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Key Points:

- We conduct an integrative crop-soil-management assessment of global phosphorus losses from major crop cultivations
- Phosphorus losses are concentrated on small hot spot regions, while crop yields do not show consistent patterns
- Optimizing phosphorus inputs in regions with excessive uses can significantly reduce phosphorus losses without compromising crop yields

Supporting Information:

- Supporting Information S1

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Integrative Crop-Soil-Management Modeling to Assess Global Phosphorus Losses from Major Crop Cultivations

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Abstract Fertilization, crop uptake followed by plant harvest, runoff and erosion, and transformations of phosphorus (P) in soil are the major factors influencing the P balance of croplands. It is important to integrate plant-soil-management interactions into consistent modeling systems to determine the effect of P fertilization conditions on yields and to quantify P losses. Previous assessment of P losses on large scales did not consider the interactions among these factors. Here we applied a grid-based crop model to estimate global P losses from three most produced crops: maize, rice, and wheat. The model was forced by detailed P input data sets over the period 1998–2002. According to our simulations, global P losses from the three crops reached 1.2 Tg P/year, and about 44% of it was due to soil erosion. The global total P losses were dominated by contributions from a few hot spot regions. Reducing P fertilizer in regions experiencing excessive P uses and hence losses, especially in China and India, could achieve the same yields as today and save about two thirds of global total P inputs, with the cobenefits of declining global total P losses by 41% and downstream water quality improvement. Reducing soil erosion and retaining more crop residues on croplands could further save P inputs and alleviate P losses. This study is of significance to determine the major factors influencing P balance across regions of the world and help policy makers to propose efficient strategies for tackling P-driven environmental problems.

1. Introduction

Phosphorus (P) is a key nutrient element for agricultural production, but it is less studied than nitrogen (N; Elser & Bennett, 2011; Filippelli, 2008; Obersteiner et al., 2013; Sutton et al., 2013). Unlike N, P is a nonrenewable mineral resource with an extremely uneven spatial distribution (Chen & Graedel, 2016; Yuan et al., 2018). Hence, ensuring availability of this finite resource for sustainable crop production is essential for human well-being (Nemery & Garnier, 2016). At present, P fertilization is viewed as inefficient, which is reflected by an overuse of the resource, on the one hand, and substantial losses to the environment, on the other (Carpenter, 2008; Childers et al., 2011; Grizzetti et al., 2012; W. Liu et al., 2017; Powers et al., 2016). It is estimated that P emissions to the environment have significantly transgressed its safe planetary boundary (Carpenter & Bennett, 2011; Kahiluoto et al., 2014; Steffen et al., 2015). The use of P for agriculture is constrained by the extraction costs and the available reserves of mineral P to produce fertilizers, which poses a threat to long-term global food security (Cordell et al., 2009; van Vuuren et al., 2010). Therefore, conceiving development pathways with a more efficient use of P has become a key challenge for scientists and policy makers in the 21st century.

Spatially explicit assessment of global P losses from croplands and identification of regions and crop types with inappropriate P fertilization are essential to make plans for improving the efficiency of P fertilization. P losses from croplands depend on the balance between fertilization, crop uptake and harvest of P, runoff and soil erosion, and soil P transformations. This necessitates considering plant-soil-management as a coupled system. Previous studies did not achieve such integration, as they either were only based on the balance of P inputs and removal of P in harvested biomass while ignoring soil erosion (A. F. Bouwman et al., 2009; L. Bouwman et al., 2013; Lun et al., 2017; MacDonald et al., 2011; West et al., 2014) or only assessed

the impacts of soil erosion without taking P fertilization, crop uptake, and within-system cycling into account (Bennett et al., 2001; Y. Liu et al., 2008; Quinton et al., 2010). In addition, they often focused on agriculture as a whole and did not differentiate between crops (L. Bouwman et al., 2013; Lun et al., 2017; MacDonald et al., 2011; Mekonnen & Hoekstra, 2017). However, P losses and fertilizer requirements vary substantially among different crops (Ringeval et al., 2017). Taking account of these differences is important in attempts to improve agricultural nutrient management (W. Liu, Yang, Liu, et al., 2016).

Here we applied a global gridded crop model PEPIC (W. Liu, Yang, Folberth, et al., 2016; W. Liu, Yang, Liu, et al., 2016) to estimate global P losses for the period of 1998–2002 with a 0.5° spatial resolution associated with the cultivation of maize, rice, and wheat. On a global scale, these three crops account for ~63% of all P fertilizers applied and for ~62% of the calories provided by the 17 food crops most commonly produced (West et al., 2014). The PEPIC model is a grid-based version of the Environmental Policy Integrated Climate (EPIC) model (Williams, 1995; Williams et al., 1984). It explicitly accounts for the interactions between fertilization, crop uptake and harvest, runoff and erosion, and soil P transformations. The simulated P losses to the environment (outside crop fields) for each grid include P losses from surface runoff and leaching, and soil erosion. The harvested fraction of P in yields and residues removed from fields is not defined as a loss to the environments since it enters the food chain. P removed by residues returned to the field is not a loss, but rather a recycling flux. The PEPIC model has been used to simulate global crop-water relations (W. Liu, Yang, Folberth, et al., 2016), assess the trade-offs between global N losses and yields (W. Liu, Yang, Liu, et al., 2016; W. Liu et al., 2018). It also contributes to the Global Gridded Crop Model Intercomparison in the Agricultural Model Intercomparison and Improvement Project (Müller et al., 2017; Porwollik et al., 2017). In addition to the baseline P fertilization schedule, that is, applying P before crop planting with actual P inputs based on the EarthStat data set (Mueller et al., 2012; West et al., 2014), we used the PEPIC model to determine an optimal P input rate (the optP scenario), which provides optimal P concentration in soil for crop uptake in each grid cell, keeping other factors unchanged. In addition to optimizing P inputs, we also investigated the impacts of reducing soil erosion and recycling crop residues to reduce losses. Optimal P inputs were also quantified for three alternative scenarios, that is, the optP-ero scenario (50% reduced soil erosion relative to the baseline), the optP-res scenario (only 25% of crop residues removed from croplands compared to 75% under the baseline), and the optP-ero-res scenario (both reduced erosion and less residues removed).

2. Materials and Methods

2.1. Simulation Framework

The EPIC model (Williams, 1995; Williams et al., 1984) was initially developed to investigate the impacts of soil erosion on crop productivity at daily scale. In its current form, it couples submodels of soil processes to a crop growth model. It has been widely used to assess P losses from agricultural cultivations (Della Peruta et al., 2014; Pierson et al., 2001). EPIC distinguishes three mineral inorganic P pools (Jones et al., 1984), that is, labile, active, and stable P, and two organic P pools, that is, a fresh and a stable organic matter (Figure 1). P inputs (P_{in}) included P fluxes associated with mineral fertilizer and manure application, while P outputs included P fluxes with surface runoff and leaching, and soil erosion, as well as P exports with crop yields (P_y) and residue removal (P_{res}). P losses through surface runoff and leaching (P_{r+l}) were calculated from the respective fluxes and P concentrations in surface runoff and percolation water, while P losses with erosion (P_{ero}) were calculated from the concentration of P in the top soil layer, soil erosion yields, and an enrichment ratio which is the concentration of P in the sediment divided by that in the soil (Williams et al., 2008). P losses to the total environment (P_{tot}) includes P_{r+l} and P_{ero} . Details of P transformations among different pools and calculation of P losses are provided in the supporting information.

To apply EPIC on the large scale of this study, we used the grid-based version of EPIC in the Python environment (PEPIC) developed by W. Liu, Yang, Folberth, et al. (2016). The PEPIC model used elevation, slope, climate, soil, nutrients, irrigation, planting and harvesting dates, potential heat units (PHU), and crop fractional cover as input data at a spatial resolution of 30 arc min. Climate data, including precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed were derived from Weedon et al. (2014). Data on soil properties, for example, depths of soil layers, organic carbon content, pH, silt and clay content, and bulk density were obtained from Batjes (2006). The data on P and N inputs

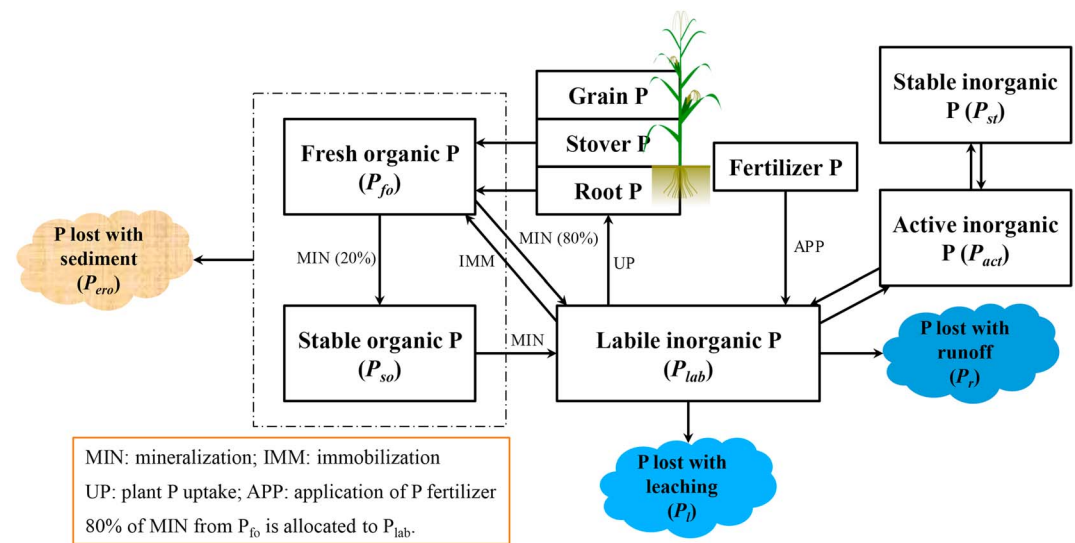


Figure 1. Schematic of phosphorus (P) routines in the EPIC model. EPIC = Environmental Policy Integrated Climate.

with the application of mineral fertilizers and manure were taken from the EarthStat data set (<http://www.earthstat.org>), which were based on Mueller et al. (2012) and West et al. (2014). These nutrient data relate to the situation in the study period 1998–2002 and are currently the most updated spatially explicit and crop-specific fertilizer data. Crop-specific calendars were obtained from Sacks et al. (2010). The PHU was calculated by using the PHU Calculator (<http://swat.tamu.edu/software/potential-heat-unit-program>), which is based on crop calendar and temperature. Crop-specific rainfed and irrigated cultivated land areas in each grid cell were downloaded from Portmann et al. (2010). Default EPIC parameters were used in this study based on the EPIC user's manual (Gerik et al., 2015) without considering spatial variability. This is a common parameterization of large-scale crop simulation, as it is a challenge to set regional specific model parameters on a global scale (Müller et al., 2017). However, model uncertainties and parameter sensitivities were investigated systematically by performing model runs with parameters varied in a range of uncertainty determined from literature and expert judgment (Table S1). Details of this uncertainty and sensitivity analysis are given in section 2.3.

2.2. Model Setup

The simulations spanned a period from 1981 to 2002. In this period, global P fertilizer consumption was relatively stable (Chen & Graedel, 2016). The first 17 years were used to phase out the influence of unknown initial conditions. In the simulations, N was applied automatically with a maximum amount equal to the current annual input from the EarthStat data set based on Balković et al. (2013). Rainfed and irrigated cultivations were simulated separately. Given the unavailability of irrigation amount data, an automatic irrigation schedule was used without water limitation for the irrigated cultivation. Compared to upland crops (maize and wheat), paddy management practices were considered for rice simulations. Paddy fields were first built, followed by puddling the rice paddy before planting. Puddling is a tillage operation with saturated soil and shallow ponding water to break clods and flatten the rice paddy, which makes the top soil layer more suitable for rice planting and also reduces sediment generation (Choi et al., 2017). Rice transplanting was simulated by setting leaf area index of 0.1 at the time of transplanting based on Steglich et al. (2016). Before harvesting, the puddling condition was destroyed. Details regarding how to set paddy rice simulation can be found in Steglich et al. (2016).

Under the baseline scenario, P fertilizer from the EarthStat data set was applied before crop planting considering removing 75% of crop residues from croplands (Del Grosso et al., 2009; W. Liu, Yang, Liu, et al., 2016; Table S2). Besides the baseline P fertilization, a dynamic P fertilization schedule was used (the optP-D scenario). This method applies P fertilizer automatically without limitation based on the optimal P concentration in the soil for crop taking up and can be used to derive the optimal P inputs after a long-term simulation (e.g.,

Table 1

Comparison of Phosphorus (P) Inputs (P_{in}), P Losses to Total Environment (P_{tot}), P Losses With Soil Erosion (P_{ero}), and Crop Production Among Different Scenarios

Crop	Variable	Baseline	optP	optP-ero	optP-res	optP-ero-res
Maize	P_{in} (Gg P/year)	2,795.12	1,849.43	1,840.75	1,458.55	1,442.73
	P_{tot} (Gg P/year)	409.23	293.07	211.57	351.42	240.01
	P_{ero} (Gg P/year)	261.84	220.99	139.19	272.03	160.61
	Production (Tg/year)	808.72	812.24	815.12	820.37	824.25
Rice	P_{in} (Gg P/year)	3,761.10	674.50	670.33	359.87	354.68
	P_{tot} (Gg P/year)	429.04	240.69	225.40	270.91	248.20
	P_{ero} (Gg P/year)	83.45	52.58	37.32	70.82	47.92
	Production (Tg/year)	740.46	740.65	741.05	743.46	743.90
Wheat	P_{in} (Gg P/year)	4,293.79	1,296.97	1,291.37	1,009.12	1,002.30
	P_{tot} (Gg P/year)	391.92	191.69	142.61	213.05	155.38
	P_{ero} (Gg P/year)	194.81	126.84	77.44	144.81	86.70
	Production (Tg/year)	584.90	585.27	586.38	592.57	593.85

Note. Scenarios are defined in Table S2 in the supporting information.

longer than 20 years). The average annual P inputs for the period 1981–2002 from the optP-D scenario was treated as the optimal P inputs and was applied before crop planting for the optP scenario. In addition to optimizing P inputs, we also investigated the impacts of reducing 50% soil erosion (the optP-ero scenario), removing only 25% crop residues from croplands (the optP-res scenario), and combining the two managements (the optP-ero-res scenario) on P fertilization and P losses. Similar to the optP scenario, optimal P inputs for the three scenarios, that is, optP-ero, optP-res, and optP-ero-res, were also quantified under the scenarios of optP-ero-D, optP-res-D, and optP-ero-res-D (Table S2).

All outputs in this study represent averages for the five years from 1998 to 2002. For each grid cell, they were aggregated by area weighting of rainfed and irrigated outputs. Evaluation of model performance is described in the supporting information.

2.3. Uncertainty and Sensitivity Analyses

The Latin Hypercube Sampling (LHS) method (Mckay et al., 1979) was used to sample the model parameters to explore uncertainties in P loss simulations derived from uncertain parameter values. LHS was applied in our previous study for investigating global N loss uncertainties (W. Liu, Yang, Liu, et al., 2016). This method first divides the range of parameters into a number of segments. Then the parameter segments are randomized. Finally, a random sample is chosen in each segment. LHS is more efficient than Monte Carlo (Mckay et al., 1979) and has been used in the SWAT-CUP software (Abbaspour, 2011) for calibrating the Soil and Water Assessment Tool model parameters (Abbaspour et al., 2007; Yang et al., 2008) as well as for the LPJ global vegetation model (Zaehle et al., 2005). Model parameters associated with crop growth, water balance, as well as P and carbon routines in PEPIC and their possible ranges for uncertainty analysis were carefully selected based on Gerik et al. (2015) and Wang et al. (2012; Table S1). In this study, 100 parameter segments were considered in the LHS method.

A global sensitivity analysis method was used to determine the most sensitive model parameters. This method first builds the multiple regression relationship between LHS-generated parameters and simulated output variables, for example, P_{ero} and P_{tot} . A t test is then employed to identify the relative significance of each model parameter based on its corresponding t value. Parameters with larger t value are assessed to be more sensitive for the selected model output. A detailed description of this sensitivity analysis method is given in Abbaspour (2011).

3. Results

3.1. Global Phosphorus Loss Assessment

According to the baseline simulation results with actual P fertilizer applications during 1998–2002, global P losses into the environment from leaching and erosion totaled 409, 429, and 392 Gg P/year ($\text{Gg} = 10^9 \text{ g}$) for maize, rice, and wheat, respectively, accounting for 15%, 11%, and 9% of the respective P inputs (P_{in} ; Table 1).

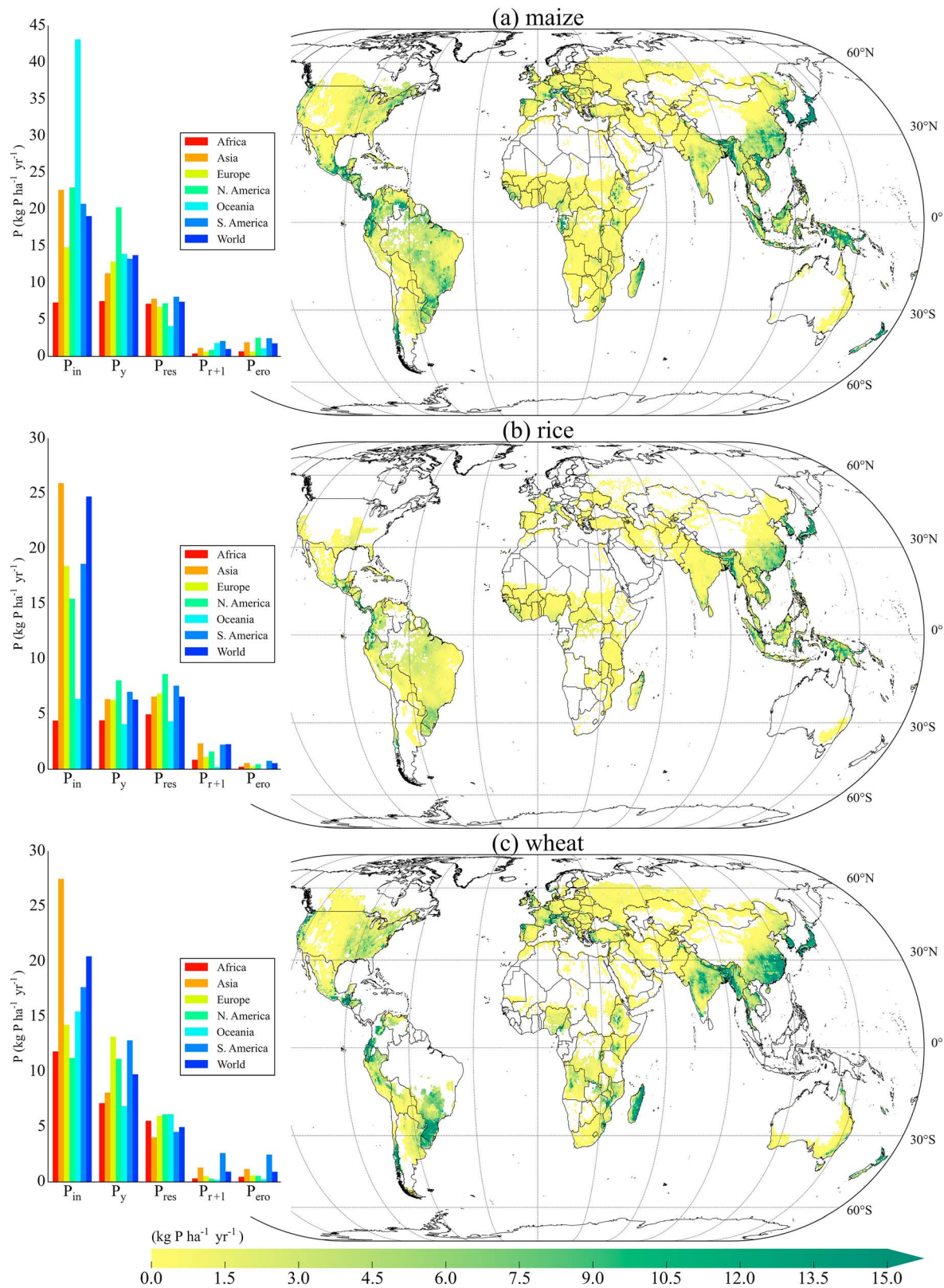


Figure 2. (a–c) Global maps of phosphorus (P) losses to total environment for the study period 1998–2002. Information of P inputs (P_{in}), P uptake in crop yields (P_y) and crop residues (P_{res}), P losses with surface runoff and leaching (P_{r+l}), and P losses with erosion (P_{ero}) is presented at the global and continental levels for each crop.

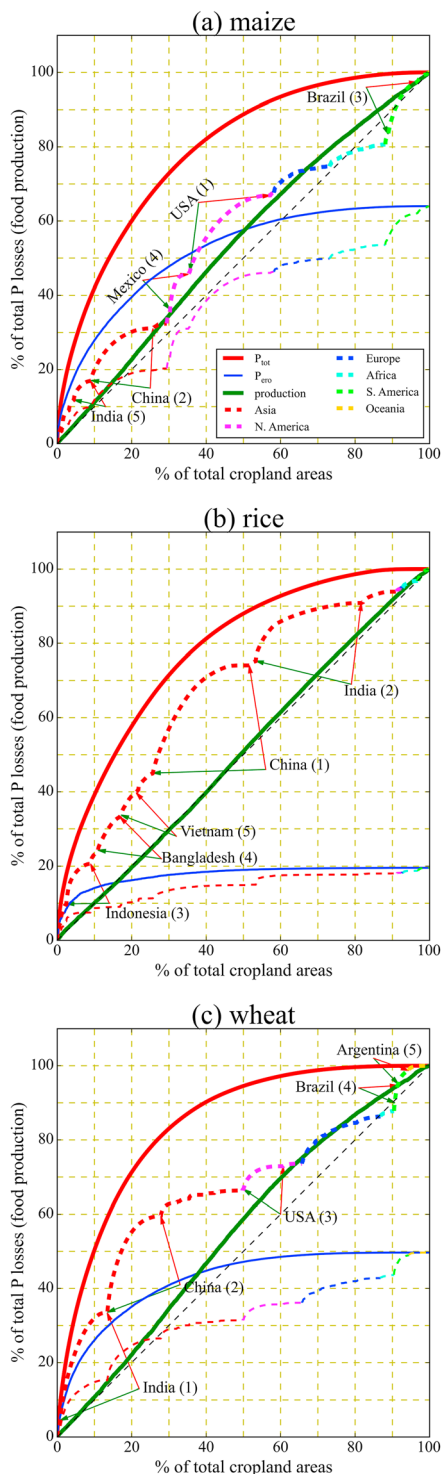


Figure 3. (a–c) Distributions of cumulative phosphorus (P) losses (or food production) in relation to cumulative cropland areas. Solid lines are for P losses to the total environment (P_{tot} red color), crop production (green color), and P losses with soil erosion (P_{ero} blue color) sorted from highest grid P_{tot} to lowest one. Dashed lines are first grouped by continents; countries are then sorted from highest country average P_{tot} to lowest one in each continent; grids are finally sorted from highest grid P_{tot} to lowest one in each country for P_{tot} (bold dashed line) and P_{ero} (slim dashed line). Top five P loss countries are presented with number in bracket indicating their rankings.

About 64%, 19%, and 50% of these P_{tot} losses were contributed by the process of erosion. P_{ero} was lower for rice production compared with maize and wheat production, due to the special paddy management practices considered for rice simulation. South Korea, Japan, southeastern China, southeastern Asia, and northeastern India, Brazil, and Chile accounted for high loss rates (Figure 2). Maize had the highest P recovery rate in yields (with a ratio of P_y/P_{in} of 0.72), followed by wheat (0.48), while rice had the lowest value (0.26). European and North American agriculture was found to be more efficient in transferring P_{in} to crop yields, by contrast with Asia. Meanwhile, a large amount of P was also removed from croplands containing harvested crop residues (P_{res}).

We found that P_{tot} and P_{ero} losses are highly concentrated over small hot spot regions (Figures 2, 3, and S1), with differences in loss rates between the three crops. The percentages of total P losses contributed from the 20th percentile of cultivated areas with highest P_{tot} rates being 60%, 58%, and 71% for maize, rice and wheat, respectively. The 20th percentile of areas with lowest P_{tot} rates only account for 1.5%, 1.4%, and 0.4% of the respective total P losses. By contrast, crop yields do not show a coincident distribution. This means that there is a significant potential to reduce P losses and avoid P pollution by focusing on a small fraction of cropland areas. At the continental level, Asia and North America almost equally contributed to the majority of P losses for maize, whereas in the case of rice and wheat, Asia was the main contributor, mainly due to excessive P inputs there (Tables S3–S5).

3.2. Global Phosphorus Fertilization Conditions

By comparing this baseline simulation with the optP simulation where P input rates were optimized for crop uptake, we identified regions with overapplication or underapplication of P fertilizer. This comparison shows that P_{in} could be reduced substantially, especially for rice and wheat cultivation (Table 1 and Figure 4). This would correspond to annual P fertilizer savings of 946, 3,087, and 2,997 Gg P/year for maize, rice, and wheat, respectively, suggesting that currently 34%, 82%, and 70% of P applications for the three crops could be eliminated without reducing crop yields (Table S6). The differences in P_{in} between optP and baseline present similar spatial patterns for the three crops (Figure 4). Japan, South Korea, New Zealand, China, India, and Brazil, western Europe, and parts of the United States show high potentials for reducing P_{in} , with potential savings of 50 kg P·ha^{−1}·year^{−1} in Japan and South Korea. On the contrary, P_{in} needs to be slightly increased in many parts of Africa and the Middle East, with a general increase of less than 10 kg P·ha^{−1}·year^{−1} throughout these regions. Simulations with the optP-ero, optP-res, and optP-ero-res scenarios show that reducing soil erosion could translate only in small savings of P_{in} (Table 1), mainly because P bound to soil is not available for crop uptake (Jones et al., 1984). On the other hand, leaving 75% instead of 25% of the crop residues in the field would further substantially decrease the consumption of total P fertilizer inputs from 3,821 Gg P/year in the optP simulation to 2,800 Gg P/year in the optP-ero-res simulation.

3.3. Reduction of Global Phosphorus Losses

The decreases in P_{in} between optP and baseline also lead to a significant decrease in P losses for the three crops, with reductions of 116, 188, and 200 Gg P/year for maize, rice, and wheat, respectively (Table 1). These

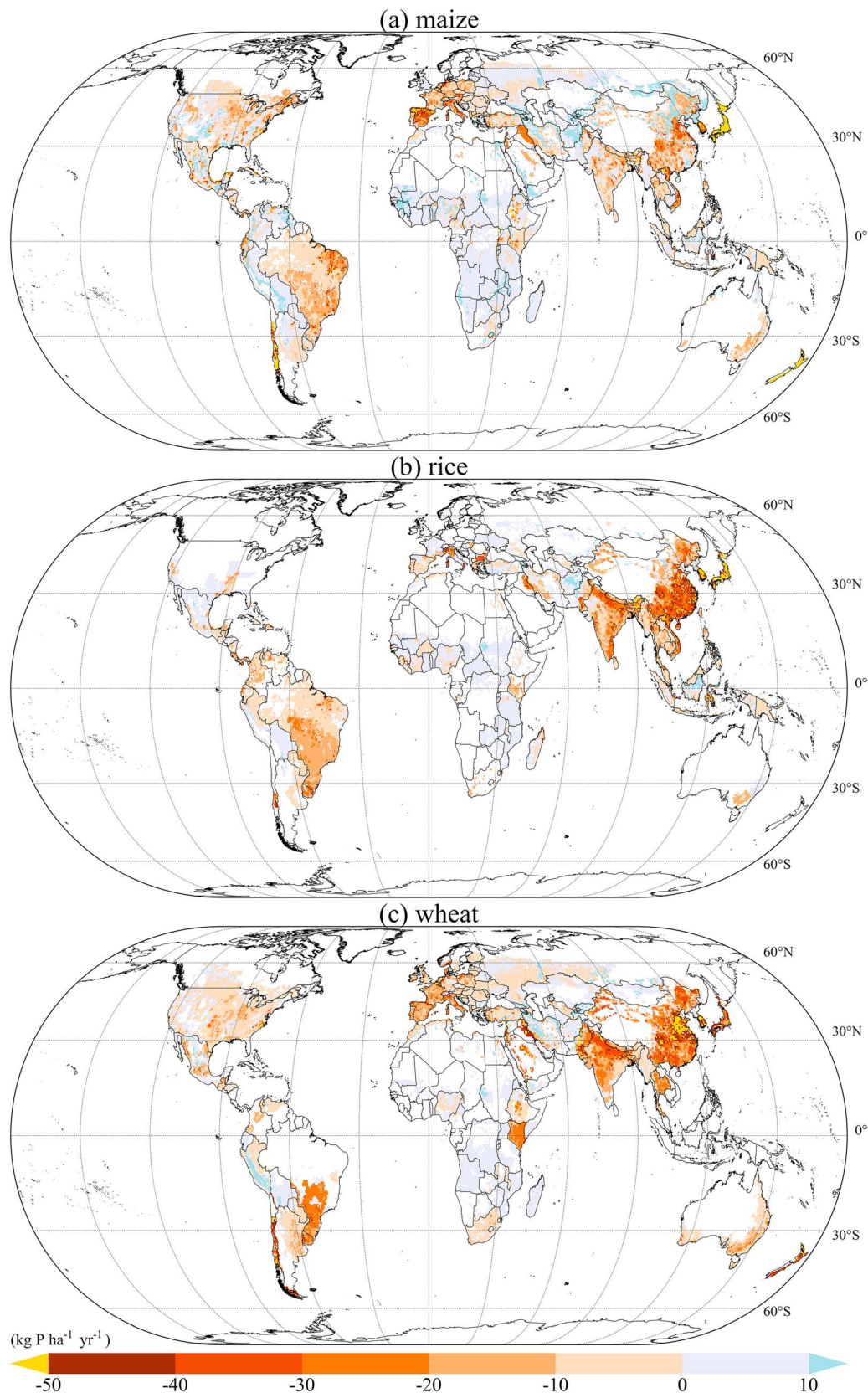


Figure 4. (a–c) Global maps of differences in phosphorus (P) inputs between scenarios optP and baseline. Negative values indicate decreases in P inputs; positive values indicate increases in P inputs. Definition of scenarios refers to Table S2.

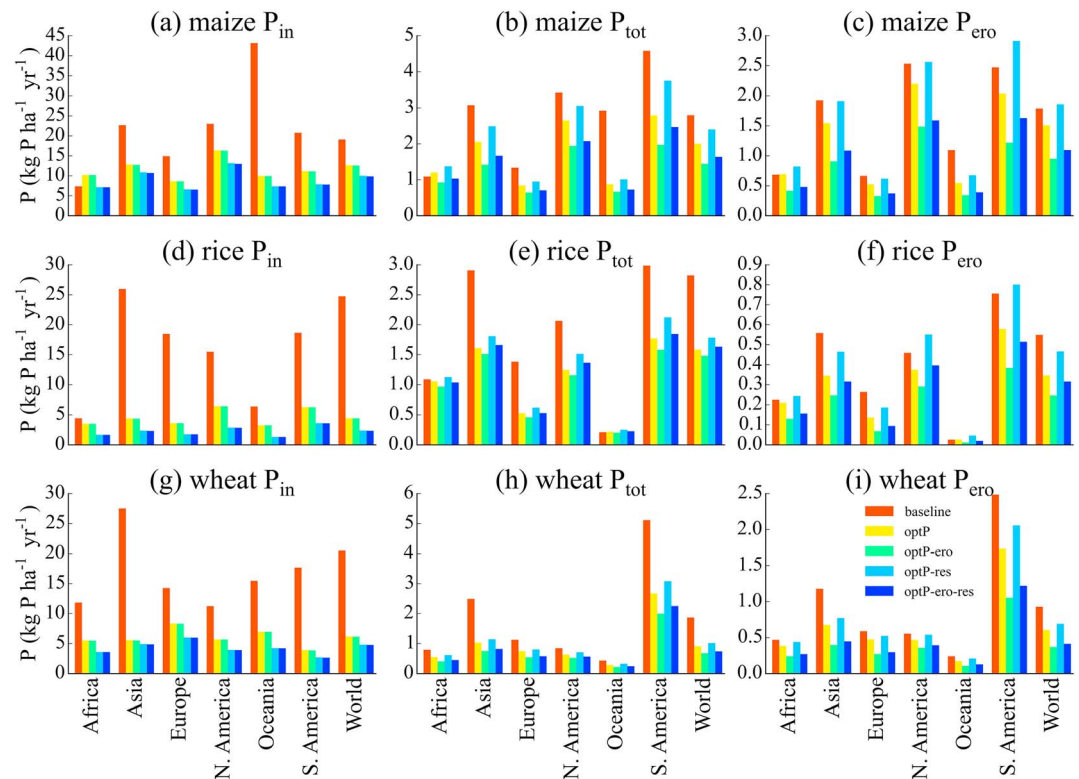


Figure 5. Global and continental phosphorus (P) inputs (a, d, g: P_{in}), P losses to the total environment (b, e, h: P_{tot}), and P losses with soil erosion (c, f, i: P_{ero}) under different scenarios. Definition of scenarios refers to Table S2.

decreases correspond to 28%, 44%, and 51% of the current total P losses for the three crops, which are mainly due to reduction in P losses with surface runoff and leaching but less because of reduction in P losses with soil erosion (Tables S3 and S4). The spatial patterns of P_{tot} reduction are quite similar to P_{in} reduction (Figure S2). Reducing soil erosion could further decrease P_{ero} and hence also P_{tot} (the optP-ero scenario), but leaving more crop residues in croplands, on the other hand, could increase P_{ero} and P_{tot} (Figure 5). Overall, combining the managements of reducing soil erosion and leaving more crop residues could lead to more benefits in terms of reducing global P inputs and P losses, while also slightly increasing crop production (Table S6).

3.4. Model Uncertainties

Simulations with 100 sets of model parameters indicate high uncertainties in estimating P_{ero} and P_{tot} (Figure 6). The standard deviations of global average P_{ero} and P_{tot} are 0.19–0.45 and 0.27–0.71 $\text{kg P ha}^{-1} \text{ year}^{-1}$, respectively, for the three crops (Table S7). This translates into large coefficients of variation (CV) in the P loss estimates in the range of 21%–29%, from uncertain model parameters. Sensitivity analysis indicates that the maximum depth for biological soil mixing (P24), the modified Universal Soil Loss Equation (RUSLE2) threshold transport capacity coefficient (P72), the soluble P runoff coefficient (P08), and the upward movement of soluble P by evaporation coefficient (P43) of PEPIC are the most sensitive/influential parameters in controlling P losses (Table S7).

4. Discussion

We found that the average ratio of P_{tot} to P_{in} (P_{tot}/P_{in}) is 11.3% for the three major crops, indicating that about 11% of the inputs of P were lost to the environment. The P_{tot}/P_{in} ratio estimated in this study falls in the middle of the range of previous studies going from between 2.8% and 23% (Table 2). The large range illustrates uncertainties in estimating P losses, which was captured in our simulations with CV as high as 30% (Table S7). A similar CV was reported by Ringeval et al. (2017) in modeling farm P inputs and outputs with a global

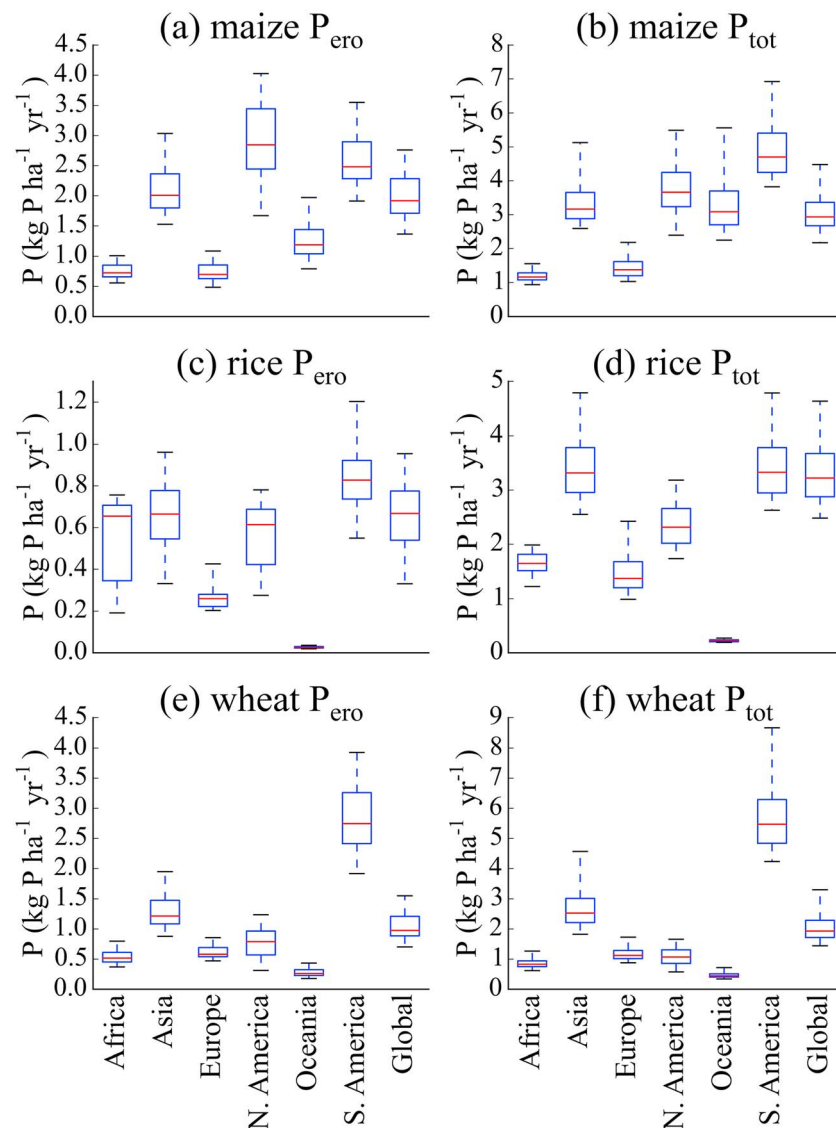


Figure 6. Uncertainties of phosphorus (P) losses with (a, c, e) soil erosion (P_{ero}) and P losses to the (b, d, f) total environment (P_{tot}) continentally and globally. Lines from top to bottom are 95th, 75th, 50th, 25th, and 5th percentiles, respectively.

empirical soil P balance model. Regional comparison shows that our P loss estimates are in line with previous studies (Table S8). For instance, the simulated average P_{tot} in this study of $1.2 \text{ kg P ha}^{-1} \cdot \text{year}^{-1}$ in Europe, falls in the range of $0.09\text{--}2 \text{ kg P ha}^{-1} \cdot \text{year}^{-1}$, reported for 10 large river basins in Europe (Kronvang et al., 2007). Besides, our model also performs well in representing the FAO statistical yields (<http://www.fao.org/fao-stat/en/#home>), with the coefficients of determination of the linear regression between reported and simulated yields ranging between 0.33 and 0.64 for the three crops (Figure S3). The acceptable match of yields (for a global crop model with generic parameters) and of P compared with statistics and previous results provides support for the reliability of our approach.

The current estimate of the *safe planetary boundary* for P losses from agricultural systems to water bodies was set to 1.0 Tg P/year ($\text{Tg} = 10^{12} \text{ g}$; Kahiluoto et al., 2014), based on an arbitrary target P concentration of 24 mg P m^{-3} in freshwaters (Carpenter & Bennett, 2011). Our simulations indicate that total P losses from the three major crops today have exceeded this boundary, reaching 1.2 Tg P/year by 2002 (Table 1). There is thus an urgent need to reduce P losses from these three crops. Application of optimal P inputs (the optP scenario) could reduce losses by 0.5 Tg P/year without negatively affecting crop yields (Tables 1,

Table 2*Ratio of Phosphorus (P) Losses to Total Environment (P_{tot}) to P Inputs (P_{in}) in the Current Study Compared to Previous Studies*

Study	P_{in} (Tg P/year)	P_{tot} (Tg P/year)	$P_{\text{tot}}/P_{\text{in}}$ (%)	Study period
A. F. Bouwman et al. (2009)	31 ^a	3	10	2000
L. Bouwman et al. (2013)	31 ^a	4	12.5	2000
Lun et al. (2017)	20.4 ^b	3.2	15.7	2000
MacDonald et al. (2011)	23.8 ^b	2.4	10	2000
Mekonnen and Hoekstra (2017)	24 ^b	0.6	2.8	2002–2010
Penuelas et al. (2013)	21.8–26.8 ^c	5	19–23	2000–2010
Sattari et al. (2012)	16.6 ^b	1.70	10	2007
Current study	10.8 ^d	1.2	11.3	1998–2002

^a P_{in} for croplands and grasslands from mineral fertilizer and manure. ^b P_{in} for croplands from mineral fertilizer and manure. ^c P_{in} for croplands and grasslands from only mineral fertilizer. ^d P_{in} only for maize, rice, and wheat from mineral fertilizer and manure, explaining why it is lower than estimates for all croplands and grasslands given above.

S3, and S6). Total P inputs from fertilizers could be reduced by 7.0 Tg P/year under the optP scenario (and by 8.0 Tg P/year under the optP-ero-res scenario) compared to 11 Tg P/year currently. These savings of P resources will alleviate the depletion of global P reserves and sustain long-term food security (Cordell et al., 2009; Van Vuuren et al., 2010).

The PEPIC model includes several crop growth limiting factors, for example, water, temperature, N, and P and takes the highest one as the major factor to limit crop yields. In our simulations, the simulated optimal level of P inputs would not significantly increase crop yields in under-application regions, for example, in Africa. It implies that P may not be the major growth limiting factor in our simulations, but rather N (Kvakić et al., 2018; W. Liu, Yang, Liu, et al., 2016). However, it is still important to increase P inputs in the P limited regions to maintain soil fertility especially under a continuous cultivation (Ringeval et al., 2014; Zhang et al., 2017).

The spatially concentrated P losses to the environment found in this study provide an option to mitigate the environmental problems caused by P losses from agricultural areas through more evenly distributing P fertilizer application, that is, redistribute P inputs from overuse regions to regions showing a deficit. Due to the different concentration patterns among the three crops, it is important to identify crop-specific P fertilization conditions. In this study, crop management practices, for example, P fertilizer inputs (Figure S4), fraction of irrigated areas to total cultivation areas in each grid cell (Figure S5), and crop growing conditions, especially growing season precipitation (Figure S6), are responsible for the differences among the three crops. The different management approaches and climatic conditions further highlight the significance of crop-specific assessment. Compared with upland crops, for example, maize and wheat, paddy rice systems have quite different management practices, leading to low P_{ero} estimates (Table 1). We also conducted a rice simulation without considering paddy condition, which is a common setup of global rice modeling (Müller et al., 2017). In this condition, P_{tot} and P_{ero} of rice were estimated to be about 1 Tg P/year and 0.5 Tg P/year, respectively, being much higher than the simulation with paddy systems. The large differences in estimating P losses between with and without considering paddy practices call for explicitly simulating paddy rice cultivation on a global scale.

We acknowledge some limitations of our simulation results. First, the P losses to the environment estimated in this study relate to the situation around the year 2000 and not the current period, due to limitation in available crop-specific P input data. The more recent situation can be inferred from the trend in total P fertilizer consumption globally and for the top 10 producing countries (W. Liu, Yang, Liu, et al., 2016) of the three crops (Figure S7). Global total P consumption increased by ~25% between 2002 and 2013, particularly in India, China, and Brazil. This signals potentially severe P-driven environmental issues (e.g., eutrophication) today and calls for actions to address them. Second, we only considered the effects of better fertilization, reducing soil erosion, and crop residue management on mitigating P losses. Other options, for example, precision farming and increasing the fraction of manure returned to croplands, will further minimize P losses. Future assessment needs to take all these measurements into account. Despite these limitations, this study is the first comprehensive attempt to evaluate the P fertilization and P loss conditions for the three major crops on a global scale, to help policy makers ameliorate global P-related issues.

5. Conclusions

In this study, we conducted an integrative crop-soil-management assessment of global P losses from the cultivations of three major crops, that is, maize, rice and wheat, by using a grid-based crop model with detailed management information. Several mitigation scenarios were proposed to investigate pathways toward balance among P uses, crop yields, and P losses. We found that global total P losses from the three major crops reached 1.2 Tg P/year by 2002, which have significantly exceeded the safe planetary boundary of P losses to water bodies, and soil erosion contributed 44% of it. Meanwhile, simulations demonstrate, for the first time to our knowledge, that global P losses showed quite different patterns to crop yields, as P losses were concentrated over a few hot spot regions while yields did not present coincident distribution. Through identifying appropriate P inputs throughout the cultivated areas of the three crops, we found that P inputs could be reduced in many regions due to excessive uses, especially in China and India, therefore reducing P losses without compromising crop yields. Reducing soil erosion and integrating more crop residues for cycling could further reduce P losses. Additionally, these mitigation measures could also save a large amount of P inputs, which is essential to slowdown the depletion of our finite P resources. In order to ensure long-term availability of P for crop production and simultaneously address severe environmental problems associated with P losses, there is an urgent need to conserve global P resources and reduce P losses. This study is particularly important for informing policy makers the hot spot regions of global P losses and guiding them to propose strategies for tackling P-related issues.

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