented in ReCiPe (Goedkoop et al. 2013) was recommended by the European Commission (JRC 2011). Helmes et al. (2012) calculated global spatially explicit fate factors of P describing its residence time in the aquatic environment which is mainly affected by advection and Azevedo et al. (2013b) derived the corresponding effect factors relating P concentration to potential decrease in relative species richness or the potentially not occurring fraction (PNOF, dimensionless) (Azevedo et al. 2013a) which can be set equal to the potentially disappeared fraction (PDF) commonly used for assessing impacts on ecosystem quality (Azevedo et al. 2014). The product of these fate and effect factors (that is, the characterisation factors) is available at a resolution of 0.5 ° within the LC-IMPACT project (LC-Impact 2014). However, data on P emissions to water (inventory) are still scarce and patchy: widely used databases, such as the ecoinvent database (ecoinvent Centre 2014), include a global estimate and a few country estimates (for mostly developed countries).

P emissions vary spatially and temporally (Withers and Jarvie 2008). Temporal differentiation is beyond the scope of this study, rather, focusing on spatial differentiation, the goal is to broaden the scope of the existing inventory to the global scale and to increase the spatial resolution by accounting for relevant environmental processes. For that purpose, the Universal Soil Loss Equation (USLE; Wischmeier and Smith 1978) model to predict erosion is coupled with the Swiss Agricultural Life Cycle Assessment (SALCA)–Phosphor (Prasuhn 2006) model to determine the P emissions reaching water bodies. The same model combination with many simplifications was already used in the Sustainability Quick Check for Biofuels (SQCB; Emmenegger et al. 2009), in the World Food LCA Database (Nemecek et al. 2014) and by Siegerist and Pfister (2013). Among others, the main limitations of these models are the use of a globally constant P concentration in soil and predefined tabulated values for soil erodibility.

This study builds on the model by Siegerist and Pfister (2013), improving the aforementioned main limitations and extending it from 3 to 169 crops (>99.9 % of all harvested crops). Detailed sensitivity analyses are carried out to improve the model and determine the gravity of any remaining limitations. The inventory results are coupled with the spatially explicit characterisation factors mentioned above in order to calculate the aquatic eutrophication impact of P for each crop and location. Finally, by accounting for the uncertainties, we calculated the contribution to variance of each model step to the overall impacts.

2 Methods

Multiple models were combined in order to determine phosphorus emission from agricultural fields to freshwater and to estimate their impact on species richness. The coupling is displayed in Fig. 1 and subsequent sections will further describe the individual models.

2.1 USLE model

The USLE model predicts average long-term soil loss caused by runoff (Wischmeier and Smith 1978). The USLE equation as modified by Emmenegger et al. (2009) is defined as:

$$A = R \cdot K \cdot \mathrm{LS} \cdot C_1 \cdot C_2 \cdot P \quad (1)$$

where A is the annual soil loss rate ($t\mathrm{ha}^{-1}\ \mathrm{a}^{-1}$), R is the erosivity factor (MJ mm ha^{-1} h^{-1} a^{-1}), K is the erodibility factor (th MJ^{-1} mm^{-1}), LS is the slope length factor (−), C_1 is the crop factor (−), C_2 is the tillage factor (−) and P is the practice factor (−).

The erosivity factor (R) expresses the erosion pressure. It is derived from precipitation and irrigation with a correction factor (f_w) for winter-type precipitation distributions (at least one winter month whose precipitation exceeds 15 % of the annual average) (E2; Emmenegger et al. 2009). Precipitation data were obtained from the WorldClim database (Hijmans et al. 2005) and irrigation data from Pfister et al. (2011).

$$R = \begin{cases} f_\mathrm{w} \cdot 0.0483 \cdot P^{1.61} \ \text{if} \ P \leq 850 \ \text{mm} \\ f_\mathrm{w} \cdot (587.8 - 1.219 \cdot P + 0.004105 \cdot P^2) \text{if} \ P > 850 \ \text{mm} \end{cases} \quad (2)$$
$$\text{where}$$
$$P = \text{precipitation} + 0.1 \cdot \text{irrigation}$$

The erodibility factor (K) describes the vulnerability of the soil to erosion. It was calculated based on an empirical equation developed by Williams and Singh (1995) which takes into account soil texture (m_sand, m_silt and m_clay as percent sand, silt and clay content) and organic carbon content (orgC; E3). Soil properties were extracted from the Harmonized World Soil Database (HWSD; Nachtergaele et al. 2012). For some European Union (EU) countries, K was readily available (Panagos et al. 2014). Compared to those values, we underestimated K and therefore applied a multiplicative bias correction to the HWSD global estimates. In

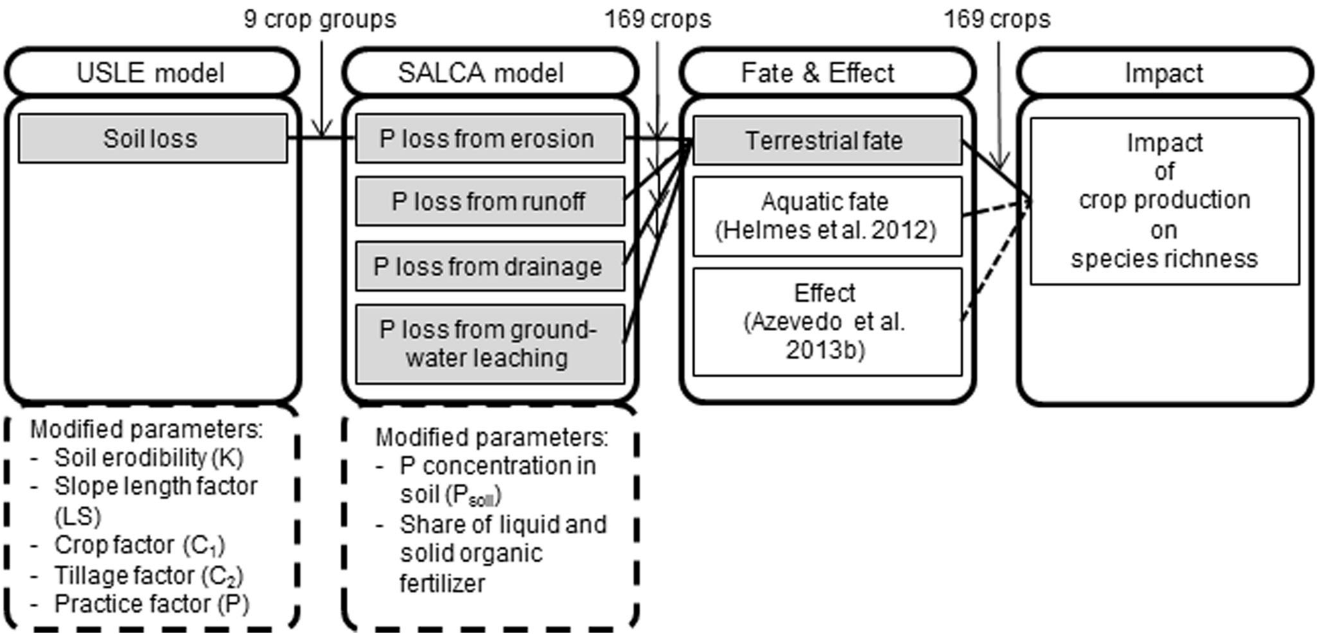

Fig. 1 Flow chart of model coupling (*grey boxes* indicate processes we modelled while *dashed connecting lines* indicate inputs from processes we did not model.)

addition, we replaced K for those EU countries with the data from Panagos et al. (2014).

$$K = f_{\text{csand}} \cdot f_{\text{clay-silt}} \cdot f_{\text{org}} \cdot f_{\text{hsand}}$$
where
$$f_{\text{csand}} = 0.2 + 0.3 \cdot \exp[-0.256 \cdot m_{\text{sand}} \cdot (1 - m_{\text{silt}}/100)]$$
$$f_{\text{clay-silt}} = \left(\frac{m_{\text{silt}}}{m_{\text{clay}} + m_{\text{silt}}}\right)^{0.3}$$
$$f_{\text{org}} = 1 - \frac{0.0256 \cdot \text{orgC}}{\text{orgC} + \exp(3.72 - 2.95 \cdot \text{orgC})}$$
$$f_{\text{hsand}} = 1 - \frac{0.7 \cdot \left(1 - \frac{m_{\text{sand}}}{100}\right)}{1 - \frac{m_{\text{sand}}}{100} + \exp\left[-5.51 + 22.9 \cdot \left(1 - \frac{m_{\text{sand}}}{100}\right)\right]} \quad (3)$$

The slope length factor (LS) was derived from a digital elevation model (GMTED2010; Danielson and Gesch 2008) using the GRASS GIS module r.watershed (output parameter: length.slope; GRASS Development Team 2014).

The crop factor (C_1) expresses the effectiveness of a crop cover in preventing soil loss (Table 1). A table with predefined values provided in the OMAFRA factsheet (Stone and Hilborn 2012) was expanded to include the nine crop groups of the 169 crops (Table S1, Electronic Supplementary Material) obtained from Monfreda et al. (2008).

The tillage factor (C_2) compares the effectiveness in preventing soil loss of different crop management systems. In this study, C_2 is estimated on country level based on the human development index (HDI; UNDP 2014) and the score for pesticide regulation within the environmental performance index for agriculture (EPIA; Hsu et al. 2014). We assumed that countries with a low HDI use less machinery, while countries with a high HDI consciously take preventive action against erosion and avoid tillage. In contrast, countries with a medium HDI (around 0.65) cause more erosion. Therefore, we transformed the HDI to HDI* (E4). We further assumed that countries that regulate the use of pesticides also perform other measures in the agricultural sector to reduce the environmental impact such as erosion in this case. Based on these assumptions, we set C_2 for countries with a HDI* of at least 0.9 to 0.3 (best case scenario would be C_2=0.25), while for countries with low HDI* and EPIA (on average below 50 % of their maximum), the worst case scenario was assumed (C_2=1.0). For values between 50 and 100 % of the two indicators, we linearly scaled between 0.3 and 1, giving equal weights to HDI* and EPIA:

$$C_2 = \begin{cases} 0.3 \ \text{if} \ \text{HDI}^* \geq 0.9 \\ 1.7 - 0.7 \cdot \left(\text{HDI}^* + \frac{\text{EPIA}}{100}\right) \\ 1 \ \text{if} \frac{\text{HDI}^* + \text{EPIA}/100}{2} < 0.5 \end{cases} \quad (4)$$
where
$$\text{HDI}^* = \begin{cases} -2 \cdot \text{HDI} + 1.6 \ \text{if} \ \text{HDI} \leq 0.65 \\ 2.3 \cdot \text{HDI} - 1.2 \ \text{if} \ \text{HDI} > 0.65 \end{cases}$$

The practice factor (P) reflects the effectiveness of different cropping practices in reducing runoff and thereby erosion. It was determined by analogy with the determination of C_2, based on the untransformed HDI and EPIA and resulting in the intermediate variable P*. Additionally, it was assumed that the practices are most effective for slopes between 3 and 8 % (Wischmeier and Smith 1978) and P was increased for slopes

Table 1 C_1 factors for different crop types

Crop type	C_1 factor	Crop type in Stone and Hilborn (2012)
Maize	0.4	Grain corn
Forage, pulses, and oil crops (except for trees)	0.5	Silage corn, beans, and canola
Cereals (except for maize)	0.35	Cereals (spring and winter)
Vegetables, roots, tubers, melons	0.5	Seasonal horticultural crops
Fruits, nuts, and other trees	0.1	Fruit trees
Grasses	0.02	Hay and pasture
Sugar crops	0.4[a]	
Fibres (except for trees)	0.5[b]	
Others (except for trees)	0.5[c]	

[a] Based on the average of sugar beet and sugar cane as used by Emmenegger et al. (2009)

[b] Based on the combined value of C_1 and C_2 for flax in the ArcSWAT (Olivera et al. 2006) database when scaled to the range of C_1

[c] Worst case

outside of this range based on correction factors P_{corr} as presented in Table 2, but constraint to a maximum of 1:

$$P = P^{*} \cdot P_{corr} \tag{5}$$

2.2 SALCA model

The SALCA model predicts phosphorus emissions from the initial phosphorus content in soils and the application of mineral and organic fertilizers to water bodies via four different processes: erosion (P_e; E4), surface runoff (P_r; E5), drainage (P_d; E6) and groundwater leaching (P_g; E7) (Prasuhn 2006). Emmenegger et al. (2009) incorporated the crop yield into the equations in order to relate the emissions to 1 kg of harvested product:

$$P_e = A \cdot r \cdot e \cdot P_{soil} \cdot \frac{1}{1000 \cdot Y} \tag{6}$$

r is the fraction of P loss reaching the aquatic environment (−). The default value valid for Swiss conditions amounts to 0.2. This was extrapolated to the global scale based on the aridity index (Zomer et al. 2008) as described in Siegerist and Pfister (2013).

Table 2 Correction factors for practice factor (P_{corr})

Slope range (%)	P_{corr}
0–3	1.2
3–8	1.0
8–12	1.2
12–16	1.4
16–20	1.6
20–24	1.8
24–28	2.0
28–32	2.2

e is the enrichment factor (−) and was set to 2 as suggested by Roy et al. (2003). It reflects a higher nutrient content in eroded soil compared to the original soil because finer particles which the nutrients are more associated with are eroded first.

P_{soil} is the P concentration in soil (kg P t^{-1}) and was derived from the P area density (Yang et al. 2013) disregarding occluded P as it was assumed to be biologically unavailable. The area density was multiplied with the bulk density of the soil obtained from the HWSD (Nachtergaele et al. 2008) and a depth of 0.5 m (Yang et al. 2013). Gaps in P area density and soil bulk density were initially filled applying focal statistics with a moving window of 11x11 cells and remaining gaps were set to the global mean.

Y is the crop-dependent yield ($t\,ha^{-1}$) and was obtained from Monfreda et al. (2008).

$$P_r = s \cdot k_r \cdot \left(1 + \frac{0.2}{80} \cdot f_m + \frac{0.7}{80} \cdot f_{ol} + \frac{0.4}{80} \cdot f_{os}\right) \cdot \frac{1}{1000 \cdot Y} \tag{7}$$

s is the slope factor (−). The binary variable was set to zero for slopes less than 3 % and to 1 for slopes equal or greater than 3 % (Prasuhn 2006). Slopes were derived from the same digital elevation model as described above (GMTED2010; Danielson and Gesch 2008).

k_r is the average phosphorus leaching by runoff (kg P ha^{-1} a^{-1}) and was categorised by land use (Table 3). Land use categories were provided by Ellis and Ramankutty (2008) as anthropogenic biomes.

f_m, f_{ol} and f_{os} denote mineral, liquid organic and solid organic fertilizer application rates (kg P ha^{-1}). Since organic fertilizer and especially liquid organic fertilizer are more easily washed off than mineral fertilizer, they are associated with a higher factor (Prasuhn 2006). The application rates were obtained from Potter et al. (2010). P content in manure production was assumed to correspond to that in the total organic

Table 3 Average phosphorus leaching by runoff (k_r) and drainage or groundwater leaching (k_l) assigned to different biomes

Biome	k_r (kg P ha^{-1} a^{-1})	k_l (kg P ha^{-1} a^{-1})	Land use in Prasuhn (2006)
Cropland and villages with crops	0.175	0.07	Open arable land
Rangeland and pastoral villages	0.25	0.06	Pastures and meadow
Forests and wildlands	0.1	0.05	Unproductive vegetation
Dense settlements	0.1	0.05	

fertilizer. Siegerist and Pfister (2013) split it into liquid manure (slurry) and solid manure by assuming a globally constant ratio of 40:60. In this study, a higher fraction of liquid organic fertilizer was assumed for intensive livestock farming (60:40) and a lower fraction otherwise (40:60). A location was considered to use intensive livestock farming when cattle and/or pig intensity exceeded 250 head/km^2 and/or chicken intensity exceeded 10,000 head/ km^2. The livestock intensities were obtained from Robinson et al. (2014).

$$P_d = k_l \cdot \left(1 + \frac{0.2}{80} \cdot f_{ol}\right) \cdot d_d \cdot \frac{1}{1000 \cdot Y} \tag{8}$$

$$P_g = k_l \cdot \left(1 + \frac{0.2}{80} \cdot f_{ol}\right) \cdot d_g \cdot \frac{1}{1000 \cdot Y} \tag{9}$$

k_l is the average phosphorus leaching by drainage or groundwater and is categorised by land use (Table 3). d_d and d_g are the drainage and groundwater factors. As suggested by Emmenegger et al. (2009), the drainage factor was set to 6.0 and the groundwater factor to zero if conventional drainage was performed, and were otherwise set to zero and one, respectively. Information on drainage was given in the HWSD (Nachtergaele et al. 2012). Conventional drainage was assumed for drainage classes above 3, which is at least 'moderately well drained'.

2.3 Sensitivity analyses

Sensitivity analyses were carried out on soil erodibility, initial P concentration in soil and multiple cropping (MC) systems. Soil erodibility and initial P concentration in soil were chosen because both parameters were modified compared to previous global assessments of P emissions and both were determined based on physical relationships and improved input data instead of empirical relationships and new assumptions.

We tested how using the erodibility values calculated according to Williams and Singh (1995) without bias correction and overlay with the EU data from Panagos et al. (2014) would affect the model outcome.

Regarding initial P concentration in soil, two cases were considered as follows: (i) the total P concentration including potentially biologically unavailable occluded P is used and (ii) only the sum of organic and labile inorganic P as P from secondary minerals or apatite becomes biologically available at a much slower rate (Smits et al. 2012; Yang et al. 2013).

In order to locate potential regions for multiple cropping, the length of growing period (LGP; van Velthuizen et al. 2007) was compared to the length of crop cycle for six different climate zones (LCC; Chapagain and Hoekstra 2004). If the LPG allowed for multiple crop cycles, the overall annual yield was increased accordingly while the harvested area was decreased.

2.4 Impacts

The P emissions calculated with the USLE-SALCA model combination reflect the inventory or environmental exchanges with the aquatic environment (EE in kg P/kg crop) of P applied to agricultural fields and naturally contained in soils. Its persistence in the water bodies is described by spatially explicit fate factors (FF in days; Helmes et al. 2012) while the effect factors (EF in m^3/kg P; Azevedo et al. 2013b) describe the potential decrease in relative species richness due to the P concentration in freshwater. The product of the FF and the EF define the characterisation factors (CF in days m^3/kg crop), and multiplying the CF in turn by the EE results in the impacts (I in days m^3/kg crop):

$$I = \mathrm{EE} \cdot \mathrm{FF} \cdot \mathrm{EF} = \mathrm{EE} \cdot \mathrm{CF} \tag{10}$$

Since the FF and EF were only available at a resolution of 0.5 arc degrees, the rasters were disaggregated to a resolution of 5 arc-minutes.

2.5 Production-weighted averages

Global, production-weighted average P emissions and impacts on species richness were calculated for each crop after treating outliers at the upper end. Production was derived by multiplication of crop yield with the harvested area in each location. Outliers were defined according to the adjusted boxplot for skewed distributions (Hubert and Vandervieren 2008) and were replaced with the cut-off value in order to avoid distorted results.

2.6 Contribution to variance

The contribution to variance (CTV) was applied by Mutel et al. (2013) within a 2-step sensitivity analysis approach which they especially recommended for regionalised LCAs.

Table 4 Phosphorus emissions to water for different crop productions

Crop	P (kg P/kg crop)	Cut-off quantile	Ecoinvent dataset	P (kg P/kg crop)
Maize	0.00088	0.95	Maize grain production (GLO)	0.00010
Rice	0.00214	0.96	Rice production (GLO)	0.00015
Soybean	0.00210	0.95	Soybean production (GLO)	0.00031
Wheat	0.00057	0.94	Wheat production (GLO)	0.00031

In this study, we used CTV to investigate how much compared to the CF the inventory data contribute to the spatial variability of the impacts. We considered the P emissions from field to the aquatic environment (environmental exchange) and the product of fate and effect factors as CF. CTV is based on squared rank-order correlation coefficients (ROCC). While Mutel et al. (2013) used Spearman's ROCC, we additionally applied Kendall's ROCC (Kendall 1938). The ROCC were also weighted by production. In the case of Kendall's ROCC the product of weights for each data pair was used (Shieh 1998). The calculation of Kendall's ROCC is computationally demanding as it considers all data pairs individually, therefore the raster was randomly split into 100 equally sized data chunks and their ROCC were averaged.

3 Results

3.1 Inventory modelling

The phosphorus emissions to the aquatic environment represent the inventory. Their crop-specific averages are compiled in Table 4 for four of the most produced crops worldwide. As a comparison, the values from the ecoinvent database (ecoinvent Centre 2014) are also listed. The newly calculated global average emissions are 7 to 14 times higher than the ecoinvent estimates with the exception of those for wheat which are less than twice as high. The average emissions for the remaining 165 crops are provided in the Electronic Supplementary Material. Additionally, the average emissions of the four selected crops were compared to ecoinvent data at the country level where national estimates were available (Table S2, Electronic Supplementary Material), showing a high discrepancy.

The spatial distribution of phosphorus emissions to water is displayed in Fig. 2. If no crop was produced (yield equalled zero), the emissions were set to zero and are shown in grey on the maps.

Four processes influence phosphorus emissions to the aquatic environment: erosion, surface runoff, drainage and groundwater leaching. Globally, erosion is clearly the dominant process (Table 5). But it was ascertained that also groundwater leaching plays a key role in phosphorus emissions to aquatic environments. It contributes on average 34 % to the total emissions and is the dominant cause for 18 % of the crops (31 out of 169). While erosion is dominant in the tropics, groundwater leaching plays a major role in the temperate climate zone (Fig. 3).

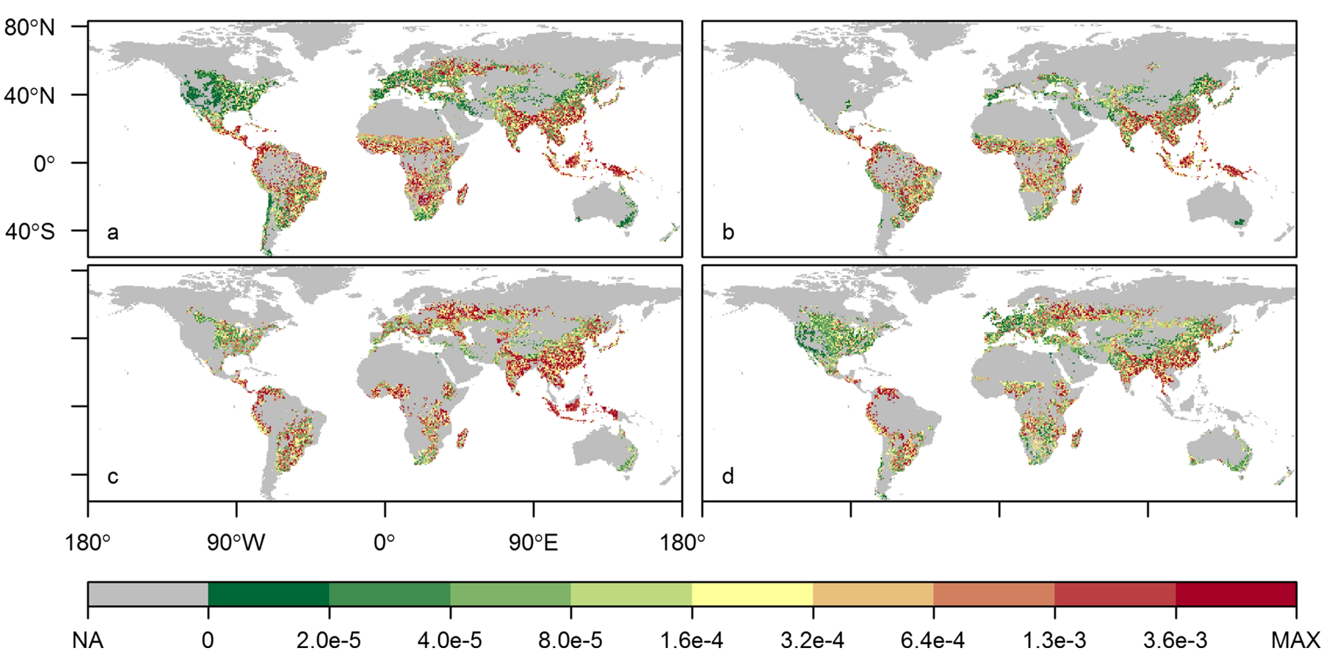

Fig. 2 Phosphorus emissions of different crops (**a** maize, **b** rice, **c** soybeans, **d** wheat) to water (kg P/kg crop)

Table 5 Percentages of processes on total phosphorus emissions (global)

Crop	Erosion	Runoff	Drainage	Groundwater
Maize	61.7	2.9	6.4	29.0
Rice	65.6	3.1	5.3	26.0
Soybean	67.1	2.6	3.9	26.4
Wheat	55.7	3.4	6.3	34.6

3.2 Sensitivity analyses

The effects of a lower soil erodibility (K), a lower or higher P concentration in soil (P_{soil}) and multiple cropping (MC) on the P emissions to water were tested (Table 6). P_{soil} affects the model output the most. The influence of MC largely depends on the crop cycle. With the shortest crop cycle (85 to 150 days) soybean is the only crop that allows for triple cropping in some regions of the world while for the other crops investigated at most double cropping is possible.

3.3 Impacts

The environmental impacts are calculated using fate and effect factors (Table 7). Soybeans have the most severe impacts on species richness among the four crops exemplified. Although wheat caused the lowest emissions, its impacts on species richness were the second highest.

The spatial variability of impacts on species richness is displayed in Fig. 4. The impacts are especially high around Lake Victoria and along the Russian border to Kazakhstan. Both hotspots are not that notable in the inventory results (Fig. 2). On the other hand, hotspots in the inventory such as in Indonesia do not stand out as impacts anymore.

3.4 Contribution to variance

The contribution to variance (CTV) analyses revealed that most of the spatial variability in impacts on species richness was associated with the CF (Table 8). However, the

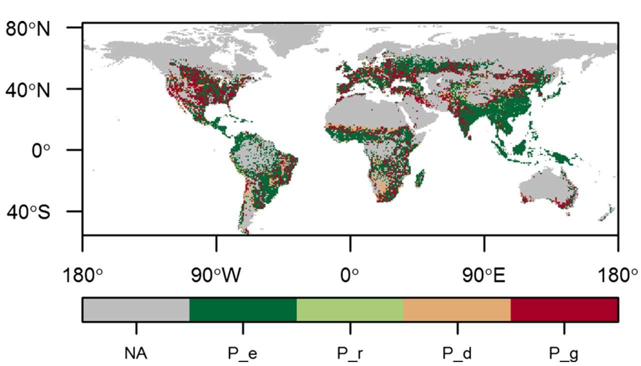

Fig. 3 Dominant process causing phosphorus loss based on the mode for maize, rice, soybeans and wheat

contribution of EE was also considerable with an average about 40 % (Table S7 and S8, Electronic Supplementary Material). Summary statistics of the tested parameters are given in the Electronic Supplementary Material (Table S9, Electronic Supplementary Material).

4 Discussion

The phosphorus emissions to the aquatic environment represent the environmental exchanges, in accordance with the definition of inventory for the crop production stage in the ecoinvent database. Another way of looking at phosphorus emissions could be by differentiating the receiving compartment. Accordingly, there would be terrestrial/agricultural fate factors, as well as aquatic fate factors, as already calculated by Helmes et al. (2012). The emissions would then have to be split into multiple parts depending on what is used as inventory. The inventory could be land occupation or land transformation in case of erosion and different types of fertilizer for runoff, drainage or groundwater leaching. The second approach allows for a more detailed assessment, but also requires more input data which might not always be available.

Due to these effects, the phosphorus emissions are crop-dependent. On the one hand, the annual soil loss rate estimated with the USLE model takes into account the crop factor C_1 which distinguishes several crop types in their effectiveness to prevent soil loss (Table 1). On the other hand, the crop yield is considered in the SALCA model in order to get a crop-specific output (per kilogramme product) instead of an area-specific one (per hectare).

The USLE model only considers sheet and rill erosion, but not gully or stream channel erosion (Wischmeier and Smith 1978) which would occur at higher rainfall intensity or longer rainfall duration. Furthermore, the USLE model disregards wind erosion. Wind erosion is only half as important as water erosion with regards to affected area (Batjes 1996). Nevertheless, soil loss and related P emissions might be underestimated in some regions, especially where the wind erosion vulnerability is high (Emmenegger et al. 2009). Furthermore, the transfer of P between model cells which mainly occurs via river flows was only considered in the aquatic fate factors via advection (Helmes et al. 2012). The inner-cell transfer of P during the agricultural and terrestrial fate is likely to be negligible considering the large cell size of 5 arc-minutes (about 10 km). The yields used as model input in this study were available for the year 2000, but they are likely have increased since then (Foley et al. 2011), while they might also have stagnated or even collapsed in some parts of the world (Ray et al. 2012). In addition, the model still relies on some assumptions such as the assignment of C_1 factor based on crop groups thereby neglecting further crop-specific variations as well as the derivation of C_2 and P based on HDI and

Table 6 Sensitivity analyses

Crop	Original	*K* (−31 %)	P_{soil} (−55 %)	P_{soil} (+43 %)	MC[a]
Maize	0.00088	0.00061 (−31 %)	0.00046 (−47 %)	0.00139 (57 %)	0.00070 (−21 %)
Rice	0.00214	0.00145 (−32 %)	0.00116 (−46 %)	0.00349 (63 %)	0.00176 (−18 %)
Soybean	0.00210	0.00143 (−32 %)	0.00104 (−51 %)	0.00350 (67 %)	0.00150 (−29 %)
Wheat	0.00057	0.00040 (−30 %)	0.00031 (−46 %)	0.00085 (48 %)	0.00053 (−8 %)

[a] Crop specific (Maize +28 %, rice +16 %, soybean +61 %, wheat +21 %)

EPIA without empirical verification. It was also assumed that all P from fertilizers is bioavailable which might lead to an overestimation of the impacts in some parts of the world. These aspects should be improved in future research.

Despite the above-mentioned limitations of the model, it was still greatly improved compared to the hitherto existing global assessments (Nemecek et al. 2014; Siegerist and Pfister 2013). The most significant improvements made concerned soil erodibility (*K*), slope length factor (LS) and P concentration in soil (P_{soil}). All three parameters are related to soil erosion which was identified as the dominant process in P emissions. While P_{soil} was not explicitly addressed in previous work, our results show that it is one of the most important parameters.

This study built on the model by Siegerist and Pfister (2013), but the resulting P emissions are by a factor of 6 to 12 lower for the three crops maize, rice and wheat investigated by them. The slope length related to the slope length factor LS (Wischmeier and Smith 1978) was on average higher than the default assumed by Siegerist and Pfister (2013) and therefore counteracted a reduction in P emissions. On the other hand, C_1, C_2, P, P_{soil} and the ratio of f_{ol}/f_{os} were on average lower and thereby decreased the emissions. The global averages of soil erodibility *K* in the two studies matched well, but the spatial patterns differed. The contribution of the outlier treatment to the reduction of P emissions is minimal, as cut-off levels were higher or only slightly lower than the default cut-off level at 95th quantile assumed previously (Siegerist and Pfister 2013).

Despite the above-mentioned reduced estimates in emissions, results are still significantly higher than values provided in the ecoinvent database (ecoinvent Centre 2014; Table 4). Even the combined effect of a lower *K*, a lower P_{soil} and MC as investigated in the sensitivity analysis cannot explain the huge differences in estimates compared to ecoinvent data with the exception of wheat where the discrepancies are lowest. The values for global P emissions in the ecoinvent database are rough estimates based on a few national estimates from European countries and the USA (wheat with the most national datasets is represented by five countries). Due to the high spatial variability of environmental parameters, but also large socio-economic differences especially with developing countries, this limited country dataset is not well suited to extrapolate to the rest of the world. Furthermore, similar limitations as discussed for other previous global assessments such as a global value for P_{soil} apply here as well (Nemecek and Schnetzer 2011). In addition, they used a different erosion model which was specifically developed for Switzerland and in which many of the predefined tabulated input values are classified into five Swiss regions (Oberholzer et al. 2006) which cannot easily be translated into regions in other countries. Thus, we advise against using their global estimates. Instead, the large differences highlight the importance of a regionalised assessment.

Table 7 Global average freshwater eutrophication impacts on species richness for different crops

Crop	*I* (days m^3/kg crop)	Cut-off quantile
Maize	2.67e-08	0.94
Rice	2.94e-08	0.94
Soybean	5.50e-08	0.94
Wheat	3.89e-08	0.94

Erosion is the dominant process leading to P emissions and this is especially true for the tropics (Peel et al. 2007) whose soils have on average a low bulk density (Nachtergaele et al. 2012). In contrast, groundwater leaching plays a major role in the arid climate zone with soils of a higher bulk density. The relatively high contributions of groundwater leaching seem to contradict the long-held view that dissolved P is quickly immobilised by adsorption and metal complex formation. However, Holman et al. (2008) also suggest that groundwater leaching might be an overlooked contributor to eutrophication.

Among the four main crops exemplified (maize, rice, soybeans, wheat) soybean, a crop mainly used as animal feed (Brown 2009), caused the largest impact on species richness per kilogramme. This is not only explained by high emissions (which are also high for rice), but also by a high vulnerability to biodiversity loss in the presented effect factors of the soybean production areas. For all four crops, the spatial pattern between P emissions and impacts on species richness differ. While the emissions are especially high in Indonesia (except for wheat) and in South and Southeast Asia (wheat), the hotspots of impacts are located around Lake Victoria and along the Russian border to Kazakhstan. High emissions are often associated with high precipitation and thus high erosivity (*R*). The relatively lower influence of the emissions on the actual impacts was confirmed by the contribution to variance analysis, which on average, attributed more than a third of the spatial variability in

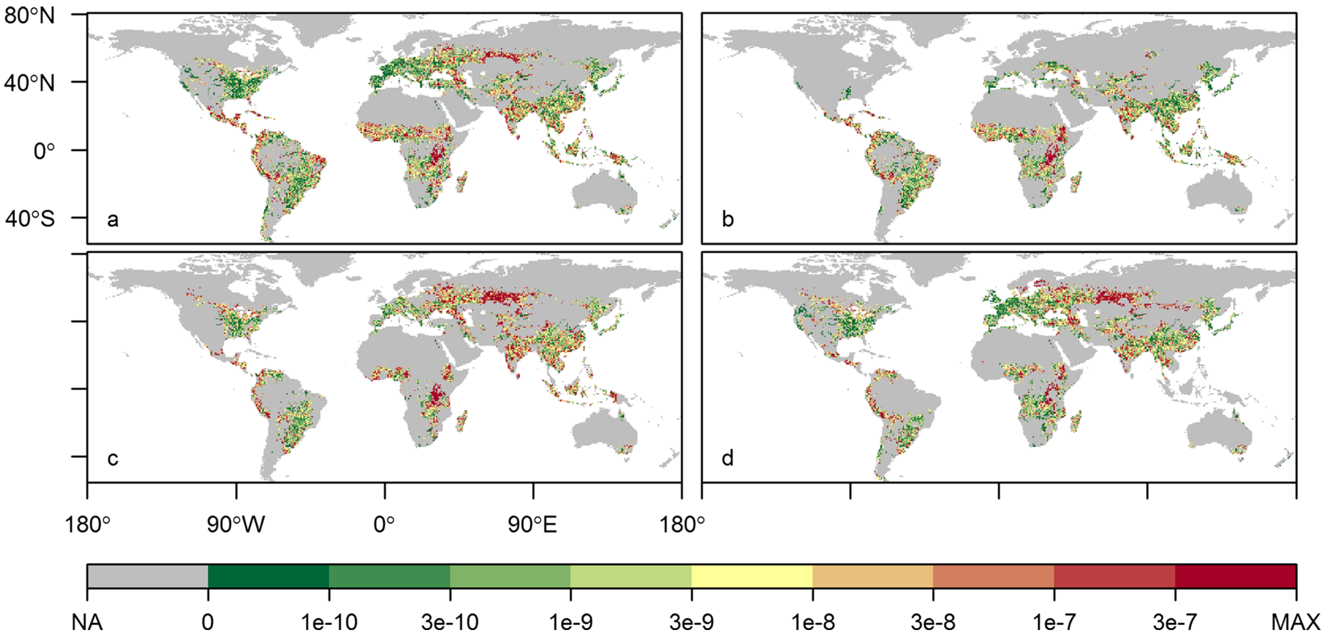

Fig. 4 Impacts of different crops (**a** maize, **b** rice, **c** soybeans, **d** wheat) on species richness (days m^3/kg crop)

impacts to the emissions, while most of the spatial variability was associated with the characterisation factors.

The response of organisms to increased phosphorus levels was investigated without taking interactions with other stressors into account (Azevedo et al. 2013b). In particular, nitrogen (N) has been reported to be equally essential for primary production as phosphorus (Elser et al. 2007). Although primary production is not directly linked to biodiversity, its changes are an indicator of changes in ecosystem quality and specifically of eutrophication (Andersen et al. 2006). Additionally, simultaneous enrichment of both nutrients creates strong synergetic effects (Elser et al. 2007). This limitation constitutes a source of uncertainty in the applied effect factors and might lead to an underestimation of coupled impacts in some parts of the world. Even if most freshwater systems are P limited (Schindler 1974; Correll 1998), nitrogen emissions still affect aquatic eutrophication (Seppälä et al. 2004) and their mass fluxes are often higher than those of phosphorus (Carpenter et al. 1998; Seppälä et al. 2004). Although the effects of N and P cannot be truly compared by mass, it still points out that the effects of N should not be neglected.

A full LCA study evaluates the impacts on three areas of protection or damage categories: human health, biodiversity/ecosystem services and natural resources (Hellweg and Milà i Canals 2014). Impact pathways for depletion of phosphate rocks, a source for phosphorus, exist since a long time (Brentrup et al. 2002). The impacts on biodiversity were considered in this study based on recently developed effect factors (Azevedo et al. 2013b). But there is currently no methodology available to assess the impacts of phosphorus scarcity on human health as a consequence of limited food production and malnutrition. The latter could be assessed analogously to impacts of water scarcity on human health as in the method developed by Pfister et al. (2009).

5 Conclusions

This study improved the global assessment of phosphorus emissions to the aquatic environment on a high spatial level

Table 8 Contribution to variance analyses

	Spearman		Kendall	
Crop	EE (kg P/kg crop)	CF (days m^3/kg P)	EE (kg P/kg crop)	CF (days m^3/kg P)
Maize	0.46	0.54	0.44	0.56
Rice	0.51	0.49	0.43	0.57
Soybean	0.47	0.53	0.46	0.54
Wheat	0.34	0.66	0.32	0.68

of detail for >99.9 % of all harvested crops. Compared to previous studies, the modelling schemes for soil erodibility and length slope factor as well as the input data for phosphorus concentration in soils were refined. Since these parameters are related to soil erosion, which stood out as the dominant process in phosphorus emissions, the model is considerably improved. Compared to our results, the data available in the ecoinvent database highly underestimate the emissions. We therefore discourage from using their estimates for global analyses.

The magnitude of the emissions and the associated impacts depend on the crop and on the local conditions under which the crops are produced. Among the four crops exemplified (maize, rice, soybeans, wheat) rice induced the largest phosphorus emissions but soybeans caused the largest impacts on species richness. The spatial patterns of emissions and impacts differ, owing to the lower contribution to variance of the specific emissions, while most of the spatial variability in impacts was related to the characterisation factors. Nevertheless, accounting for spatially explicit inventory or environmental exchanges is crucial, since it explains more than a third of the spatial variability of freshwater eutrophication impacts in global crop production.

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