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A dynamic optimization of soil phosphorus status approach could reduce phosphorus fertilizer use by half in China

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Sustainable phosphorus (P) management is essential for ensuring crop production while avoiding environmental damage and the depletion of phosphate rock reserves. Despite local demonstration scale successes, the widespread mobilization of smallholder farmers to adopt sustainable management practices remains a challenge, primarily due to the associated high costs and complicated sampling. Here, we propose a dynamic optimization of soil P status (DOP) approach aimed at managing long-term soil P status within the range of agronomic and environmental soil P thresholds, which facilitates the precise determination of optimal P application rates without the need for frequent soil testing. We evaluate the DOP approach in 35,575 on-farm trials, and the results show that it is agronomically acceptable. Our evaluation extends to estimating future soil P status and P fertilizer inputs across all counties in China for three cereal crops (wheat, rice, and maize). The results indicate that, compared to current practices, the DOP approach can achieve a 47.4% reduction in P fertilizer use without any yield penalty. The DOP approach could become an effective tool for global P management to safeguard food security and enhance environmental sustainability.

The planetary phosphorus (P) boundary has been substantially transgressed in many regions[1,2]. Agriculture is the primary driver contributing to global P depletion, consuming over 80–90% of global P reserves through the 2010s[3]. The massive input of P fertilizer to agriculture has led to substantial P accumulation in agricultural soils. Globally, croplands experience an annual soil P accumulation of 6.6 Tg P yr^{-1} (ref. 3), exacerbating P loss to the environment and contributing to freshwater eutrophication[4–6]. It is estimated that the total P fertilizer input needs to be reduced by at least 50% globally to maintain the global P cycle within suggested planetary boundaries[7,8]. Meanwhile, phosphate rock is unevenly distributed globally and non-renewable[9]. Higher phosphate rock prices can further hinder access to affordable P fertilizers for millions of farmers in low-income countries, exacerbating the already low efficiency of crop production[10]. In-season P management strategies have been developed to optimize P inputs based on real-time soil testing[10]. However, these methods require substantial investments of time and human resources, presenting scalability challenges, particularly in regions predominated by smallholder farming, such as sub-Saharan Africa, India, and China[11]. Mobilizing smallholders to adopt advanced P technologies that do not require sophisticated soil testing for significant P reduction is a priority for global sustainable development goals.

China is at a point where P fertilizer consumption has increased 5-fold from 1978 (1.0 million tons) to 2017 (5.0 million tons) for food security[12]. Smallholders in China tend to adopt a cautious approach to P management, in which P inputs are significantly higher than crop P removal, with an average soil P surplus of 39.3 kg P ha^{-1} yr^{-1} (refs. 12,13). This substantial soil legacy P contributes to elevated

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leaching and runoff, threatening the wellbeing of aquatic organisms and humans[14–16]. These problems have become increasingly pronounced in recent years, carrying substantial global implications. Notably, from 2011 to 2020, 18.8% of the increase in global P consumption is attributed to China[17]. In 2020, China consumes >30% and produced 35% of the global P fertilizer annually[18,19], while possessing only 4.6% of the global phosphate rock reserves[20]. Thus, improved soil P management practices in China are of significant interest globally, as an indicator of P-related pollution and scarcity challenges.

Optimal P management strategies entail the annual monitoring of soil P levels and determination of the additional P amounts required for the subsequent crop[21]. In soils with a low P status, high P fertilizer application rates increase soil P levels over time, resulting in augmented yields and higher residual soil P levels[22]. For soils with moderate P levels and little P fixation, management efforts must focus on balancing inputs and outputs at the scales of field and farm to maximize profitability, avoid excessive accumulation, and minimize the risk of P losses[23,24]. However, limited information on soil P status has impeded the development of rational P management strategies on smallholder farms, and the static soil Olsen P testing method is tedious, which discourages its routine use by smallholder farmers or for regional monitoring. Numerous studies have noted that changes in soil P status can be represented by the balance of P inputs and outputs, which are directly determined soil available P[25,26]. Currently, methods for the dynamic simulation of annual soil P status annually remain limited due to their unsatisfactory extrapolation performance (e.g. climate, soil, and management) in treating complex correlations in various locations and the lack of strongly correlated covariates. Such uncertainty is a significant barrier to accurate P management and improved policies to sustain economic crop benefits and food sufficiency with minimum P-related pollution.

To fill these research gaps and to inform policymaking for optimizing P management, we develop an approach termed dynamic optimization of soil P status (DOP) to assist farmers in determining optimal P application rates without the need for frequent soil testing. The first step in developing the DOP approach is to calculate the soil available P efficiency (APE), defined as the change in soil available P (mg kg^{-1}) per unit of soil P balance (kg ha^{-1}) for a specific field. Then, the geographical distribution of APE across major agroecological zones in China is used to estimate P application rates based on the simulated soil P status. The fundamental objective of the DOP approach is to optimize the root-zone soil P status within prescribed agronomic and environmental soil P thresholds by modulating the soil P balance. The DOP approach is tested in tens of thousands of controlled field trials with maize (n = 15,851), rice (n = 7424), and wheat (n = 12,300) across China. Finally, we apply the DOP approach to predict yearly recommended P application rates and soil available P for cereal crops (wheat, rice, and maize) in ~3000 counties in China. Our findings will guide policymakers and facilitate region-specific P management in China, while also being applicable to other countries striving to enhance food security and reduce P-related pollution simultaneously.

Results

Soil available P efficiency in China

We collected 424 published observations from 68 locations to estimate soil APE (Supplementary Fig. 1). The APE across all in-situ observations ranged from 0.01 to 0.21 mg kg^{-1}/kg ha^{-1} (5th–95th percentile), with a mean of 0.08 mg kg^{-1}/kg ha^{-1}. Notably, APE values were consistently highest in soils under wheat, followed by those under maize and rice. The largest APE was observed in Cambisols, which was about 42.9% higher than in semi-hydromorphic soil, followed by Luvisols, Ferralsols, Semi-luvisols, Anthropic soil, and Calcisols. Furthermore, APE values varied based on the type of P fertilizer used. Monoammonium phosphate and diammonium phosphate demonstrated higher APE values compared to super-phosphate and triple super-phosphate, whereas the lowest values were observed with calcium magnesium phosphate used (Fig. 1a).

We performed the random forest (RF) modeling to assess the influence of environmental factors on APE. The results showed that the mean annual temperature (MAT), soil available P (AP), bulk density (BD), microbial biomass P (MBP), microbial biomass carbon (MBC), soil organic carbon (SOC), region, soil clay content (Clay), and soil total nitrogen (TN) emerged as the most influential factors (Supplementary Fig. 2). Direct relationships between continuous explanatory variables and APE were further analyzed using a nonparametric smooth regression model (Fig. 1b). APE increased with higher levels of MAT, AP, SOC, Clay, pH, and TN initially. However, above certain thresholds, such as a MAT of 12°C, soil AP of 30 mg kg^{-1}, SOC of 14 g kg^{-1}, Clay of 18%, pH 7.8, and TN of 0.8 g kg^{-1}, APE was substantially decreased. APE tended to increase, stabilize, and then further increase at BD levels of <1.2, 1.2–1.3, and >1.3 g cm^{-3}, respectively. MBP exhibited a non-linear relationship with APE, with increases observed below 12 mg kg^{-1} and above 18 mg kg^{-1}. Conversely, higher MAP values were associated with decreases in APE. MBC showed a distinct pattern with APE, with increases observed below 220 mg kg^{-1} and above 500 mg kg^{-1}.

We developed an RF regression model using machine learning techniques to elucidate the detailed spatial patterns of APE. The RF regression model links APE with climate, soil, and region, according to high-spatial-resolution raster datasets (Supplementary Fig. 3). A comparison of observed and simulated APE by RF modeling produced a regression coefficient of determination (R^2) of 0.75, indicating that the fitted RF models explained 75% of the impact by input variable impacts on APE (Supplementary Fig. 2b). The models effectively captured the spatial patterns of APE, demonstrating their suitability for upscaling to the national level.

APE values were estimated by the model at a grid scale of 1 km × 1 km (Fig. 1c). The estimated area-weighted mean grid-level APE was 0.08 mg kg^{-1}/kg ha^{-1} (0.05–0.11 mg kg^{-1}/kg ha^{-1}, 5th–95th percentile), which is consistent with the value obtained for the synthesized dataset (0.08 mg kg^{-1}/kg ha^{-1}). Cropland APE exhibited pronounced spatial heterogeneity, ranging from 0.03–0.13 mg kg^{-1}/kg ha^{-1}. Notably, our findings also highlight large spatial variability in APE among regions. APE was highest in Central China (CC), with an average of 0.10 mg kg^{-1}/kg ha^{-1}, and lowest in South China (SC), with an average of 0.06 mg kg^{-1}/kg ha^{-1}.

Estimation of the current soil P status

Maintaining soil available P concentrations at safe P levels through sustainable cropland P management is a prerequisite for maximizing food security and minimizing environmental risks. These safe soil P levels lie between the agronomic and environmental soil P threshold values (Fig. 2a). The agronomic soil P threshold is the level of soil P that is considered optimal for crop growth and yield. We determined agronomic soil P threshold values in farm trials during 2005–2014 at 11,079, 7492, and 8325 sites for maize, rice, and wheat, respectively (Supplementary Fig. 4). For double-crop rotation, we adopted the higher agronomic soil P threshold for maize and wheat as the agricultural soil P threshold. The recommended agronomic soil P thresholds for upland soils (wheat and maize) in the Northwest (NW), Northeast (NE), CC, Yangtze Plain (YP), and SC regions were 25.8, 19.2, 23.9, 26.7, and 24.4 mg kg^{-1}, respectively, whereas those for rice production, were 22.1, 23.2, 19.7, 18.7, and 25.3 mg kg^{-1}, respectively (Fig. 2b and Supplementary Fig. 5). The environmental soil P thresholds were determined according to critical levels for P leaching potential, as 39.9, 51.6, 51.0, 40.2, and 50.3 mg kg^{-1} for the NW, NE, CC, YP, and SC regions, respectively (Fig. 2b), as described in previous studies[27–30].

Employing data from nationwide soil testing campaigns conducted in 2018, we estimated soil available P status for maize (n = 79,131, Supplementary Fig. 6a), rice (n = 62,360, Supplementary

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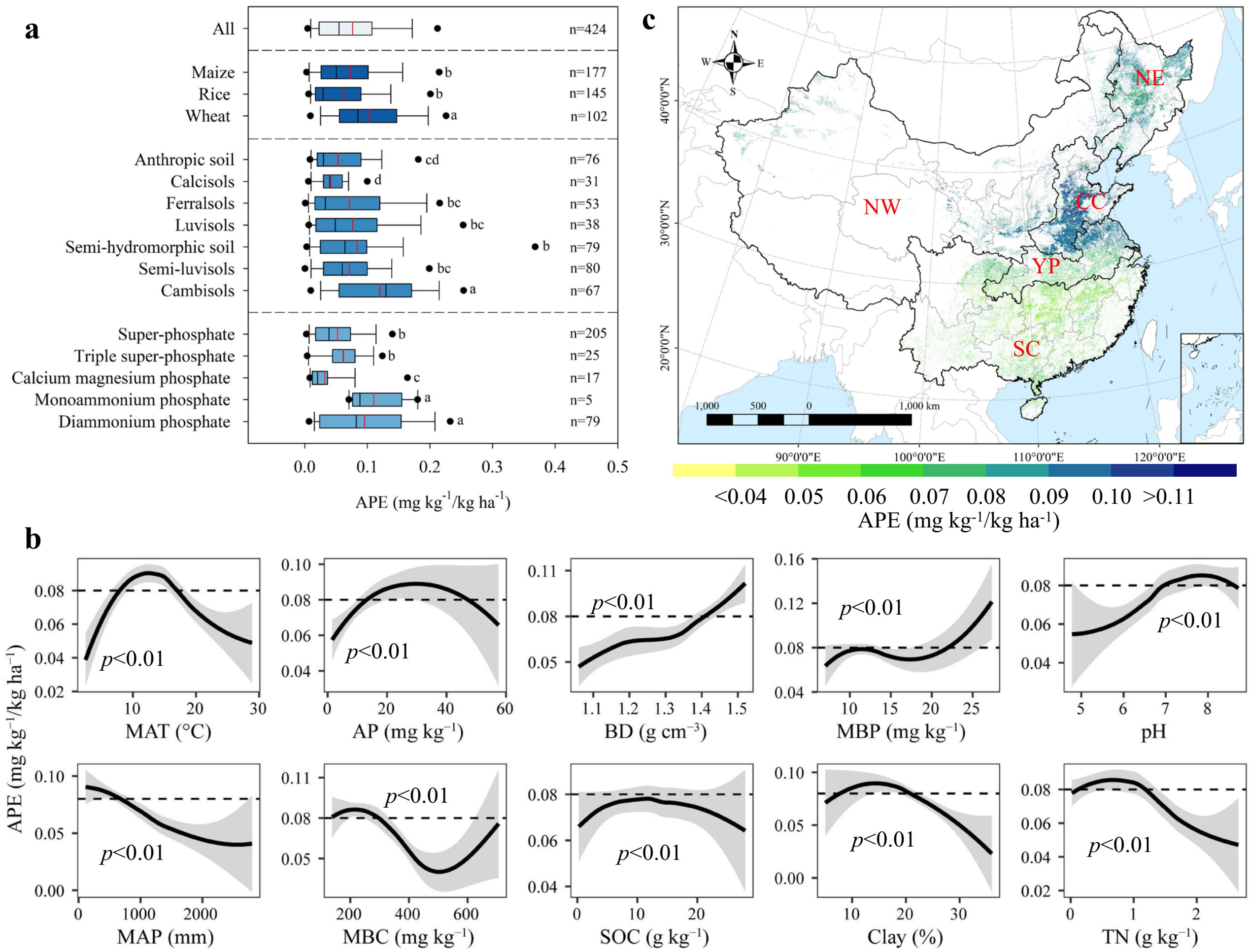

Fig. 1 | Soil available phosphorus (P) efficiency in China. a Soil available P efficiency from literature-based dataset. The solid line within the box indicates the median value, while the red solid line represents the mean. The left and right edges of the box mark the 25th and 75th percentiles, respectively. The short lines (whiskers) at both ends denote the 5th and 95th percentiles, respectively, and the solid black dots represent outliers. Different lowercase letters indicate significant differences between groups within each category at the $p < 0.05$ level. **b** The relationship between observed soil available P efficiency and predicted, determined by random forest modeling. The error bands (shaded areas) correspond to the 95% confidence intervals of the relationships, and the dashed lines represent the average soil available P efficiency. Statistical analysis was performed using a two-sided *t*-test, and all results were considered significant at the $p < 0.01$ level. **c** Maps showing the predicted soil available P efficiency of cropland. AP soil available P, BD soil bulk density, MBP microbial biomass P, MBC microbial biomass carbon, SOC soil organic carbon, Clay soil clay content, TN soil total nitrogen, APE soil available P efficiency, CC Central China, YP Yangtze Plain, NE Northeast, NW Northwest, SC South China. Source data are provided as a Source Data file. Base map data adapted from GS(2020)4619, http://bzdt.ch.mnr.gov.cn/. Map created using ArcGIS software.

Fig. 6b), and wheat ($n = 28{,}487$, Supplementary Fig. 6c) systems in China. The interpolation method was used to standardize the resolution of all data to a 1 km × 1 km grid-level; the estimated national average soil available P for maize, rice, and wheat were 30.2, 25.0, and 24.2 mg kg^{-1}, respectively (Supplementary Fig. 6d–f). Soil available P levels exhibited large spatial variation at the national scale. P deficiency (soil available P <agronomic soil P threshold) was observed for maize, rice, and wheat, accounting for 58.5%, 59.9%, and 69.5% of all land, respectively. The relative proportions of land with optimal P levels (agronomic soil P threshold ≤soil available P <environmental soil P threshold) were 24.6%, 28.3%, and 21.3% for maize, rice, and wheat, respectively. The proportions of total arable land exhibiting P leaching risk (soil available P ≥environmental soil P threshold) were 16.9%, 11.8%, and 9.2% for maize, rice, and wheat, respectively (Fig. 2c–e).

Implementation of DOP approach with smallholder fields

The DOP approach was specifically designed to improve soil P status in P deficient soil, and limit the accumulation of soil P in soils with high risk of P leaching. The P fertilizer application rates recommended based on the DOP approach can be less than, more than, or equal to crop P removal, depending on whether the soil P level is at a P leaching risk, P deficient, or optimal. The DOP approach was derived from on-farm P rate experiments conducted during 2005–2014 at 15,851, 7424, and 12,300 sites for maize, rice, and wheat, respectively (Supplementary Fig. 7). Plots were established for four treatments: no P application, optimum P application rates (OPR), 50% OPR, and 150% OPR, where OPR was determined by local extension staff based on county-specific ranges. In soils with P deficiency, high P inputs (150% OPR) were required to maintain high crop yields. Conversely, in soils with P levels exceeding the leaching risk, crop yields in the OPR, 50% OPR, and 150% OPR treatments did not differ significantly from the no P treatment. In soils with optimum P levels, OPR treatments with equal P input and P removal rates achieved the highest yields, and the further addition of P beyond OPR did not increase yield. P application rates below the OPR resulted in reduced yields (Fig. 3).

Employing data from 8.64 million farmer surveys, we mapped county-specific soil P balance for the three cereal crops in China. The

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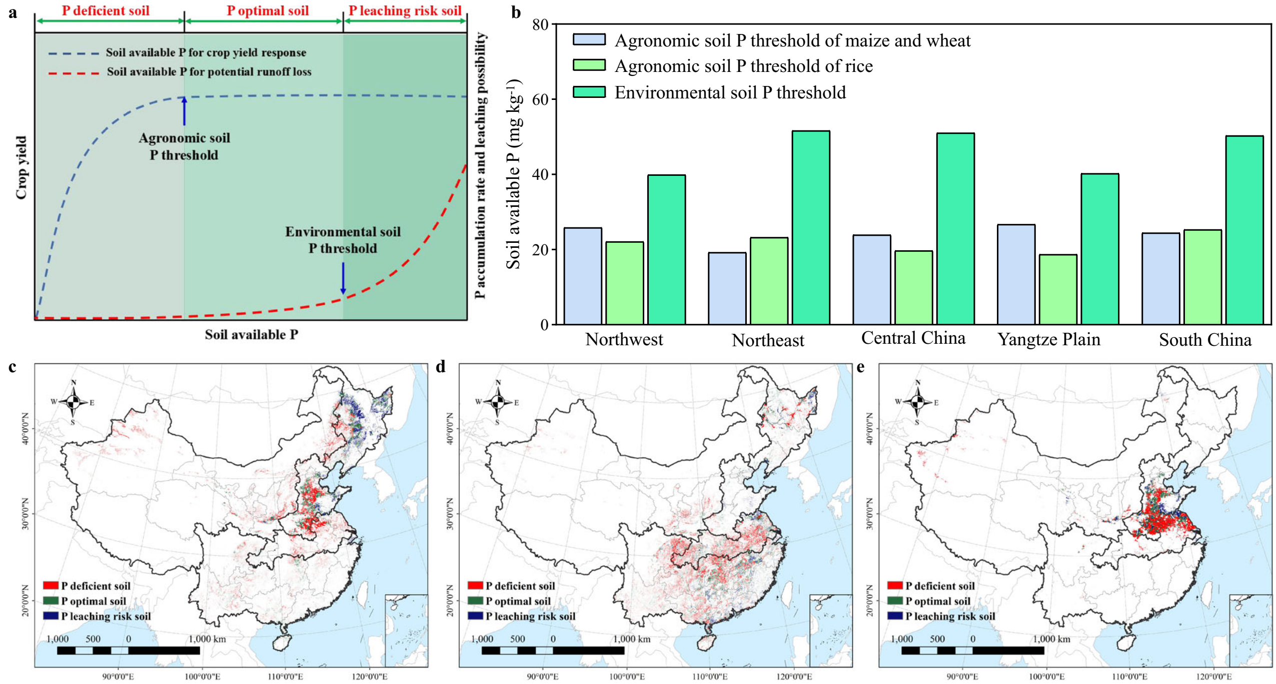

Fig. 2 | Estimation of soil available phosphorus (P) levels in China. a Theoretical model of agronomic and environmental assessment of soil available P levels. Agronomic and environmental soil P thresholds are delineated based on the soil available P concentration of the soil, either directly measured or inferred from another soil P availability index, as outlined by ref. 30. **b** Critical level of soil available P for production of different crops and for P leaching potential in the five P management zones in China. **c** Grid-scale soil available P levels for maize production. **d** Grid-scale soil available P levels for rice production. **e** Grid-scale soil available P levels for wheat production. Source data are provided as a Source Data file. Base map data adapted from GS(2020)4619, http://bzdt.ch.mnr.gov.cn/. Map created using ArcGIS software.

soil P balance across all counties averaged 23.4 kg P ha^{-1} for maize (ranging from −24.1 to 118.5 kg P ha^{-1}), 11.9 kg P ha^{-1} for rice (ranging from −23.2 to 102.8 kg P ha^{-1}), and 25.8 kg P ha^{-1} for wheat (ranging from −30.7 to 130.1 kg P ha^{-1}) (Supplementary Fig. 8). The estimated national average soil available P levels were 29.2 (ranging from 7.0 to 129.6 mg kg^{-1}), 27.1 (ranging from 6.2 to 125.6 mg kg^{-1}), and 24.2 mg kg^{-1} (ranging from 5.8 to 129.8 mg kg^{-1}) in 2020 for maize, rice, and wheat, respectively. The DOP approach was used to optimize P application rates for all counties and summarized at the country level. The optimized country-scale P application rates were estimated to be 23.6, 31.2, and 20.9 kg P ha^{-1}, which are 47.1%, 19.0%, and 51.4% less than those currently applied by farmers (Supplementary Fig. 9).

Managing P over time in China

We predicted the time required to bring soil P to the optimal level (agronomic soil P threshold ≤ soil available P < environmental soil P threshold) at the county-level (see Methods). Assuming that all counties adopt the DOP approach, the estimated time for soil P to reach the optimal level was 45 years for maize, 49 years for rice, and 57 years for wheat (Fig. 4a–c). The corresponding county-specific soil available P increased by 12.5%, 12.8%, and 24.0% compared to 2018 levels (Fig. 4d–f). The optimal P application rates were thus estimated to be 21.2, 26.5, and 17.1 kg P ha^{-1} for maize, rice, and wheat, respectively, representing reductions of 52.5%, 31.2%, and 59.2% compared to 2018 levels. The overall net reduction in P use would be 1.8 Tg (0.8 Tg for maize, 0.3 Tg for rice, and 0.7 Tg for wheat), representing 47.4 % of the national P use for cereal crop production in 2018 (Fig. 4g–i). Notably, if the DOP approach is not implemented, 1521 (81.4%), 772 (59.3%), and 1243 (85.7%) counties would face high risk of P leaching under maize, rice, and wheat production, respectively (Supplementary Fig. 10).

Discussion

Achieving investments to build up soil P availability is critical to meet the growing food demand while addressing the multiple challenges of exacerbating P-related pollution and depleting phosphate rock reserves[10,31]. Over the past century, P-related pollution has grown in association with increasing population, agricultural intensification, and a warming climate[32,33]. Although efforts are now focused on reversing this problem through frequent real-time in situ field monitoring, the long history of P overuse to maximize crop yields in some developed regions continues to drive high stream P concentrations and coastal eutrophication[16,34]. We propose an innovative DOP approach for achieving dynamic, region-specific P management by conducting soil tests every few years and continuously improving the model as new data become available. In the long term, the DOP approach has the potential to reduce fertilizer use significantly, by 47.4% without compromising crop yields in China, compared to current practices. Our study provides a simple and useful tool for establishing a county-specific P fertilizer program, enabling local farmers to manage soil P precisely, thereby enhancing productivity and improving environmental performance.

Our study constitutes an important addition to the range of viable solutions aimed at informing policymaking with regard to addressing P-related challenges. Effective P management requires tailored approaches, considering that larger P inputs are necessary for low P soils, while lower inputs suffice for higher P soils to minimize P movement into the environment[34]. However, both P-poor and P-rich regions lack the means to assess soil P levels and determine soil P balance at larger scales, and farmers lack incentives to promote the adoption of P conservation practices[5,35,36]. Our study presents national high-resolution maps with spatial estimates of APE, offering a method for simulating soil available P to predict, accurately, annual crop P application. Using the DOP approach, policymakers could develop

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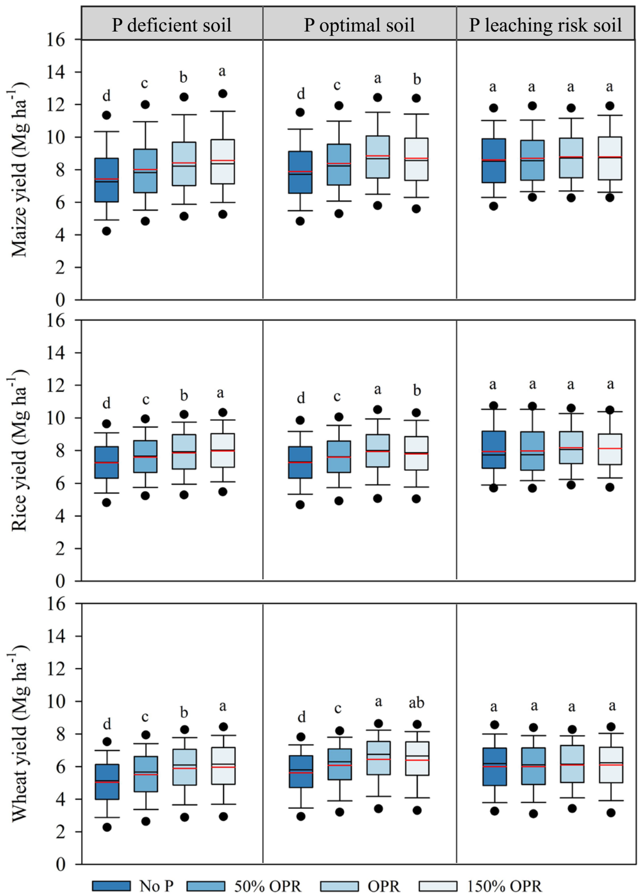

Fig. 3 | Implementation of the dynamic optimization of soil phosphorus (P) status approach with smallholder fields. Crop yields with different P treatments during 2005 to 2014 were observed at 15,851, 7424, and 12,300 sites for maize, rice, and wheat, respectively. The P treatments include no P application (No P), as well as 50%, 100%, and 150% of the optimal P rate (OPR). The solid line within the box indicates the median, while the red solid line represents the mean. The upper and lower edges of the box denote the 75th and 25th percentiles, respectively. The whiskers (short lines extending from the box) correspond to the 95th and 5th percentiles, respectively, and the solid black dots represent outliers. Different lowercase letters indicate significant differences in cereal crop yield among the various P treatments ($p < 0.05$). Source data are provided as a Source Data file.

location-specific P fertilizer rates as obligatory fertilization quotas, avoiding uniform fertilization rates at the national scale. Governments could also regulate total national P consumption, invest in domestic P fertilizer production, and participate in global trade. Global P consumption may be overestimated if based solely on past global P use trends and per capita gross domestic product[37,38]. In many developed countries, cereal yields have increased over the past 20 years without a significant rise in P fertilizer use, and in some areas, P use has even substantially declined[39,40]. Historically high P fertilization has boosted soil P fertility and increased P movement from agricultural systems to the environment in the USA and UK, where national soil P levels average 17.6 and 46.6 mg kg^{-1}, respectively[41]. Recently, crop production has continued to rise without significant increases in P fertilizer in the USA and with substantial declines in the UK. Consequently, P fertility in both countries has remained stable or even declined in regions with high soil P levels.

The DOP approach is agronomically robust and relatively flexible, making it accessible for smallholders, despite variation in P management across different counties and locations. We suggest that this approach may be extended to other regions, particularly in counties with large disparities between agronomic P inputs and outputs, such as many parts of Asia and North America[39,42]. A sizeable fraction of the global cropland area (69%) exhibits large negative or positive P imbalances, corresponding to P deficient soils and the P leaching rich soil, respectively[42]. Considering the numerous challenges confronting farmers and the low adoption rate of improved P management practices, the successful implementation of the DOP approach will depend on the establishment of incentive frameworks in each region, with governmental subsidies serving as indispensable policy tools to incentivize improved P management for smallholders[43]. In terms of technological support, a national county-based evaluation platform is needed to obtain more precise optimal P rate recommendations that are revised without frequent soil testing, similar to the Comprehensive Nutrient Management Plans implemented in the USA[44].

We amalgamated existing experiments, modeling, statistics, and surveys of Chinese crop production, and found that the DOP approach is a useful tool for developing region-specific P management recommendations. Nevertheless, these comprehensive analyses presented are subject to limitations. First, although field measurements for analyzing APE were distributed across five major P management regions, relatively few in situ field experiments have been performed to estimate APE across China, which may have led to uncertainties in our analysis. The types of P fertilizer were not considered in the construction of the APE model, due to current lack of grid data on the specific forms of P fertilizers used. Moreover, the gridded dataset included climate factors and soil properties from different periods may have contributed to uncertainty in our estimations. Nationwide APE monitoring studies and detailed data should be conducted to correct these uncertainties in the future. Soil available P change can be influenced by soil P accumulation, thus influencing APE. Studies should pay attention to this process to refine this models[26]. Second, fluctuations in weather and future climate change could potentially impact P recommendations[45,46]. Significant uncertainties exist in our DOP approach for obtaining precise optimal P rate recommendations since we cannot predict the frequency and extent of future extreme climate events. Establishing a research infrastructure that can react rapidly to changing environmental conditions, similar to a previously proposed nitrogen (N) rate strategy[47], is essential for increasing the feasibility of our method amidst a changing climate. Third, specific cropland management factors were not explicitly considered in our analyses. The methods and timing of P fertilizer application, irrigation practices, and the incorporation of straw/stover may influence soil P cycles and, consequently, impact APE. Therefore, the DOP approach should be routinely updated and refined to ensure that it remains suitable for various locations and cropping systems.

Achieving investments to promote soil P availability to secure future productivity and mitigate environmental losses by smallholders necessitates further refinement of P recommendations. These management strategies should be routinely updated to ensure that they are suitable for various locations, genetics, cropping systems, and climates. Coupling our county-specific DOP approach with other advanced P fertilizer management techniques (e.g., P fertilizer coating and fertigation) and other practices (e.g., cropping system patterns and residue retention) would further increase the benefits of adopting optimal P rates, creating a virtuous circle of food security and environmental sustainability[48]. Our study contributes to the creation of a precise county-level inventory for sustainable P management, offering a valuable solution to simultaneously achieve the co-benefits of conserving P resources and enhancing environmental performance. The DOP approach is pivotal for ensuring the long-term sustainability of food production and has the potential to inspire a global vision for P sustainability.

Methods

The research reported here consists of four components (Fig. 5): (i) Data collection from peer-reviewed articles derived from field trials

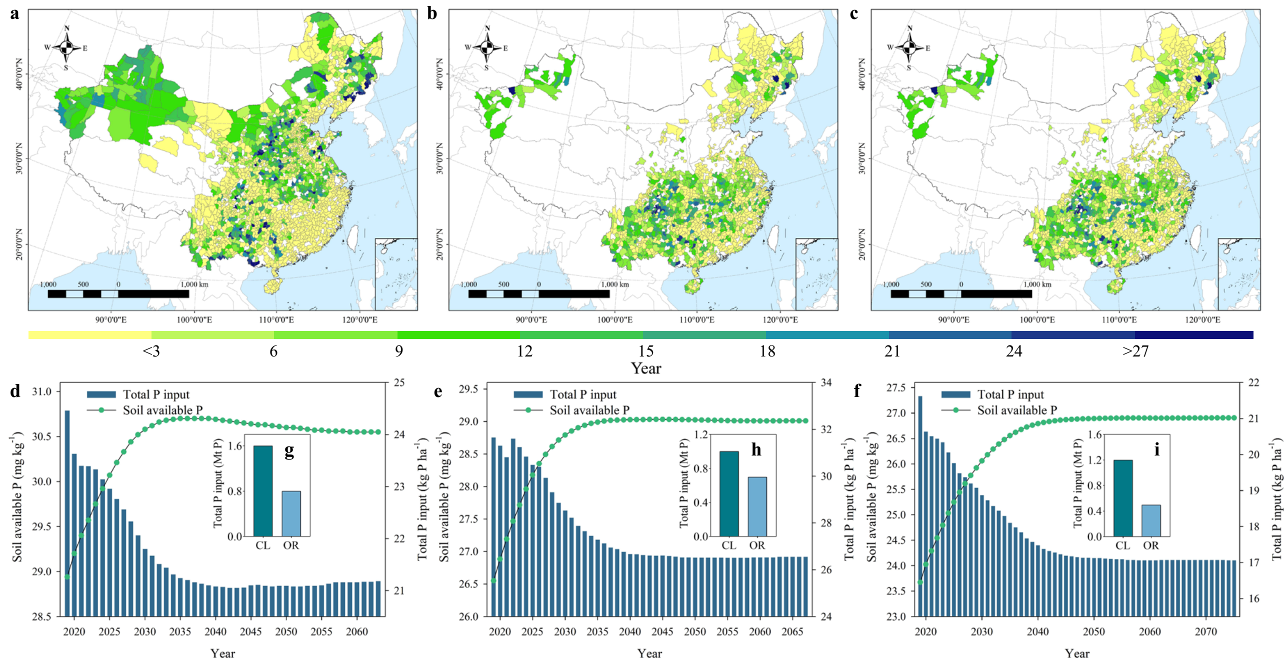

Fig. 4 | Managing phosphorus (P) over time in China. a–c Predicted years required to bring P to the optimal level for maize, rice, and wheat production. **d–f** Trends of annual P application and soil available P for maize, rice, and wheat production. **g–i** Current total P fertilizer input level (CL) and the recommended P fertilizer input after optimization (OR) for maize, rice, and wheat production. Source data are provided as a Source Data file. Base map data adapted from GS(2020)4619, http://bzdt.ch.mnr.gov.cn/. Map created using ArcGIS software.

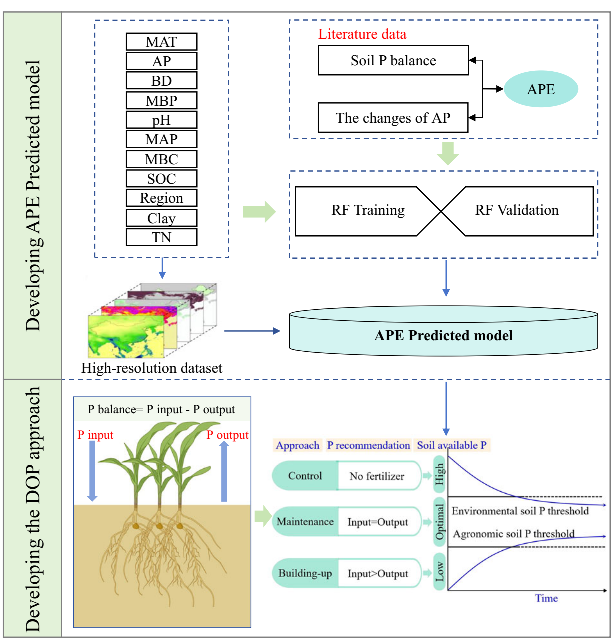

Fig. 5 | Framework of the procedure for a dynamic optimization of soil phosphorus (P) status approach. MAT mean annual temperature, AP soil available P, BD bulk density, MBP microbial biomass P, MAP mean annual precipitation, MBC microbial biomass carbon, SOC soil organic carbon, Clay soil clay content, TN soil total nitrogen, APE soil available P efficiency, RF random forest. Some elements of this figure were created in BioRender. B, A. (2024) https://BioRender.com/d39q892.

conducted across major agroecological zones, which were used to develop RF models to predict current grid-level national cropland APE; (ii) Development of the DOP approach to determine optimal P application rates by simulating soil P status through the geographic distribution of APE across China; (iii) Testing of the DOP approach in 35,575 on-farm trials during 2005–2014 to assess its applicability; and (iv) Prediction of optimal P application rates and changes in soil available P based on the DOP approach, assuming that crop yields remain would consistent with 2018 levels.

Data collection for soil APE estimation

With the aim of constructing a comprehensive database of experimentally determined APE values across major agroecological zones in China, we searched for peer-reviewed research papers published from January 1980 to December 2022 on the Web of Science (https://www.webofscience.com), Google Scholar (http://scholar.google.com) and China National Knowledge Infrastructure (http://www.cnki.net). The search terms included the keywords “phosphorus”, “soil available phosphorus”, “soil phosphorus balance”, “soil phosphorus budget”, and “phosphorus fertilizer” in combination with “field application”, “phosphorus uptake”, and “crop yield” in the article title, abstract or keywords. The results from the three databases were aggregated and relevant articles were carefully selected.

To be included in the database, published experiments were required to satisfy the following criteria: (1) the experiment reported in the study was conducted in the field, excluding any laboratory, greenhouse, or pot experiments; (2) initial and final soil available P content as well as experiment start and end dates were reported; (3) to reflect the P balance, detailed descriptions of total P use and crop P uptake were reported; (4) the publications reported comparisons between control (i.e., no P input) and P treatments (i.e., with P input). Using these constraints, a total of 424 pairs of observations across China were selected from 68 published studies for our analysis (Supplementary Fig. 11). The full list of all publications used in our analysis is included at the end of the Supplementary Information (Supplementary Note 1), and detailed information on each of the locations of the experimental sites is provided in Supplementary Fig. 1.

Soil properties, climate variables, and management-related variables were extracted from each record. Soil properties included soil pH, soil available P (AP, mg kg^{-1}), soil total nitrogen content (TN, g kg^{-1}), soil organic carbon (SOC, g kg^{-1}), bulk density (BD, g cm^{-3}), microbial biomass carbon (MBC, mg kg^{-1}), microbial biomass P (MBP, mg kg^{-1}), and soil clay content (Clay, %). Climate variables included mean annual temperature (MAT, °C) and mean annual precipitation (MAP, mm). Management-related variables mainly comprised the type of P fertilizer used. Graphical data were extracted using the GetData Graph Digitizer (https://sourceforge.net/projects/getdata/files/latest/download). Missing soil and climate factor data from several sites were either provided by the study authors through direct correspondence, or obtained from the spatial gridded databases based on latitude and longitude. These data were analyzed to determine the impact of the environment on cropland APE and develop a model for predicting national grid-level cropland APE.

The gridded dataset included climate factors and soil properties (Supplementary Fig. 3). Climate variables, such as MAT and MAP, were obtained from the Climatic Research Unit Time Series (1-km resolution grid) (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.05/cruts.2103051243.v4.05/). Spatial SOC, TN, Clay, BD, and pH data were acquired from the Harmonized World Soil Database v1.2 (1-km resolution grid) (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012), which contains data predominantly collected around 1995 and compiled into harmonized database by 2012. MBC and MBP were acquired from a previous study[49], which compiled data from peer-reviewed journal articles published before 2022 for use in an RF model. Soil available P data were compiled from a national campaign conducted by the Cultivated Land Quality Monitoring and Protection Center, Ministry of Agriculture and Rural Affairs in 2018, and re-gridded to a resolution of 1 km × 1 km using a first-order conservative interpolation.

Estimation of soil APE

The APE was defined as the change of soil available P (AP, mg kg^{-1}) per unit of soil P balance (Pb, kg ha^{-1})[50]. To mitigate the influence of environmental factors on APE, we used the following formula to estimate APE (mg kg^{-1}/kg ha^{-1}):

$$APE = (AP_{treatment} - AP_{ck})/(Pb_{treatment} - Pb_{ck}) \tag{1}$$

Where $AP_{treatment}$ (mg kg^{-1}) is the soil available P in the P addition treatment and AP_{ck} (mg kg^{-1})is the soil available P for the control (no P input). $Pb_{treatment}$ (kg ha^{-1}) is the soil P balance (P input into agricultural systems minus P removal via agricultural products) for the P treatment, and Pb_{ck} (kg ha^{-1}) is that for the control.

Application of RF modeling to predict grid-level national cropland APE

We constructed an RF model using machine learning techniques to predict current grid-level national cropland APE. The RF model was developed using an observation dataset that we collected from peer-reviewed research papers. Significant factors, including MAT, AP, BD, MBP, MBC, SOC, Clay, region, and TN, were included in the RF model (Supplementary Fig. 2a). Prior to building the RF model, we determined the best “mtry” and “ntrees” values though bootstrap sampling of the training dataset using the *e1071* package in R software. First, we constructed an RF model with m features selected from a total of n ($m < n$), and created nodes and daughter nodes among the chosen features. Subsequently, the process was iterated to assemble a forest comprising n decision trees. Finally, the model was run using a test dataset to generate a decision tree and forecast new outputs. All computations were performed using the *RandomForest* package in R software.

To develop the machine learning model for predicting grid-level national cropland APE, we divided the entire dataset into 10 subsets of equal size, and used 70% of the data subsets to train the RF model through 10-fold cross-validation, with the remaining 30% of the data used for model validate[51]. The model was evaluated based on the coefficient of determination (R^2) and root-mean-square error (RMSE) according to the following equations:

$$R^2 = 1 - \frac{\sum_{m=1}^{n}(y_m - \hat{y}_m)^2}{\sum_{m=1}^{n}(y_m - \bar{y})^2} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{n}(y_m - \hat{y}_m)^2}{n}} \tag{3}$$

where y_m represents an observation ($m = 1, 2, 3, \ldots$), $\hat{y}_m$ represents the corresponding prediction, $\bar{y}$ represents the mean value of observations, and n represents the total number of observations.

Climate and soil parameters (Supplementary Fig. 3) were incorporated into the model to obtain the best-fit simulation based on R^2 and RMSE. Model validation indicated that the model was robust, with an adjusted coefficient of R^2 of 0.75 and low RMSE value of 0.03, and the model showed good consistency between observed and predicted value with a slope of 0.71 for estimating national APE (Supplementary Fig. 2b). These results affirm the suitability of the developed models for predicting grid-level APE.

Development of the DOP approach

We developed the DOP approach at the county level based on the P build-up and maintenance approach. For counties where soil available P levels are lower than the agronomic soil P threshold, P fertilizer should be added to meet the agronomic soil P threshold. For counties where soil available P levels are within the range of the agronomic and environmental soil P thresholds, P fertilizer rates are adjusted to match the amount of P removed by crops, representing a zero-surplus P fertilizer management strategy. For counties where soil available P levels exceed the environmental soil P threshold, P fertilizer application should be terminated in the short term to reduce soil surplus P and reduce the risk of environmental P loss, then resumed following the P replacement rate based on crop removal[21].

Under the DOP approach, P fertilizer application rates (PF, kg P ha^{-1}) were calculated for each county as follows:

$$PF_{n+1} = \begin{cases} \begin{cases} \frac{AP_r - AP_n}{APE_{County}} + P_{rem} & if\ PF_n < 1.5 * P_{rem} \\ 1.5 * P_{rem} & if\ PF_n \geq 1.5 * P_{rem} \end{cases} & if\ AP_n < AP_r \\ P_{rem} & if\ AP_r \leq AP_n < AP_l \\ 0 & if\ AP_n \geq AP_l \end{cases} \tag{4}$$

where AP_r (mg kg^{-1}) is the agronomic soil P threshold, AP_l (mg kg^{-1}) is the environmental soil P threshold, P_{rem} (kg ha^{-1}) is P removal by plants, and n is the year. AP_n (mg kg^{-1}) is the soil available P, and APE_{County} (mg kg^{-1}/kg ha^{-1}) is the APE for each county, which re-gridded from the grid to the county level using first-order conservative interpolation. The recommended P fertilizer application rates was defined as a rate that does not exceed 1.5 times the crop P removal.

The soil available P (AP, mg kg^{-1}) using DOP approach for each county was estimated as follows:

$$AP_{n+1} = AP_n + P_{balance} \times APE \tag{5}$$

$$P_{balance} = PF_n - P_{rem} \tag{6}$$

where $P_{balance}$ (kg P ha^{-1}) is the P balance, and APE (mg kg^{-1}/kg ha^{-1}) is the soil available P efficiency. When $P_{balance} = 0$, n represents the year in which soil P reaches the optimal level (agronomic soil P threshold $\leq AP_n$ <environmental soil P threshold).

On-farm testing trials for the DOP approach

We tested the DOP approach in 35,575 on-farm trials conducted during 2005–2014 for the three cereal crops (15,851, 7424, and 12,300 sites for maize, rice, and wheat, respectively) during the National Soil Test and Fertilizer Recommendation Projects of the Ministry of Agriculture and Rural Affairs across all agroecological zones in China (Supplementary Fig. 7). All trials were designed and managed by local agricultural experts and/or trained extension personnel[11]. Four treatments were established at each experimental site: no P, application at the OPR as recommended by local agricultural extension employees based on soil tests and target yields (developed specifically for each county), 50% OPR, and 150% OPR. We included a 50% OPR treatment to explore the potential to further reduce P fertilizer and a 150% OPR treatment to ensure maximum crop yield. All experimental fields received optimal N and potassium (K) application rates based on soil testing and target yields at mean levels of 204, 173, and 192 kg N ha^{-1} for maize, rice, and wheat, respectively, and 95, 103, 94 kg K_2O ha^{-1}, respectively, for the three cereal crops. No organic amendments or straw was used in any of the field experiments.

On-farm trials for agronomic soil P thresholds

To establish a quantitative understanding of agronomic soil P thresholds across China, data from a total of 26,896 field sites were collected (11,079 for maize, 7492 for rice, and 8325 for wheat) (Supplementary Fig. 4). Four P fertilizer application rates were used in each trial, including 0, 0.5, 1.0 and 1.5 times the optimum P rate at optimum N and K rates. Optimum N, P, and K rates were recommended by local agricultural experts and/or trained extension personnel based on an integrated nutrient management strategy[24]. Notably, none of these experiments had inputs of animal manure or other organic P sources. We used the optimum P rate as a starting point for setting the gradient of P fertilizer rates (0, 0.5, 1.0 and 1.5 times the optimum P) for each field experiment, which allowed us to establish reliable relative yield–soil available P response curves.

The relative yield (Y_r, %) was calculated as follows:

$$Y_r = Y_{no\,P}/Y_{\max} \times 100 \tag{7}$$

where $Y_{no\,P}$ (kg ha^{-1}) is the crop yield of the no P input treatment in each on-farm trials, and $Y_{\max}$ (kg ha^{-1}) is the maximum crop yield of treatment (0, 0.5, 1.0, and 1.5 times the optimum P) in all experiments.

To identify agronomic soil P thresholds, we determined the relationship between relative yield and soil available P using the Mitscherlich equation[52]:

$$Y = A \times [1 - \exp(-bx)] \tag{8}$$

where Y (%) is relative yield of the prediction, A (%) is the maximum relative yield, and b is the coefficient of the relative yield of the soil available P (x) value. The soil available P content is the agronomic P threshold when the Mitscherlich model simulates a relative yield of 90%.

Estimation of soil P balance

To understand the current soil P balance across China, survey data were obtained from a nationwide farmer survey campaign conducted during 2005–2014, which was organized by the Ministry of Agriculture and Rural Affairs of China and carried out by various local agrotechnical extension departments. Survey data were collected from 31 provincial administrative regions of China and comprised 73% of the total area planted (66.4 million ha) in 1,978 counties for maize, rice, and wheat[53]. We filtered the data and included a total of 8.64 million individual farmers who participated in the survey (3.01, 3.37, and 2.26 million for maize, rice, and wheat, respectively). The survey was conducted via face-to-face interviews by county agricultural extension agents using a questionnaire designed to obtain information on crop yield and fertilizer use. Details information can be found from ref. 11.

The P balance (Pb, kg ha^{-1}) was calculated as follows:

$$Pb = P_{input} - P_{rem} \tag{9}$$

$$P_{input} = P_{fer} + P_{org} \tag{10}$$

$$P_{rem} = P_{grain} + P_{straw} \tag{11}$$

where P_{input} (kg ha^{-1}) is the total P input; P_{fer} (kg ha^{-1}) is the mineral P fertilizer input, and was obtain directly from the farmer survey data; P_{org} (kg ha^{-1}) is organic P input, P_{grain} (kg ha^{-1}) is the P uptake in grain, P_{straw} (kg ha^{-1}) is the P in crop straw removed from the field, and P_{rem} (kg ha^{-1}) is the P removal with P_{grain} and P_{straw}. P_{grain} and P_{straw} were calculated by multiplying the grain yield by the grain P concentration and harvest index. Grain P concentration and harvest index parameters are shown in Supplementary Table 1.

Organic P input was calculated as follows:

$$P_{org} = \sum\nolimits_{1}^{n} (\mathrm{Num}_j \times \mathrm{Mrate} \times \mathrm{L}_j \times \mathrm{PM}_j) + \sum\nolimits_{1}^{m} (\mathrm{CY}_i \times \mathrm{RS}_i \times \mathrm{A}_i \times \mathrm{PS}_i) \tag{12}$$

where Num represents the total count of humans and animals per unit area at the end of the year; j ($j = 1, 2, 3, \ldots n$) represents the types of human and animal wastes; Mrate is the rate of return of human and animal waste to the field[54]; L (kg head^{-1} yr^{-1}) refers to the annual human and animal excrement. i ($i = 1, 2, 3, \ldots m$) is the straw type; PM (%) is P contents of human and animal wastes; CY is the yield of the economic portion of crops; RS is the proportion of straw that is reintegrated into the field, and straw cycling ratios were 0.30 for maize, 0.42 for rice, and 0.74 for wheat[55], and A is the ratio of grain to straw from published literature[54]; PS (%) is P contents of straw. The P contents of different manure sources and straw were taken from the Nutrient Content in Organic Fertilizer of China report[56].

Data analysis and management

Microsoft Excel 2010 (Version 14.0.4763.1000; Microsoft Corp., Redmond, WA, USA) was used for creating databases of peer-reviewed publications. Daily weather analyses were performed using MATLAB R2017a software (version 9.2.0.538062; MathWorks Inc., Natick, MA, USA). R software (version 3.5.1; R Development Core Team, Vienna, Austria), GraphPad Prism (version 9.0.0; GraphPad Software, La Jolla, CA) and SigmaPlot (version 12.5; Systat Software Inc., San Jose, CA, USA) software were employed for graph generation and data visualization. ArcGIS 10.2 software (https://www.esri.com/en-us/arcgis/products/index) was used to perform map-related operations. The publicly available map of China was obtained from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). All computations, including the implementation of the RF and a nonparametric smooth regression model, were conducted using the R software environment (version 3.5.1; R Development Core Team, Vienna, Austria).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The literature search, survey data, on-farm testing trial data, and on-farm demonstration data generated in this study have been deposited the Data Repository on Zenodo (https://zenodo.org/records/14553798). Source data are provided with this paper.

Code availability

The code used in this study in the Data Repository on Zenodo (https://zenodo.org/records/14553798).

References

1. Rockström, J. et al. Safe and just Earth system boundaries. *Nature* **619**, 102–111 (2023).
2. Sandström, V. et al. Disparate history of transgressing planetary boundaries for nutrients. *Glo. Environ. Chang.* **78**, 102628 (2023).
3. Lun, F. et al. Global and regional phosphorus budgets in agricultural systems and their implications for phosphorus-use efficiency. *Earth Syst. Sci. Data* **10**, 1–18 (2018).
4. Brownlie, W. et al. Global actions for a sustainable phosphorus future. *Nat. Food* **2**, 71–74 (2021).
5. McDowell, R. et al. Phosphorus applications adjusted to optimal crop yields can help sustain global phosphorus reserves. *Nat. Food* **5**, 1–8 (2024).
6. Demay, J. et al. Half of global agricultural soil phosphorus fertility derived from anthropogenic sources. *Nat. Geosci.* **16**, 69–74 (2023).
7. Steffen, W. et al. Planetary boundaries: guiding human development on a changing planet. *Science* **347**, 1259855 (2015).
8. Jin, X. et al. Spatial planning needed to drastically reduce nitrogen and phosphorus surpluses in China's agriculture. *Environ. Sci. Technol.* **54**, 11894–11904 (2020).
9. Cordell, D. & White, S. Life's bottleneck: sustaining the world's phosphorus for a food secure future. *Annu. Rev. Environ. Resour.* **39**, 161–188 (2014).
10. Zou, T. et al. Global trends of cropland phosphorus use and sustainability challenges. *Nature* **611**, 81–87 (2022).
11. Cui, Z. et al. Pursuing sustainable productivity with millions of smallholder farmers. *Nature* **555**, 363–366 (2018).
12. Zhang, W. et al. Management strategies to optimize soil phosphorus utilization and alleviate environmental risk in China. *J. Environ. Qual.* **48**, 1167–1175 (2019).
13. Langhans, C. et al. Phosphorus for sustainable development goal target of doubling smallholder productivity. *Nat. Sustain.* **5**, 57–63 (2022).
14. Gong, H. et al. Phosphorus supply chain for sustainable food production will have mitigated environmental pressure with region-specific phosphorus management. *Resour. Conserv. Recy.* **188**, 106686 (2023).
15. Liu, X. et al. Intensification of phosphorus cycling in China since the 1600s. *Proc. Natl. Acad. Sci. USA* **113**, 2609–2614 (2016).
16. Shen, W. et al. Phosphorus use efficiency has crossed the turning point of the environmental Kuznets curve: opportunities and challenges for crop production in China. *J. Environ. Manage.* **326**, 116754 (2023).
17. IFA. *Production and International Trade Statistics*. https://www.ifastat.org/databases/plant-nutrition (2022).
18. Jiang, S. et al. Phosphorus footprint in China over the 1961-2050 period: historical perspective and future prospect. *Sci. Total Environ.* **650**, 687–695 (2019).
19. USGS. *Mineral Commodity Summaries* https://pubs.usgs.gov/publication/mcs2024 (2022).
20. Cui, R. et al. Development strategy of phosphate rock in China under global allocation of resources. *Strat. Stud.Chinese Acad. Eng.* **21**, 128–132 (2019).
21. Wang, Y. et al. The agronomic and environmental assessment of soil phosphorus levels for crop production: a meta-analysis. *Agron. Sustain. Dev.* **43**, 35 (2023).
22. Khan, A. et al. Phosphorus efficiency, soil phosphorus dynamics and critical phosphorus level under long-term fertilization for single and double cropping systems. *Agr. Ecosyst. Environ.* **256**, 1–11 (2018).
23. Wang, J. et al. Managing mineral phosphorus application with soil residual phosphorus reuse in Canada. *Glob. Change Biol.* **30**, e17001 (2024).
24. Zhang, F. et al. Integrated nutrient management for food security and environmental quality in China. *Adv. Agron.* **116**, 1–40 (2012).
25. Bindraban, P. et al. Exploring phosphorus fertilizers and fertilization strategies for improved human and environmental health. *Biol. Fertil. Soils* **56**, 299–317 (2020).
26. Muntwyler, A. et al. Assessing the phosphorus cycle in European agricultural soils: looking beyond current national phosphorus budgets. *Sci. Total Environ.* **906**, 167143 (2024).
27. Bai, Z. et al. The critical soil P levels for crop yield, soil fertility and environmental safety in different soil types. *Plant Soil* **372**, 27–37 (2013).
28. Li, H. et al. Past, present, and future use of phosphorus in Chinese agriculture and its influence on phosphorus losses. *Ambio* **44**, 274–285 (2015).
29. Tang, X. et al. Determining critical values of soil Olsen-P for maize and winter wheat from long-term experiments in China. *Plant and Soil* **323**, 143–151 (2009).
30. Steinfurth, K. et al. Conversion equations between Olsen-P and other methods used to assess plant available soil phosphorus in Europe - a review. *Geoderma* **401**, 115339 (2021).
31. Prietzel, J. et al. Soil phosphorus status and P nutrition strategies of European beech forests on carbonate compared to silicate parent material. *Biogeochemistry* **158**, 39–72 (2022).
32. Hou, E. et al. Effects of climate on soil phosphorus cycle and availability in natural terrestrial ecosystems. *Global Change Biol* **24**, 3344–3356 (2018).
33. Li, B. et al. Assessing the sustainability of phosphorus use in China: flow patterns from 1980 to 2015. *Sci. Total Environ.* **704**, 135305 (2020).
34. Ning, C. et al. Mineral fertilizers with recycled manure boost crop yield and P balance in a long-term field trial. *Nutr. Cycl. Agroecosys* **116**, 271–283 (2020).
35. Alewell, C. et al. Global phosphorus shortage will be aggravated by soil erosion. *Nat. Commun.* **11**, 4546 (2020).
36. Martín-Hernández, E. et al. Analysis of incentive policies for phosphorus recovery at livestock facilities in the Great Lakes area. *Resour. Conserv. Recy.* **177**, 105973 (2022).
37. Lwin, C. et al. The implications of allocation scenarios for global phosphorus flow from agriculture and wastewater. *Resour. Conserv. Recy.* **122**, 94–105 (2017).
38. Tilman, D. Global environmental impacts of agricultural expansion: the need for sustainable and efficient practices. *Proc. Natl. Acad. Sci. USA* **96**, 5995–6000 (1999).
39. Lu, C. & Tian, H. Global nitrogen and phosphorus fertilizer use for agriculture production in the past half century: Shifted hot spots and nutrient imbalance. *Earth Syst. Sci. Data* **9**, 181–192 (2017).
40. Mogollón, J. et al. Future agricultural phosphorus demand according to the shared socioeconomic pathways. *Glob. Environ. Change.* **50**, 149–163 (2018).
41. McDowell, R. et al. A global database of soil plant available phosphorus. *Sci. Data* **10**, 125 (2023).
42. Sattari, S. et al. Residual soil phosphorus as the missing piece in the global phosphorus crisis puzzle. *Proc. Natl. Acad. Sci. USA* **109**, 6348–6353 (2012).
43. Springmann, M. et al. Options for keeping the food system within environmental limits. *Nature* **562**, 519–525 (2018).
44. Khoshnevisan, B. et al. A critical review on livestock manure biorefinery technologies: Sustainability, challenges, and future perspectives. *Renew. Sust. Energ. Rev* **135**, 110033 (2021).
45. Ockenden, M. et al. Major agricultural changes required to mitigate phosphorus losses under climate change. *Nat. Commun.* **8**, 161 (2017).

46. Hou, E. et al. Global meta-analysis shows pervasive phosphorus limitation of aboveground plant production in natural terrestrial ecosystems. *Nat. Commun.* **11**, 637 (2020).
47. Cai, S. et al. Optimal nitrogen rate strategy for sustainable rice production in China. *Nature* **615**, 73–79 (2023).
48. Mogollón, J. et al. More efficient phosphorus use can avoid cropland expansion. *Nat. Food* **2**, 509–518 (2021).
49. Gao, D. et al. Three-dimensional mapping of carbon, nitrogen, and phosphorus in soil microbial biomass and their stoichiometry at the global scale. *Glob. Change Biol.* **28**, 6728–6740 (2022).
50. Cao, N. et al. Change in soil available phosphorus in relation to the phosphorus budget in China. *Nutr. Cycl. Agroecosys* **94**, 161–170 (2012).
51. Liu, Q. et al. Biochar application as a tool to decrease soil nitrogen losses (NH_3 volatilization, N_2O emissions, and N leaching) from croplands: options and mitigation strength in a global perspective. *Glob. Change Biol.* **25**, 2077–2093 (2019).
52. Singh, J. et al. Impact of long-term phosphorous fertilization on Olsen-P and grain yields in maize-wheat cropping sequence. *Nutr. Cycl. Agroecosys* **106**, 157–168 (2016).
53. Yin, Y. et al. A steady-state N balance approach for sustainable smallholder farming. *Proc. Natl. Acad. Sci. USA* **118**, e2106576118 (2021).
54. Zhang, Q. et al. Outlook of China's agriculture transforming from smallholder operation to sustainable production. *Glob. Food Secur.* **26**, 100444 (2020).
55. Zhang, Y. et al. Virtual nitrogen factors and nitrogen footprints associated with nitrogen loss and food wastage of China's main food crops. *Environ. Res. Lett.* **13**, 014017 (2018).
56. Price Bureau of the National Development and Reform Commission of China. *Nutrient Content in Organic Fertilizer of China*. https://www.eolss.net/sample-chapters/c10/E5-24-08-06.pdf (1999).

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Author contributions

H.G., Y.Y., and Z.Cu. conceived and designed the research. Z.Cu. led the study. H.G. contributed to the method construction, data analysis and writing. Y.Y., Z. Ch., Q.Z., X.T., Z.W., and Y.W. provided the data. Y.Y. has revised the study.

Competing interests

The authors declare no competing interests.

Additional information

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