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Phosphorus footprint in China over the 1961-2050 period: Historical perspective and future prospect

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Abstract

The phosphorus footprint (PF) is a novel concept to analyze human burdens on phosphorus resources. However, research on PF approach is still limited, and current several PF studies include incomplete phosphorus sources and have limited quantitative interpretation about the drivers of PF changes, which can help understand future trends of PF. This study develops a more comprehensive PF model by considering crop, livestock and aquatic food, and non-food goods, which covers the mainly phosphorus containing products consumed by human. The model is applied to quantify China's PF from 1961 to 2014, and the results of the model are also used to analyze the factors driving the PF changes and explored China's PF scenarios for 2050 using an econometric analysis model (STIRPAT). The result shows that China's PF increased over 11-fold, from 0.9 to 10.6 Tg between 1961 and 2014. The PF of livestock food dominated China's PF, accounting for 57% of the total in 1961 and 45% in 2014. The key factors driving the increase in China's PF are the increase in population and urbanization rate, with contributions of 38% and 33%, respectively. We showed that in the baseline scenario, China's PF would increase by 70% during 2014-2050 and cause the depletion of China's phosphate reserves in 2045. However, in the best case scenario, China's PF would decrease by 15% in 2050 compared with that in 2014, and it would have 50% of current phosphate reserve remaining by 2050. Several mitigation measures are then proposed by considering China's realities from both production and consumption perspective, which can provide valuable policy insights to other rapid developing countries to mitigate the P footprint.

Key words: phosphorus footprint; scenario analysis; driving factors; phosphorus demand; China

1 Introduction

Phosphorus (P) plays an increasingly important role in sustaining food production for an expanding population [*Simons et al.*, 2014]. Since World War II, global extraction of phosphate rock increased 15-fold, reaching 223 million tons in 2015 [*The United States Geological Survey* (*USGS)*, 2016]. As global food demand is projected to almost double by 2050 compared with than of 2005 [*Tilman et al.*, 2011], demand for non-renewable phosphate rock will inevitably increase as modern agriculture is more dependent on the availability of chemical P fertilizer [*Chen and Graedel*, 2016]. Therefore, long-term availability of affordable P resources attracts a global concern [*van den Berg et al.*, 2016]. China, regarding P resource availability is of particular interest, because of its important role in the global P resource supply-demand network. In 2015, China mined 49% of global phosphate rock extraction, produced 37% of global chemical P fertilizer and consumed 33% of these fertilizer [*USGS*, 2016; *Food and Agriculture Organization of the United Nations (FAO)*, 2017], because China needs to feed 19% of global population using 7% of the world's arable land [*FAO*, 2017; *World Bank*, 2017]. However, China only accounts for less than 6% of global phosphate rock reserves [*USGS*, 2016], thus it is facing major P resource pressures. Moreover, large anthropogenic P inputs have caused widespread eutrophication of waterbodies in China [*Liu et al.*, 2016], which impairs water quality and damages aquatic ecosystem [*Chau and Jiang*, 2002; *Wang et al.*, 2014]. Accordingly, there is a great urgency to assess the burdens on P resource, especially in China.

Footprint analyzes is an effective way to quantitatively describe how human activities impose various burdens on environment and resources [*Čuček et al.*, 2012]. In the "family" of footprint tools, ecological footprint, carbon footprint and water footprint are among the most established [*Wiedmann and Minx*, 2008; *Hoekstra*, 2009; *Galli et* *al.*, 2012]. These footprint tools have been widely applied to assess sustainability issues, like climate change, water resources and environmental carrying capacity and have garnered a lot of attention [*Tom et al.*, 2016; *Venter et al.*, 2016]. The nitrogen (N) footprint is a more recent extension of footprint concept to measure anthropogenic N losses [*Leach et al.*, 2012]. Gu et al., (2013) adapted the N footprint tool based on the mass balance approach, and applied it to assess China's N footprint of production and consumption of food, energy and industrial products [*Gu et al.*, 2013]. Cui et al., (2016) combined material flow analysis with input-output analysis approach to assess China's N footprint, with a focus on the effects from international trade [*Cui et al.*, 2016]. Oita et al. used a more complicated method, by combining a global emissions database, nitrogen cycle model, and input–output database to assess the effects of international trade on N footprint of 188 countries [*Oita et al.*, 2016].

While many publications focus on the N footprint, the P footprint (PF) has still been received little concern. Wang et al. first used the PF concept to measure P demand of China's food chain based on substance flow analysis approach [*Wang et al.*, 2011]. Grönman et al. developed a framework to calculate the PF for individual crops from a life cycle perspective [*Grönman et al.*, 2016]. However, existing studies consider the PF of partial human activity like food subsystem, and thus cannot help understand the PF of human activities from a social-economic system perspective. Furthermore, these studies have limited quantitative interpretation about the drivers of PF changes, which can help understand future trends of PF.

In this study, we developed a more comprehensive PF model that considers mainly P containing products including crop food, livestock food and aquatic food, and non-food goods. Then, the PF for China from 1961-2014 was quantified based on the developed model to measure holistic P demand in China. To facilitate the analysis of the PF result, we also extended the Stochastic Impacts by Regression on Population, affluence, and Technology (STIRPAT) model to quantitatively evaluate the factors driving the changes in China's PF and examined future scenarios of China's PF by 2050. The contribution of this study is providing a more comprehensive PF model to measure the phosphorus demand of an entire economy, which can help to understand human burden on P resources of other countries worldwide. The case study in China can provide valuable policy insights to other rapid developing countries to reduce the P footprint.

2 Materials and methods

2.1 Phosphorus footprint method

The PF in this study is defined as the total P demand as a result of population's consumption, including direct P contained in the products consumed by populations and virtual P of the consumed products (P demand in the production stage). The main types of products considered are crop food, livestock food, aquatic food and non-food goods (Figure 1a). Analogous to others footprint methods [*Ewing et al.*, 2010], the PF is calculated by the following equation:

$$PF = PF_P + PF_I - PF_E \quad (1)$$

where PF is the holistic PF; PF_P is the PF of the 4 types of products, calculated by Eq. 2; PF_I and PF_E are the PF in imported and exported products. The PF can be expressed in total units of P, or in unit of P per capita for the ease of comparison.

$$PF_P = PF_c + PF_l + PF_a + PF_g \quad (2)$$

where PF_c, PF_l, PF_a and PF_g represent PF of crop food, livestock food, aquatic food and non-food goods, respectively.

Figure 1 Schematic of the PF model. (a) Framework of the PF model. (b) Calculation principle

of the PF model.

The PF of the product type *i* (*c, l, a and g*) in a certain year is calculated at the sector level based on the mass balance principle (Figure 1b). As it has been shown in Figure 1a, the products of a certain sector *i* consist of two parts: (1) one is transferred to downstream sector; (2) the other is consumed by population. In this study, the PF of the product type *i* refers to the part consumed by population, which can be expressed by Eq. 3:

$$I_i = O_i + PF_{i\_d} + PF_{i\_v} \tag{3}$$

where I_i is the P inflows to sector *i*, but excluding the recycled P from wastes, like manure, straws and sludge; O_i is the PF associated with the part transferred to downstream sector; PF_{i_d} is the direct PF of product type *i* that is consumed by population; PF_{i_v} is the virtual PF (or P loss) in the process of production of product type *i*, which is calculated by Eq. 4.

$$PF_{i\_v} = (I - PF_{i\_t}) \times \frac{PF_{i\_d}}{PF_{i\_t}} = \frac{PF_{i\_d}}{\varepsilon_i} - PF_{i\_d} \tag{4}$$

where PF_{i_t} is the P contained in the total products of sector *i*; ε_i is the averaged P use efficiency of sector *i*, calculated by Eq. 5.

$$\varepsilon_i = \frac{PF_{i\_t}}{I_i} \tag{5}$$

The PF_I and PF_E are also calculated for each product type *i* using Eq. 6.

$$PF_{i\_I/E} = \frac{PF_{id\_I/E}}{\varepsilon_{i\_I/E}} \tag{6}$$

where $PF_{i\_I/E}$ is the PF of imported/exported product type *i*; $PF_{id\_I/E}$ is the direct P contained in imported/exported product type *i*; ε_{i_E} equals to ε_i; ε_{i_I} is the P use efficiency of the product type *i* of the country produced it.

Based on the developed model above, the PF of the four types of products were calculated for China. The details can be found in Supporting Information (SI).

Indicators of phosphorus footprint and comparisons. Following the study by Gu et al. (2013), we calculated several indicators as the feature PF results:

● P use efficiency of crop farming (PUE_c), defined as the ratio of direct PF in crop products to inflow of crop farming sector (see Text SI, S2).

● P use efficiency of livestock breeding (PUE_a), defined as the ratio of direct PF of livestock food to the inflow of livestock breeding sector (see Text SI, S3).

● Dietary choice, defined as the ratio of direct PF of animal food (P_{l_d} +P_{a_d}) to direct total PF of food (PF_{c_d} +PF_{l_d} +PF_{a_d}) (see Text SI, S2-S3).

● Dependence on mineral P, defined as ratio of PF from mineral P to the total PF.

2.2 STIRPAT model

The driving factors can be analyzed by Logarithmic Mean Divisia Index (LMDI) decomposition method and the Impact-Population-Affluence-Technology (IPAT) model [*Ehrlich and Holdren*, 1971]. LMDI method is usually used to analyze the factors driving the carbon emissions, while the IPAT model can be used to quantitatively evaluate the driving factors of various environmental pressure [*Li et al.*, 2018]. Thus, IPAT model is more suitable in this study regarding to assess driving factors of P demand. However, the IPAT model is unable to deal with non-proportional effects. To overcome the weakness, Dietz and Rosa (1994) developed the STIRPAT model by introducing randomness based on the IPAT model [*Dietz and Rosa*, 1994]. The

STIRPAT model is more flexible as it enables users to add adequate variables, thus it has been successfully used to examine the impact of anthropogenic factors on various material consumption and pollution emission [*Longo and York*, 2008; *Cui et al.*, 2013; *Wang et al.*, 2013]. Accordingly, this study used the STIRPAT model and extended it to analyze factors driving China's PF.

The STIRPAT model can be expressed as:

$$I = aP^b A^c T^d e \tag{1}$$

where a is the constant; b, c and d are the exponents of P, A and T, respectively; e represents the error term. However, the standard STIRPAT model is a nonlinear multivariate equation, thus it is difficult to calculate the coefficients of a, b, c, d, and e. In the typical application, all the variables in Eq. (1) are often converted to logarithmic form to facilitate the calculation:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \tag{2}$$

Following Jiang et al. (2018), we expanded the STIRPAT model by including factors of urbanization rate, dietary choice, technology level of crop farming and animal breeding, dependence on mineral P, resulting in following extended STIRPAT model:

$$\ln I = \ln a + b \ln P + c \ln A_u + d \ln A_d + f \ln T_c + g \ln T_a + h \ln D + \ln e \tag{3}$$

where P is population; A_u and A_d are urbanization rate and diet choices, which are proxies of affluence; T_c and T_a are PUE_c and PUE_a, which are proxies of technology level; D is the dependence on mineral P.

In a multiple regression model, multicollinearity refers to a phenomenon in which one predictor variable can be linearly predicted from the others, causing an irregularly change of the regression coefficients in response to a slight change in variables. The problems can generate an invalid regression result and thus obtain a misleading conclusion. To examine the multicollinearity of the predictor variables, the ordinary least squares (OLS) regression is used to obtain their variance inflation factors (VIFs) [*Wang et al.*, 2013]. Generally, if a VIF exceeds 10, there exists an obvious multicollinearity of the corresponding variable [*Marquaridt*, 1970]. In such situation, ridge regression is usually used to overcome the risk of multicollinearity [*Hoerl and Kennard*, 1970], which uses a variable coefficient (λ) to improve the stability of regression coefficient estimations (Eq. 4) [*Wang et al*. 2013].

$$y = \boldsymbol{X}\boldsymbol{\beta} \rightarrow \boldsymbol{\beta}(\lambda) = (\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{I})\boldsymbol{X}^T y \quad (4)$$

Here, OLS regression and ridge regression are performed in R using “ridge” package.

2.3 Scenario description

The projection of the PF is based on the Eq. 3, which involves with six independent variables, including population, urbanization rate, diet choices, PUE_c, PUE_a and dependence on mineral P. The projections of the first two variables by 2050 were obtained from population projection by the United Nations (UN) and urbanization rate projection by He and the UN [*He*, 2014; *UN*, 2014; 2017a]. To project the other variables, we first constructed the curves describing the relationships between these variables and gross domestic product (GDP) per capita (see Figure 4 and section 3.2). The projection of China’s GDP per capita by 2050 is from Organization for Economic Co-operation and Development [*OECD*, 2017]. Then, the latter four variables were obtained based on the curves and the projected GDP per capita. In general, five scenarios were constructed showing as follows.

We first constructed a baseline scenario (BL) to represent a continuation of the current situation into the future without any policy interventions. In this scenario, the increase in population scale is from the medium-fertility population projection of the United

Nations [*UN*, 2017a]. Urbanization rate is the high projection by He [*He*, 2014]. The other four variables are based on the curves and the projected GDP per capita mentioned above.

The population growth scenario (PC) is inspired by the conduction of universal two-child policy China's in October 2015 [*Zeng and Hesketh*, 2016]. In this scenario, population scale is the high-fertility population projection of the United Nations [*UN*, 2017a].

The economic adaption scenario (EC) is characterized by a moderate urbanization rate and optimal diet choices. The urbanization rate by 2050 is the medium projection by He [*He*, 2014] and the diet choices are based on the advice optimal diet structure by China Nutrition Society [*CNS*, 2016].

The technology improving scenario (TC) describes a situation of improved P use efficiency of crop farming and animal breeding, which are assumed to reach the current level of the EU27 by 2050 [*van Dijk et al.*, 2016].

The sustainability scenario (SC) is characterized by medium-fertility population increase projected by the United Nations [*UN*, 2017a], moderate urbanization rate and optimal diet choices in EC scenario and improved P use efficiency in TC scenario, accompanied by a decrease in dependence on mineral P to current level of the EU27 [*van Dijk et al.*, 2016].

Table 1 Drivers and assumptions for each scenario

2.4 Data sources

The data and parameters used for calculating the PF in China are presented in Table S1. Phosphate rock, fertilizer and element P production data were mainly from the International Fertilizer Association database [*IFA*, 2017]. Crops and livestock production data were from the Food and Agricultural Organization of the United Nations database [*FAO*, 2017]. In this study, we analyzed 8 kinds of staple crops, 7 kinds of oil crops, 2 kinds of sugar crop, 17 kinds of vegetables, 22 kinds of fruits, and 7 kinds of livestock (Table S1). Aquatic product production data were obtained from China statistical year book [*National Bureau of Statistics of China (NBSC)*, 2017]. International trade data were obtained from the UN Comtrade Database [*UN*, 2017b]. All parameters were obtained from published literature (Table S2-S3).

3 Results and discussion

3.1 Historical changes of phosphorus footprint in China

The PF in China increased 11-fold, from 0.9 Tg (1.4 kg capita^{-1}) in 1961 to 10.6 Tg (7.8 kg capita^{-1}) in 2014 (Figure 2a). The virtual PF of livestock food (PF_{l}_v) was the single dominant component, increasing from 0.8 kg capita^{-1} in 1961 to 3.5 kg capita^{-1} in 2014 (Figure 2b). Along with the increase in the amount, the composition of livestock also changed. The proportion of PF_{l}_v associated with draft animals (draft cattle, horse, donkey, and camel) to total decreased from 61% in 1961 to 16% in 2014. For the same period, the proportion of PF_{l}_v associated with pig increased from 23 to 42%, beef and dairy cattle from 1 to 17%, and poultry from 6 to 14%. This change was driven by rapid developments in China's socio-economy after 1978, when reform and opening up policy was conducted to industrialize. Rapid industrialization and modern machinery has largely replaced draft animals for transportation and agricultural tillage. In China, there was a 10-fold increase in agricultural machinery power, from 1.2 to 11.2 gigawatts between 1978 and 2015 [*NBSC*, 2017]. The per capita disposable income increased 93- and 80-fold for urban and rural residents between 1978 and 2015 [*NBSC*, 2017]. The increase in household disposable income made meat, dairy and eggs more affordable, and promoted the expansion of livestock farming. Increase in protein consumption also contributed to the increase in the virtual PF associated with aquatic product (PF_{a_v}), which grew at a rate of 8.2% per year between 1961 and 2014.

For crop food PF, the direct part (PF_{c_d}) was 0.4 kg capita^{-1} in 1961, around 1.5 times the number of virtual part (PF_{c_v}) (Figure 1b). However, the PF_{c_v} increased at a faster rate than the PF_{c_d}, and by the middle of the 1970s, PF_{c_v} exceeded PF_{c_d}, reaching 1.9 kg capita^{-1} by 2014 (4 times the P_{C_d}). This is a result of expansion in use of chemical P fertilizers (0.05 to 6.6 Tg P yr^{-1} between 1961 and 2014) [*NBSC*, 2017], with chemical P fertilizer application in excess of crop demand. There was also an increase in vegetables and fruits as a proportion of total crop production (measured by P), from 19 to 30% and 7 to 14% between 1961 and 2014, respectively. The increase in vegetable and fruit production decreased the PUE_c of the crop farming sectors, because P application in China's vegetable and fruit system (111 and 251 kg P ha^{-1}) was 2-5 times more than that of cereals (50-55 kg P ha^{-1}) [*Fan et al.*, 2015], resulting in much lower P use efficiency of the vegetable and fruit production (8-21%) compared with cereals production (42-69%) [*Ma et al.*, 2011; *Yan et al.*, 2013].

The non-food goods PF (PF_{g_d}+ PF_{g_v}) was the fastest growing category, with an 80-fold increase during 1961-2014 (Figure 1b), reaching 0.8 kg capita^{-1} in 2014. Since the mid-1960s, mineral nonfood goods, including pesticides, detergent, bonderite, flame retardants and various additives had become dominant component of P_G, which accounted for 92% of the total in 2014, increasing from 33% in 1961. Since the early 21st century, China has started to prohibit the use of P-rich detergent, thus P in detergent currently only accounted for 30% of mineral nonfood goods [*Liu et al.*, 2016].

Figure 2 Phosphorus footprint in China between 1961 and 2014. (a) Total PF. (b) Composition of PF per capita. PF_g = PF of non-food goods; PF_{c_d} = direct PF of crop food; PF_{c_v}=virtual PF

of crop food; PF_{l_d}=direct PF of livestock food; PF_{l_v}=virtual PF of livestock food; PF_{a_d}=direct PF of aquatic food; PF_{a_v}=virtual PF of aquatic food.

3.2 Features of phosphorus footprint in China and comparison with other countries

In China, the PUE_c decreased from over 100% before 1986 to 47% in 2014, as the cheaper chemical fertilizers and a lack of guidance for fertilization application resulted in widespread over-fertilization in China. For example, it has been estimated that China's producers are overusing P fertilizer by up to 51%, 27% and 25% for cultivation of corn, wheat and rice, respectively [*Shi et al.*, 2016]. The growth of chemical fertilizer use increased in the PF dependence on mineral P, from less than 10% in 1961 to 78% in 2014. In contrast to the PUE_c, the PUE_a grew significantly from 1.4% in 1961 to 6.2% in 2014, as a result of the expansion of industrial-scale livestock operations, which have shorter feeding periods and improved breeding technologies than small-scale backyard breeding systems [*Bai et al.*, 2014]. The expansion of modern livestock breeding industry benefitted from projects to improve people's livelihood, like the Food Basket Project and the reformation of the economic system in Chinese countryside, which created a favorable market environment and policy support [*Zhao*, 2010]. This facilitated a change of diet choice toward more animal protein, and an increase in proportion of P from animal-based food increased from less than 5% in 1961 to 23% in 2014.

We tested the relationship between these indicators and economic development (GDP per capita) and compared China's results with other countries, including Austria, EU27, Finland, France, Germany, India, Japan, Malaysia, Netherlands, New Zealand, South Korea, Sweden, Switzerland, Thailand, Turkey, Uganda, the United Kingdom and the United States [*Antikainen et al.*, 2005; *Jeong et al.*, 2009; *Matsubae-Yokoyama et al.*, 2009; *Seyhan*, 2009; *Ghani and Mahmood*, 2011; *Matsubae et al.*, 2011; *Suh and Yee*, 2011; *Linderholm et al.*, 2012; *MacDonald et al.*, 2012; *Senthilkumar et al.*, 2012; *Cooper and Carliell-Marquet*, 2013; *Cordell et al.*, 2013; *Jedelhauser and Binder*, 2015; *Lederer et al.*, 2015; *Li et al.*, 2015; *Smit et al.*, 2015; *Liu et al.*, 2016; *Prathumchai et al.*, 2016; *Keil et al.*, 2017]. The results show that national PFs range from 3.5 kg capita^{-1} in India to 11.1 kg capita^{-1} in the USA, while China has a middle ranking (6.4 kg capita^{-1}), lying between EU27 and Switzerland. The PF has minor correlation with level of economy development (Figure 3). Similar to China, the PF in most countries was dominated by animal production. We found that PUE_a and the ratio of P from animal food to total food increased significantly (p<0.001) with economic development (Figure 4b, 4c). The PUE_c decreases up to 18 000 dollars per capita and increases thereafter, while an opposite trend was observed for the curve of dependence on mineral P (Figure 4a, 4d). The curves of the two indicators fit the the Environmental Kuznets Curve hypothesis, which postulates an inverted-U-shaped relationship between different pollutants and per capita income [*Dinda*, 2004].

Figure 3 Comparison PF by countries. USA=the United States of America; FR=France; FI=Finland; NZ=New Zealand; GER=Germany; AT=Austria; EU=EU27; CHA=China; CH=Switzerland; SWE=Sweden; KO=South Korea; JA=Japan; UK=the United Kingdom; NE=Netherlands; TRL=Turkey; IN=India. PF of China is the averaged data from 2000-2015.

Figure 4 Relationship between GDP per capita and the PF related indicators.

3.3 Driving forces of changes in China's phosphorus footprint

The correlation test shows that high correlations exist in the variables (Table S5), which indicates that there may be multicollinearity among them. Further, the results of OLS show that the VIFs of predictor variables are generally larger than 10 (Table S6), thus we judged that OLS regression is not suitable for our study because of the obvious multicollinearity among the variables. Performing equation (3) using “ridge” package in R, we obtained the ridge regression result when λ=0.00052 (Table 1). We found that the overall fit is very good (R^2=0.998, p<0.001) and the predicted value is fitting well with the true value (Figure 5a). The fitted regression equation is:

$$\ln I = 1.293 \ln P + 0.672 \ln A_u + 0.15 \ln A_d - 0.637 \ln T_c - 0.201 T_a + 0.067 \ln D - 1.644 \quad (5)$$

According to the regression coefficient in Eq. (5), population scale (P), diet choice (A_d), urban rate (A_u), and dependence on mineral P (D) had positive effects on the changes of the PF in China, while PUE_c (T_c) and PUE_a (T_a) had negative effects (Table 1). Among these factors, population had the largest contribution to the changes of PF in China, while every 1% increase in population was linked to a 1.293% increase in PF. Annual average population growth in China was 1.36%, which contributed 38% to the changes in PF during 1961-2014. This result emphasizes the importance of population growth to the PF in China. Following population, the factors, including urbanization rate and diet choices had another important positive effects, with contributions of 33% and 11%, respectively. In fact, the increasing urbanization rate and changing diet choices toward higher animal protein intake is reflection of economic development, which make various products more affordable to ordinary people and thus increase individual’s PF. The PUE_c and PUE_a correlated negatively with the changes of the PF, illustrating the importance of improving P use efficiency in restraining the increase in the PF. However, the negative annual growth rate of the PUE_c (-1.39%) resulted in a positive contribution (19%) to the increase in PF, while the PUE_a, with an increasing trend (2.77%), had a negative contribution of -12%. In spite of the fastest annual growth rate of 3.97%, the dependence on mineral P had the weakest relationship with the PF (0.067), resulting in a minimal contribution (6%) to increase in PF.

As a whole, population growth, diet choices, urbanization rate, PUE_c and dependence on mineral were the key factors driving the increase of the PF in China, together accounting an increase of 5.14% in PF per year. Combined with the restraining factor of PUE_a, these factors have resulted in an annual growth of 4.59% in the PF in China.

Table 2 Contributions of factors influencing the change in the PF in China.

3.4 Phosphorus footprint for 2050 in China

The PF in China was projected to increase for the baseline scenario (BL), the population growth scenario (PC), and the economic adaption scenario (EC), increasing by 7.4 Tg P (+69%), 9.8 Tg P (+92%) and 5.5 Tg P (+51%) between 2014 and 2050, with a peak in 2042, 2045 and 2040 respectively. In the technology improving scenario (TC), China's PF remained unchanged by 2050 compared with 2014. However, the sustainability scenario (RC) is the only situation, in which China's PF was reduced by 2050 compared with 2014, decreasing by 1.6 Tg P yr^{-1} (-15%), and peaking at 11.4 Tg P yr^{-1} in 2025.

As the only source of P is non-renewable phosphate rock, the phosphate reserve base in China is 477 Tg P according to USGS data [*USGS*, 2016]. To assess the availability of P resources in China by 2050, we calculated annual phosphate rock demand by multiplying the PF and the dependence on mineral P, and plotted the depletion rate of total phosphate reserves for all five scenarios (Figure 5b). In the BL, PC and EC scenario, all of China's current phosphate reserves (not considering future potential reserves) will be depleted by the middle 2040s, while only 18% will remain by 2050 under the TC scenario. In the SC scenario, 50% of current phosphate reserves will remain by 2050 in China.

Figure 5 (a) Phosphorus footprint scenarios for 2050. (b) Projected depletion of phosphate

reserves. BL: the baseline scenario; PC: moderate population scenario; EC: the economic adaption scenario; TI: the technology improving scenario; SC: the sustainability scenario.

3.5 Implications for mitigating phosphorus footprint

The results show that China's PF increased dramatically during the study period, which was dominated by the livestock PF. Although all the scenarios for the PF show the inverted U curve, the PF of China in 2050 would only be lower than that in 2014 under the SC scenario. If our projection is reasonable, it indicates that even in the SC scenario, 50% of current phosphate reserves would be depleted by 2050 in China. Thus, it is urgent for China to take actions immediately to slow down depletion of phosphate rock reserves.

However, not all of the mitigating options are accessible to China. For example, China has replaced the one-child policy by a universal two-child policy to maintain a constant population in October 2015 [*Zeng and Hesketh*, 2016], making it hard to mitigate the PF by population control. Besides, urbanization is an inevitable result of industrialization, thus it is also an unchangeable trend for future China. Thus, the remaining options are improving the PUEc and PUEa, guiding reasonable diets and reducing dependence on minerals based on RC scenario. In this section, we provided a discussion about the feasibility of these options.

Improving P use efficiency of crop farming. The results show that the improvement of PUE_c will be necessary, as it is still trending downward in China (Figure 4a) and is identified as a key factor driving the changes in PF (Table 1). To achieve an increase in PUE_c, policy measures including removing fertilizer subsidies, introducing fertilizer taxes and recommending precision fertilization, may be feasible to reduce applications of chemical P fertilizer. Cultivation techniques, like conservation tillage, optimized fertilization, gypsum application, crop rotation and intercropping can also be effective in improving P uptake. For example, a previous study in China found that conservation tillage and optimized fertilization can reduce P losses by 23~30% [*Wang et al.*, 2014].

Increasing animal production efficiency. As we mentioned above, current livestock systems in China are characterized by large-scale modern feeding operations, which have contributed to an increase in P use efficiency in animal breeding, but still have not reached the same level as developed countries (Figure 4b). To achieve further improvements, measures like phase feeding, adding enzymes, genomic selection technology and modern reproductive technology are highly recommended [*Kebreab et al.*, 2012; *Hayes et al.*, 2013]. However, these measures are technology-intensive and costly and thus may not be easily attained in the near future.

Guiding reasonable diet choices. Measures involving prompting a lower-P diet by encouraging reductions in meat consumption, may offer another way of reducing the PF. The first step is to educate people about the impact of diet choices on the environment, through multimedia broadcasting tool, like China's popular community platforms of "Sina Weibo" and "Wechat". Economic means, including taxes on meat and subsidy on soybean protein, are also helpful to reduce meat consumption. However, the economic means have high uncertainty in their practical effects [*Röös et al.*, 2017], thus the education means are more feasible for current China because of its low costs.

Reducing dependence on minerals. China's soil has accumulated 52 Tg P over the last century, meaning a large surplus of new P input via fertilizer application [*Liu et al.*, 2016]. Thus, it is feasible to reduce dependence on utilization of mineral P to reduce China's PF. Three measures are likely to contribute to this reduction: (1) raising farmers' awareness for fertilizer control; (2) taxing mineral P products; and (3) improving P recycling from livestock manure and human excreta, municipal sludge, crop and food residues, to diversify P sources. In China, around 1.2 Tg P in animal manure (equivalent to 20% of P fertilizer application) is emitted in the form of wastewater in 2012 [*Fang et al.*, 2015], making recovering P from waste not only significant to save P resources, but also beneficial to reduce P losses to water and water-quality impairment.

3.6 Limitations discussion

The uncertainties may come from two main sources: assumptions for simplifying calculation and uncertainties from data used in calculation [*Taormina and Chau,* 2015; *Wu and Chau*, 2011]. There are three major assumptions in calculation. Firstly, due to many categories of crops and livestock, this study only considered the main categories of them. Accordingly, the result of PF of crops and livestock may be slightly smaller than the actual values. Besides, the virtual P is calculated based on the averaged P use efficiency of sector i (Eq. 5) following the study by Jiang and Yuan (2015) and Matsubae et al. (2011), because it is difficult to get P use efficiency for different crops or animal during different time period. Furthermore, the P demand of livestock are calculated by the sum of P contained in live animal and that contained in excretions following Jiang et al. (2018), because feed consumption data were not available for China.

There is inevitably various degrees of uncertainties from the data used in the study. For one thing, there is inherent uncertainties in the activity data of production of crops and animals and consumption of fertilizer from statistics system. The other parts of the data uncertainties come from parameters used. For example, the P content in crops and animals and the daily P excretion of livestock used in this study (Table S2 and Table S3) are averaged values from literature, which may vary among different varieties of the same crops and animals and the producing areas. Moreover, the P loss rates used to production of fish, shrimp and shell used in this study are the mean value from a meta-analysis study in China (Text S3), which may vary quite different among different regions. To assess the sensitivities of the parameters used on the calculation of PF in China, we first assigned a prior CV of 10% to all the parameters used in this study. Then, a Monte Carlo simulation was performed with 10 000 iterations to quantitatively assess the uncertainties. As is shown in Table 3, the most sensitivity parameters are daily P excretion of pig and cattle. However, the contribution of daily P excretion of cattle to total variance showed declining trend, while that of pig and poultry showed the reverse trends. The reason is related to the higher increase rate in the breeding numbers of pig and poultry than that of cattle. In general, the daily P excretion rate is the most sensitive parameters to final result in the PF model.

Table 3 Results of sensitivity analysis of the parameters (%)

4 Conclusion

This study constructed a holistic PF model to examine the P demand caused by human consumption in China, and applied the STIRPAT model to analyze the drivers of the PF changes and to examine future scenarios of China's PF. China's PF was estimated to increase from 0.9 to 10.6 Tg between 1961 and 2014, with an annual growth rate of 4.6%. Livestock food accounted for more than half of China's PF. The key factors driving the intensification in China's PF were increasing population, rapid urbanization, decreasing PUE_c and changing diet choice, with a combined contribution of 101%.

In the baseline scenario, China's PF would increase by 70% from 10.6 Tg in 2014 to 18.0 Tg in 2050 and cause the depletion of China's phosphate reserves in 2045. However, in the best case scenario (SC), China's PF would show decreasing trend, and

50% of phosphate reserves will remain by 2050. The results show that it is urgent but also possible for China to reduce the P footprint to mitigate the P resource crisis. Several mitigation measures are proposed by considering China's realities such as conservation tillage, optimized fertilization, phase feeding, adding enzymes, recommending vegetable protein for diet, etc.

In general, this study provides a novel method to measure the PF of an entire economy, which is easy to apply to assess PF of countries worldwide and the case study in China can provide valuable policy insights to other rapid developing countries to the sustainable management of P resources. As the parameters used in this study are mainly from literature conducted in China, it is important to adjust some key parameters based on local conditions, especially for the key sensitive parameter like daily P excretion of pig and cattle.

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Appendix A. Abbreviation list

1. PF = Phosphorus footprint
2. PF_P = PF of crop food, livestock food, aquatic food and non-food goods
3. PF_I = PF of imported products
4. PF_E = PF of exported products.
5. PF_c = PF of crop food
6. PF_l = PF of livestock food
7. PF_a = PF of aquatic food
8. PF_g = PF of non-food goods
9. BL = Baseline scenario
10. PC = Moderate population scenario
11. EC = Economic adaption scenario
12. TI = Technology improving scenario
13. SC = Sustainability scenario
14. P = Population
15. A_u = Urbanization rate
16. A_d = Diet choices
17. T_c = Phosphorus us efficiency of crop farming
18. T_a = Phosphorus us efficiency of animal breeding
19. D = Dependence on mineral phosphorus

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Table 4 Drivers and assumptions for each scenario

Drivers	Baseline (BL)	Population growth (PC)	Economic adaption (EC)	Technology improving (TC)	Sustainability (SC)
Population (billion)	Medium 2020: 1.425 2030: 1.441 2050: 1.364	High 2020: 1.437 2030: 1.491 2050: 1.506	As in BL	As in BL	Low 2020: 1.412 2030: 1.391 2050: 1.231
Urbanization rate (%)	High 2020: 60.2 2030: 69.6 2050: 80.8	As in BL	Low 2020: 60.0 2030: 68.5 2050: 76.0	As in BL	As in EC
Diet choices (%)	High 2020: 30.2 2030: 33.4 2050: 38.4	As in BL	Low 2020: 23.4 2030: 23.6 2050: 24.0	As in BL	As in EC
PUEc	Low 2020: 41.6 2030: 34.9 2050: 33.1	As in BL	As in BL	High 2020: 50.6 2030: 57.2 2050: 73.0	As in TC
PUEa	Low 2020: 6.7 2030: 7.1 2050: 7.9	As in BL	As in BL	High 2020: 6.8 2030: 7.3 2050: 9.0	As in TC
Dependence on mineral P (%)	High 2020: 87.1 2030: 95.5 2050: 88.5	As in BL	As in BL	As in BL	Low 2020: 71.5 2030: 61.6 2050: 45.6
GDP (thousand USD capita^{-1})			2020: 8.3 2030: 12.2 2050: 22.4		

Table 5 Contributions of factors influencing the change in the PF in China.

Factors	Unit	Growth rate (%)	Regression coefficient	*t*-Statistic	Effect on change of PF[a]	Contribution to PF change (%)[b]
PF	Tg yr^{-1}	4.59				
P	10^8	1.36	1.293***	11.096	1.76	38
A_u	%	2.22	0.672***	11.739	1.50	33
A_d	%	3.30	0.150*	2.376	0.49	11
T_c	%	-1.39	-0.637***	11.124	0.88	19

T_a	%	2.77	-0.201**	2.694	-0.56	-12
D	%	3.97	0.067**	3.282	0.27	6
Others			-1.644		0.24	5
λ	0.00052					
R-square	0.998					

[a] Effect on changes of input=average annual growth rate × regression coefficient

[b] Contribution to changes =effect on changes of input × average annual growth rate

*** Significance is at the 0.0001 level; ** Significance is at the 0.001 level; * Significance is at the 0.01 level.

Table 6 Results of sensitivity analysis of the parameters (%)

	1961	1980	2000	2014
Cattle daily P excretion	82.1	32.8	39.4	33.4
Pig daily P excretion	12.3	60.9	44.6	45.5
Goat and sheep daily P excretion	2.8	2.5	3.1	3.2
Poultry daily P excretion	0.1	0.3	3.3	3.1
P content in Pig	0.2	1.7	2.5	3.2
P loss rate of freshwater fish	<0.1	<0.1	1.7	3.9
Others	2.5	1.8	5.4	7.7
Total	100	100	100	100

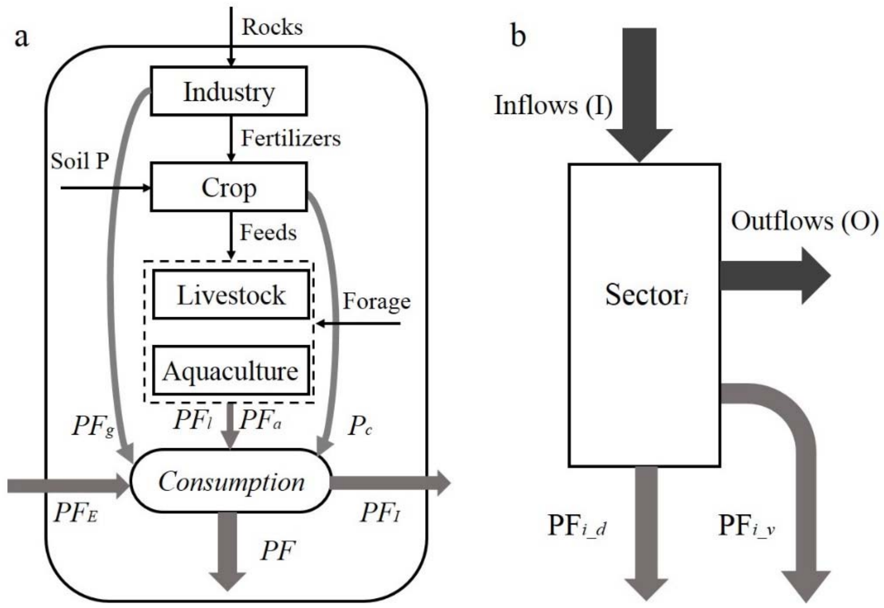

Figure 6 Schematic of the PF model. (a) Framework of the PF model. (b) Calculation principle of the PF model.

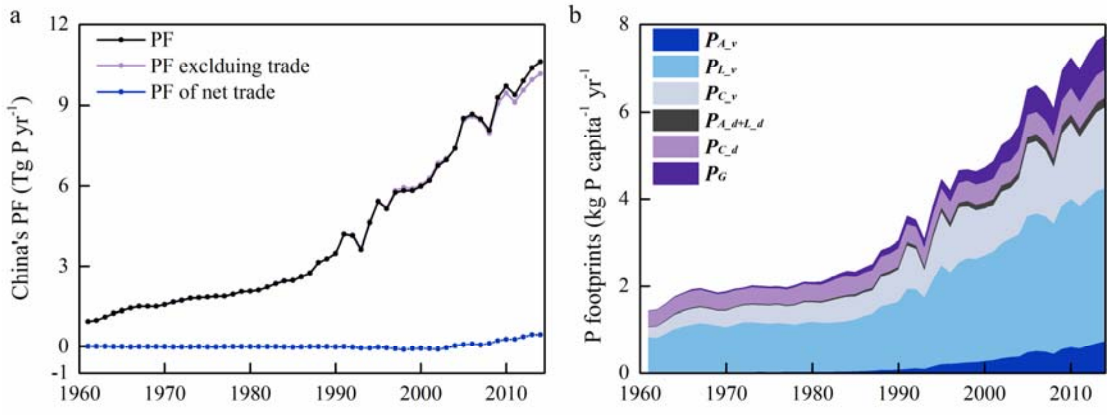

Figure 7 Phosphorus footprint in China between 1961 and 2014. (a) Total PF. (b) Composition of PF per capita. PF_g = PF of non-food goods; PF_{c_d} = direct PF of crop food; PF_{c_v}=virtual PF of crop food; PF_{l_d}=direct PF of livestock food; PF_{l_v}=virtual PF of livestock food; PF_{a_d}=direct PF of aquatic food; PF_{a_v}=virtual PF of aquatic food.

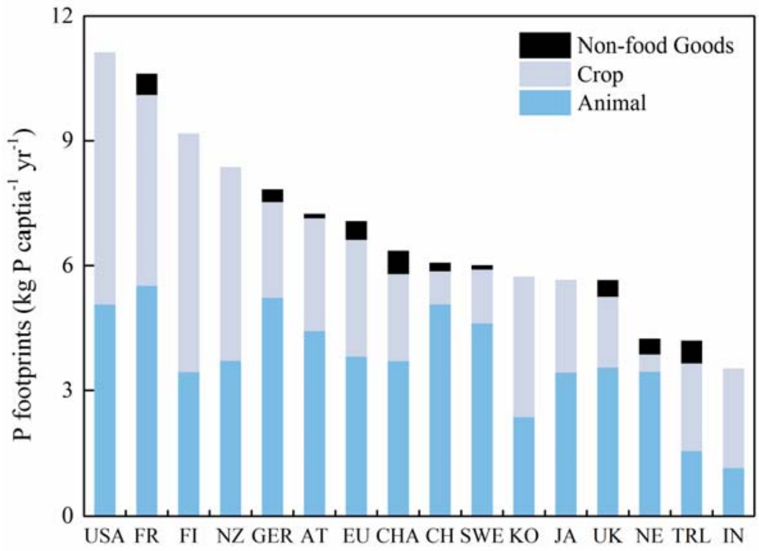

Figure 8 Comparison PF by countries. USA=the United States of America; FR=France; FI=Finland; NZ=New Zealand; GER=Germany; AT=Austria; EU=EU27; CHA=China; CH=Switzerland; SWE=Sweden; KO=South Korea; JA=Japan; UK=the United Kingdom; NE=Netherlands; TRL=Turkey; IN=India. PF of China is the averaged data from 2000-2015.

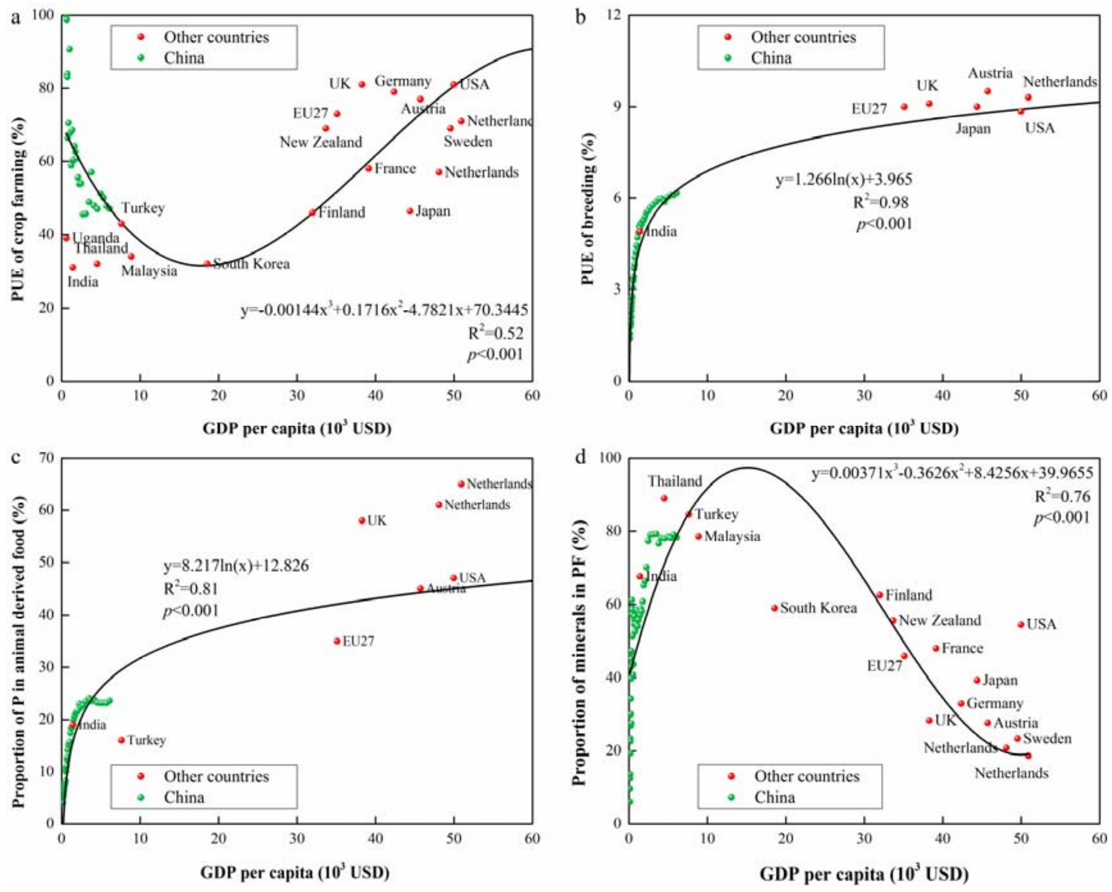

Figure 9 Relationship between GDP per capita and the PF related indicators.

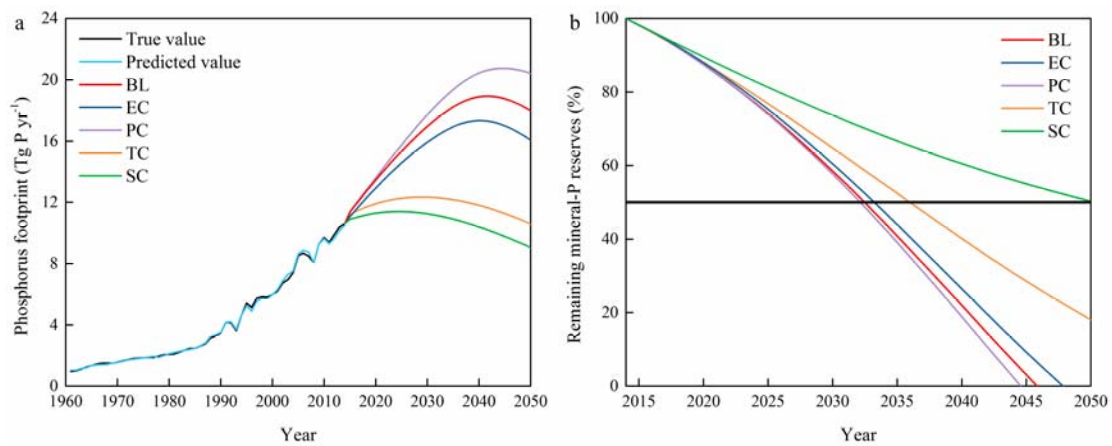

Figure 10 (a) Phosphorus footprint scenarios for 2050. (b) Projected depletion of phosphate reserves. BL: the baseline scenario; PC: moderate population scenario; EC: the economic adaption scenario; TI: the technology improving scenario; SC: the sustainability scenario.