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Global Biogeochemical Cycles

RESEARCH ARTICLE

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Key Points:

- Limits to global cereal production (maize, winter wheat, and rice) due to soil P status is assessed for year 2000 with process based models
- As a global average, the soil P levels can sustain potential crop yields due to history and nature of global fertilizer P use
- In spite of this, we estimate a global P yield gap of 22–55% that is not markedly diminished with today's global P application practice

Supporting Information:

- Supporting Information S1

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Quantifying the Limitation to World Cereal Production Due To Soil Phosphorus Status

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Abstract Phosphorus (P) is an essential element for plant growth. Low P availability in soils is likely to limit crop yields in many parts of the world, but this effect has never been quantified at the global scale by process-based models. Here we attempt to estimate P limitation in three major cereals worldwide for the year 2000 by combining information on soil P distribution in croplands and a generic crop model, while accounting for the nature of soil-plant P transport. As a global average, the diffusion-limited soil P supply meets the crop's P demand corresponding to the climatic yield potential, due to the legacy soil P in highly fertilized areas. However, when focusing on the spatial distribution of P supply versus demand, we found strong limitation in regions like North and South America, Africa, and Eastern Europe. Averaged over grid cells where P supply is lower than demand, the global yield gap due to soil P is estimated at 22, 55, and 26% in winter wheat, maize, and rice. Assuming that a fraction (20%) of the annual P applied in fertilizers is directly available to the plant, the global P yield gap lowers by only 5–10%, underlying the importance of the existing soil P supply in sustaining crop yields. The study offers a base for exploring P limitation in crops worldwide but with certain limitations remaining. These could be better accounted for by describing the agricultural P cycle with a fully coupled and mechanistic soil-crop model.

1. Introduction

Phosphorus (P) is recognized as one of the foremost concerns for global crop production (Cordell et al., 2009) because, as a macroelement, it is indispensable for plant function and thus growth. P is a relatively immobile element compared to carbon (C) and nitrogen (N) as it reacts with soil constituents that buffer its availability to plants, and through time becomes unavailable altogether (Filippelli, 2002; Sample et al., 1980). In agriculture, natural levels of P in most soils are not adequate to sustain crop production in the long term, so additional inputs in the form of chemical fertilizer or manure are needed. Depending on the access to fertilizer (chemical or manure), P management in agricultural systems shows a wide variety of outcomes (Vitousek et al., 2009) ranging from soil nutrient depletion and degradation on one extreme to fertilizer overconsumption and pollution of water resources on the other.

These issues have recently been highlighted in studies (MacDonald et al., 2011; Mueller et al., 2012) showing the imbalance of nutrient flows in croplands globally. Looking at the soil's P budget, 30% of the worldwide cropland area experiences a P deficit (MacDonald et al., 2011) despite a global positive P balance. Even more, it has been estimated that around 70% of underachieving areas could resolve their yield losses by solely focusing on nutrient limitation and not irrigation infrastructure (Mueller et al., 2012). These studies give a strong case for P mismanagement on the global scale, but how this ultimately affects yields requires further attention.

Nutrient limitation in crops is most commonly estimated in field trials (Dai et al., 2013; Dobermann et al., 1998; Gallet et al., 2003; Shen et al., 2004; Takahashi & Anwar, 2007; Tonitto & Ricker-Gilbert, 2016; Valkama et al., 2009; Wissuwa & Ae, 2001), where the crop yield is recorded and related to soil nutrient availability or the amount of applied fertilizer. It is often shown that P addition can significantly increase yields, especially through its interaction with N (V. D. Fageria, 2001). These studies give a precise measure of nutrient requirement, but the variety of experimental conditions makes a general estimate of P limitation hard to obtain, especially when dealing with the issue globally. More importantly, yield increases due to P are highly

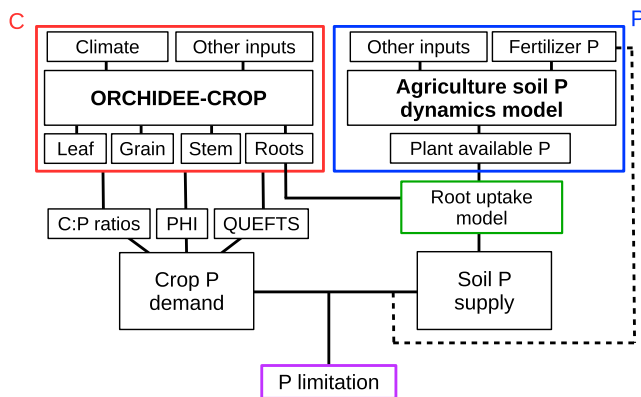


Figure 1. Information flow diagram describing the methodology of this study. The red and blue rectangles delineate the main sources of data and correspond to carbon and phosphorus, respectively. The box in green delineates the root uptake model, which acts as an interface for P in soil that is available for plant uptake. These three (colored) boxes form the basis for estimating potential crop P demand and soil P supply, and finally P limitation. An additional sensitivity test takes into account fertilizer P (chemical + manure) in addition to soil P supply (dotted line).

dependent on the properties of the soil underneath. Soil texture and organic content play a significant role (Tonitto & Ricker-Gilbert, 2016; Valkama et al., 2009) by changing the P buffering capacity of the soil, whereas soil metal or carbonate content (Shen et al., 2004; Takahashi & Anwar, 2007) determines the effectiveness of applied fertilizer through formation of less available P compounds. P availability is thus an important factor in sustaining crop yields, and one that is intimately tied with the soil underneath.

Nutrient limitation manifests most importantly as a loss of yield or a yield gap (van Ittersum & Rabbinge, 1997). To estimate it on a global level, a set of methodologies is usually employed as summarized by van Ittersum et al. (2013). They are broadly categorized into statistical and crop-modeling approaches. Statistical approaches rely on yield census data of varying size, which are then combined with global data (e.g., climate, fertilizer inputs, and irrigation area). Based on climate binning techniques (van Wart et al., 2013), they divide the world into contingent areas of similar growth environment, looking at main drivers of yield variation within. On the other hand, global gridded crop models (GGCMs) simulate growth and yield using relatively generic parametrizations and calibrated parameters to mimic the effects of genetics (e.g., maximum leaf area index

and harvest index). These models can be run globally on a grid, typically 0.5° to 1° , forced by daily weather and management-related data (e.g., planting date, sowing density, irrigation, and annual fertilizer application). Only a few GGCMs participating in intercomparison projects have an explicit representation of nutrient cycling in soils and plants (Rosenzweig et al., 2014), and their parametrization remains rather coarse, with no representation of key process such as the limitation of root uptake by soil P diffusion. Moreover, the use of crop models to estimate limitation due to soil P globally has been limited by a lack of information on the distribution of P in agricultural soils.

Recent attempts (Ringeval et al., 2017; Zhang et al., 2017) have simulated the evolution of P in agricultural soils, by combining spatially explicit data sets on soil P inputs/outputs and a soil P dynamics model. Such data can be combined with GGCMs output of potential yield, to assess the yield limitation due to insufficient P supply compared to the potential crop P demand. Here we attempt to diagnose P limitation due to soil P status in three major cereals in the world (winter wheat, maize, and rice) for the year 2000, by combining the outputs of a generic GGCM known as ORCHIDEE-CROP (Wu et al., 2016) and an agricultural soil P model (Ringeval et al., 2017), while accounting for the mechanism of soil to plant P transfer by diffusion (De Willigen & van Noordwijk, 1994).

2. Methods

2.1. Overview

Quantifying P limitation on yield is attempted using a supply versus demand approach (Figure 1). Crop P demand is the P needed to achieve a certain level of yield, which is in our case the *potential* one or one that is limited only by climate (temperature and light) and genetic makeup. On the other hand, the soil P supply is derived from the soil P availability by accounting for the diffusive nature of P transport at the soil-root boundary. To estimate crop P demand, we used ORCHIDEE-CROP (Wu et al., 2016) (red box in Figure 1), a GGCM that simulates plant growth in irrigated conditions without any other stress (nutrients, pests, or weeds) at 0.5° resolution over the globe. From the modeled crop carbon pools, we derive spatially explicit estimates of P demand using three different approaches described in the following sections. To estimate soil P supply, we used an agricultural soil P dynamics model (Ringeval et al., 2017), which gives the amount of soil P available for plant uptake (blue in Figure 1). Because the soil P supply is determined both by soil P availability and the plant's ability to take it up, a model of root uptake (green box in Figure 1) was employed to compute potential P uptake by plants. By comparing crop P demand to soil P supply, the limitation to crop production due to soil P status can be quantified. Additionally, a scenario with an improved soil P supply is carried out, which assumes that a part of the fertilizer P inputs (chemical and manure) could be incorporated into crop

biomass (dotted line in Figure 1). We focus on the year 2000, as most frequently used world gridded data sets (for crop model validation and assessing the global yield variability) are centered around this year.

2.2. Crop P Demand

P demand is diagnosed from the different plant C pools simulated by ORCHIDEE-CROP: leaf, grain, stem, and root (the model has also a pool for carbohydrate reserves, which is assumed to contain no P). The simulations used here were performed following the ISIMIP2a protocol (Warszawski et al., 2014) assuming no stress occurs (water, nutrient, weed, and pests). To estimate P demand, we used three different methods: an empirical relationship between yield and uptake (QUEFTS), P harvest index (PHI), and stoichiometric ratios (C:P). These methods provide us information on the amount of P needed to achieve a certain biomass or yield at maturity. When searching for methods to infer crop P demand, we have tried to pick ones whose data encompass a wide range of growing conditions (genetic variety, geographic location, etc.) to obtain a general and a robust estimate. Additionally, the use of multiple methods allows us to give a range of possible values and account for their inherent bias. Details of the crop model and estimation of P demand are detailed in the following subsections.

2.2.1. ORCHIDEE-CROP

Crop biomass pools are simulated by ORCHIDEE-CROP (Wu et al., 2016), a version of the ORCHIDEE dynamic global vegetation model (Krinner et al., 2005) modified to simulate phenology, temporal evolution of leaf area index (LAI), and C allocation (including grain filling that determines yield) of crops by integrating some parameterizations of the generic crop model STICS (Brisson et al., 2003). The model has been calibrated and evaluated for maize and winter wheat in temperate areas (Wu et al., 2016) and extended to include rice (Wang et al., 2017). Concerning wheat, ORCHIDEE-CROP is able to simulate *winter* wheat only. Spring wheat differs from winter one mainly in terms of phenology, and simulating both would require two different parameterizations (with specific vernalization requirements and photoperiod effects). ORCHIDEE-CROP is subject to constant improvements, with plans to introduce spring wheat in the following stages.

The simulated crop growth is divided into seven development stages (e.g., emergence, vegetative growth, and grain filling). The timing and duration of each stage is calculated based on development units, which describe the physiological requirements of crops. These development units are calculated as growing degree days weighted by limiting functions to account for photoperiodism and vernalization. LAI is the primary driver of canopy photosynthesis and is described by a logistic curve depending on the plant phenology stage. LAI is used in conjunction with the leaf-scale models for C3 and C4 plants used in ORCHIDEE (Krinner et al., 2005) to determine gross primary productivity (GPP). Carbon assimilates from GPP are distributed daily to leaves, stem, grain, roots, and reserves. A fraction of GPP and biomass is used for maintenance and growth plant respiration, to calculate net primary productivity (NPP). The priority of C allocation changes in the model with the plant development stage and reflects different resource use strategies. ORCHIDEE-CROP also has water and nutrient modules, whose purpose is to regulate plant growth. Water uptake is modeled as a function of plant transpiration and root water availability using a detailed and realistic multilayer soil hydrological model (Guimberteau et al., 2014). The nutrient component is highly idealized: it considers only N, whose soil-plant budget is not explicitly simulated. Instead, leaf-scale photosynthetic capacity is increased with N fertilizer addition through an empirical relationship, with no feedbacks to C allocation (Wu et al., 2016).

The crop simulations used here follow the protocol set out by “The Global Gridded Crop Model Intercomparison” project (Elliott et al., 2015). It specifies crop species, their management, and a set of inputs (gridded climate and crop management data) to insure comparability among different models. The most important crops are maize, rice, and wheat as they comprise 43% of total global food intake (Elliott et al., 2015). The output used to calculate crop biomass pools in this study was the mean monthly values, which were simulated with a daily time step at a 0.5° resolution globally with irrigated conditions in the year 2000. Irrigated conditions were simulated by setting the soil moisture to field capacity everywhere. N was assumed nonlimiting by setting a high N fertilizer application rate (150 kg N/ha) everywhere.

2.2.2. QUEFTS, PHI, and C:P Ratios

QUEFTS (Janssen et al., 1990) is an empirical model used to estimate yield response according to fertilizer inputs and soil fertility. It was developed to provide advice on optimal nutrient application in tropical soils in a simple and robust way and has been extensively used to characterize cereal production worldwide (Sattari et al., 2014). It consists of four different steps that define the supply and demand of the three

nutrients mostly widely used in agriculture (N, P, and K) to give a final yield estimate. The model sections of interest in this study are the optimal nutrient supply combinations and the uptake-yield curves (details in supporting information). The latter one provides the yield response depending on the potential yield as function of the plant uptake of P. In our calculation, the yield potential is defined as the ORCHIDEE-CROP simulated yield (irrigated and high N application everywhere). We calculated the crop P demand as the P uptake that enables the crop to achieve 95% of the yield potential. Hereafter, this crop P demand is called $P_{\text{demand}}^{\text{QUEFTS}}$ (kg P/ha/yr).

The PHI method is based on a combination of yield simulated by ORCHIDEE-CROP (the grain biomass, Y_{grain} in (kg/ha)) and parameters derived from literature corresponding to (1) the ratio of P contained in grain versus P in the aboveground biomass (known as P harvest index or PHI (kg P grain/kg P shoot)) and (2) P concentrations in plant organs. With this method, the total P demand ($P_{\text{demand}}^{\text{PHI}}$) is computed by distinguishing the P demand according to P in shoot (P_{shoot}) and P in root (P_{root}) as follows:

$$P_{\text{demand}}^{\text{PHI}} = P_{\text{shoot}} + P_{\text{root}} = \frac{P_{\%,\text{grain}} \cdot Y_{\text{grain}}}{\text{PHI}} + P_{\%,\text{root}} \cdot Y_{\text{root}} \quad (1)$$

where $P_{\%,\text{grain}}$ and $P_{\%,\text{root}}$ are grain and root P concentrations (g P/g biomass), respectively. PHI (kg P grain/kg P shoot) is the P harvest index while HI (kg grain/kg shoot) is the harvest index. We have included the root biomass to avoid underestimating the P demand, even though this method should rely on grain only. Crop-specific values for P concentrations are taken from literature and correspond to values at plant maturity (references in supporting information). Both PHI and HI were taken from a study (van Duivenbooden, 1992) compiling fertilizer trial data on nutrient uptake and yield response, coming from a multitude of climatic and socioeconomic environments. Values were derived from field experiments in stressed conditions focusing on the lower, linear part of the uptake-yield curve when nutrient use efficiency is maximal. Consequently, the PHI method gives us an estimate of the minimum amount of P required to achieve a certain grain yield.

The C:P ratio method relies on the stoichiometry of crop tissue (grain, stem, leaf, and roots) at maturity based on data found in literature, in combination with the magnitude of each crop C pool given by ORCHIDEE-CROP at harvest. This method has been used for projecting future P demand (Peñuelas et al., 2013) in natural ecosystems, with models that do not describe the P cycle and its constraints on primary productivity. The P demand for the whole plant was calculated as follows:

$$P_{\text{demand}}^{\text{C:P}} = \sum_i \frac{P_{\%,i}}{C_{\%,i}} \cdot C_i \quad (2)$$

where $P_{\%,i}$ and $C_{\%,i}$ are the P and C concentration of a biomass pool (g P,C/g biomass), respectively. C_i is the amount of carbon in that pool (g C/m²) given by ORCHIDEE-CROP. The different C pools considered here are C_{leaf} , C_{grain} , C_{stem} , and C_{root} . Concentration values were obtained from literature (references in supporting information) for crops, corresponding to plant maturity. If a nutrient factorial design existed, values were taken from the most nutrient limited one (usually the control experiment) to avoid bias in concentrations due to luxury consumption.

2.3. Soil P Supply

The soil P supply is determined by two factors: the amount of plant available P in the soil and the plant ability to take it up. The first factor was provided by a modeling approach (Ringeval et al., 2017) simulating the yearly evolution of soil P status during the twentieth century. The second factor, or the ability of a crop to take up P, is determined by the plant root system and the nature of P transport in soil solution. Uptake of P depends almost exclusively on diffusion (Barber, 1980), as concentrations are often too low to provide P by mass flow (or advection). A model of root uptake describing the diffusive flux of P in the root vicinity was thus employed (De Willigen & van Noordwijk, 1994).

2.3.1. Agricultural Soil P

The global distribution of plant available P was given by a modeling approach (Ringeval et al., 2017) that combined global data sets describing the drivers of P cycle and a soil P dynamics model. The soil P dynamics model is based on the Hedley fractionation concept (Hedley et al., 1982), where P is distributed among various pools of different chemical extractability. These pools interact on different timescales and correspond to flows of P between mobile forms at a biological level (mineralization, immobilization, uptake) and highly stable or "occluded" forms of P that are unavailable to plants (Cross & Schlesinger, 1995;

Walker & Syers, 1976). From a global vegetation or crop modeling perspective, this representation has emerged favorably in attempts to include nutrient limitation (Goll et al., 2012; Wang et al., 2010; Yang et al., 2014) on plant development.

The soil P dynamics model combines multiple sources of spatially explicit data that are deemed main drivers of the P cycle: soil biogeochemical background, soil inputs/outputs resulting from farm practices (chemical fertilizer, manure, crop uptake, and residues), land use and land cover change, soil temperature and humidity, losses through erosion, atmospheric deposition, and soil-order dependent buffering capacity (Ringeval et al., 2017). The soil P model calculates bulk transformations in the first 30 cm with a yearly time step from 1900 to 2005, separating crop and pasture land use at 0.5° resolution globally. The different P pools are (from the most to the least mobile) labile inorganic, labile/stabile organic, secondary mineral, apatite, and occluded P. The only pool used to calculate the supply of P in our approach is the labile inorganic pool (P_{ILAB}), consisting of water soluble, resin, and bicarbonate inorganic Hedley fractions. In the model, P_{ILAB} is used as proxy of the plant available P. It depends strongly on farm soil inputs/outputs and is assumed to be in equilibrium with P bound on secondary minerals (P_{SEC}) at a yearly timescale. Here we assume no interaction between P_{ILAB} and P_{SEC} during the growing season. Thus, P_{ILAB} represents plant available P at the beginning of the growing season, before fertilizer is applied and a new equilibrium with P_{SEC} is formed.

We used gridded P_{ILAB} estimates for the year 2000 (Figure S3 in the supporting information) that consist of 30 different simulations according to the uncertainty analysis of the original study (Ringeval et al., 2017). In the analysis, all of the previously mentioned drivers varied (except land use change) within a predefined range to estimate how each driver's uncertainty affects the spatial distribution of P_{ILAB} .

2.3.2. Potential Root P Uptake

The potential root uptake model (De Willigen & van Noordwijk, 1994) describes roots as a system composed of parallel and vertically placed root cylinders, which are uniformly distributed in the soil column and take up nutrients at the same constant rate. Every single root has a cylinder of influence whose radius depends on total root density. By assuming uniform water flow across this cylinder of influence, the authors (De Willigen & van Noordwijk, 1994) found an analytical solution describing solute transport in a homogeneous soil medium. We use a special case of this solution, when concentration at root surface reaches zero and uptake of P is the same as the rate at which it diffuses there. The root uptake model enabled us to calculate the potential root P uptake (P_{uptake}) (kg P/ha) determined by soil P availability and the crop root system:

$$P_{\text{uptake}} = \sum_{i(\text{month})=1}^{12} \pi \cdot \Delta z \cdot L_{rv,i} \cdot D \cdot \frac{\rho^2 - 1}{G(\rho)} \cdot C_p \quad (3)$$

where Δz is soil depth (cm), L_{rv} is monthly root length density (cm cm^{-3}), D is the coefficient of P diffusion ($\text{cm}^2 \text{d}^{-1}$), C_p is the mean concentration of orthophosphate ions in soil solution in the top 0.0–0.3 m (mg P L^{-1}), ρ is a dimensionless ratio of soil cylinder to root radius, and $G(\rho)$ is a dimensionless geometric function related to uptake by diffusion only. Further details on ρ and $G(\rho)$ can be found in the supporting information.

L_{rv} was calculated from ORCHIDEE-CROP monthly root biomass values with specific root length (SRL), which was held constant. SRL varies during the vegetative stage, but this effect was deemed negligible compared to seasonal changes in root biomass and the root-shoot ratio. SRL and root diameter values were taken at maturity stage (references in supporting information).

D was computed by a “constant slope impedance factor” model (Olesen et al., 2001), to mimic decreased diffusivity in porous media. This effect is due to the amount of water-filled pore space, which determines the diffusion path length (details in supporting information).

C_p (mg P/L) was derived from P_{ILAB} (mg P/kg soil) thanks to an empirical relationship fitted from a database (Achat et al., 2016) compiling isotopic dilution measurements (providing orthophosphate concentration in soil solution) and Hedley measurements (providing P_{ILAB}) in various ecosystems (forests, croplands, and grasslands). It was calculated using a Freundlich-type equation, which describes the soil solution equilibrium:

$$P_{\text{ILAB}} = a \cdot (C_p)^b \quad (4)$$

where a and b varied as a function of soil order (details in supporting information) to roughly account for the sensitivity of sorption/desorption to soil properties like pH and oxide concentration. In our approach, we

assumed that C_p is constant during the growing season (given the fact that P_{ILAB} is computed at a yearly time step) and thus not modified by the here computed potential plant uptake (equation (3)). A map of bulk density (Hengl et al., 2014) was used to convert P_{ILAB} from (kg P/ha) to (mg P/kg soil) as needed in equation (4).

2.4. P Limitation and Yield Gap Due To P Limitation

We compare the crop P demand and the soil P supply by computing the following ratio, hereafter called R :

$$R^{method} = \frac{P_{supply}}{P_{demand}^{method}} \quad (5)$$

where P_{demand}^{method} is the crop P demand (kg P/ha) and the superscript *method* refers to QUEFTS, PHI, or C:P ratio methods (section 2.2.2). P_{supply} is the P supply (kg P/ha) calculated in the following manner:

$$P_{supply} = \begin{cases} P_{uptake} & \text{(I)} \\ P_{uptake} + 0.2 \cdot P_{fert}/CI & \text{(II)} \end{cases} \quad (6)$$

Case I consists of the soil P supply, calculated via the root P uptake model (P_{uptake} , kg P/ha), (equation (3)) and serves as a baseline of P supply. Case II includes farm P inputs (P_{fert} , kg P/ha) along with soil P supply, to include the effects of today's P management practice. P_{fert} is the labile fraction of annual fertilizer P input (chemical and manure) used as one of the drivers of the soil P dynamics model (Ringeval et al., 2017). We assume that only 20% of applied fertilizer P can be directly available to the plant in the same growing season, bypassing the P diffusion pathway (Balemi & Negisho, 2012; Syers et al., 2008). CI (year^{-1}) is the number of crop harvests per year. CI was estimated from a data set on observed cropping areas around the year 2000 (Portmann et al., 2010), which is defined as the ratio of annually cropped area to the cropland extent area excluding fallow land (equation (2), section 3.3 in Portmann et al., 2010). The reason for using the CI parameter is to avoid a high bias in the annual P application rate in multicropping areas. Case I represents P limitation due to either low soil P legacy or a biophysical limit to P diffusion, whereas case II gives an estimate on how much the current fertilizer application alleviates this limitation. Case II could be considered as a lower limit to crop P limitation where only 20% of the applied fertilizer is directly incorporated into plant biomass.

We calculate the yield gap (van Ittersum & Rabbinge, 1997) due to P limitation ($Y_{gap,P}$ in (%)) by assuming a linear relationship between the $Y_{gap,P}$ and the demand:supply ratio (equation (5)) as follows:

$$Y_{gap,P}^{method} = \max(0, 1 - R^{method}) \quad (7)$$

We restrict our computation to cases where P supply is smaller than P demand, assuming that plants cannot take up more P than needed. P limitation was computed using the ORCHIDEE-CROP simulations in irrigated and high N fertilizer conditions, which should represent the yield potential. We compared our estimates to a globally gridded data set (Mueller et al., 2012) on the observed yield gaps. In this data set, the world grid points are divided into climate bins, defined by different combinations of growing degree days and amount of yearly precipitation. Within a climate bin, the potential yield is defined as the area-weighted 95th percentile of the observed within the same climate bin. The yield gap then is the difference of the mean and the potential yield within the same bin. These yield gaps were expressed as fractions of their yield potential to make them comparable with our estimates.

2.5. Analysis of Uncertainty, Commonality Analysis, and Global Averages

A Monte Carlo (MC) method was used to estimate uncertainty in the P limitation estimates. Namely, the parameters were varied around their mean in 1,000 replicates according to their standard error (SE) provided by the source literature. If SE was not provided, we assumed it as a fraction of the mean as either 5% or 20% (supporting information). In PHI (equation (1)) and C:P ratios (equation (2)) methods, and parameters/variables whose uncertainty was considered are nutrient concentration of the plant organs, PHI, and the HI parameters. In the QUEFTS method, we varied the parameters related to optimal nutrient uptake (supporting information). In equations (3) and (4), an uncertainty was considered for P_{ILAB} , Freundlich equation parameters, constant-slope impedance diffusion parameters (supporting information), SRL, and root diameter. In equation (6), P_{FERT} uncertainty was considered.

A commonality analysis (Reichwein Zientek & Thompson, 2006) (CA) was used to explain factors contributing to the spatial and the grid point variability of the root uptake relation (equation (3)). At every world grid point,

we calculate the time average value and take the median of the 1,000 MC replicates. Following this, we calculate deviations from the global mean at every grid point. Once these deviations are log transformed and normalized (around the global mean), we obtain a multiple linear model of the dependent variable P_{uptake} with predictors L_{rv} , D , C_p , and P_{ILAB} . Similarly, to estimate the contribution of the predictors at every grid point, the variables were averaged in time, log transformed, and z scored around the mean of the 1,000 MC replicates. The CA protocol determines variance belonging to all possible combinations ($15 = 2^4 - 1$) of predictor variables. It then successively assigns unique or common (due to collinearity) variance to each of the predictors, by combining the R^2 values of each multiple linear model combination. In the spatial variability CA, 1,000 bootstrap samples were taken to obtain the 95% uncertainty interval around the global median CA coefficients. The bootstrap procedure was not performed for the grid point uncertainty estimates.

In the following, global averages of P supply, demand, and limitation are calculated by weighting the grid cell values with the total observed crop area (Portmann et al., 2010), and 95% uncertainty interval is given (in brackets) to the median value of the 1,000 MC replicates. A similar technique was applied when presenting histograms of these quantities in each grid cell, where the contribution of every grid cell depends on the fraction of crop area within it. When presenting histograms, uncertainty is shown as the 68% interval around the median value of 1,000 MC replicates for every grid cell. The 68% interval would correspond to 1 standard deviation, if the 1,000 MC values at each cell were normally distributed.

We masked and filtered some grid cells before performing our calculation. For each crop, we started from grid cells where the observed crop area is non-null (Portmann et al., 2010). We then kept grid cells for which a value of P_{ILAB} is provided by the soil P dynamics model. These criteria reduce the considered crop area to 78%, 71%, and 63% of the observed crop area for wheat, maize, and rice, respectively. The previous drop in coverage is mainly due to the coverage of the soil biogeochemical background data set (Yang et al., 2013) used in the soil P dynamics model (Ringer et al., 2017). Additionally, we have removed grid cells for which ORCHIDEE-CROP simulated no grain or where the simulated plants remain in the vegetative phase during the whole growing season. Once these were removed, the final crop area covers 35%, 67%, and 61% of the observed area (Portmann et al., 2010) for wheat, maize, and rice respectively. The notable decrease in wheat coverage is mainly explained by the observed crop area data set (Portmann et al., 2010) in which spring and winter wheat are not distinguished, whereas we simulate winter wheat only. In other areas (e.g., parts of Central Europe) the vernalization requirements are not fulfilled during the simulation (leading to no grain) even though winter wheat might be present in reality.

3. Results

3.1. Potential Root P Uptake

Global averages of potential root P uptake are 20.2 (15.5–26.3), 20.9 (15.3–31.9), and 13.6 (10.5–16.8) kgP/ha, respectively, for winter wheat, maize, and rice. The ranking of potential uptake between different crops (maize \approx winter wheat $>$ rice) is explained by the root biomass potential of each crop, maize having the highest and rice the lowest. Winter wheat might be additionally biased, as our calculation concerns only 35% of the global observed wheat area that is concentrated in areas with high soil P levels (Northern Hemisphere). Figure 2 shows the spatial variability of potential root P uptake, which does not vary much among crop species. The top 25% values consistently show up in Western Europe, South-East Asia, and Central America corresponding to high production intensity areas. Interestingly, North America and Brazil show widespread low potential P uptake. This is explained by low levels of P_{ILAB} (supporting information Figure S3) and high Mollisol and Oxisol coverage, with high P sorption and hence low C_p (supporting information equation (9)). Other areas that show low potential P uptake such as Africa, Eastern Europe, Argentina, and Paraguay are characterized by low P_{ILAB} levels, likely due to negative soil P input/output balance (MacDonald et al., 2011).

The spatial distribution of potential uptake closely follows that of P_{ILAB} (supporting information Figure S3). At least 80% of the spatial distribution of the potential root P uptake can be explained by the amount of P_{ILAB} (Figure 3, top). In this figure, the commonality coefficient CC12 describes common variance to variables P_{ILAB} and C_p , whereas CC1 (P_{ILAB}) and CC2 (C_p) describe the additional variance not shared with the other variable. Since C_p is a function of P_{ILAB} , CC2 shows the additional variability from the fitted Freundlich equation (4), whereas CC1 has no new information. Other variables are much less important than C_p or P_{ILAB} in determining the spatial distribution of potential uptake. This comes as no surprise, as high soil water content

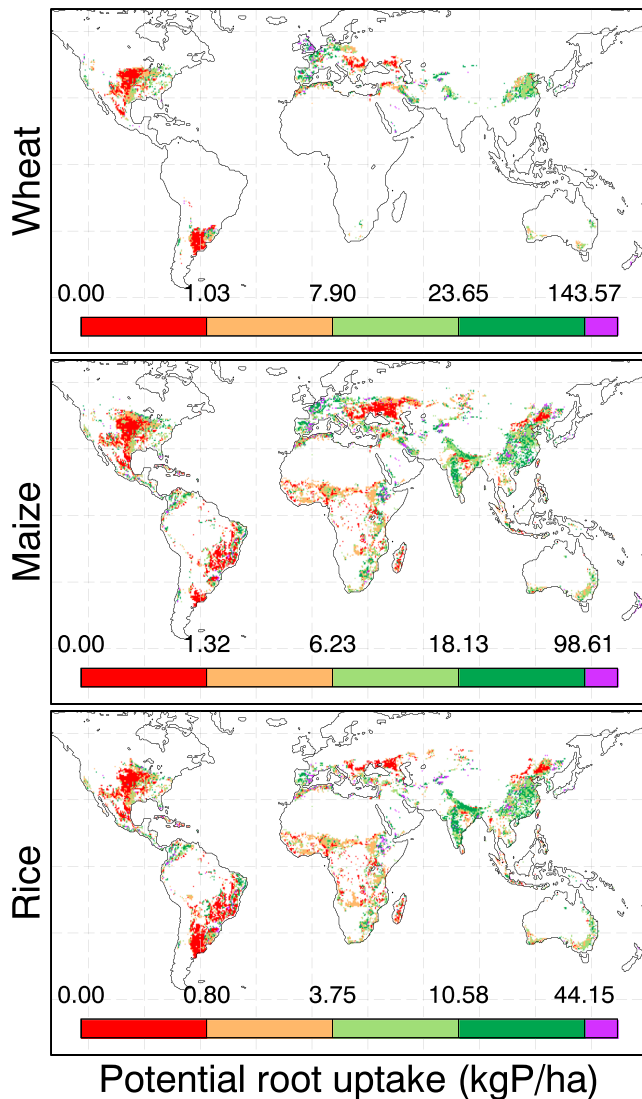


Figure 2. Potential root P uptake during the growing season (P_{uptake} , kgP/ha) determined as the median from 1,000 MC replicates. The colorbar depicts quantiles (0–25–75, 90). Rows are winter wheat, maize, and rice.

supply and demand are plotted side by side (Figure 4), they represent the case of most optimal redistribution of the two. In this case, only 15–40% of winter wheat and maize area would achieve its potential yield using soil P only and 25–65% in case of rice, which points to the inefficiency of P distribution in agricultural soils worldwide.

Lastly, the difference in the shapes of the demand and potential uptake curves (Figure 4) can be explained by their respective source of spatial variability. Since the crop P demand is calculated from the ORCHIDEE-CROP biomass pools in irrigated conditions, the climate determines the yield potential and subsequently the distribution shape. For potential root P uptake, we have shown that 80% of the spatial variability is explained by the P_{ILAB} distribution (section 3.1), which in turn depends mostly on the historical farm input/output balance and soil biogeochemical background (Ringer et al., 2017).

3.3. P Limitation and Yield Gap

The global average of the supply:demand ratio showed that the world soil P supply by itself is largely adequate in satisfying crop P demand. The three demand methods give an average of 160 (81–473)% in winter wheat, 132 (55–263)% in maize, and 205 (69–544)% in rice. By adding P from fertilizer the global average

(consequence of the irrigated conditions) presents no obstacles to P diffusion. Another point to note is the lack of influence of root length density (L_{rv}) on the spatial distribution of rice P uptake (Figure 3, top, CC4). This is explained by the fact that the root system of rice achieves its biomass potential in most of the considered grid cells, thus exhibiting no climate variability in our crop simulations.

Uncertainty at each grid point level is mainly due to the amount of plant available P or P_{ILAB} (Figure 3, bottom) and is higher than variability due to other variables (C_p , D , L_{rv}) in 70–80% of the world grid points (not shown). The uncertainty shifts from P_{ILAB} to other variables in areas of low soil P levels such as North America, South America, and Eastern Europe (supporting information Figure S3).

3.2. Crop P Demand

The values of the global average of crop P demand are given in Table 1. We found that the demand is larger for maize than for the two other crops (winter wheat and rice). In general, we found a relative consistency between the three methods except for rice, where the C:P ratio method leads to higher P demand compared to the PHI and QUEFTS methods. This could be explained by the fact that QUEFTS and PHI parameters are obtained in stressed environments where nutrient use efficiency is highest, while the C:P ratio parameters are obtained in conditions of luxury consumption (see sections 2 and 4).

There were some inconsistencies between the methods, especially for the C:P method. The deviation between C:P and the two other methods was larger for rice, and this could be explained by the difference in allocation between the crops. In ORCHIDEE-CROP simulations, grain receives about 35% of NPP in case of rice against 65 and 50% for winter wheat and maize, respectively. This tends to decrease further the contribution of grain in the demand estimate by the C:P method for rice. This is amplified by interspecies differences in organ P concentrations (supporting information; Figure 2), which was mentioned earlier in the previous paragraph and is further presented in the discussion.

Comparing global average values of demand (Table 1) and potential root uptake (section 3.1), we observed that the demand was not larger than the soil P supply. A different picture emerges though, if looking at the range of these values across croplands worldwide. If histograms of P

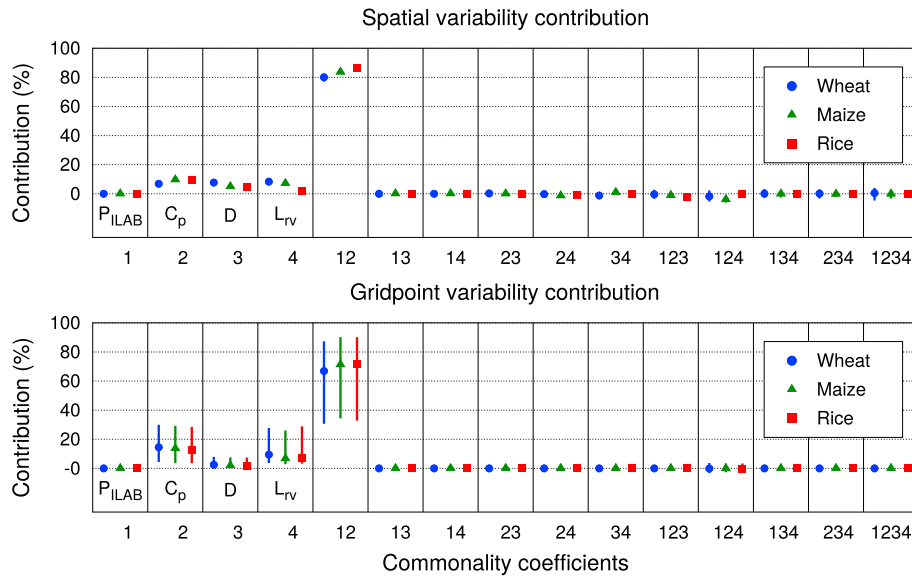


Figure 3. Commonality analysis of potential P root uptake (equation (3)). The plots show the contribution of each of the drivers (P_{ILAB} , C_p , D , and L_{rv}) to the (top) spatial variability and (bottom) variability at each grid point of the calculated root P uptake. Values 1 to 4 show the unique contribution not shared with others. Other combinations (12 to 1234) show variance common to all variables within that combination. Different markers and colors correspond to different crop species (see legend). In Figure 3 (top), error bars show the 95% uncertainty interval around the global median value (obtained with 1,000 bootstrap samples). In Figure 3 (bottom), error bars show the 68% quantile interval around the global median value. P_{ILAB} is soil inorganic labile P, C_p is P in soil solution, D is the P diffusion coefficient, and L_{rv} is the root length density.

increases to 182 (98–514)% in winter wheat, 155 (72–299)% in maize, and 278 (96–624)% in rice. The differences among species are due to their geographic location as mentioned in section 3.1. Even though the addition of fertilizer increases the amount of available P, it is hard to distinguish the increase due to high uncertainty of the initial P_{ILAB} data.

A clearer picture of global P limitation is presented when looking at the spatial distribution of the supply: demand ratio (Figure 5, focusing on the QUEFTS method; see supporting information for the PHI and C:P based ones). The soil supply only sustains the demand of P for potential yields in certain parts of the world like South-East Asia, Western Europe, Central America, Ethiopia, and Oceania. By contrast, large parts of Central Asia, Africa, North America, and South America experience severe limitation that needs to be amended with additional inputs to increase yields. These areas have a known low soil P supply, due to high sorption capacity (Mollisols in North America and Oxisols in Brazil) and historically low to negative P balance (Ringeval et al., 2017) (Central Asia and Africa). When including fertilizer P from the current year in the supply, the limitation is somewhat relieved except in the western part of North America, Africa, Central Asia, and southern South American states (Argentina, Paraguay, and Uruguay).

The histogram of the yield gap is plotted in Figure 6 (top row). We found that on average 52–57% of winter wheat area, 69–79% of maize area, and 36–63% of rice area show a yield gap due to P limitation in some form.

Differences between the three crops are mainly explained by their geographic location. Maize is the most limited crop because its potential biomass is higher in ORCHIDEE-CROP, leading to a higher demand (see section 3.2), and also because it is grown all over the world, including in areas of low soil P supply (Central Asia and Africa). Winter wheat limitations are in between those from maize and rice because it is grown mostly in northern latitudes, where soil P supply is relatively higher. Rice shows the lower P limitation because its production is highly concentrated in South-East Asia, an area with high levels of soil P supply (Figure 2). The overall uncertainty is large and comparable across species (except for rice) and across methods. Because the potential P uptake is common to all

Table 1
Global Average of P Demand (kgP/ha/yr) Calculated With Different Methods (QUEFTS, PHI, and C:P Ratios)

	Crop P demand (kgP/ha/yr)		
	Winter wheat	Maize	Rice
QUEFTS	6.6 (4.9–10.1)	14.6 (10.4–22.1)	5.5 (4.5–6.3)
PHI	7.8 (7.8–7.9)	19.0 (18.7–19.3)	6.8 (6.7–7.0)
C:P ratios	7.1 (4.6–9.9)	21.4 (18.3–24.7)	13.1 (12.2–14.0)

Note. Values in brackets are the 95% quantile interval around the median value from 1,000 MC replicates.

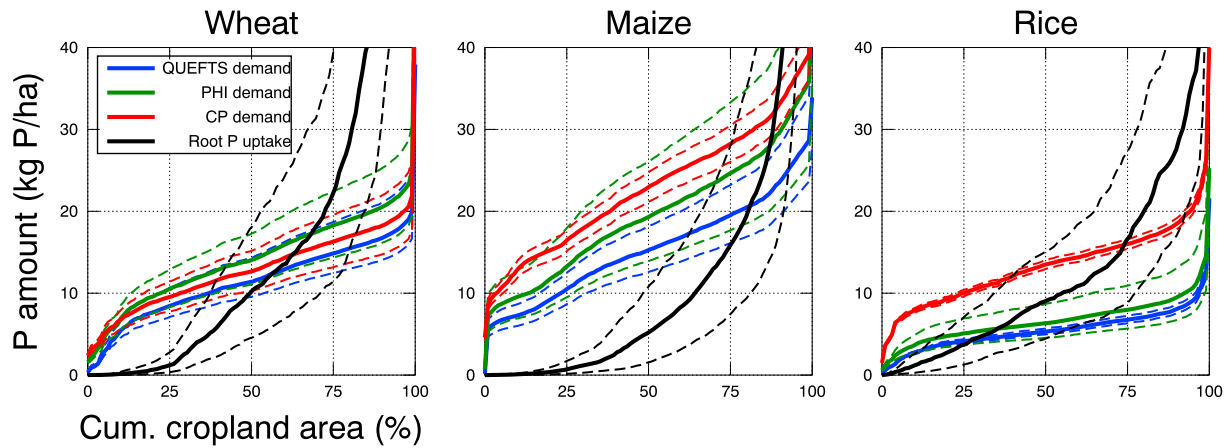


Figure 4. Cumulative histograms of crop P demand and potential root P uptake globally (kg P/ha). Demand is drawn with color, while potential root uptake is drawn in black. Each color represents a different way of calculating P demand (blue for QUEFTS, green for PHI, and red for C:P ratios). Dashed lines correspond to the 68% quantile interval around the median of 1,000 MC replicates.

crops/methods, this points to the uptake as the main determinant of the yield gap uncertainty. Since the uncertainty in the potential root P uptake is largely explained by P_{ILAB} (Figure 3, bottom), this uncertainty can be traced back to the uncertainty of the main drivers in the P_{ILAB} pool, which are the history of farm inputs/outputs and the soil biogeochemical background (Ringer et al., 2017). For rice, there is a notable

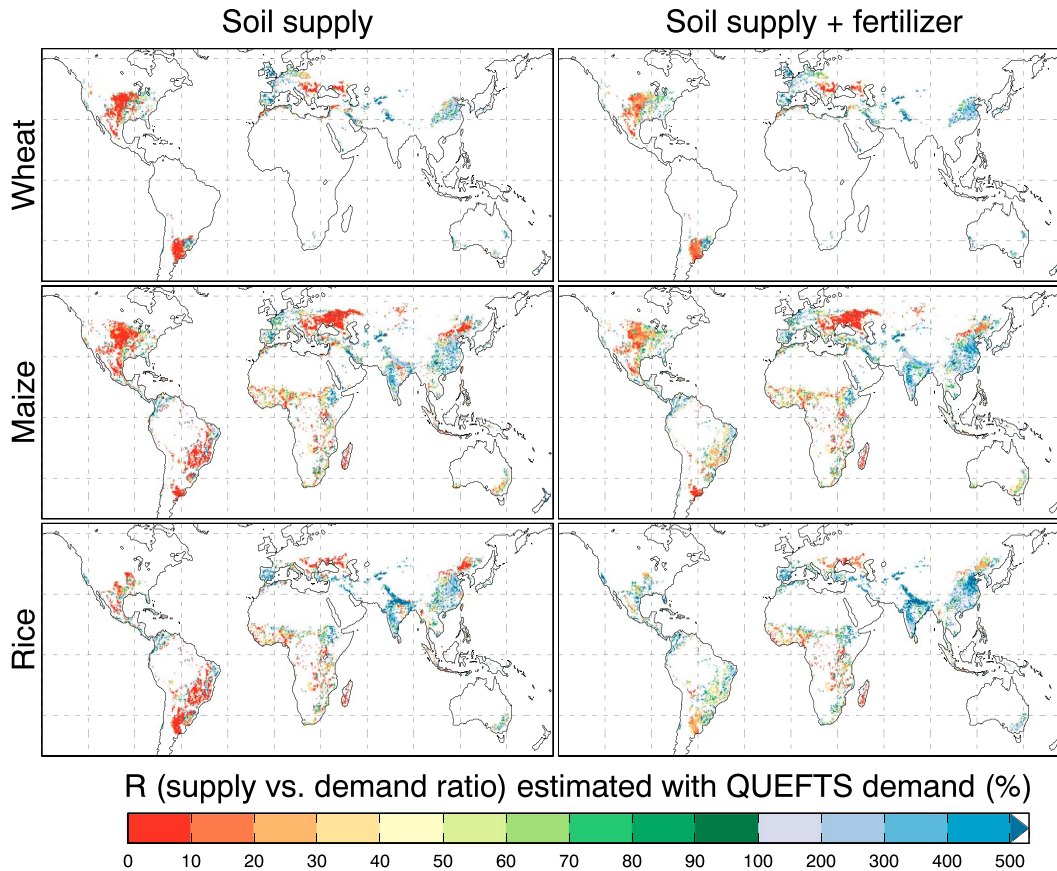


Figure 5. Spatial distribution of the R ratio (supply:demand; in percent) calculated using the QUEFTS method to estimate the demand. The ratio is provided when (left column) only the soil P supply is considered (case I in equation (6)) as well as when (right column) both soil P supply and fertilizer P are considered (case II in equation (6)). Rows are different species (top to bottom: winter wheat, maize, and rice). Plots of ratios when PHI and C:P ratios are used to estimate the demand can be found in the supporting information.

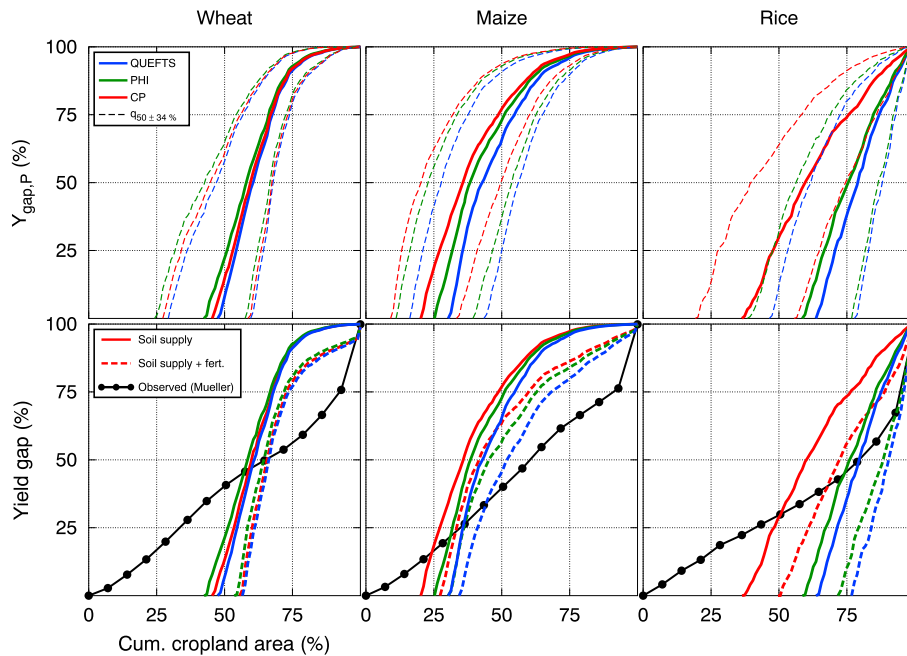


Figure 6. Cumulative histogram of the P yield gap in irrigated simulations (percent). (top row) The global P limitation (due to potential root uptake P) calculated with different P demand methods. Full lines are the median of the 1,000 MC replicates, with 68% quantile range around it in dashed lines. (bottom row) The limitation due to root uptake P (full colored line) amended with fertilizer P (dashed colored lines). Additionally, the yield gap from Mueller et al. (2012) (black line with circles) is plotted for comparison.

difference between the three limitation methods (Figure 6, top right) that is due to differences between the methods to estimate the demand (as explained in section 3.2). Adding P from fertilizer to the potential root P uptake, the total area experiencing P limitation decreases to 43–46% for winter wheat, 65–72% for maize, and 23–50% for rice (dashed lines in Figure 6, bottom row). But as mentioned earlier, the decrease in limitation is hardly noticeable due to variability of the initial P_{LAB} data.

Based on our different estimates, the global average of the P yield gap is 22 (18–28)% in winter wheat, 55 (47–66)% in maize, and 26 (18–46)% in rice. Amended with fertilizer P, the yield gap drops to 17 (14–21)% in winter wheat, 46 (36–55)% in maize, and 15 (10–32)% in rice. Comparing our P yield gap estimates to the ones observed (Mueller et al., 2012) (black lines in Figure 6, bottom), we found that P limitation explains only a portion of the observed yield gap. The difference could be due to us considering only P as the limiting factor, whereas the observed yield gaps include all of the macronutrients (NPK) as well as contributions from irrigation, weed, pests, and disease.

4. Discussion

We have investigated how soil P supply can lead to P limitation of crop yields, by combining data on the current global distribution of agricultural soil P and an idealized crop simulation while accounting for the basic nature of plant-soil transfer of P. Whereas previous studies estimate the global nutrient yield gap through statistical approaches (Mueller et al., 2012), our diagnostic approach aims to represent more explicitly key variables and processes involved in the P limitation, namely the cropland soil P, soil P diffusion, and root uptake. We showed that P is a key factor of yield gap at the global scale with estimated global yield gap due to P of 22, 55, and 26% for winter wheat, maize, and rice, respectively. Although the global average of the potential soil P supply is larger than P demand, due to the amount of soil legacy P in highly fertilized areas, we found that a significant portion of cropland area has soil P levels too low to sustain the climate potential yield. These results corroborate the heterogeneity of today's global P management practice and its potential impacts on food production (MacDonald et al., 2011; Mueller et al., 2012) that need to be dealt with a comprehensive set of global measures like more equitable access to fertilizer P, P redistribution, and reducing P waste through technological improvements. (Obersteiner et al., 2013; Tilman et al., 2011).

Soil P availability plays a more important role than current fertilizer application, according to our results. A sensitivity test, where we assumed that 20% of the annual applied P in fertilizer is directly incorporated into crop biomass, showed that P limitation can be relieved only slightly, with a global yield gap reduction of 5–10%. This small alleviation suggests, as mentioned in the previous paragraph, that the spatial distribution of current fertilizer application is relatively nonoptimal. Surprisingly, we found significant P limitation in intense production areas (e.g., North America and Brazil) even in our fertilizer sensitivity test. Even though these areas largely consist of high-fixing P soils (Roy et al., 2016), we suspect the P limitation stems from the nature of the models used. One explanation is the simplicity of the root uptake model, which does not include some key processes that increase P acquisition (Hinsinger et al., 2011) like root branching/architecture, exudates/phosphatase, and mycorrhizae association. Even though there are recent attempts at producing world databases of the latter two quantities (Margalef et al., 2017; Soudzilovskaia et al., 2015), their implementation stays problematic due to the complexity of the processes involved (Hinsinger et al., 2011) and the lack of their quantification with respect to P mineralization/uptake (Goll et al., 2017). Another reason for the severe P limitation in high production areas could be the bulk nature of the soil P model, which homogeneously mixes the fertilizer P in the first 30 cm. In reality, plant nutrient uptake can be increased (Randall & Hoef, 1988) through a practice called banding, whereby fertilizer is placed close to the roots to increase its efficiency, especially in soils with low P levels and high fixing capacity (Randall & Hoef, 1988). This shows that simple bulk flow calculations might not be sufficient in diagnosing P limitation, and that a more process-oriented description of P exchange is needed.

Global yield gaps have so far been studied (Licker et al., 2010; Mueller et al., 2012; Neumann et al., 2010) in a spatial manner using globally gridded yield census data (Monfreda et al., 2008) and relating it to crop management information. These provide a robust picture of current limitation in world's crop production and can be a valuable knowledge source for targeted regional management. But the strength of these approaches, which is in dealing with aggregated effects of agricultural practices, is also a limit if one wants to take a closer look at each limiting factor. Irrigation and nutrient application are strongly related to yield variation globally (Mueller et al., 2012), but separating their contribution remains a problem, since these factors exhibit a high degree of correlation. A more process-based approach would enable us to isolate the effects of P limitation from others (like water and N). However, the use of a generic crop model gives estimates that are partly disconnected from reality and makes the comparison with the observed yield gap difficult. The parametrization of crop models against rich data sources for local climate and soil conditions, for example, the GYGA project (van Ittersum et al., 2013), would allow both distinction of the limiting factors and connection to a local context.

Our estimates contain considerable grid point uncertainty, which is mainly due to the amount of plant available P in soil (P_{LAB}). In the source of the P_{LAB} information (Ringeval et al., 2017), the initial uncertainty stems from the soil's biogeochemical history that is poorly constrained by the original data (Yang et al., 2013). Additionally, in the sensitivity study of the soil P model (Ringeval et al., 2017) farm P inputs/outputs driving the model varied with a considerable spread (a CV of 30%), further contributing to the uncertainty of this pool at year 2000. Apart from this, there are notable differences across the three P demand methods (Table 1 and Figure 4). In PHI and QUEFTS, the estimates are based on traditionally measured quantities of aboveground nutrient off take and provide comparable values as they incorporate data from a large set of growing environments (van Duivenbooden, 1992; Sattari et al., 2014). Measurement of C:P ratios in plant organs (references given in supporting information) does not seem to be a common practice in agriculture, given by the fact that we are using literature from year 1934 for maize. In the case of rice, the data come from an experiment in highly fertilized soil (average application of 240 kg N ha⁻¹, 120 kg P₂O₅ ha⁻¹, and 120 kg K₂O ha⁻¹ annually) and lead to a notable P demand bias compared to the other two, possibly due to luxury consumption even in the nutrient omission plot. The scarcity of C:P ratio data in agriculture might serve as a call for more experimental inquiry, as ecosystem models move toward a description of the plant's carbon cycle that includes the effects of nutrient availability (Goll et al., 2017; Wang et al., 2010; Yang et al., 2014). Finally, an even more robust estimate could be obtained if one was to employ a whole ensemble of models like recent attempts by Martre et al. (2015).

This study is a step toward a process-based assessment of the P limitation in agricultural ecosystems. However, to arrive to these estimates, a number of broad assumptions and constraints had to be

considered: missing representation of the plant response to P limitation, rudimentary description of P in soil solution, and linear reduction of yield according to the supply:demand ratio. First, P limitation affects C allocation during plant development (Mollier & Pellerin, 1999), redirecting assimilates to roots instead of leaves to increase the plant's P foraging ability. The consequence is a lower shoot biomass that demands less P and also relatively greater roots with higher capacity for P uptake. Second, our description of the soil solution at an annual time step is simple (equation (4)), with a relation that describes the long-term equilibrium between soil solution and sorbed P without any seasonal change; this limitation is evident in our treatment of fertilizer P (equation (6)). When added to P_{ILAB} prior to computing the $C_p - P_{\text{ILAB}}$ equilibrium, the additional P has no effects on the simulated potential uptake (not shown). This points to the importance of transient and short-term effects in fertilizer P sorption (Barrow, 1983), a process that is highly dependent on soil composition and chemical properties. Finally, we calculated the yield gap as a linear decrease according to the supply:demand ratio, which is not an unreasonable simplification. Studies looking at the effects of nutrient deficiency show that (Amanullah & Inamullah, 2016; Batten et al., 1984; N. K. Fageria & Oliveira, 2014) the harvest index stays relatively stable at low P additions, with greater variability due to genetics and climate. However, this might not be true in extreme situations (Sahrawat et al., 1995), where allocation to grain might be disrupted to insure functioning of other plant parts.

The above mentioned issues could be tackled by coupling the soil P dynamics (Ringeval et al., 2017) and the ORCHIDEE-CROP model (Wu et al., 2016). For example, a dynamic representation of P stress on a daily basis would allow us to simulate the interaction of P with other factors, notably water and N. Furthermore, physiological responses to P stress could be simulated such as a decrease in leaf area index (Plénet et al., 2000) or change in the shoot:root ratio (Mollier & Pellerin, 1999), which would influence the final grain yield and more faithfully describe yield loss. Exchange of P between the soil and crop through crop uptake/residues, fertilizer application, and their incorporation into the soil would allow us to model long-term effects of P management on crop yields. We surmise that, by properly accounting for the flow of P between the soil and plant, more accurate estimates and a better understanding of P limitation in agricultural ecosystems is possible, which are needed in the face of the growing phosphorus issue worldwide (Cordell et al., 2009; Obersteiner et al., 2013; Peñuelas et al., 2013).

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