Impact of Agricultural Management Practices on Mitigating Soil Phosphorus Loss: A multi-scale study

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Abstract

The widespread use of inorganic phosphorus (P) fertilizers has had a profound impact on the global P cycle, leading to increased crop yields but also contributing to P pollution in freshwater and coastal ecosystems. Canada, a world-leading agricultural producer, is facing water pollution challenges due to agricultural P losses, which not only affect water quality but also impact the economy. In addressing this challenge, many efforts have explored the effects of agricultural practices on sustainable P management. However, the outcomes have been somewhat controversial, likely due to variations in field design and experimental conditions. Furthermore, historical (residual) P from previous applications has garnered substantial attention in recent years due to its potential to sustain crop yields while mitigating P runoff. Despite this, a comprehensive national-scale assessment of its benefits for Canada remains unclear. My research endeavors to tackle the P pollution challenge in Canada by employing various methodologies. To begin, I conducted a meta-analysis to assess the efficacy of different agricultural practices in reducing soil P loss while considering their impact on crop yields. Our synthesis of field data suggests that conservation practices tend to be the most practical and effective approach for sustainable P management. Subsequently, I employed machine learning (ML) techniques to evaluate the effectiveness of conservation practices in mitigating P export from the Maumee River watershed to Lake Erie over the coming decades. The ML models indicate that additional practices may still be urgently required to address the ongoing P pollution in Lake Erie. Finally, I assessed the potential of reusing residual soil P to reduce P losses across Canadian agricultural land. Developing a P cycling model allowed me to analyze Canada's P dynamics. Coupled with a soil P dynamics model, my findings suggest that using residual P could reduce mineral P demand in Canada. The Atlantic provinces, Quebec, Ontario, and British Columbia exhibit the highest potential for reducing P applications. Notably, the Atlantic provinces and Quebec are poised to experience the greatest reductions in runoff P loss with this strategy, while Ontario, Manitoba, and British Columbia may experience relatively lower reductions. In conclusion, my research contributes to safeguarding water ecosystems and achieving long-term P sustainability. It underscores the importance of considering residual soil P as a valuable resource and its potential role in mitigating P pollution.

Résumé

L'utilisation généralisée d'engrais phosphorés inorganiques a eu un impact profond sur le cycle mondial du phosphore, entraînant une augmentation des rendements agricoles mais contribuant également à la pollution par le phosphore des eaux douces et des écosystèmes côtiers. Le Canada, l'un des principaux producteurs agricoles au monde, est confronté à des problèmes de pollution de l'eau en raison des pertes de phosphore agricole, qui affectent non seulement la qualité de l'eau, mais aussi l'économie. Pour relever ce défi, de nombreux efforts ont été déployés pour étudier les effets des pratiques agricoles sur la gestion durable du phosphore. Cependant, les résultats ont été quelque peu controversés, probablement en raison des variations dans la conception des champs et des conditions expérimentales. En outre, le P historique (résiduel) provenant d'applications antérieures a fait l'objet d'une attention particulière ces dernières années en raison de son potentiel à maintenir les rendements des cultures tout en atténuant le ruissellement de P. Malgré cela, une évaluation complète à l'échelle nationale de la gestion durable du P a été réalisée. Malgré cela, on ne dispose toujours pas d'une évaluation complète à l'échelle nationale de ses avantages pour le Canada. Ma recherche vise à relever le défi de la pollution par le P au Canada en utilisant diverses méthodologies. Pour commencer, j'ai effectué une méta-analyse pour évaluer l'efficacité des différentes pratiques agricoles dans la réduction de la perte de P dans le sol tout en tenant compte de leur impact sur le rendement des cultures. Notre synthèse des données de terrain suggère que les pratiques conservatrices tendent à être l'approche la plus pratique et la plus efficace pour une gestion durable du P. Par la suite, j'ai utilisé des techniques d'apprentissage automatique pour évaluer l'efficacité des pratiques conservatrices dans l'atténuation de l'exportation de P du bassin versant de la rivière Maumee vers le lac Érié au cours des prochaines décennies. Les modèles d'apprentissage automatique indiquent que des pratiques supplémentaires peuvent encore être nécessaires de toute urgence pour lutter contre la pollution actuelle du lac Érié par le P. Enfin, j'ai évalué le potentiel de la réintroduction du P dans les eaux du lac Érié. Enfin, j'ai évalué le potentiel de réutilisation du P résiduel du sol pour réduire les pertes de P sur les terres agricoles canadiennes. Le développement d'un modèle de cycle du P m'a permis d'analyser la dynamique du P au Canada. Couplés à un modèle de dynamique du P du sol, mes résultats suggèrent que l'utilisation du P résiduel pourrait réduire la demande en P minéral au Canada. Les provinces de l'Atlantique, le Québec, l'Ontario et la Colombie-Britannique présentent le plus grand potentiel de réduction des applications de P. En particulier, les provinces de l'Atlantique et le Québec ont un potentiel de

réduction des applications de P minéral. Notamment, les provinces de l'Atlantique et le Québec sont sur le point de connaître les plus grandes réductions de pertes de P par ruissellement grâce à cette stratégie, tandis que l'Ontario, le Manitoba et la Colombie-Britannique pourraient connaître des réductions relativement plus faibles. En conclusion, mes recherches contribuent à la sauvegarde des écosystèmes aquatiques et à la durabilité à long terme du phosphore. Elle souligne l'importance de considérer le P résiduel du sol comme une ressource précieuse et son rôle potentiel dans l'atténuation de la pollution par le P.

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Contributions of authors

The thesis was written in manuscript-based format. For each manuscript, Jiaxin Wang, Ph.D. candidate under the supervision of Dr. Zhiming Qi, developed the study objectives, formulated mathematical solutions to address the research, performed model simulations, analyzed results and prepared the draft papers. Dr. Zhiming Qi provided writing guidance and assisted in manuscript drafting for chapters 3-6 as a co-author. Dr. Elena Bennett, who was a co-author on chapters 5-6, provided valuable scientific views on writing and assisted in manuscript drafting. Dr. Chong Wang, a co-author on chapter 3, offered initial code support for the meta-analysis. Dr. Viveka Nand, a co-author on chapter 4, provided climate datasets for future P loss modeling. Dr. Ziwei Li, a co-author on chapter 4, shared valuable insights for manuscript drafting. All co-authors reviewed each of the respective manuscripts they were involved with.

Scientific manuscripts included in this thesis

Chapter 3. **Wang, J.**, Qi, Z., & Wang, C. (2023). Phosphorus loss management and crop yields: A global meta-analysis. *Agriculture, Ecosystems & Environment*, *357,* 108683. https://doi.org/10.1016/j.agee.2023.108683

Chapter 4. **Wang, J.**, Qi, Z., Nand, V., & Li, Z. (2023). Modeling 1974-2040 phosphorus dynamics in the outlet of Maumee River watershed. (under review)

Chapter 5. **Wang, J.**, Qi, Z., & Bennett, E. M. (2022). Changes in Canada's phosphorus cycle 1961–2018: surpluses and deficits. *Global Biogeochemical Cycles*, *36*(8), e2022GB007407.

Chapter 6. **Wang, J.**, Qi, Z., & Bennett, E. M. (2023). Managing mineral phosphorus application with soil residual phosphorus reuse in Canada. *Global Change Biology*, e17001.

Related scientific manuscripts

In the below studies, I assisted with coding for meta-analysis and manuscript drafting.

Wen, S., Cui, N., Gong, D., Xing, L., Wu, Z., Zhang, Y., ... & **Wang, J.** (2023). Optimizing nitrogen fertilizer application for achieving high yield with low environmental risks in apple orchard. *Agricultural Water Management*, *289,* 108501. https://doi.org/10.1016/j.agwat.2023.108501

Wen, S., Cui, N., Gong, D., Liu, C., Xing, L., Wu, Z., ... & **Wang, J.** (2023). A global meta-analysis of yield and water productivity of woody, herbaceous and vine fruits under deficit irrigation. *Agricultural Water Management*, *287*, 108412. https://doi.org/10.1016/j.agwat.2023.108412

Conference and workshop presentations

Poster presentation (Dec. 2023)

American Geophysical Union Conference Fall 2023 Meeting

• Title: Modeling residual soil phosphorus reuse to reduce phosphorus applications and losses in Canada

Poster presentation (Aug. 2022)

Global Health Week Bicentennial Celebrations at McGill University: “Unlocking the Potential toward Healthy Food Systems”

• Title: Feed the crop without phosphorus applications: estimating the role of soil residual phosphorus in food production

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Nomenclature

Commonly used abbreviations, acronyms and symbols are listed below. Other symbol definitions appear with equations in the text.

P	Phosphorus
SRP	Soluble reactive phosphorus
TP	Total phosphorus
TSS	Total suspended solids
N	Nitrogen
BMPs	Best management practices
ML	Machine learning
MLR	Multiple Linear Regression
Bagging	Bootstrap Aggregating
RF	Random Forest
GBM	Gradient Boosting Machine
LSTM	Long Short-Term Memory
4R	Right fertilizer source at the right rate, right time, and right place
MFA	Material flow analysis
R^2	Coefficient of determination
d	Index of agreement
$N_{Crop}(i,t)$	Surplus P applied at the soil surface to cropland
$N_{Past}(i,t)$	Surplus P applied at the soil surface to pastureland
$FERT_{p,crop}(i,t)$	Annual mineral P fertilizer applied to cropland
$FERT_{p,past}(i,t)$	Annual mineral P fertilizer applied to pastureland
$SLU_p(i,t)$	Recycled sludge applied to cropland
$MAN_{p,crop}(i,t)$	Manure P applied to cropland and pastureland

$MAN_{p,past}(i,t)$	Manure P applied to cropland and pastureland
$RRES_p(i,t)$	Crop residues P returned to cropland
$IRR_p(i,t)$	Irrigation water P applied into cropland
$ATM_{p,crop}(i,t)$	Atmospheric deposition P on cropland
$ATM_{p,past}(i,t)$	Atmospheric deposition P on pastureland
$WEA_{p,crop}(i,t)$	Weathering P on cropland
$WEA_{p,past}(i,t)$	Weathering P on pastureland
$Crop_p(i,t)$	Crop P removal
$GRAZ_p(i,t)$	Grass P consumption by grazing livestock
$L_{Crop}(i,t)$	Soil labile P pool in cropland
$L_{Past}(i,t)$	Soil labile P pool in pastureland
$S_{Crop}(i,t)$	Soil stable P pool in cropland
$S_{Past}(i,t)$	Soil stable P pool in pastureland
f	The percentage of P applications that transfers to soil labile P pool
$\alpha_{crop}(i)$	Coefficient of crop P removal
$\alpha_{past}(i)$	Coefficient of grass P grazing
$\mu_{LS,crop}(i)$	Rates of annual soil P transfer from labile P to stable P in cropland
$\mu_{SL,crop}(i)$	Rates of annual soil P transfer from stable P to labile P in cropland
$\mu_{LS,past}(i)$	Rates of annual soil P transfer from labile P to stable P in pastureland
$\mu_{SL,past}(i)$	Rates of annual soil P transfer from stable P to labile P in pastureland
$k_{run}(i,t)$	Runoff P loss coefficient
$IN_{Crop}(i,t,j)$	P applications for a specific crop type field
$LO_{Crop}(i,t,j)$	Soil P loss for a specific crop type field
$LO_{Past}(i,t)$	Soil P loss for pastureland
$PUE_{Crop}(i,t)$	Provincial-scale cropland P use efficiency

Chapter 1
Introduction

1.1 Background

Human activities have significantly altered the global phosphorus (P) cycle, a limiting resource essential for crop and animal growth (Elser and Bennett, 2011). Since the 1940s, the widespread use of inorganic phosphate fertilizers has contributed to increased global crop yields (Ringeval et al., 2014). However, this intensified P application has led to approximately 70% of croplands globally suffering soil P surplus (Macdonald et al., 2011), and the excess P discharged into the environment has caused severe eutrophication in freshwater and coastal ecosystems (Schindler et al., 2008), which underscores the need to assess P mobilization from terrestrial to aquatic systems to support future practices for long-term P sustainability (Filippelli, 2018).

Canada, a world-leading agricultural producer (Sarkar et al., 2018), is facing water pollution challenges (Council of Canadian Academies, 2013). Given that only about 4% of its land is arable, Canada heavily relies on agrochemicals, including P fertilizers, to sustain its high food productivity (Malaj et al., 2020). However, increased P application has resulted in the loss of P from agricultural systems, leading to severe eutrophication in Canadian rivers and lakes (Ali and English, 2019). This has brought about significant economic costs, with algal blooms in Lake Erie alone estimated to cost about $272 million per year for Canadian government (Smith et al., 2019).

To address the sustainable P use challenge, many efforts have investigated the effects of best management practices (BMPs) on Canadian agricultural land. These practices include the 4R stewardship approach for P fertilization (*i.e.*, right fertilizer source at the right rate, right time, and right place), conservation tillage methods, controlled drainage, and soil amendments (Grant and Flaten, 2019; Duits, 2019; Sunohara et al., 2016; Eslamian et al., 2018). While some results demonstrate the effectiveness of these practices in reducing soil P loss, others yield inconsistent and debated results (Jarvie et al., 2017; Zhang et al., 2017; Chi et al., 2020), which may attribute to context-specific field designs influenced by climate, management practices, methodologies, and soil physicochemical properties (Macdonald et al., 2012; Macrae et al., 2021; Li et al., 2023). This makes it challenging to draw general conclusions and guide management decisions for Canada. Additionally, individual studies may suffer from limited statistical power, small sample sizes, or other experimental limitations that could affect their accuracy and reliability.

Reducing excessive P applications tends to be one of the most efficient solution to prolonging P supply and reducing P loss (Carpenter and Bennett, 2011). Current observations indicate that P applications generally exceed crop P removals, with 42-54% of applied annual P fertilizer remaining in the soils (Syers et al., 2008; de Oliveira et al., 2019). Although residual P can be bound to organic matter or precipitated in forms not readily available to crops, it can be released into the soil solution slowly, potentially becoming available to crops in subsequent years due to microbial activities and chemical-physical reactions (Aulakh et al., 2007; Liu et al., 2015; Roy et al., 2016; Liu et al., 2017; Lemming et al., 2019; Zhang et al., 2022). With concerns about global P pollution raised by Zou et al. (2022), who anticipate an exacerbation by 2050 that will exceed the environmental thresholds (Springmann et al., 2018), the significance of reusing residual P to reduce soil P runoff and safeguard water ecosystems becomes evident (Withers et al., 2014). Field trials in Quebec, Ontario, Manitoba, and Saskatchewan have demonstrated that residual P can sustain crop yields while reducing runoff P loss (Liu et al., 2015; Liu et al., 2019; Parent et al., 2020; Zhang et al., 2020). However, a comprehensive national-scale evaluation of the benefits of using residual P to mitigate P applications and losses is lacking, which is crucial when implementing sustainable P management and national policies.

1.2 Objectives

The main objective of this study was to help address the P pollution challenge in Canada. To achieve this goal, this study is structured around four journal articles, each with its specific objectives:

i. To apply a meta-analysis to assess the effectiveness of BMPs in mitigating soil P loss by synthesizing results from peer-reviewed experimental trials.

ii. To evaluate the effectiveness of the best practice identified through the meta-analysis in reducing P loss under climate change.

iii. To calculate the long-term spatial soil P balance across Canadian agricultural land.

iv. To explore the potentials for using residual soil P to reduce P applications and losses.

1.3 Thesis structure

The thesis follows a "manuscript-based" format, with Chapter 1 offering a general introduction that encompasses the research background, knowledge gaps, objectives, and an outline of the thesis. Chapter 2 comprises a comprehensive literature review, including history and current situation of agricultural P use, overview of agricultural P management, and overview of agricultural P modeling. Chapters 3, 4, 5, and 6 align with the four specific objectives and present the research accordingly. Each of these chapters is structured as an independent research paper. Connecting text is provided to link the research. The papers are formatted according to the requirements of Library and Archives Canada. Supplementary tables and figures are provided at the end of each paper since they appear with the papers online and are referred to often. All references are located at the end of the thesis.

Chapter 2
Literature review

2.1 History and current situation of agricultural P use

P is a non-renewable and diminishing mineral resource, with a conservative estimate of existing resources will be depleted in 300 years (Satteri et al., 2012). However, P is an essential nutrient for sustaining life system. Globally, approximately 80% of P is used in agricultural production (Cordell et al., 2009). Unlike nitrogen, which is potentially unlimited that can be biologically fixed from the atmospheric reservoirs, crop P removal is historically depended on the previous soil P levels and the addition of organic P fertilizers (Bennett, 2013), runoff carrying (Christopher et al., 2019), and weathering (Wang et al., 2014). In China, organic fertilizer use can be traced back to the BC period (Yang et al., 2010). In Europe, when it came to the 18th century, benefiting from industrial revolution, the increasing soil degradation and famines accelerated the trade of other phosphate fertilizers, like England, which imported large quantities of crushed bones (Cordell et al., 2009), and the same trade took place in the US (Fig. 2.1) (Ashley et al., 2011). Bone ash was considered the major source of P till the mid-to-late 19th century, when people began to use guano and phosphate-rich rocks as commercial fertilizer. Guano was rich in nitrogen and also contained substantial amounts of phosphate. Small volume of guano often gave greatly improved crop yields from worn-out fields (Richard, 1979), thus world trade of guano grew continuously, whereas because of the limited volume, guano depleted rather rapidly by the end of the 19th century. At the same time, the introduction of the electric arc furnace in 1890 emancipated the exploitation of phosphate rock, making phosphate rock becoming the main source of P in modern agriculture (Smil, 2000).

Figure 2.1 Large pile of bison skulls that will be ground into fertilizer in the US around 1870. Adapted from Ashley et al. (2011).

Phosphate rock extraction has experienced a significant increase over the past decades (Fig. 2.2). Global phosphate rock production in 2018 was estimated at around 249 million metric tons (MT) (USGS, 2018). The world's leading producers were China (120 million MT), Morocco (34.8 million MT), the U.S. (25.8 million MT), Russia (14 million MT), Jordan (8 million MT), and Saudi Arabia (6.1 million MT). However, the export volume from these major producers is relatively low. In 2018, the total exports were around 17 million MT, less than 7% of the world's total production. The primary phosphate rock exporters were China (5.7 million MT), Morocco (3.5 million MT), Russia (3.1 million MT), the U.S. (2 million MT), and Saudi Arabia (1.6 million MT). China and the U.S. hold a prominent position in both phosphate production and exports globally (FAO, 2016); however, despite their substantial production capabilities, they tend to prioritize domestic P consumption. For instance, China has enforced a 135% export tariff on phosphate rock to limit P export and ensure a stable domestic supply (Liu et al., 2016). Additionally, the adverse environmental consequences stemming from the mining industry have further strained phosphate production (Li et al., 2011). Morocco and Western Sahara produce considerably less phosphate rock compared to China, while they hold the largest phosphate reserves, approximately 70% of the global reserves. In 2019, their production together reached approximately 36 million MT (USGS, 2019). Ironically, even though Africa possesses the largest phosphate resources, it is also the continent grappling with the most severe food shortages (Magnone et al., 2022). This dire situation is exacerbated by factors like geopolitical conflicts (Cordell et al., 2009).

Canada only holds 0.1% of the world's phosphate rock reserves (Ross and Omelon, 2018), rendering the output from potential P mines negligible on a global scale (USGS 2015, 2016). Currently, Canada primarily produces P fertilizer from the imported phosphate rocks. While the supply situation for phosphate rock in Canada is not a concern, it is expected that the planned mining of phosphate rock in Canada may be depleted within 30 years (Jasinski, 2016).

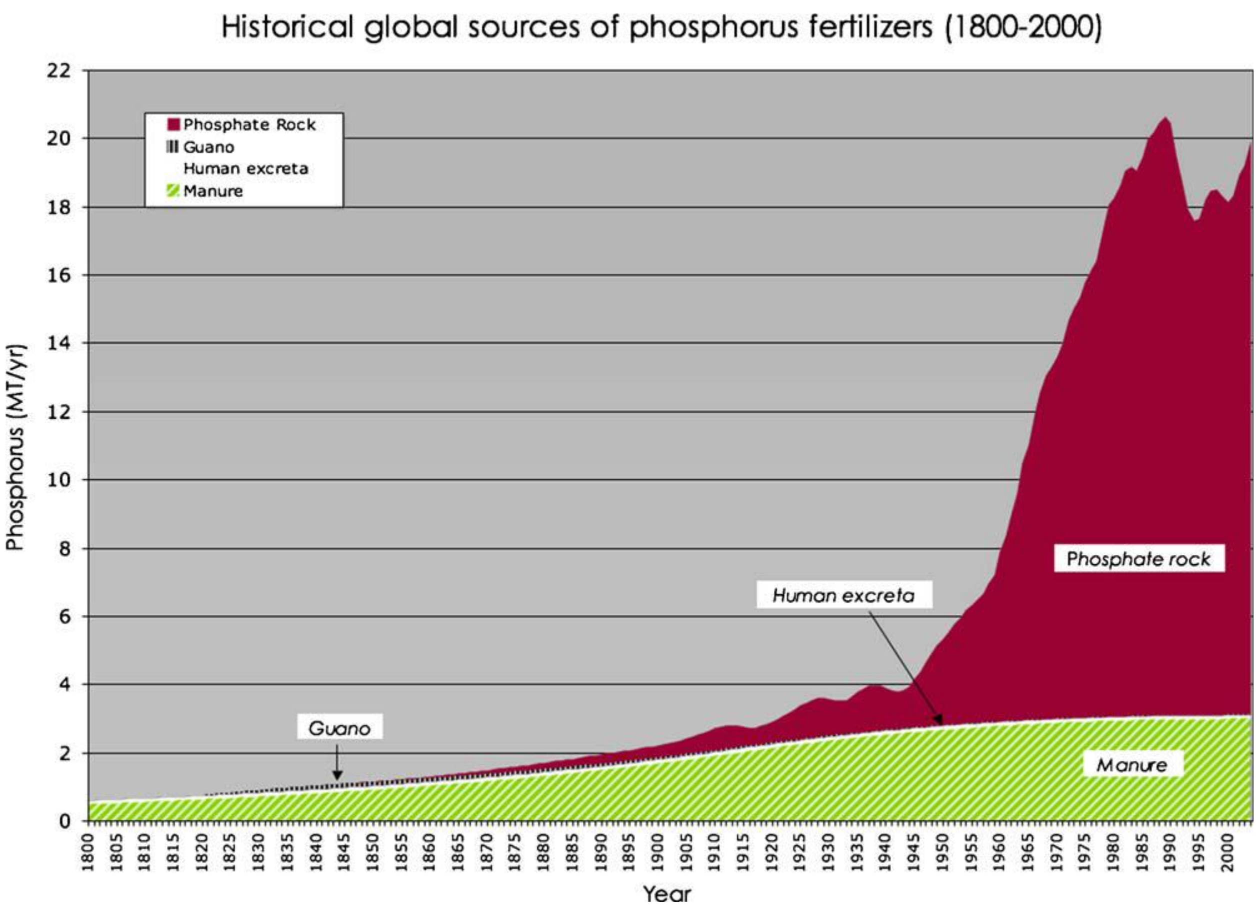

Figure 2.2 Historical sources of phosphorus for use as fertilizers, including manure, human excreta, guano and phosphate rock (1800–2000). Adapted from Cordell et al. (2009).

Additionally, the increasing P fertilizer demand has affected the price of global phosphate market (Cordell et al., 2009). The phosphate rock price has increased from approximately $20 per tonne in 1961 to $120 per tonne in 2015 (Mew, 2016). This was particularly evident during the global food crisis of 2007-2008 when the demand for phosphate rock and fertilizer outstripped the supply, which led to a tenfold increase in the phosphate rock price in 2009. This price hike had resulted in farmer riots and even deaths in countries where heavily relies on P imports, which underscores this market's sensitivity and the critical role of P plays in global food security (Cordell et al., 2009).

2.2 Overview of agricultural P management

Given the critical role of P in agricultural productivity, and considering the challenges of mineral P depletion and eutrophication (Alewell et al., 2020), there has been an increasing focus in sustainable P use in agriculture (Mogollón et al., 2021; Barbieri et al., 2022). BMPs include 4R stewardship for P fertilization (Grant & Flaten, 2019), conservative tillage practices to reduce soil erosion to thus reduce particulate P losses (Duits, 2019), control drainage to manage soil water levels to mitigate dissolved P losses (Sunohara et al., 2016), or adding soil amendments to immobilize soil P to reduce dissolved P leaching (Eslamian et al., 2018). Notably, balancing fertilizer input and crop removal has been recognized as a critical step to ensure P sustainability (Simpson et al., 2011). Approximately 70% of the world's cropland area is estimated to suffer a soil P surplus (Macdonald et al., 2011), and it is expected to consistently accumulate P under current P use strategies (Zou et al., 2022). The most likely method in the short-term to stop soil P accumulating is to reduce excess P applications (Satteri et al., 2012). Six-year corn experiments in Quebec showed it was unnecessary to apply inorganic P fertilizer when manure was applied at rates following field application guidance (Parent et al., 2020). A high P buildup field trial in Saskatchewan demonstrated that wheat grew just as well with only nitrogen fertilization as when fertilized with additional P fertilizer over a 15-year period (Liu et al., 2015). Similar field experiments in Ontario showed soil residual P sustained corn and soybean yields compared to those with continuous P addition over 11 years (Zhang et al., 2020). These results demonstrate the potentials for reducing P applications without significantly impacts on crop production in P accumulation regions (Satteri et al., 2012).

Soil P accumulation could also be mitigated by increasing crop uptake, either by increasing the proportion of crops with high P uptake (*e.g.*, oilseed crops) or by adding additional crops into the rotation (Welsh et al., 2009). A review of the literature suggests winter forages as cover crops could successfully reduce soil residual nitrogen (N) (Ketterings et al., 2015), which would have the side benefit of increasing P removal (Reid et al., 2019), while suitable species for Canada require further research because of frigid conditions (Zhang, Tan, Zheng, et al., 2017). A few studies have also suggested that winter cover crops might undesirably release dissolved reactive P because of the disruption of plant cells caused by freeze-thaw cycles (Lozier et al., 2017; Lozier & Macrae, 2017; Miller et al., 1994), but it may still be effective in the areas with the greatest P surplus (Cober et al., 2019). Additionally, crop breeding to enhance crop P uptake levels might be another promising way to reduce soil P accumulation (Veneklaas et al., 2012), which still requires more careful investigations.

Reducing manure application and transporting excessive manure from P surplus areas to P deficits areas appears to be a promising way to save P fertilizer applications (Wang et al., 2022). However, manure freight costs over large distances seem to be a major challenge (Hadrich et al., 2010). While Metson et al. (2016) showed distances between surplus recyclable P manure and crop demands could be shorter than expected, the cost of transporting manure remains substantial. Another concern is that animal excreta often contains antimicrobial additives such as heavy metals and veterinary drugs, which could affect soil biology (Li et al., 2011). Several recent studies have focused on the role of renewable energy production as a way to overcome manure cost issues (Metson et al., 2022; Vanttinen, 2022); however, the manure transportation and fermentation process can also produce greenhouse gases, resulting in potential environmental problems (Guo et al., 2022).

In livestock farming, ensuring an adequate dietary supply of P is crucial to meet the daily nutritional requirements of animals. However, the extensive use of mineral feed P additives, which account for approximately 9% of global phosphate rock consumption, often results in an excess of P in animal diets (Reid et al., 2019). Studies have shown that the total P content in animal manure increases with higher dietary P levels (Reid et al., 2019), emphasizing the importance of finding the right balance between the supplementation and requirement for P feed additives to minimize manure P loss into the environment (Li et al., 2011). The addition of enzyme additives to nonruminant animal diets (*e.g.*, pigs and poultry) has been considered as a strategy to enhance the efficiency of P recovery (Augspurger et al., 2003; Lei and Stahl, 2001; Kim et al., 2006). Moreover, the percentage of manure recycled has decreased from 100% in 1949 to 50% in 2005 due to the rapid expansion of intensive animal feeding operations without a corresponding increase in cropland available for livestock manure disposal (Li et al., 2016). This has led to an open-ended P cycle, with a significant accumulation of P in some agricultural regions while other areas still face P deficiencies (Wang et al., 2022). Therefore, a more intensive integration of crop fields and livestock systems is considered an alternative approach to improve P use efficiency (Wang et al., 2022). Furthermore, studies have shown that a meat-based diet necessitates approximately 11.8 kg of phosphate rock per person per year, which is considerably higher than the 4.2 kg requirement for a vegetarian diet (Cordell et al., 2009). Ma et al. (2013) suggested that shifting from meat-based diets to more cereal-based diets can substantially reduce the demand for arable land, water, and P applications. Metson et al. (2012) highlighted that meat consumption is the most significant contributor to 'dietary P footprints'. Therefore, reducing meat consumption in the future might play an important role in sustainable P use strategies. While altering dietary habit looks like a considerable challenge, as it is closely linked to increasing urbanization and higher incomes.

Additionally, urban wastewater infrastructure is basically designed for public health, but it is increasingly focusing on P recovery from both urban and industrial wastewaters (Reindl, 2007). Struvite, a compound recovered during the wastewater treatment process, represents a promising avenue for recycling P and serves as an alternative to commercial P fertilizer (Huang et al., 2018; Benjannet et al., 2020). However, this approach requires a sanitation service infrastructure that prevents the mingling of human excreta with other wastewater streams containing heavy metals and other toxic wastes, which may require large investments.

2.3 Overview of agricultural P modeling

2.3.1 Soil P pools

Soil P models are proposed based on relationships between P applications, soil P pools and crop P removal observed through field trials (Jones, Cole, Sharpley, & Williams, 1984; Williams, 1990). Generally, soil P models consider three inorganic soil P pools (*i.e.*, labile, active, and stable mineral P) and two organic soil P pools (*i.e.*, fresh and stable P) (Fig. 2.3) (Jones et al., 1984). Since labile P pool is the primary source for plant P uptake (Jones et al., 1984), its accurate simulation is crucial in soil P modeling. In many models, including Environmental Policy Impact Climate (EPIC), Agricultural Policy/Environmental eXtender (APEX), and Soil and Water Assessment Tool (SWAT), soil solution P is assumed to be equivalent to labile P. Running SWAT requires to provide an initial value for labile P or use the default value of 5 mg kg^{-1} as the initial solution P concentration (Wang et al., 2020).

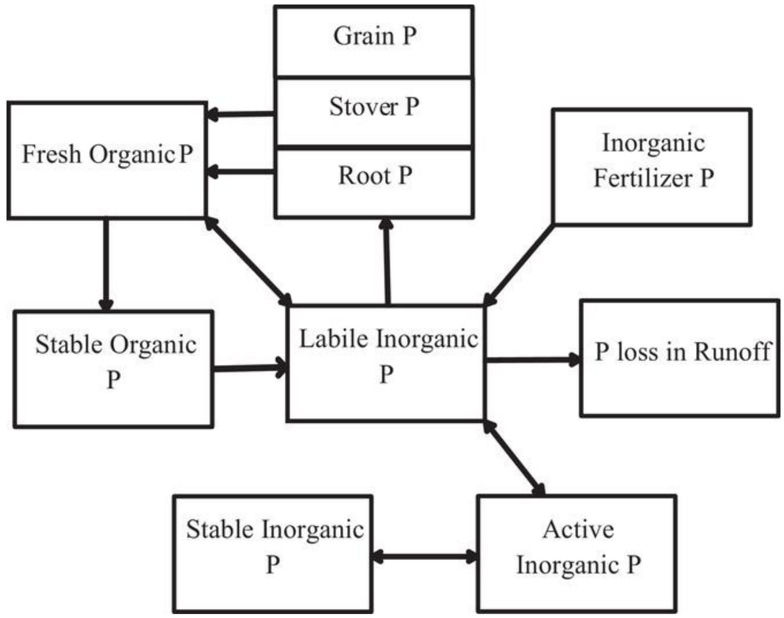

Figure 2.3 A brief introduction of soil-crop P dynamics model. Adapted from Wang et al. (2020).

One challenge in soil P modeling is the identification of the measurable form of soil P (*e.g.*, water-extractable P), which correlates with different soil P pools, including labile, active, and stable pools. Vadas and White (2010) assumed that soil solution P equaling half of Mehlich-3 P and Bray-1 P, while equaling to Mehlich-1 P, Olsen P, Fe-oxide strip-extractable P, and anion exchange resin-extractable P. Some work also proposed pedotransfer functions to establish the relationships between P pools and soil properties (*e.g.*, clay content and calcium carbonate) (Peruta, 2013; Wang et al., 2022).

Another challenge is the calculation of P transfer rate among different soil pools, as increasing the ratios of P transfer will enhance P loss assessment (White et al., 2010). Some studies assumed a constant ratio in soil P transfers (*e.g.*, 0.1, Equation 1, Table 2.1), while others used the temporal ratios between the inorganic labile and active P pools (Vadas, Krogstad, & Sharpley, 2006). They assumed that the dynamic ratios were depended on the cumulative number of days when there is an imbalance between the labile P and active P pool (Equations 2 and 3, Table 2.1), and Vadas et al. (2006) had shown that the implementation of dynamic ratios enhanced the prediction accuracy of soil P loss.

Table 2.1 Different equations for P movement and P sorption coefficient. Adapted from Vadas et al. (2006) and Wang et al. (2020).

Equation	Description	no.
$P_{moved} = 0.1(P_{lab} - \frac{PSC}{1-PSC}P_{act})$	P movement between labile P and active P	1
$P_{sorp} = \left(P_{lab} - \frac{PSC}{1-PSC}P_{act}\right)(0.918e^{-4.603PSP})[T^{-0.238\ln(0.918e^{-4.603PSP}-1.126)}]$	Dynamic sorption rate factors between inorganic labile and active P pool	2
$P_{desorp} = \left(P_{lab} - \frac{PSC}{1-PSC}P_{act}\right)(-1.08PSC + 0.79)(T^{-0.29})$	Dynamic desorption rate factors between inorganic labile and active P pool	3
$PSC = -0.0061CA + 0.58$	Calcareous soil	4
$PSC = 0.0043BS + 0.0034P_{lab} + 0.11pH - 0.7$	Slight weathering	5
$PSC = 0.014BS + 0.02$	Slight weathering	6
$PSC = 0.0054BS + 0.116pH - 0.73$	Moderate weathering	7
$PSC = 0.097pH - 0.413$	Moderate weathering	8
$PSC = -0.047\ln(CL) + 0.0045P_{lab} - 0.053C_{org} + 0.39$	High weathering	9
$PSC = -0.0916\ln(CL) + 0.78$	High weathering	10
$PSC = -0.053\ln(CL) + 0.001P_{lab} - 0.029C_{org} + 0.42$	High weathering	11

Note. PSC is the P sorption coefficient between active P (P_{act}) and labile P (P_{lab}); 0.1 is the sorption rate factor. The desorption rate factor for P moves from active P to labile P is also 0.1; T is the cumulative number of days when there was an imbalance between labile P and active P pool; CA is calcium carbonate content; BS is base saturation; CL is clay content; and C_{org} is organic carbon.

Furthermore, many studies have made efforts to enhance the calculation of the P sorption coefficient (PSC). The PSC value represents the proportion of inorganic P added to the soil that remains in solution once it reaches equilibrium with active P. A PSC value of 0.4, for example, signifies that 40% of added P remains in solution while the rest becomes active P (Vadas & White, 2010). In SWAT, PSC is a user-defined parameter used to initialize the quantity of inorganic P pools and calculate P movement between these pools (Wang et al., 2020). Accurate PSC value is crucial as it is assumed a constant variable. To determine PSC value, many equations have been proposed based on soil properties (Equations 4-11, Table 2.1) (Wang et al., 2022).

2.3.2 P models

Many models have been developed to simulate soil-crop P dynamics at field- or regional-scale. For instances, the World Food Studies simulation model (WOFOST), enables quantitative analysis of annual crop growth and production based on specific soil and weather conditions, crop characteristics, and management practices (Boogard et al., 2014). Recent improvements include using Landsat TM and MODIS data for regional-scale winter wheat yield estimation by assimilating leaf area index into the model (Huang et al., 2015). WOFOST operates at a daily time step and calculates plant nutrient (*e.g.*, P) requirements for achieving potential crop yields, drawing on calculations from the QUEFTS model (Janssen et al., 1990; Smaling and Janssen, 1993). Crop P uptake in QUEFTS depends on the potential supply of P and other nutrients in the soil. The potential supply of P represents the amount that can be taken up when all other nutrients are non-limiting and can be determined through experiments where other nutrients are in ample supply. QUEFTS provides guidelines for estimating potential supply from soil characteristics based on chemical properties, while this has not been integrated into the WOFOST model.

The PHOSMOD model is designed to calculate the effects of fertilizer application and soil-available P on plant growth and P concentration in plants (Kristoffersen et al., 2006). It operates on a daily basis, simulating plant growth, nutrient uptake, and the maximum P diffusion to each root segment through the soil. Model parameters have been validated based on vegetable crops in the UK (Greenwood et al., 2001) and a field fertilizer trial of spring barley in Norway (Kristoffersen et al., 2006). However, more experiments are still required to validate the model’s capacity.

APSIM, the Agriculture Production system SIMulator, offers a modular framework to simulate crop production while considering climate, genetics, soil, and management practices (Keating et al., 2003). APSIM's SoilP module describes the soil's capacity to supply P to crops under P-limiting conditions and considers inputs of both immediately available and slow-acting fertilizers. SoilP is linked to the MANURE module, which manages the release of P from manure on the soil surface. Besides, SoilP is a multi-layer module that requires assumptions about how P uptake is partitioned between soil layers.

Daroub et al. (2003) initially developed a model to simulate P cycling in the soil-plant system, which has been integrated into the Decision Support System for Agrotechnology Transfer (DSSAT). Later, Dzotsi et al. (2010) improved the DSSAT-P module by combining organic P dynamics from the CENTURY model. CENTURY is used to simulate carbon and nutrient dynamics in ecosystems (Parton et al., 1988). This model considers inorganic P pools, organic pools, and plant residues, running on a monthly time step and considering input variables including climate, soil properties, and P transformations based on empirical relations (Parton et al., 1988). While DSSAT-P primarily comprises two soil modules (*i.e.*, organic and inorganic P pools) and running on a daily time step. To run soil P module in DSSAT, in addition to general information, a value of measured extractable soil P for each soil layer is needed.

The EPIC model is a widely used field-scale model that has been widely used to study agricultural impacts on environment, including soil nutrient cycling and losses (Edwards et al., 1994; Chung et al., 1999; Pierson et al., 2001; Wang et al., 2006; Bouraui and Grizzetti, 2008; Zhang et al., 2010; Schoenhart et al., 2011; Egbendewe-Mondzozo et al., 2013). The model's soil P routines are developed based on the model by Jones et al. (1984) and encompass active and labile inorganic P, fresh and stable organic P, and P in plant components. Noteworthy, soil P routines in SWAT are also developed based on the model by Jones et al. (1984). EPIC operates on a daily time step and can simulate P uptake and transformation across different soil layers. It requires soil data, including chemical, physical, and taxonomic information (Jones et al., 1985). Recent work by Liu et al. (2018) had used EPIC to simulate field P loss for three major crops on a global scale, and predicting P losses under future rainfall scenarios (Liu et al., 2020). However, despite these efforts, the application of EPIC in large-scale P modeling remains limited.

Additionally, some of the lesser applied models include FIELD, which is a field-scale model that simulates crop productivity and changes in soil carbon and nutrient stocks (Tittonell et al., 2010). FIELD calculates nutrient-limited yield by considering the availability of light, water, and soil nutrients. It estimates P supply from organic sources based on C:P ratios of organic matter and, if data are available, uses parameters to estimate seasonal P supply from mineral soil sources. Ecosys is an ecosystem simulation model that employs multiple soil layers and operates on an hourly time step. Grand and Robertson (1997) integrated algorithms for simulating P uptake into Ecosys. P uptake is determined by solving for aqueous concentrations at root and mycorrhizal surfaces in each soil layer, considering radial transport by mass flow and diffusion. PARJIB, developed by Reid (2002), is a nutrient forecasting model that provides practical fertilizer recommendations based on initial soil nutrient supply and target yield potential in a specific field (Reid, 1999; 2002; Reid et al., 2011). HYDRUS is a model designed to simulate the movement of water, heat, and various solutes in variably-saturated media (Simunek et al., 2008). However, it requires many parameters at a high level of precision, which would be impractical to scale up to a field or regional scale (Reid and Schneider, 2021). The ICECREAM model, built upon the CREAMS model (Knisel, 1980), serves as a field-scale agricultural management tool (Larsson et al., 2007; Jaakkola et al., 2012). And Qi et al. (2017) have demonstrated its ability to satisfactorily simulate key processes of surface and subsurface P losses after adjusting model parameters. Besides, Sadhukhan et al. (2019) coupled a soil P module into RZWQM2, and demonstrated the capacity of RZWQM2-P in simulating both dissolved and particulate P losses (Pan et al., 2023).

Material Flow Analysis (MFA) offers an alternative approach to soil-crop P cycling analysis. Unlike mechanism-based models, MFA relies on mass balance principles to systematically assess and track the flow of P substances between various processes within the system, which enables to understand soil-crop P dynamics on a large scale (Wang et al., 2022). The Dynamic P Pool Simulator (DPPS) model is proposed based on MFA and a soil P model by Wolf et al. (1987). DPPS considers both labile and stable P pools, encompassing both inorganic and organic P forms (Sattari et al., 2012). Crops absorb P from the labile pool, and the stable P pool acts as a slow-release buffer that replenishes the labile P pool. To run the model, input data requirements include the rate and type of applied fertilizer, crop production, and soil properties. DPPS operates on a yearly time step and has been employed to calculate P requirements on a national scale (Sattari et al., 2014).

Recently, machine learning (ML) techniques have attracted significant attention for their potential in addressing complex water resource challenges. ML has been effectively employed in combination with geospatial data to predict soil P content from field-level to entire watersheds (Jeong et al., 2017; Sahabiev et al., 2021; Kaya and Başayığıt, 2022). Furthermore, ML has been applied to forecast nutrient concentrations within river networks (*e.g.*, Shen et al. 2020; Sadayappan et al. 2022). Chang et al. (2023) developed a ML model that using environmental variables predicted by physical models to simulate TP load in the Maumee River. Gorgan-Mohammadi et al. (2023) established decision tree models that using water chemical properties to estimate the P concentration in Lake Erie. These investigations collectively showcase the immense potential of ML techniques for advancing our understanding of soil P loss dynamics.

Chapter 3

Phosphorus loss management and crop yields: A global meta-analysis

Jiaxin Wang, Zhiming Qi and Chong Wang

Abstract

Phosphorus (P) management is critical for environmental protection as excessive or inappropriate P application can lead to water pollution. However, conflicting results from various experiments on the effectiveness of P management practices make it challenging to draw general conclusions. Moreover, there is a lack of comprehensive analysis on the effects of P management practices on crop yields during their implementation. In this study, we conducted a meta-analysis (522 paired observations), combing with previous meta-analyses, to evaluate the effectiveness of different P management practices in reducing soil P loss and the effects of these practices on crop yield during their implementation. We showed that the most effective P loss management practices do not necessarily result in the greatest improvement in crop yield. In summary, efficient irrigation, crop straw return, buffer strip, and intercropping demonstrated the greatest effectiveness in reducing soil P loss, achieving an average reduction of -94.2%, -87.7%, -87.2%, and -61%, respectively. While soil amendment, intercropping, and conservative practices had showed the largest increase in crop yields, attaining an average increase of 188.8%, 80%, and 72.9% respectively. In addition, we showed that soil available P level, crop growing season rainfall, and P addition amount are important factors influencing the effectiveness of P management practices. High soil available P

and rainfall tended to offset the effectiveness of these practices, while high P additions correlated with more effective reduction of P loss. Based on our results, we recommend prioritizing crop straw return when implementing P loss control practices.

3.1 Introduction

Modern agriculture has led to significant increases in crop yields, but at a great environmental cost (Tilman et al., 2001; Springmann et al., 2018). P is a critical nutrient for crop growth, but excessive or incorrect use of P fertilizers has led to severe P pollution worldwide (Carpenter, 2005; Khan et al., 2022), such as in Lake Eire in North America (Michalak et al., 2013) and Lake Taihu in China (Pan et al., 2011). A recent study by Zou et al. (2022) indicates that if P use strategies stay at the 2010 level worldwide, it will likely result in worsening global P pollution by 2050, making it imperative to prioritize effective management and reduction of P losses from agricultural fields.

The challenges posed by P pollution have prompted numerous studies to investigate the effectiveness of various agricultural practices in controlling P loss. These practices include reducing fertilizer application rates, optimizing the timing and placement of P fertilizers (Van Es et al., 2004; Carver et al., 2022; Su et al., 2023), using P-sorption materials (Zhang et al., 2021), implementing soil conservation practices (*e.g.*, reduced tillage and crop residue retention) (Selim et al., 2019; Klik and Rosner, 2020), and adopting crop management strategies such as vegetative buffer strips, intercropping and cover crop (Habibiandehkordi et al., 2019; Hanrahan et al., 2021; Yang et al., 2022). Although these studies have demonstrated the effectiveness of these practices in reducing soil P loss, some experiments have yielded inconsistent and controversial results (Jarvie et al., 2017; Zhang et al., 2017; Chi et al., 2020), possibly due to context-dependent field design, which can be influenced by various factors such as climate, fertilization regimes, methodologies, and soil physicochemical properties (Macdonald et al., 2012; Macrae et al., 2021; Li et al., 2023). This makes it challenging to draw general conclusions and guide management decisions. Additionally, individual studies may suffer from limited statistical power, small sample sizes, or other experimental limitations that could affect their accuracy and reliability.

Meta-analysis is a powerful tool for synthesizing existing knowledge on the effectiveness of different agricultural practices (Xiao et al., 2021). This quantitative synthesis of data from multiple studies allows for the estimation of overall effect size of a treatment, identification of sources of variation, and assessment of publication bias and other potential sources of error (Ariel de Lima et al., 2022). By pooling data from multiple studies, meta-analysis can provide a more robust and generalizable assessment of the effectiveness of P management practices in reducing soil P loss compared to individual studies.

In recent years, several meta-analyses have investigated the effectiveness of practices including crop rotation, conservation practice, no tillage, organic fertilizer, soil amendment, controlled drainage, and cover crops in reducing soil P loss (Gitau et al., 2005; Nummer et al., 2016; Daryanto et al., 2017; Wang et al., 2020; Liu et al., 2021; Young et al., 2021; Qiu et al., 2022; Zhao et al., 2023). However, these efforts have predominantly focused on the effectiveness of individual practices, and a comprehensive comparison among these P management practices is still lacking. Moreover, most of these studies have not investigated the effects of these practices on crop yield during their implementation, which is an important consideration when implementing P management strategies. While Wang et al. (2020) and Young et al. (2021) have examined the effectiveness of controlled drainage and no tillage in reducing P loss and improving crop yields, other practices have not been thoroughly explored. Many meta-analyses have evaluated the effects of various agricultural practices on crop yields, such as soil amendment, conservation practices, and nutrient management, on crop yields (*e.g.*, Knapp et al., 2018; Schütz et al., 2018; Freiling et al., 2022), but they have not specifically focused on soil P loss control. Therefore, a comprehensive examination is needed to assess the impacts of different P management practices on both P loss control and crop yields, which will contribute to a global perspective on the effectiveness of different P management practices.

The objective of this study is to conduct a meta-analysis to investigate the effectiveness of different P management practices in reducing soil P loss and their impact on crop yields. Our hypothesis posits that implementing P management practices will enhance crop yields while mitigating soil P losses. To scrutinize this hypothesis, we meticulously gathered extensive datasets from reported field experiments and relevant meta-analyses on this topic. We also considered influential experimental factors, such as topography, soil properties, climate, cropping system, and management practices, to assess their effect on the efficacy of P management practices. Our study aims to answer the following research questions: (a) Which P management practice has the greatest effectiveness in reducing soil P loss? (b) Which factors have the greatest potential influence on the effectiveness of P management practices? (c) Which P management practice has the greatest potential benefits on crop yields?

3.2 Material and methods

3.2.1 Data collection

To establish a global database of experiments on the effects of different P management practices on soil P loss reduction and crop yields, we conducted an extensive search of relevant studies using predetermined keywords. The search was conducted in several databases, including Web of Science (WoS), Google Scholar, and China National Knowledge Infrastructure (CNKI), with combinations of keywords: "phosphorus loss*" or "phosphorus leach*" or "phosphorus export" with "agricultural management" or "agricultural practice*" or "crop management" and "crop yield" or "crop production" or "crop productivity". Our search was limited to January 27th, 2023, and the selection process is illustrated in Fig. 3.1.

To ensure that the studies included in database were suitable for our meta-analysis, we established the following selection criteria: (1) the experiment measured soil total P loss (in kg ha^{-1}); (2) the study was conducted in a field setting, with both treatment and control groups subjected to the same management practices and environmental conditions; (3) there were no significant changes in land use or fertilization regimes prior to or during the experiment; and (4) other fertilizers, such as nitrogen (N) fertilizers, were applied at the same rate to avoid their confounding effect.

We compiled a total of 522 paired observations from 108 published papers. A detailed description of the P management treatments was presented in Table 3.1. Fig. 3.2 displayed the geographical distribution of the experimental locations. Among these experiments, 216 paired observations measured the corresponding impacts on crop yields. We also collected data on site characteristics and fertilization regimes to better understand the factors that influence the effectiveness of P management practices. The site characteristics we collected include location (latitude and longitude), climate (mean annual temperature and crop growing season precipitation), topography (slope), crop type, and soil properties (soil available P, soil total P, soil organic carbon, soil total N, soil pH, and clay content). Fertilization regimes included P application method and amount. In cases where raw data were unavailable and only graphs or figures were provided, we utilized the GetData Graph Digitizer software (ver. 2.24, Russian Federation) to extract the data.

In cases where the experimental site's latitude or longitude was not reported in the referenced studies, we estimated these values by the location name on Google Maps. Similarly, if mean annual temperature and crop growing season precipitation were not reported, we obtained the values from the US National Climatic Data Center (http://www.ncdc.noaa.gov/) and the WorldClimate database (http://www.worldclimate.com) using the site's geographic coordinates. In instances where soil clay content was not reported in the referenced studies, but adjacent field experiments had reported the same soil type and soil clay content, we estimated this value from the adjacent field experiments. For Chinese experiments that did not report soil clay content, we obtained this information from the China Soil Science Data Center (http://vdb3.soil.csdb.cn/) based on the site's geographic coordinates.

Table 3.1 Summary of P management treatment included in this study.

Best management practices for P loss reduction	Description	Number of paired observations
4R management*		106
Organic P fertilizer replacement	Replace mineral P fertilizer application with manure, sewage sludge	38
Reduced P fertilizer application	Optimized or reduced annual P addition amounts	55
Subsurface P fertilizer application	Compared to surface P application method	13
Conservative practices**		126
Cover crop	Covering crops when the field is fallow	15
Crop straw return	Crop residues covering soil surface or incorporated, compared to bare soil	52
Plastic mulching	Plastic mulching on the soil	2
Reduced tillage	Reduction in tillage or no tillage, compared to conventional tillage practices	57
Buffer strip	Narrow plantings of perennial plants (*e.g.*, grass) or hedges	92
Intercropping	Grow two or more crops simultaneously on the same field	49
Soil amendment	Application of organic matter such as biochar,	79

	or mineral with organic fertilizers, and inoculum of mycorrhizae or other microbes	
Efficient irrigation***	Including efficiently irrigated P fertilizers to crops according to soil water content or evapotranspiration; and drip irrigation compared to surface flooding	12
Controlled drainage	Compared to free drainage	58

*4R management group refers to organic P fertilizer replacement, reduced P fertilizer application, and subsurface P fertilizer application

**Conservative practices group refers to cover crop, crop straw return, plastic mulching, and reduced tillage

*** Efficient irrigation in our study focused solely on the irrigation components (*i.e.*, the amount and method of irrigation, such as the use of drip irrigation), without considering the use of other techniques such as bunding, land leveling, etc.

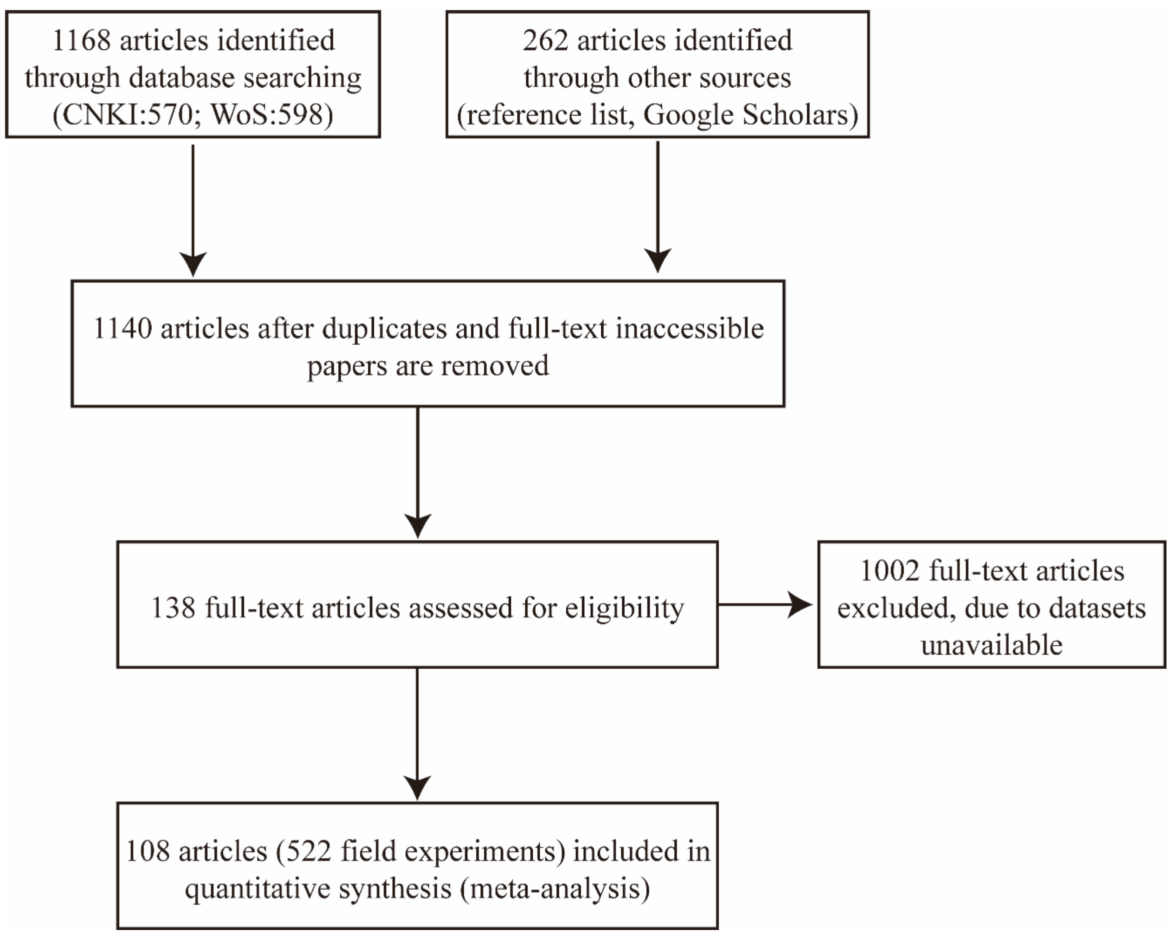

Figure 3.1 Flow diagram of article selection for meta-analysis.

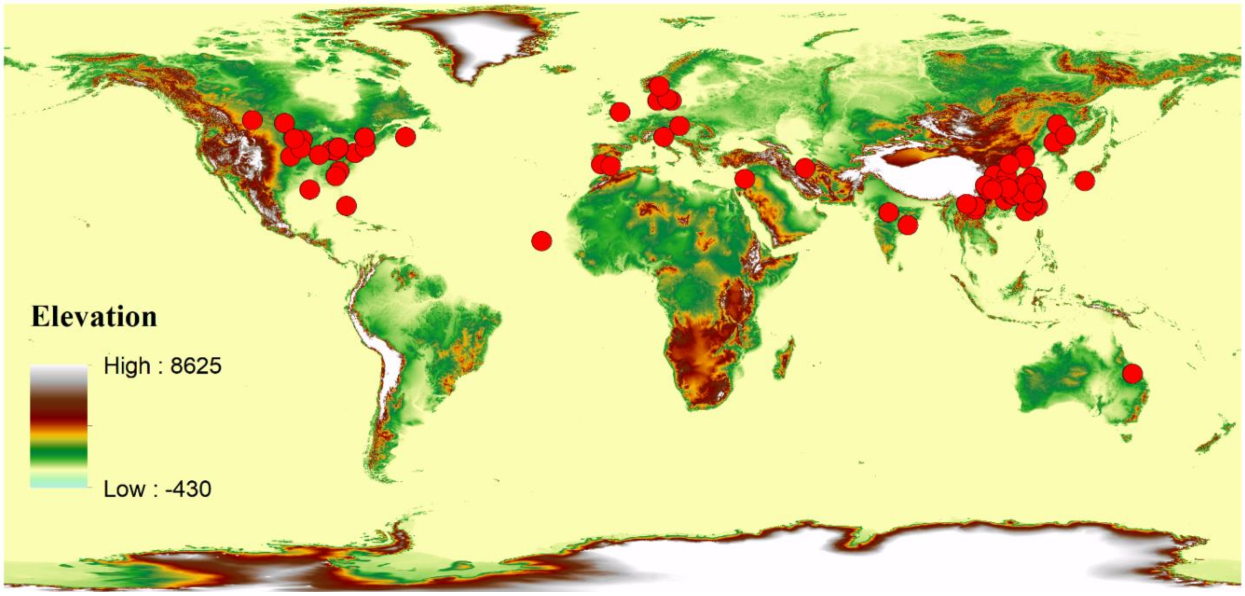

Figure 3.2 Geographical locations of 108 experiments (522 field experiments) collected in this study. The elevation data was obtained from the global multi-resolution terrain elevation data 2010 (GMTED2010) from the United States Geological Survey (https://www.usgs.gov/publications/global-multi-resolution-terrain-elevation-data-2010-gmted2010).

3.2.2 Meta-analysis

We quantified the effectiveness of P management practices on soil P loss reduction and crop yields by calculating the weighted log-transformed response ratio ($lnRR$) using a random-effects model to account for heterogeneity between studies (Hedges et al., 1999). We obtained the means, sample sizes (n), and standard deviations (SDs) from the published studies. When standard error (SE) was reported instead of SD, we calculated SD using the following formula:

$$SD = SE\sqrt{n} \tag{3.1}$$

If neither SD nor SE was reported, we approximated the missing SD by multiplying the reported mean by the average coefficient of variation of our complete dataset. If the sample size was not reported, we assigned sample sizes as the median sample size of our complete dataset.

The $lnRR$ of an experiment was calculated as follows:

$$lnRR = ln(\overline{X_t}/\overline{X_c}) = ln\overline{X_t} - ln\overline{X_c} \quad (3.2)$$

where $\overline{X_t}$ and $\overline{X_c}$ are the mean values (*i.e.*, soil P loss and crop yield) in the P management treatment and control, respectively.

The weighted mean response ratio ($lnRR_+$) of a specific P management practice was calculated using:

$$lnRR_+ = \frac{\sum_{i=1}^{m}(w_i \times lnRR_i)}{\sum_{i=1}^{m} w_i} \quad (3.3)$$

where m is the number of experiments in a specific P management practice, and w_i is the weighting factor of the ith experiment in the group. The w_i was calculated as follows:

$$w_i = \frac{1}{v_i^*} \quad (3.4)$$

where v_i^* is the variance of the ith study in the group. The v_i^* was calculated as follows:

$$v_i^* = v_i + T^2 \quad (3.5)$$

where v_i is the within-study variance of study (i), and T^2 is the between-studies variance. The v_i was calculated as follows:

$$v_i = \frac{S_t^2}{n_t \overline{X_t^2}} + \frac{S_c^2}{n_c \overline{X_c^2}} \quad (3.6)$$

where n_t and n_c are the sample size for the P management treatment and control, respectively, S_t and S_c are the standard deviation (SD) for the P management treatment and control, respectively, of study (i). The calculation of T^2 can be seen in Borenstein et al. (2010).

The standard error of the $lnRR_+$ was calculated as:

$$s(lnRR_+) = \sqrt{\frac{1}{\sum_{i=1}^{m} w_i}} \quad (3.7)$$

The 95% confidence interval (CI) for the $lnRR_+$ was calculated as follows:

$$95\%\ CI = lnRR_+ \pm 1.96 \times s(lnRR_+) \quad (3.8)$$

If the 95% CI did not overlap with zero, the overall effect in the group of experiments was considered significant. The percentage change (*i.e.*, the effect size) in soil P loss and crop yield induced by a specific P management practice in a group of experiments was measured as follows:

$$Effect\ size\ (\%) = (e^{lnRR_+} - 1) \times 100\% \quad (3.9)$$

The meta-analyses were performed using "meta" package in R version 4.2.2. We assessed the publication bias in the overall database for each P management practice by a funnel plot. If the funnel plot showed evidence of asymmetry (i.e., p < 0.05), we used trim and fill method to reestimate the summary effect size.

3.2.3 Statistical analysis

We used boosted regression tree (BRT) model to determine the impact of different variables on the effectiveness of P management practices in reducing soil P loss. These variables include climate, topography, crop species, fertilization regimes, experimental duration, and five key soil physiochemical properties (soil available P, soil total P, soil organic carbon, soil pH, and clay). We then used structural equation modeling (SEM) to explain the direct and indirect effects of these variables on the effectiveness of P loss control. Our BRT model used recommended parameter values of learning rate (0.01), bag fraction (0.75), cross-validation (10), and tree complexity (2) (Elith et al., 2008; Hou et al., 2018). Since the predicted item (*i.e.*, $lnRR(P\ loss)$) is a continuous numerical variable, we used a Gaussian distribution of errors for BRT fittings. The relative importance of each predictor variable was expressed as a percentage of the total variation accounted for by the model. We conducted BRT analyses using the “gbm” package version 2.1.1 (Ridgeway, 2015) and custom code from Elith et al. (2008) in R version 4.2.2.

The SEM was fitted by maximum likelihood estimation using “lavaan” package version 0.6-14 (Rosseel, 2012) in R version 4.2.2. A well-fitting model was characterized by the following indices: $0 \leq$ Chi-squared/df ≤ 2, $p > 0.05$, $RMSEA \leq 0.05$ ($RMSEA$ represents the root mean square error of approximation), as well as when cfi ≥ 0.95 (comparative fit index) (Xia & Yang, 2019; Ma et al., 2022).

3.3 Results

When examining the overall effectiveness of various P management practices, we observed that these practices generally led to a reduction in P loss while having no significant impact on crop yields (Fig. 3.3). The analysis revealed that the average $lnRR(P\ loss)$ and $lnRR(Yield)$ were approximately -0.5 and 0, respectively. The majority of $lnRR(P\ loss)$ values (around 84%) were negative, with 70% of them falling within the range of 0 to -1. Conversely, only 58% of $lnRR(Yield)$ values were positive.

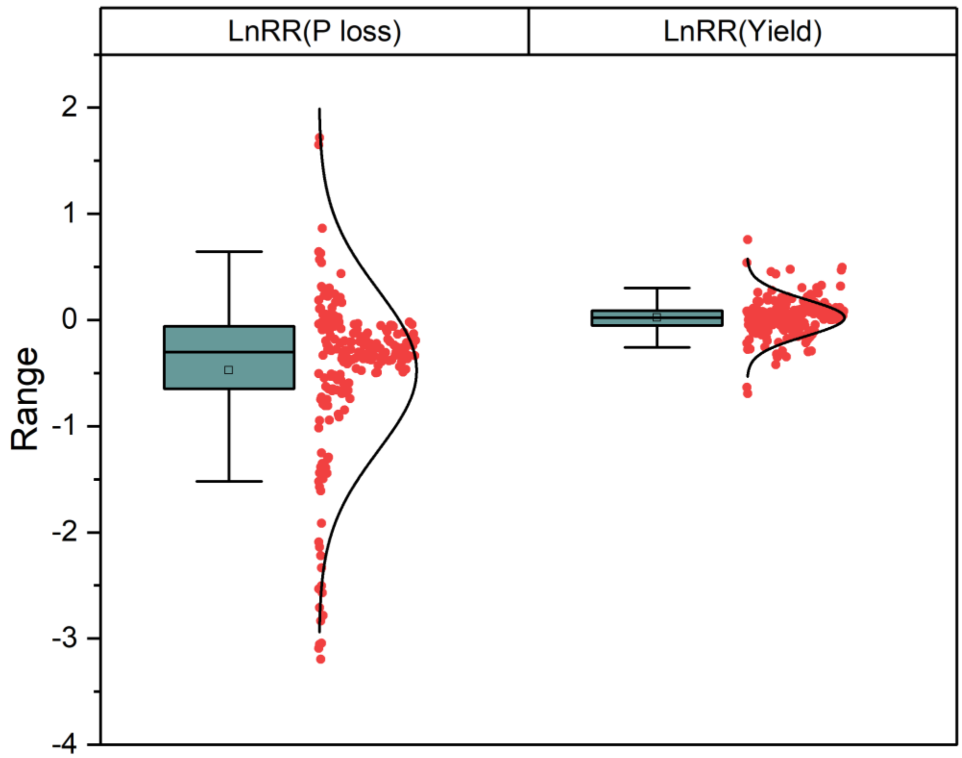

Figure 3.3 Frequency distribution of $lnRR(P\ loss)$ and $lnRR(Yield)$. A negative value of $lnRR(P\ loss)$ indicates a positive effect of P management practice on soil P loss reduction, while a positive value of $lnRR(Yield)$ indicates a beneficial effect on crop yield.

All P management practices exhibited an overall positive impact on controlling soil P loss (Fig. 3.4). Among these practices, efficient irrigation was the most effective practice with an effect size of -94.2%, followed by crop straw return (-87.7%), buffer strip (-87.2%), and intercropping (-61%). However, several practices, including subsurface P application, cover crop, reduced tillage, efficient irrigation, and controlled drainage, had the potential to increase P losses.

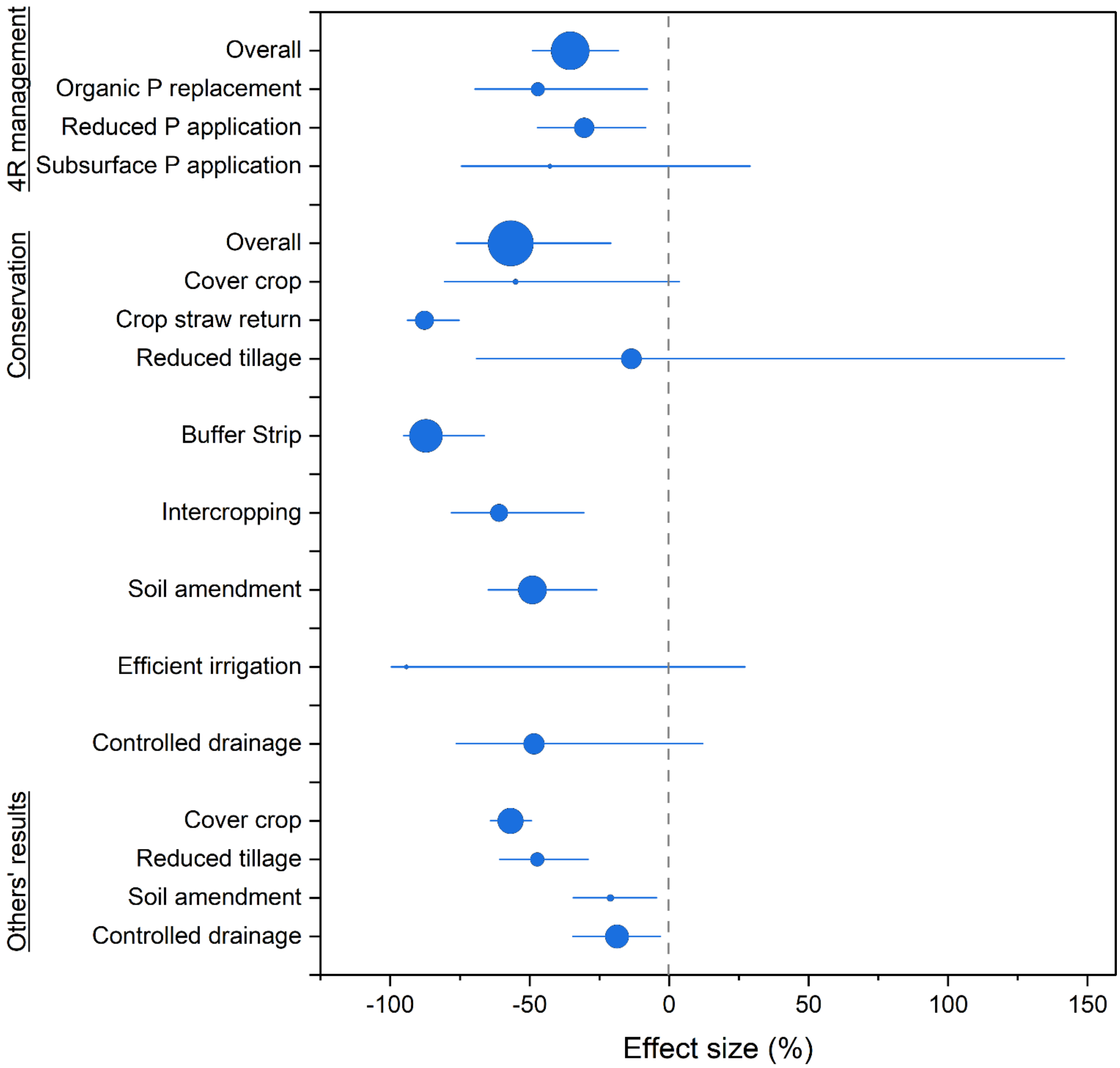

Figure 3.4 Mean effect size of P management practices on reducing soil P loss. The size of each point reflects the sample size (Table 3.1). A negative mean effect size indicates that the P management practice reduced soil P loss. Other studies included in the figure are cover crop (n = 71 observations; Liu et al., 2021), reduced tillage (n = 39; Daryanto et al., 2017), soil amendment (n = 19; Qiu et al., 2020), and controlled drainage (n = 65; Wang et al., 2020).

We then examined the relative influence of climate, fertilization regimes, and soil properties on the effectiveness of P management practices in reducing P loss (Fig. 3.5). The analysis revealed that soil available P level had the greatest influence on the effectiveness of P management practices, explaining 33.3% of the variability, followed by soil total P level (18.8%), crop growing season rainfall (11.8%), and P application amount (10%).

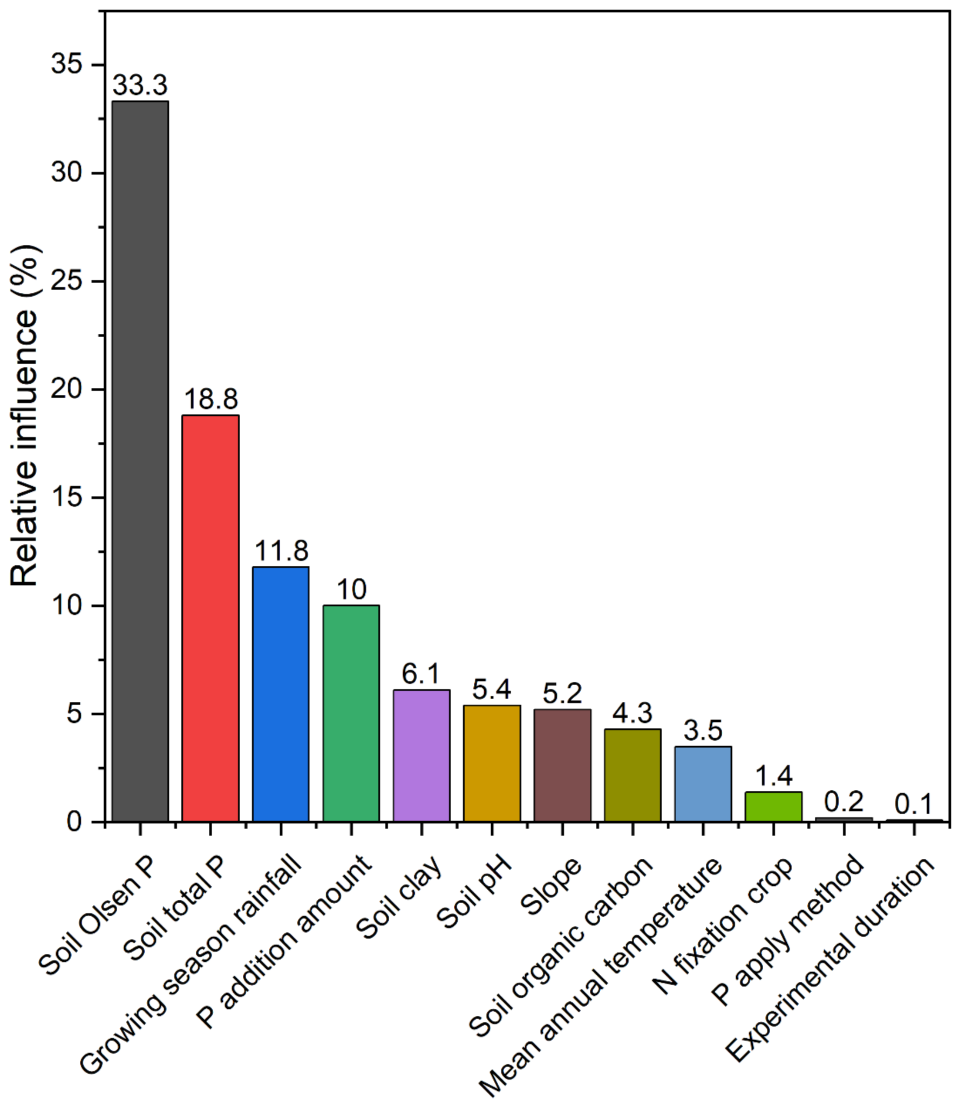

Figure 3.5 Relative influence of climate, fertilization regimes, and soil properties on the effectiveness of P management practices in reducing soil P loss.

SEM unveiled a significant positive effect ($p < 0.05$) of both soil available P and rainfall during the crop growing season on the $lnRR(P\ loss)$ values (Fig. 3.6). This suggested that higher soil available P levels and greater crop growing season precipitation tended to reduce effectiveness of P management practices in controlling P loss. Conversely, an increase in P addition amount significantly decreased the value of $lnRR(P\ loss)$, suggesting that higher P addition amounts were associated with more effective P loss control.

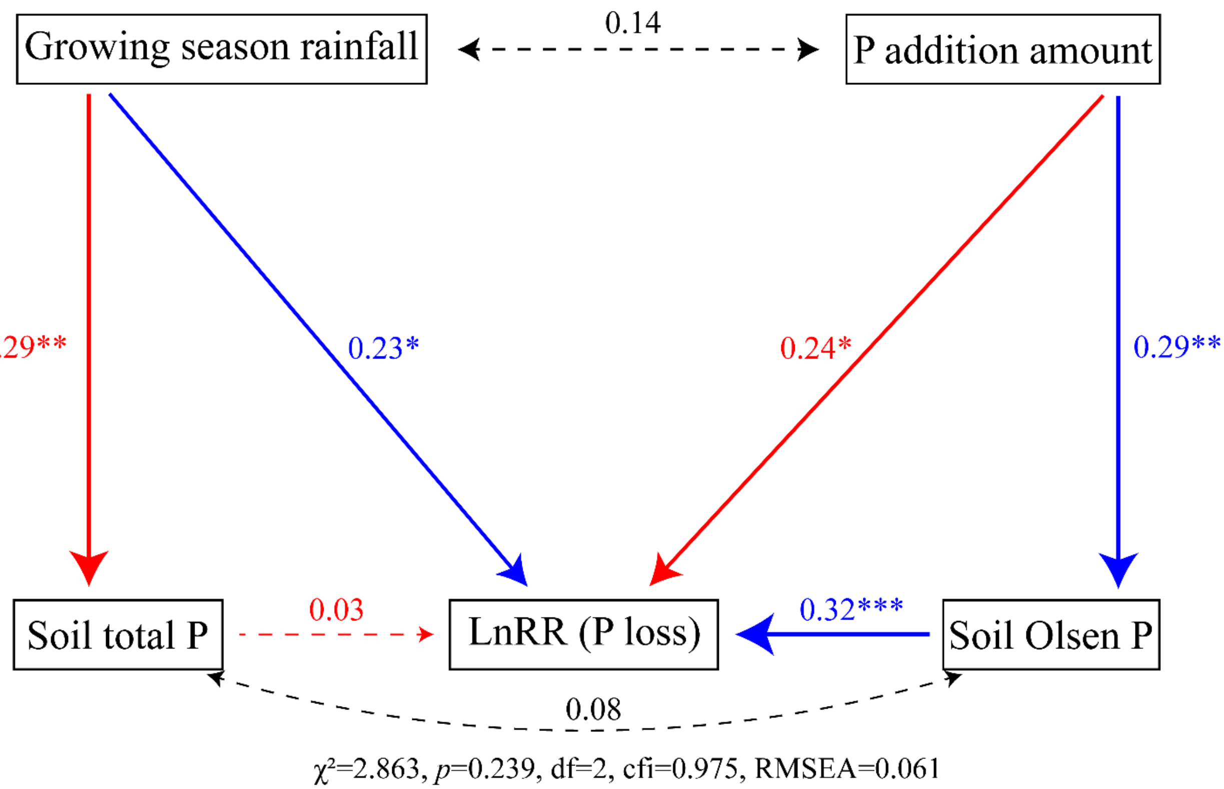

Figure 3.6 Direct and indirect impacts of crop growing season precipitation, soil P level and P addition amount on the effectiveness of P loss control. Single arrows represent regression relationships, while double arrows represent covariances. Blue arrows represent positive effects, while red arrows represent negative effects. The solid lines represent significant effects (* $p <$ 0.05, ** $p < 0.01$ and *** $p < 0.001$), while dashed lines represent insignificant effects. Number beside the arrow is the corresponding standardized coefficient with significance levels indicated.

Almost all P management practices exhibited an overall positive impact on improving crop yields, except buffer strip and controlled drainage (Fig. 3.7). Soil amendment had the largest effect size in increasing crop yields (188.8%), followed by intercropping (80%) and conservative practices (72.9%). While we observed the lowest effect size in efficient irrigation (3.6%), controlled drainage (-26.1%), and buffer strip (-47%). However, we observed that controlled drainage had a negative impact on crop yields (Fig. 3.7), which contrasted with previous meta-analyses that showed no overall effect on crop yield (Table 3.2). This discrepancy may be due to the differences in sample size.

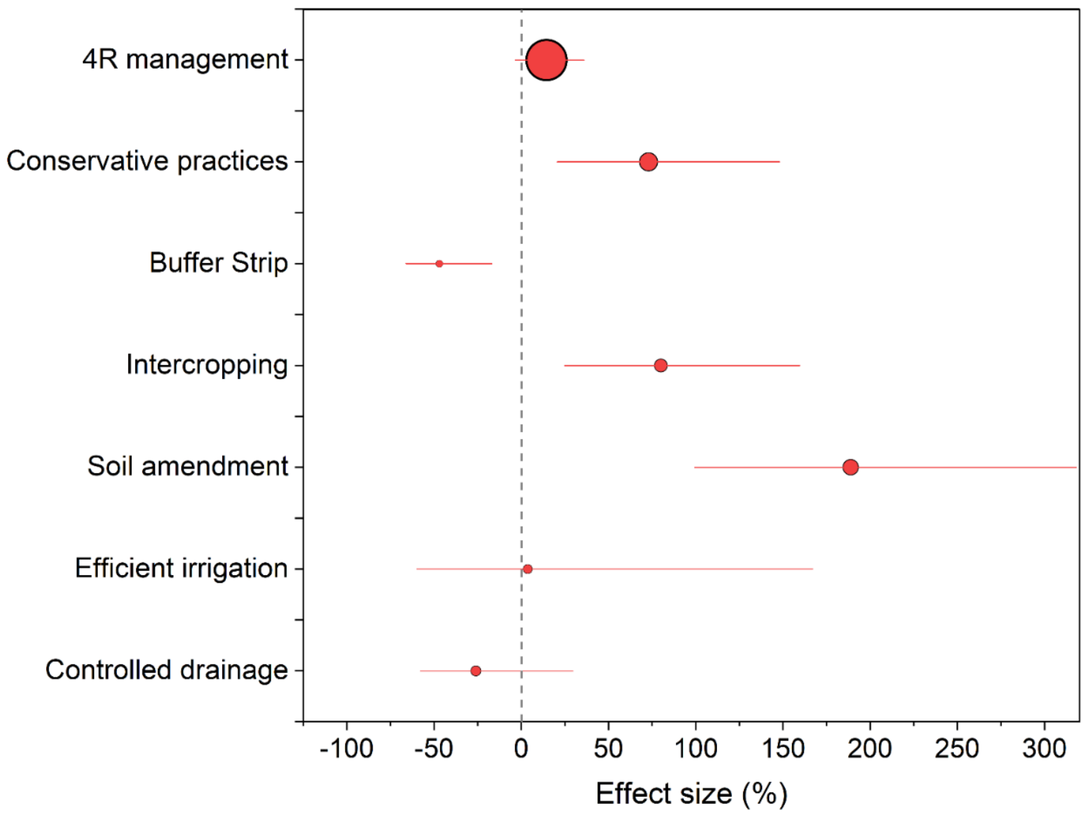

Figure 3.7 Mean effect size of P management treatment on crop yield, with the size of each point proportional to the sample size. The number of experiments for each treatment: 4R management (n = 84), conservative practices (n = 38), buffer strip (n = 15), intercropping (n = 27), soil amendment (n = 32), efficient irrigation (n = 9), and controlled drainage (n = 11).

Table 3.2 Effect size of different agricultural practices on crop yield collected from previous meta-analyses.

Agricultural practices	Pair of observations	Mean effect size (%)	95% confidence interval (%)
Band P application* (Freiling et al., 2022)	407	5.8	[3.8, 7.8]
Soil amendment* (Schütz et al., 2018)	1672	16.2	[15.2, 17.1]
Crop straw return (Ding et al., 2020)	149	4.2	[2.9, 5.7]

4R management** (Young et al., 2021)	-	-	[-5, 4.9]
Conservative practices** (Young et al., 2021)	-	-	[-4.1, 12.1]
No tillage*** (Xiao et al., 2021)	-	-	[-7.8, 10]
Crop straw return*** (Xiao et al., 2021)	-	-	[3.8, 27.9]
Controlled drainage (Wang et al., 2020)	262	0	[0,0]

* In these studies, the effect size was calculated as: $Effect\ size\ (\%) = (\frac{Yield_{treatment}}{Yield_{control}} - 1) \times 100\%$;

** Reanalyze 45 meta-analysis articles for agricultural practices on crop yield;

*** Reanalyze 22 meta-analysis articles for conservative practices on crop yield.

3.4 Discussion

This study provides a comprehensive comparison of commonly used P management practices in terms of their effectiveness in reducing soil P loss and their impacts on crop yields. We show that the most effective P loss management practices do not necessarily result in the greatest improvement in crop yield. Our results suggest that efficient irrigation has the highest effect size for P loss reduction (Fig. 3.4). This can be attributed to the ability of efficient irrigation techniques to minimize water volume by aligning irrigation with crop needs, thus reducing the likelihood of P being carried away through surface runoff (Kiggundu et al., 2012). However, it is important to note that the limited observations can lead to uncertainty in our conclusion, and potential unintended consequences of this technique on increasing P loss (Fig. 3.4) warrant further experimental investigations into its effectiveness. Vegetative buffer strip and intercropping also demonstrate relatively high efficacy in reducing P loss (Fig. 3.4). Nevertheless, these practices are primarily adopted by smallholders and small-scale farming operations in developing countries (*i.e.*, China and India). In North America, despite the severity of P loss-induced eutrophication in freshwater bodies like Lake Erie (Michalak et al., 2013), the implementation of these techniques is low. This may be due to farmers' concerns about feasibility and effectiveness (Wilson et al., 2019). While our analyses demonstrate that it may be worthwhile to consider implementing these techniques in high P loss areas. However, it is important to note that vegetative buffer strips also present the potential to reduce crop yields (Fig. 3.7), this is likely due to the allocation of land for buffer strips, which reduces the amount of land available for crop production or other agricultural activities. And establishing and maintaining vegetative buffer strips can be costly and may pose a financial burden on farmers. Therefore, a cost-benefit analysis to off-set the short-term cost and risk is necessary when implementing these techniques to control field P loss.

Crop straw return also demonstrates highly effective in reducing soil P loss (Fig. 3.4), and this technique may be more readily accepted by farmers as it does not require additional investment. Globally, conservative practices combined with other agricultural practices are increasingly adopted for crop production (Kassam et al., 2015). A global synthesis suggested conservative practices are effective in reducing soil erosion, and that this benefit is primarily attributed to crop residue retention rather than no tillage (Xiao et al., 2021). This supports our finding that crop straw return showed a greater effectiveness in reducing P loss compared to no tillage (Fig. 3.4). This can be explained by the fact that no-tillage without surface residue is likely to result in soil surface hardening caused by rain impact in the absence of ground cover, which increases surface runoff and decreases water infiltration (Verhulst et al., 2011). However, the benefits of residue retention are regionally variable and depend on agroclimatic factors. Several experiments have shown that conservative practices may unintentionally increase soluble P losses, attributable to P released from crop straw and surface P stratification during snowmelt (Baker et al., 2017; Daryanto et al., 2017; Jarvie et al., 2017). Only one synthesis analysis that we are aware of suggested that conservative practices can effectively reduce particulate P loss but increased the chance of soil soluble P loss, dependent on annual rainfall and land slope (Daryanto et al., 2017). Nevertheless, particulate P loss control may remain a priority in controlling P pollution as soluble P loss generally accounts for a relatively small proportion of total runoff P loss (Maccoux et al., 2016).

We find that soil amendment, intercropping, and conservative practices had the greatest effect on increasing crop yields (Fig. 3.7), with effect sizes larger than those reported in previous meta-analyses (Table 3.2). The larger effect sizes may be due to the differences in sample sizes. While since soil amendment requires purchasing raw materials, and intercropping may result in lower yields if the intercrops are not compatible and compete for the same nourishment and water (Mutsaers et al., 1993), conservative practices may be a more cost-effective means without additional economic inputs. Previous results suggest that crop straw return tends to be more effective in increasing crop yields than no tillage (Table 3.2). This may be due to its ability to increase soil water and porosity, create favourable soil temperature, and improve soil C and N contents (Turmel et al., 2015).

We demonstrate that soil P levels, crop growing season rainfall, and P application amount have the greatest potential to influence the effectiveness of P management practices in reducing P loss (Fig. 3.5). Notably, we find that an increase in crop growing season rainfall tends to decrease the effectiveness of P management practices (Fig. 3.6). This is likely because heavy rainfall events can lead to surface runoff and erosion, potentially resulting in the transport of P from the soil into water bodies (Xiao et al., 2021). However, previous meta-analyses showed that cover crops and no-tillage were more effective in reducing P loss under higher annual precipitation (Daryanto et al., 2017; Liu et al., 2021). The apparent discrepancy in results may be attributed to the heterogeneity in our analysis, which includes the effects of various P management practices together (Figs. S1, S2, and S3). As when we separately analyzed the relationship between crop growing season precipitation and its impact on P losses for each practice, we obtained similar results to those reported by Daryanto et al. (2017) and Liu et al. (2021) (Fig. 3.S1). These findings underscore the need for further investigation to comprehensively understand the relationships pertaining to specific P management practices. Moreover, SEM analysis reveals a consistent correlation between high P additions and more effective reduction of P loss, but it is important to note that this relationship may also be influenced by the inclusion of various P management practices in our analysis (Fig. 3.S2). Furthermore, fields with high soil available P levels tend to significantly decrease the effectiveness of P management practices (Fig. 3.6). This finding looks reasonable as field studies have consistently observed higher P losses with greater soil P levels (Hahn et al., 2012; Macrae et al., 2021). Previous work has highlighted the importance of considering soil residual P release in P loss control management (Jarvie et al., 2013), and drawing down soil P levels in regions with high P buildup may be particularly necessary (Goyette et al., 2018). One concern is that reducing soil P levels by ceasing P application may harm crop yields and adversely impact farmers' benefits. However, an increasing number of studies suggest soil residual P enable to maintain crop yields for a while (Liu et al., 2015; Lemming et al., 2019; Zhang et al., 2022). A 17-year experiment conducted in Manitoba, Canada demonstrated that drawing down soil P significantly reduced soil available P levels and runoff P load while maintaining wheat (*Triticum* spp.) and canola (*Brassica napus* L.) yields (Liu et al., 2019).

Although there is a general consensus that agriculture can meet the food needs of 8–10 billion people while reducing the proportion of the population that goes hungry, there is little agreement on how this can be achieved sustainably (Tilman et al., 2001). Agriculture is a complex system that relies on multiple practices, and investigating the effectiveness of individual P management practices in controlling soil P loss does not necessarily mean that these treatments should be used alone in practice. Instead, a combination of sustainable management practices should be adopted to maximize both yield and soil P loss reduction benefits. To achieve P loss reduction goals, many studies have examined the effectiveness of different P management practices using models (Muenich et al., 2016; Sadhukhan et al., 2019; Pan et al., 2023), while these efforts have focused on watershed or field scales. In this study, we synthesized 522 field paired observations globally and found that, alongside the essential requirement of 4R management in field practices (Grant & Flaten, 2019), prioritizing crop straw return may be a suitable approach for managing P loss. Furthermore, addressing soil P buildup in regions with high P levels becomes particularly crucial.

3.5 Conclusion

Our analysis indicates that the most effective P loss management practices do not necessarily result in the greatest improvement in crop yield. By analyzing field data and previous meta-analyses, we show that efficient irrigation, crop straw return, buffer strips, and intercropping have the greatest effectiveness in reducing soil P loss, while soil amendment, intercropping, and conservative practices have yielded the greatest potential in benefiting crop yields. Based on the BRT model, we find that soil P level, crop growing season rainfall, and P addition amount are important factors influencing the effectiveness of P management practices. The SEM result suggests that high soil available P and rainfall tend to counteract the effectiveness of P loss reduction, whereas the effectiveness tends to increase under higher P additions. In summary, prioritizing crop straw return in P loss control practices is recommended. Further research focusing on economic analysis and geographical distribution would be valuable in the future.

3.6 Supplementary Tables and Figures

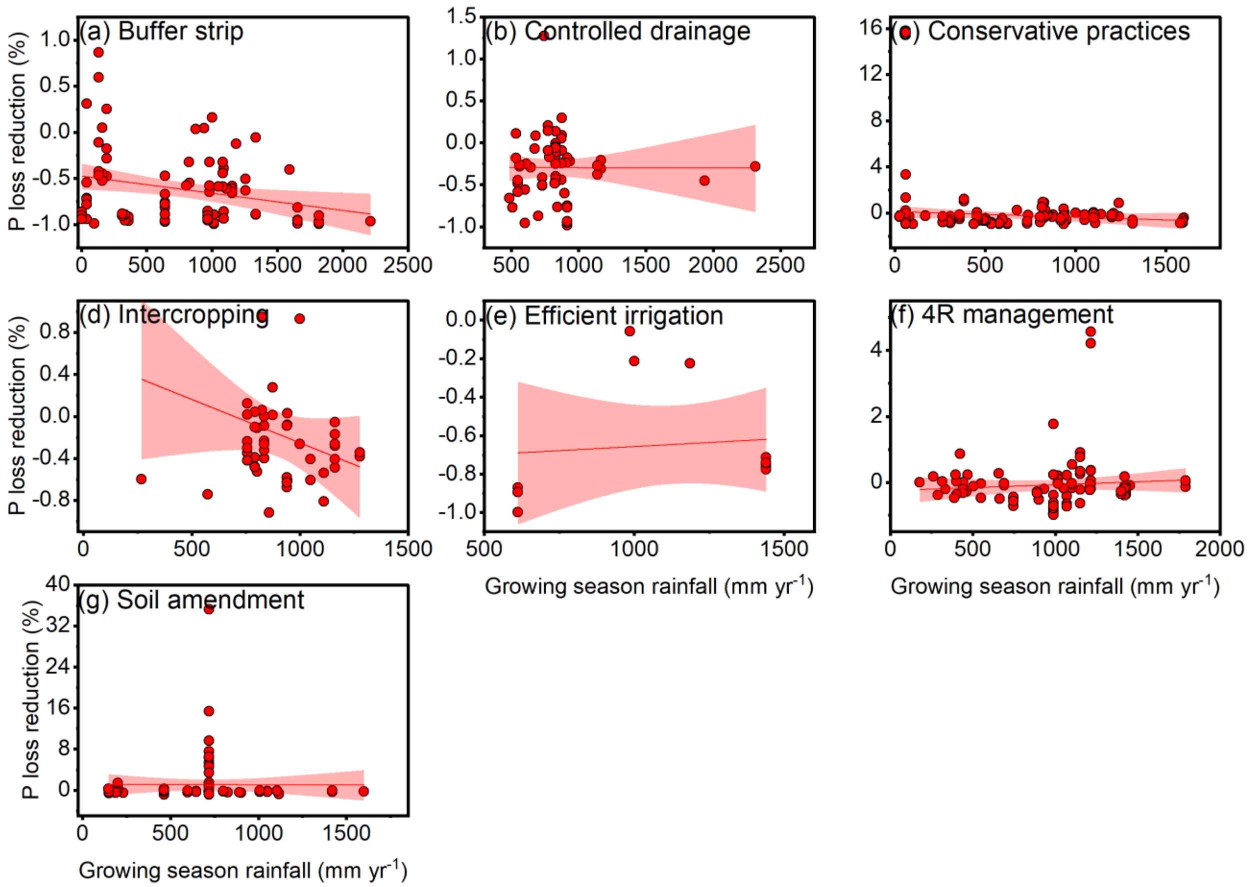

Figure 3.S1 Relationship between P loss reduction (i.e., $(TP_{treatment}\text{-}TP_{control})/\ TP_{control}$) and crop growing season rainfall. Red line represents linear fitting, and shaded area represents 95% confidential interval. A decreasing trend suggests the high rainfall is associated with more effective P loss reduction.

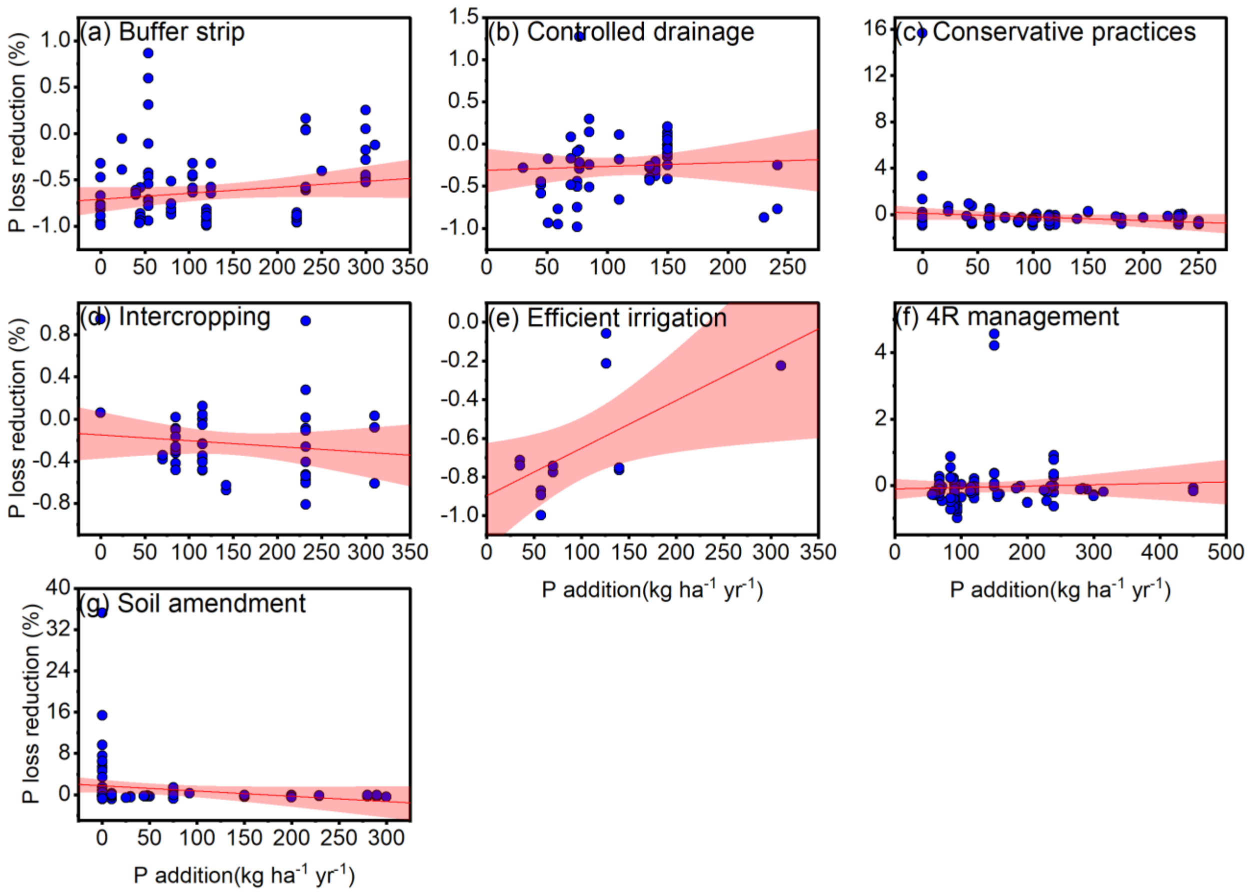

Figure 3.S2 Relationship between P loss reduction (i.e., $(TP_{treatment}$-$TP_{control})$/ $TP_{control}$) and P addition amount. Red line represents linear fitting, and shaded area represents 95% confidential interval. A decreasing trend suggests the high P addition is associated with more effective P loss reduction.

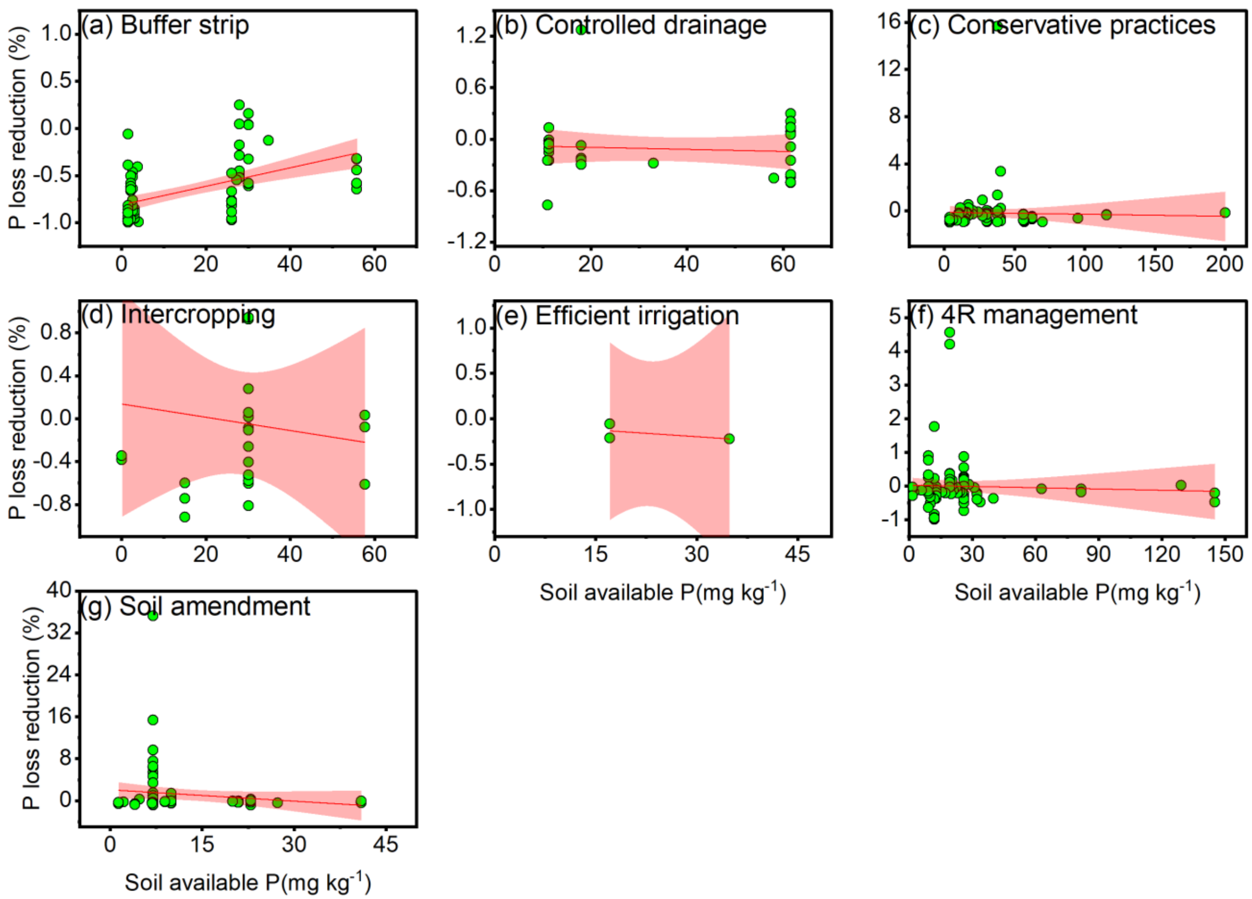

Figure 3.S3 Relationship between P loss reduction (i.e., $(TP_{treatment}\text{-}TP_{control})/\ TP_{control}$) and soil available P. Red line represents linear fitting, and shaded area represents 95% confidential interval. A decreasing trend suggests the high soil available P is associated with more effective P loss reduction.

Connecting text to Chapter 4

In Chapter 3, we investigate the efficacy of various agricultural practices in reducing soil P loss and sustaining crop productivity by synthesizing previous field experiments. We find that conservative practice tends to be an effective and practical method to implement in reality. In Chapter 4, we use machine learning techniques to simulate the impact of conservative practice on P loss reduction under climate change. We focus on Maumee River watershed, which has been the primary P sources to Lake Erie, one of the Great Lakes grappling with persistent P pollutions. We aim to understand the effects of conservation practices in addressing the eutrophication issue in Lake Erie under climate change.

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Chapter 4

Modeling 1974-2040 phosphorus dynamics in the outlet of Maumee River watershed

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Abstract

Phosphorus (P) export from the Maumee River watershed significantly impacts the water quality of Lake Erie. While previous studies have estimated P export under various agricultural scenarios in the context of climate change, we still lack a comprehensive understanding of P export trends in the coming decades under current conservation management practices. This knowledge gap is critical for informing policy decisions aimed at improving water quality. Our study gathered temporal watershed data, including meteorological data, discharge, sediment, soil P balance, and temporal information on the implementation of conservation practices. We employed five machine learning (ML) models to simulate P export from the Maumee River watershed from 1974 to 2021 and further predicted P export trends up to 2040 under current conservation practices. Additionally, we analyzed the return level of extreme discharge events. Our findings underscored the increasing influence of hydrology on P export from the Maumee River watershed. The ML models demonstrated reliable simulation of P export dynamics from 1974 to 2021 and suggested a potential continued degradation of western Lake Erie's water quality between 2023 and 2040. The projected annual total P (TP) load was anticipated to remain similar to previous years, whereas the annual soluble reactive P (SRP) load was predicted to increase. Despite considerable uncertainty in SRP loading predictions, both the annual spring TP and SRP loads were projected to fall short of the government's target of a 40% reduction. Our work emphasizes the urgent need for additional practices to manage ongoing P pollution in Lake Erie.

4.1 Introduction

Nutrient loss has led to serious lake eutrophication problems worldwide. Lake Erie, one of the Great Lakes, which provides drinking water to more than 11 million people and aquatic organisms, has been plagued by eutrophication problems in recent decades (Sayers et al., 2019). Notably, in 2015, Lake Erie experienced the largest algal bloom on record, surpassing the severity index of 10.5 observed in 2011 (https://coastalscience.noaa.gov/news/2022-lake-erie-algal-bloom-more-severe-than-predicted-by-seasonal-forecast/). Thereafter observations in early August 2019 indicated a severity index of 7.5 for that year's bloom. Phosphorus (P) loss is considered the major limiting factor for algal blooms in Lake Erie (Stow et al., 2015; Smith et al., 2019). The most severe blooms have been documented in the western basin, with the Maumee River watershed identified as a major source of P export (Maccoux et al., 2016; Scavia, 2023). Therefore, understanding and managing P export from the Maumee River watershed is crucial for the restoration and preservation of Lake Erie's ecosystem.

To address the eutrophication problem in Lake Erie, conservation practices have been prompted in the western basins since the 1990s to reduce soil erosion and field P losses. By 1993, over half of the agricultural land in the Maumee River watershed had incorporated conservation tillage (Cousino et al., 2015), and the percentage of crop area returning crop straw to the ground increased to 70% in 2015 (Jarvie et al., 2017). According to a recent government report, almost all crop area (99%) across the western Lake Erie basin have adopted at least one conservation practice (USDA-NRCS, 2016). However, controlling P loss is a complex process, despite these efforts have resulted in a slow decrease in particulate P load (Baker et al., 2014a), there has been an upward trend in soluble reactive phosphorus (SRP) observed in the Maumee River watershed outlet (Stow et al., 2015). This trend could be attributed to factors such as over-application of fertilizers, increased storm events, and field drainage (Smith et al., 2015). The increased SRP loads are believed to be a major contributing factor to the recent hypoxia and toxic algal blooms in Lake Erie (Smith et al., 2015). Furthermore, despite a decreasing trend observed in total phosphorus (TP) concentration during the 1980s and 1990s, TP export from the Maumee River has shown an increasing trend since 2000 (Stow et al., 2015). Recent work by Rowland et al. (2020) has found consistent high TP and SRP concentrations at the outlet of the Maumee River watershed from 2008 to 2018. This raises questions about the effectiveness of current agricultural measures in mitigating future algal bloom outbreaks in Lake Erie (Stackpoole et al., 2019; Macrae et al., 2021), especially since some recommended conservation practices may unintentionally exacerbate the problem (Jarvie et al., 2017). A great number of studies have explored the effectiveness of combinations of best management practices in controlling P export from the Maumee River watershed (e.g., Muenich et al., 2016; Liu et al., 2019; Martin et al., 2021; Kast et al., 2021). However, their modeling often assumes ideal agricultural practice scenarios (*e.g.*, cover crops over 100% of agricultural lands), with limited consideration of whether P export will decrease under realistic implementation of current agricultural practices.

Furthermore, hydrology plays a crucial role in implementing effective strategies to control algal blooms in Lake Erie (Williams et al., 2018; Choquette et al., 2019). Michalak et al. (2013) highlighted that one of the primary reasons for Lake Erie's severe eutrophication in 2011 was the highest discharge recorded during the crucial March-to-June period. P loads from the Maumee River are profoundly influenced by a relatively small number of high P loading storm runoff events (Baker et al., 2014b), and greater discharge could deliver P over a broader lake area (Stow et al., 2015). Building upon these insights, many studies have used watershed-scale model, such as the Soil and Water Assessment Tool (SWAT), to assess the effects of climate change on P export from the Maumee River watershed (e.g., Bosch et al., 2014; Cousino et al., 2015; Culbertson et al., 2016; Kalcic et al., 2019; Kujawa et al., 2022; Fraker et al., 2023). However, a synthesis study by Yuan and Koropeckyj-Cox (2022) revealed that a significant proportion of SWAT modeling efforts yielded unsatisfactory result in predicting P loading. One possible explanation for this result is the tool's limited capacity to effectively update temporal information of land use and agricultural practices (Chun et al., 2021). Moreover, while their modeling primarily simulates P loading trends towards the middle or end of the century, we still lack a comprehensive understanding of P loading dynamics in the coming decades. This knowledge gap is crucial for making informed policy and management decisions that are relevant to the current and near-term contexts (OEPA, 2022).

Machine learning (ML) techniques have gained significant attention for their potential in addressing complex water resource challenges. Previous studies have applied ML with geospatial data to predict soil P content at field- to watershed-scale (Jeong et al. 2017; Sahabiev et al. 2021; Kaya and Başayığıt 2022). ML has also been applied to predict nutrient concentrations in river networks (Shen et al. 2020; Sadayappan et al. 2022). For instance, Gorgan-Mohammadi et al. (2023) developed decision tree models using water chemical properties to estimate P concentrations in Lake Erie. Similarly, Chang et al. (2023) integrated ML models with meteorological and hydrological variables predicted by physical models to simulate P loads in the Maumee River from 2002 to 2017. This work showcases the potential of ML for further investigations into P loading dynamics in the Maumee River.

Our work aims to investigate whether a decrease in P export from the outlet of the Maumee River watershed can be expected in the near future, taking into account existing conservation management strategies. To address this question, we collected temporal information spanning from 1974 to 2021, including watershed meteorological datasets, soil P content, temporal changes in the implementation of conservation practices, as well as discharge and P load data at the watershed outlet. We applied five different ML models to simulate the P load at the watershed outlet. Additionally, we incorporated predicted meteorological data under two Representative Concentration Pathway (RCP) scenarios (i.e., RCP 4.5 and RCP 8.5) to estimate trends in P export from the Maumee River watershed up to the year 2040, considering current conservation practices.

4.2 Material and methods

4.2.1 P load data source

We collected daily datasets for TP concentration, SRP concentration, total suspended solids (TSS) concentration, and discharge data at the outlet of the Maumee River watershed from NCWQR (2022) (https://ncwqr.org/monitoring/) (USGS04193500, latitude: 41°30'00"N, longitude: 83°42'46"W). Briefly, water samples were collected using an automated sampler that drew water samples via a submersible pump installed in the river (Stow et al., 2015). During periods of high flow or high turbidity, water samples were collected three or four times per day; otherwise, only one or two samples were collected daily. All samples were analyzed in the laboratory, following standard United States Environmental Protection Agency (U.S. EPA) protocols (Stow et al., 2015). TP and SRP concentrations were both quantified using molybdate blue colorimetry (U.S. EPA Method 365.1). Samples for TP concentration analysis were pretreated by persulfate digestion. The TSS concentrations were estimated by measuring dry weight after filtration through a glass fiber filter (U.S. EPA Method 160.2).

We first used MATLAB R2022a to average the concentration data by day (when multiple samples were collected in a day) and to extract daily datasets that simultaneously monitored nutrient concentrations and discharge. Thereafter, we estimated daily nutrient loads by multiplying the average daily concentration by the corresponding daily discharge. For days with missing observed loads, we used linear interpolation to estimate daily observations based on data from two adjacent days.

4.2.2 Machine learning approaches

We applied multiple linear regression (MLR), bootstrap aggregating (Bagging), random forest (RF), gradient boosting machine (GBM), and long short-term memory (LSTM) models to simulate P load dynamics. These models are well-known and widely used in hydrological modeling (Zhang et al., 2018; Gauch et al., 2021; Song et al., 2022).

Briefly, MLR establishes a linear relationship between a dependent variable and two or more independent variables. While it is relatively fast, MLR may lack accuracy when dealing with complex, nonlinear relationships, or highly nonstationary data (Galelli & Castelletti, 2013; Hamaamin et al., 2013; Lima et al., 2015). Bagging, RF, and GBM are ensemble techniques that improve prediction accuracy in non-linear relationships by combining multiple weak learners (e.g., decision trees). Bagging and RF use parallel model training to reduce variance, while GBM uses sequential model training to target both bias and variance. RF introduces random feature selection at each split, enhancing its robustness to noisy and irrelevant features. GBM's sequential training focuses on relevant features, producing highly accurate predictions. LSTM, a type of recurrent neural network, is particularly useful for modeling sequential data, learning patterns over long sequences, making it suitable for time series forecasting tasks.

4.2.2.1 Discharge simulation

Zhang et al. (2018) had used Bagging and process-based models to accurately predict runoff characteristics in over 600 catchments. They found that mean annual precipitation and aridity index were the most significant factors influencing runoff predictions. We therefore considered watershed attributes including daily precipitation, daily maximum and minimum air temperature, reference evapotranspiration (Allen et al., 1998) and aridity index as input variables for five ML models to simulate discharge at the outlet of Maumee River watershed. Historical climate datasets for Maumee River watershed were collected from National Oceanic and Atmospheric Administration (NOAA) (https://www.ncei.noaa.gov/cdoweb/search;jsessionid=D74041373D57B50736C4267E7F41F7B3). In this study, we selected 28 climatic stations, and the average observations from these stations were used as inputs for our model. The locations of these 28 stations are summarized in Table 4.1.

Table 4.1 Monitoring stations used to obtain climate data in the Maumee River watershed for this study.

Station ID	Latitude	Longitude
USC00333292	41°25'04"N	83°52'18"W
USC00335669	41°23'38"N	84°6'52"W
USC00338366	41°39'00"N	83°31'60"W
USC00338822	41°31'06"N	84°8'43"W
USW00094830	41°35'13"N	83°48'19"W
USC00332791	41°2'46"N	83°39'44"W
USGS04180000	41°13′08″N	85°04′35″W
USC00203823	41°56′07″N	84°38′28″W
USC00205603	41°43′18″N	84°12′53″W
USC00120200	41°39′50″N	85°01′06″W
USC00335438	41°35′10″N	84°37′24″W
USC00330862	41°22′59″N	83°36′40″W
USC00332098	41°16′42″N	84°23′05″W
USC00121739	41°08′43″N	85°29′23″W
USC00336465	41°07′29″N	84°35′31″W
USC00333421	41°01′09″N	84°28′38″W
USW00014825	41°00′49″N	83°40′07″W
USW00014827	40°58′14″N	85°12′23″W
USC00336405	40°56′46″N	83°57′41″W
USC00338609	40°50′58″N	84°34′51″W
USC00122096	40°50′54″N	84°55′48″W
USC00120830	40°48′51″N	85°09′17″W
USC00331072	40°48′45″N	82°58′11″W
USC00334551	40°43′29″N	84°07′46″W
USC00120676	40°40′06″N	84°55′48″W
USC00331390	40°34′08″N	84°32′13″W
USC00333915	40°28′48″N	83°48′46″W
USC00201675	41°57′44″N	84°59′33″W

4.2.2.2 Sediment load modeling

We used four ML approaches (i.e., MLR, Bagging, RF, and GBM) to simulate the export of TSS load in the Maumee River watershed. We did not use LSTM because it may not be suitable as TSS load did not behave apparently seasonal or periodic patterns like discharge (such as agricultural practices' effect). The input variables included the percentage of cropland under conservation practices in the Maumee River watershed, mean daily precipitation within the watershed, surface soil clay content of the watershed, time, and the watershed discharge export. We selected these inputs based on the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997), which calculates soil erosion by considering landscape factors, rainfall-runoff impact, and cover-management effects. We collected surface soil clay content information from OEPA (2022), while the temporal percentage of cropland under conservation practices, and watershed P balance were obtained from Jarvie et al. (2017) and USDA-NRCS (2016), as shown in Fig. 4.1.

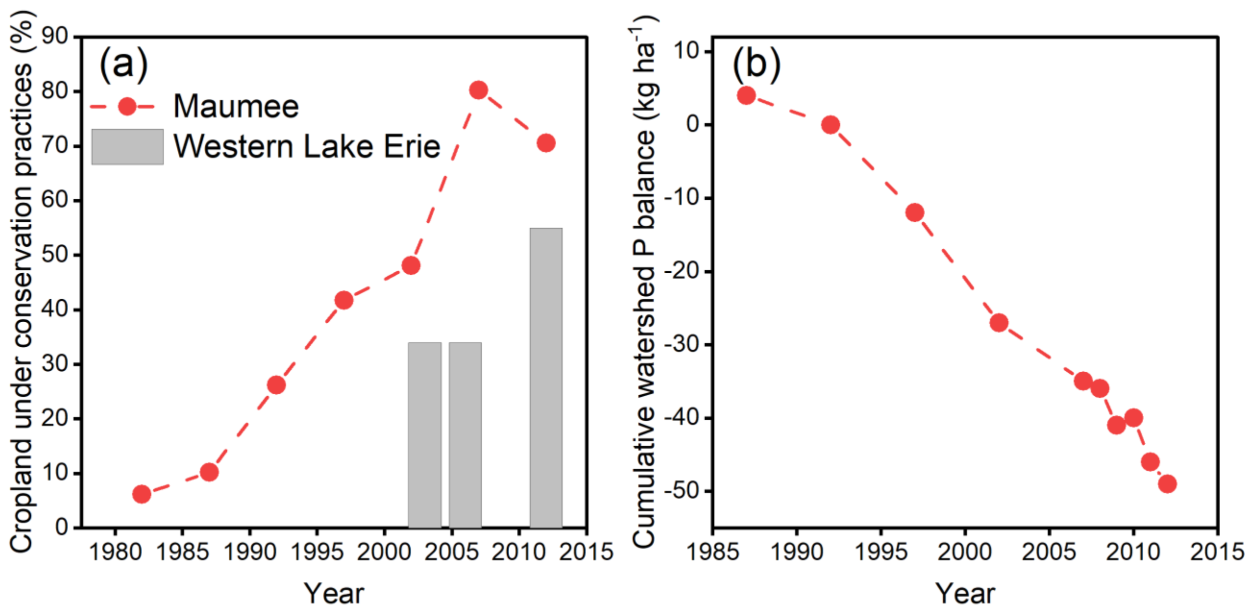

Figure 4.1 Temporal changes in (a) the percentage of cropland under conservation practices and (b) the cumulative P balance in the Maumee River watershed. The percentage of cropland under conservation practices in the western Lake Erie was collected from USDA-NRCS (2016).

4.2.2.3 P load simulation

We used MLR, Bagging, RF, and GBM to simulate the Maumee River watershed P export. In these models, we considered various input variables, including mean daily precipitation, the temporal changes of the watershed soil P balance, county-scale soil test phosphorus (STP), surface soil clay content, time, percentage of cropland under conservation practices in the Maumee River watershed, TSS export and discharge at the outlet of Maumee River watershed. Fig. 4.2 presented the relationships between daily discharge, TSS load, and daily P loads. We collected the temporal changes in watershed soil P balance from Jarvie et al. (2017) (Fig. 4.1 (b)). STP datasets were obtained from Dayton et al. (2020), who collected thousands soil test samples annually at the county-scale. The temporal changes of STP were shown in Fig. 4.3, we used the 50th percentile STP in the models. As significant changes in STP were observed in Lucas County, we solely input Lucas STP data into the model and averaged the STP data of other counties.

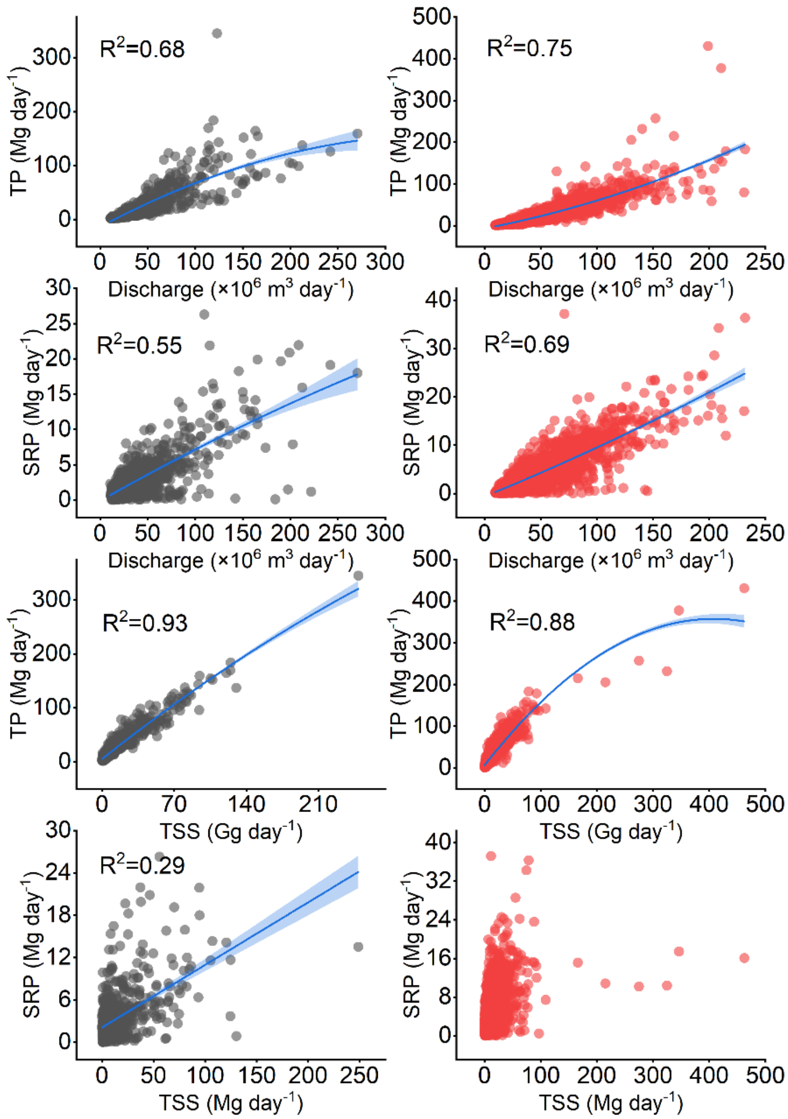

Figure 4.2 The effect of daily discharge and TSS load on daily P loads. The black dots represent

observations before 1990, while the red dots represent observations after 1990. The blue line is the regression fitting, and the shaded band indicates the 95% confidence interval.

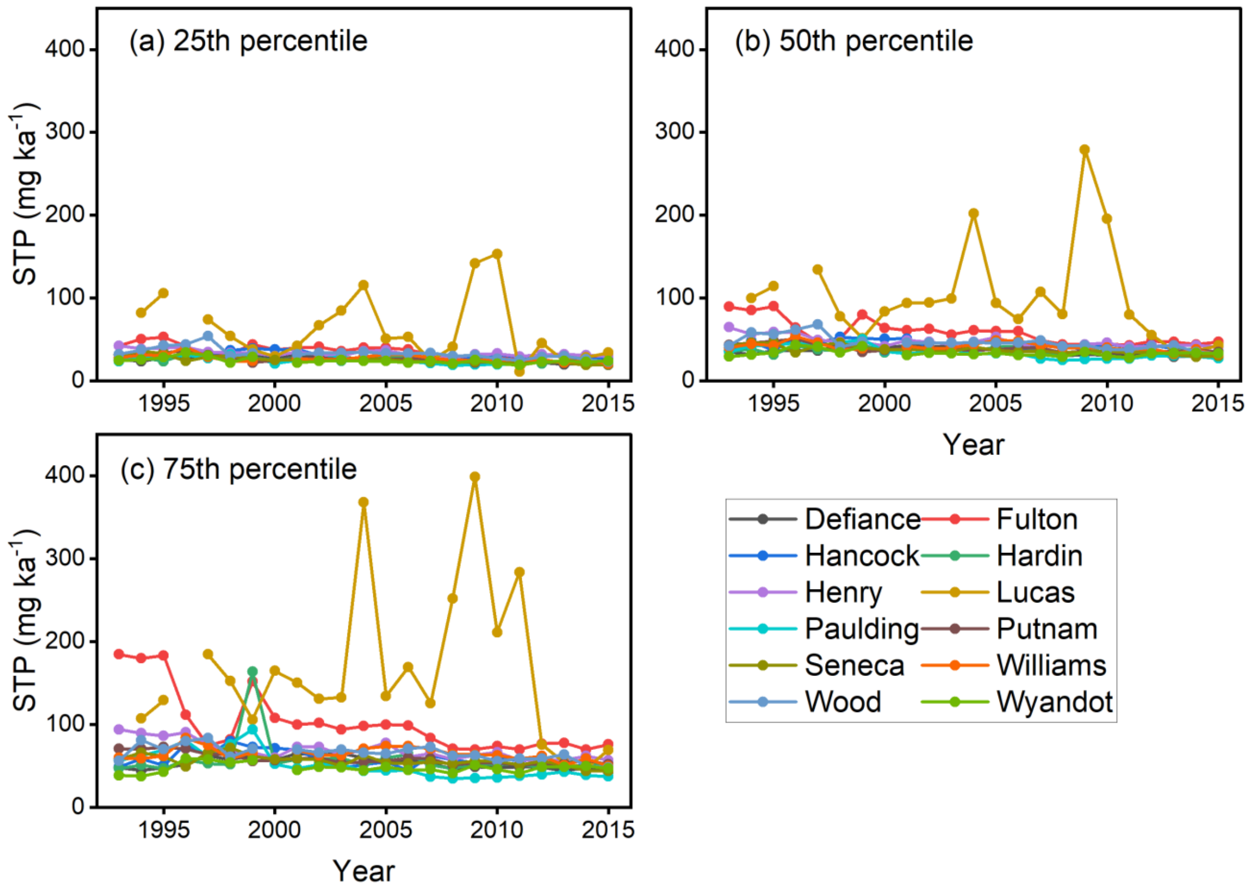

Figure 4.3 Temporal changes of county-scale STP in the Maumee River watershed: (a) 25th percentile of measurements, (b) 50th percentile of measurements, (c) 75th percentile of measurements.

4.2.3 Calibration and validation

All machine learning models were developed using the R Statistical Software (The R Core Team, 2019), and we generally used the default model parameters, which are often appropriate for building a basic regression model. In a bagging model, there are only two parameters: the number of trees to grow or the number of bootstrap samples (n), and the minimal number of observations at terminal nodes (m). High values of n and m can lead to overfitting issues, so we chose n and m values of 150 and 2, respectively, based on research by Zhang et al. (2018). For the RF model, we built 500 trees, and 3 variables were sampled for each decision tree split. Similarly, for the GBM model, we used 500 trees, a maximum depth of 5, and a learning rate of 0.1. To normalize the observations in the LSTM model, we calculated the mean values and standard deviations of the long-term variables, and we set the sequence length of 10 in the datasets. During LSTM training, the model went through the dataset 100 times, and it was updated after 32 samples.

We used a leave-one-out method to evaluate the MLR's prediction skill, which is more stable compared to k-fold cross-validation (Zhang et al., 2018). For Bagging, RF, and GBM models, we randomly split the datasets into training and validation sets, with 80% of the data for training and the remaining 20% for validation. The last 15% of datasets in terms of time were used for model testing. For the LSTM model, we used the first 80% of datasets in terms of time for model calibration and the last 20% of datasets for model testing.

We applied the coefficient of determination (R^2) and the index of agreement (d) (Wang et al., 2021; Li et al., 2022) to assess the modeling accuracy, expressed as:

$$R^2 = \left(\frac{n * \sum_{i=1}^{i=n} (Sim_i * Obs_i) - \sum_{i=1}^{i=n} Sim_i * \sum_{i=1}^{i=n} Obs_i}{\sqrt{n * \sum_{i=1}^{i=n} Sim_i{}^2 - (\sum_{i=1}^{i=n} Sim_i)^2} * \sqrt{n * \sum_{i=1}^{i=n} Obs_i{}^2 - (\sum_{i=1}^{i=n} Obs_i)^2}} \right)^2 \quad (4.1)$$

$$d = 1 - \frac{\sum_{i=1}^{i=n} (Sim_i - Obs_i)^2}{\sum_{i=1}^{i=n} (|Sim_i - \overline{Obs}| + |Obs_i - \overline{Obs}|)^2} \quad (4.2)$$

where n is the number of paired observed and simulated values, Obs_i is the ith observed value, $\overline{Obs}$ is the mean observed value, Sim_i is the ith simulated value. R^2 and d are both statistical measures used to assess the goodness of fit between observed and predicted values in a model. R^2 measures the proportion of variance explained by the model, while d evaluates the similarity between observed and predicted values. The R^2 and d values range from 0 to 1. If the evaluated model accurately depicts the datasets, R^2 and d should be close to 1.

We used the varImp() function in the 'caret' package to assess the relative importance of input variables in simulating P loads. Since the relative importance values in different models have large differences in magnitude, we applied a log transform to standardize the values across models.

4.2.4 RCP scenarios

For future prediction, we collected downscaled climate projections for Maumee River watershed, including daily precipitation, maximum and minimum air temperature, and other factors including relative humidity, wind speed, and solar radiation (*i.e.*, used to calculate ET_0), to predict discharge under two different carbon emission scenarios (*i.e.*, RCP 4.5 and RCP 8.5). We obtained the downscaled meteorological forecast datasets for Maumee River watershed from 20 global climate models from the Multivariate Adaptive Constructed Analogs (MACA) database (https://climate.northwestknowledge.net/MACA/index.php#collapseLANDING). We adopted mean values derived from these 20 climate models as inputs for our machine learning models.

4.2.5 Return level of extreme discharge events

We simultaneously used the Generalized Extreme Value (GEV) distribution model to simulate the return level of the 80th percentile discharge at the outlet of the Maumee River watershed. We specifically selected this percentile because discharge events above the 80th percentile were responsible for the majority of P exports (Fig. 4.4). The GEV model is a widely used statistical tool for analyzing the occurrence and characteristics of extreme hydrological events (Katz et al., 2002; Santos et al., 2016; Su and Smith, 2021). The GEV cumulative distribution function is given as:

$$\Psi_{GEV}(x) = exp\left\{-\left[1 + \xi \cdot (\frac{x-\mu}{\sigma})\right]^{-1/\xi}\right\} \tag{4.3}$$

where $\Psi_{GEV}(x)$ represents the probability of an extreme event exceeding a threshold x (the 80th percentile discharge). μ is the location parameter, σ is the scale parameter, and ξ is the shape parameter which defines the tail behavior of the distribution.

The GEV model can be used to make both stationary and non-stationary assumptions. In a stationary model, observations are assumed to be drawn from a probability distribution function with constant parameters, meaning that the statistics of extremes do not change over time or with respect to other covariates. In contrast, in a non-stationary model, the parameters of the underlying probability distribution function change over time or in response to a given covariate (Ragno et al., 2019). In this study, we implemented a non-stationary GEV model by setting parameters as a function of time (x_c) to investigate long-term extreme discharge trends:

$$\Psi_{GEV}(x|x_c) = exp\left\{-\left[1 + \xi(x_c) \cdot (\frac{x-\mu(x_c)}{\sigma(x_c)})\right]^{-1/\xi(x_c)}\right\} \tag{4.4}$$

Though all three parameters of the GEV distribution can vary with time, the shape parameter (ξ) is always kept time invariant because it cannot be estimated precisely and assuming to be a smooth function of time is unrealistic (Coles, 2001). In our study, only the location and scale parameters were expressed as linear functions of time (Agilan et al., 2021).

$$\mu = \mu_0 + x_c \cdot \mu_1 \tag{4.5}$$

$$\sigma = \sigma_0 + x_c \cdot \sigma_1 \tag{4.6}$$

where μ_0 and σ_0 are the intercepts, μ_1 and σ_1 are the coefficients for the time effect on μ and σ, respectively, and x_c is time.

Many packages and software can undertake nonstationary GEV simulation (Gilleland and Katz, 2016; Cheng et al., 2014). In this study, we used the Process-informed Nonstationary Extreme Value Analysis (ProNEVA), a newly-developed MATLAB-based framework that employs a Bayesian inference approach to estimate GEV parameters. ProNEVA uses a hybrid evolution Markov Chain Monte Carlo (MCMC) approach, which is computationally efficient in searching rugged response surfaces and provides a robust numerical parameter estimation and uncertainty quantification. ProNEVA also offers a comprehensive assessment of the goodness of fit, including Root Mean Square Error ($RMSE$) and Nash-Sutcliff Efficiency (NSE) coefficients. A perfect fit is associated with $RMSE = 0$ and $NES = 1$, given $RMSE \in [0 , \infty)$ and $NES \in [-\infty , 1)$.

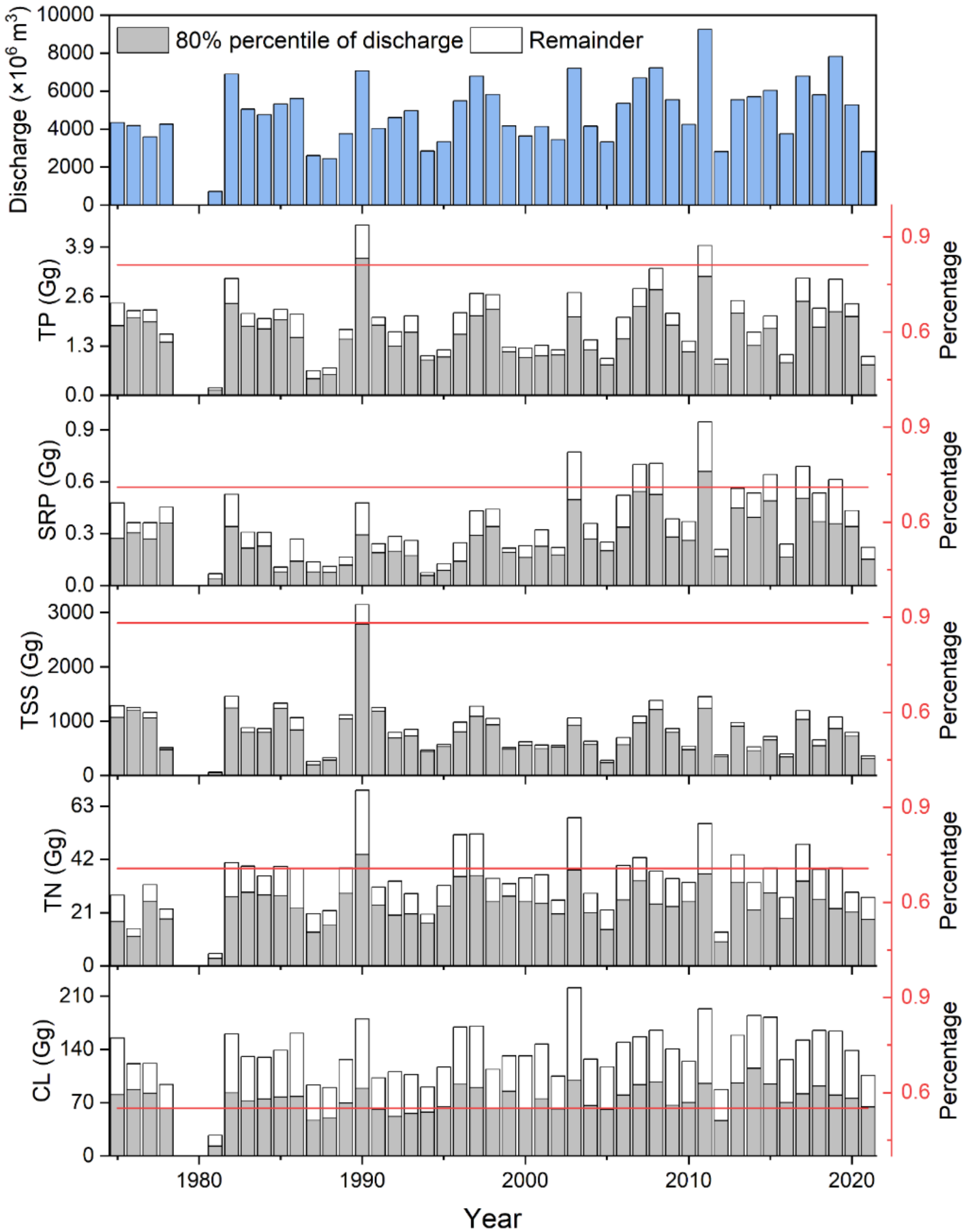

Figure 4.4 Annual observed TP load, SRP load, TSS load, TN load, CL load, and corresponding discharge at the outlet of the Maumee River watershed. The red line indicates the average percentage of annual nutrient load when the discharge rate exceeds the 80th percentile. Nitrate (NO_3^-) was analyzed using ion chromatography (U.S. EPA Method 300.1). Total Kjeldahl N (TKN) was analyzed using phenol colorimetry after pretreatment with acid digestion (U.S. EPA Method 351.2). Total N was calculated as the sum of NO_3^- and TKN. Chloride (Cl) concentrations were measured by ion chromatography (EPA Method 300.1).

4.3 Results

4.3.1 Maumee River discharge simulation

The nonstationary GEV model accurately simulated the historical pattern of the 80th percentile discharge rates (Fig. 4.S1). We found that all return levels had an increasing trend since the late 1970s, with the 2-year and 100-year return levels increased from 16 × 10^6 and 37 × 10^6 m^3 day^{-1} to 25 × 10^6 and 67 × 10^6 m^3 day^{-1}, respectively (Fig. 4.5).

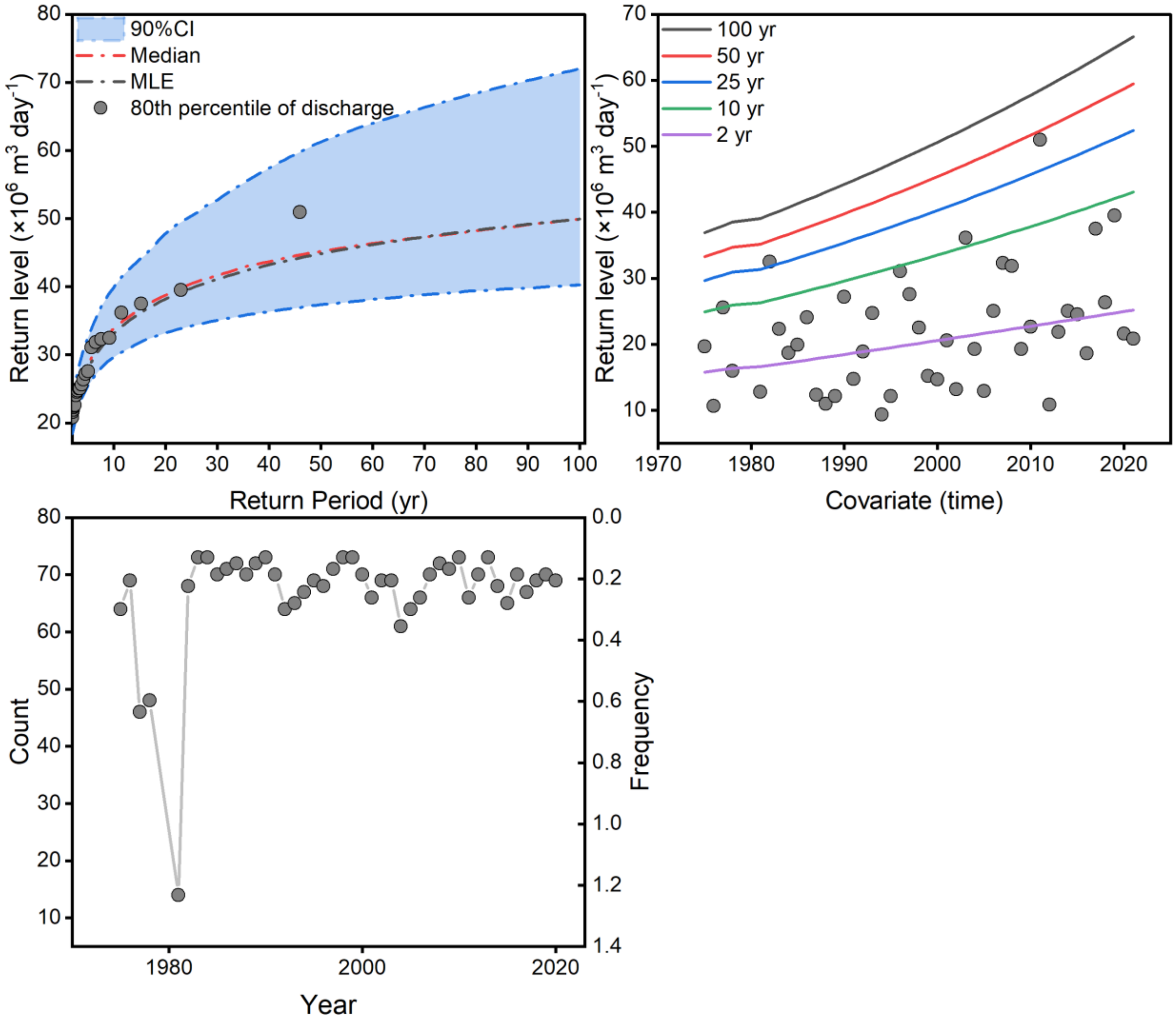

Figure 4.5 Return levels and the frequency for the 80th percentile of daily discharge at the outlet of Maumee River watershed.

All machine learning techniques reliably captured the historical monthly discharge patterns of the Maumee River (Fig. 4.6). Among these models, the Bagging and RF models showed the best performance during testing, while the LSTM model had the worst performance (Table 4.2). In terms of discharge predictions, the LSTM model also exhibited the largest fluctuations under both RCP scenarios (Fig. 4.7).

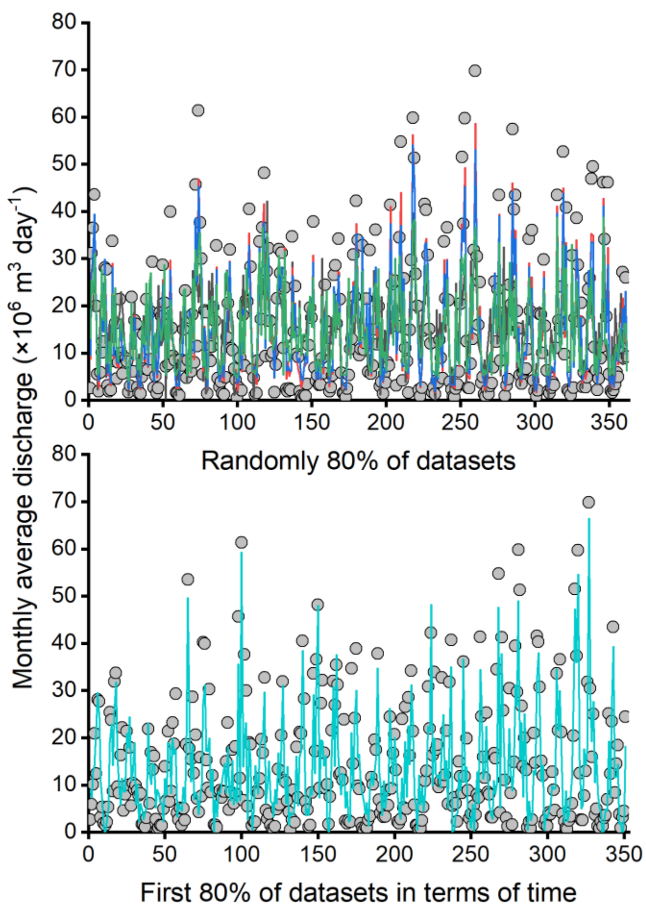

Figure 4.6 Calibration and validation of monthly average discharge at the outlet of Maumee River watershed using different machine learning models. Model performance metrics are presented in Table 4.2.

Table 4.2 Performance of machine learning models for predicting Maumee River discharge.

Model	Training		Validation		Testing	
	R^2	*d*	R^2	*d*	R^2	*d*
MRL	0.31	0.68	-	-	0.4	0.67
Bagging	0.93	0.97	0.35	0.75	0.94	0.96
RF	0.91	0.96	0.36	0.74	0.92	0.95

GBM	0.55	0.8	0.41	0.77	0.61	0.81
LSTM	0.86	0.96	-	-	0	0.38

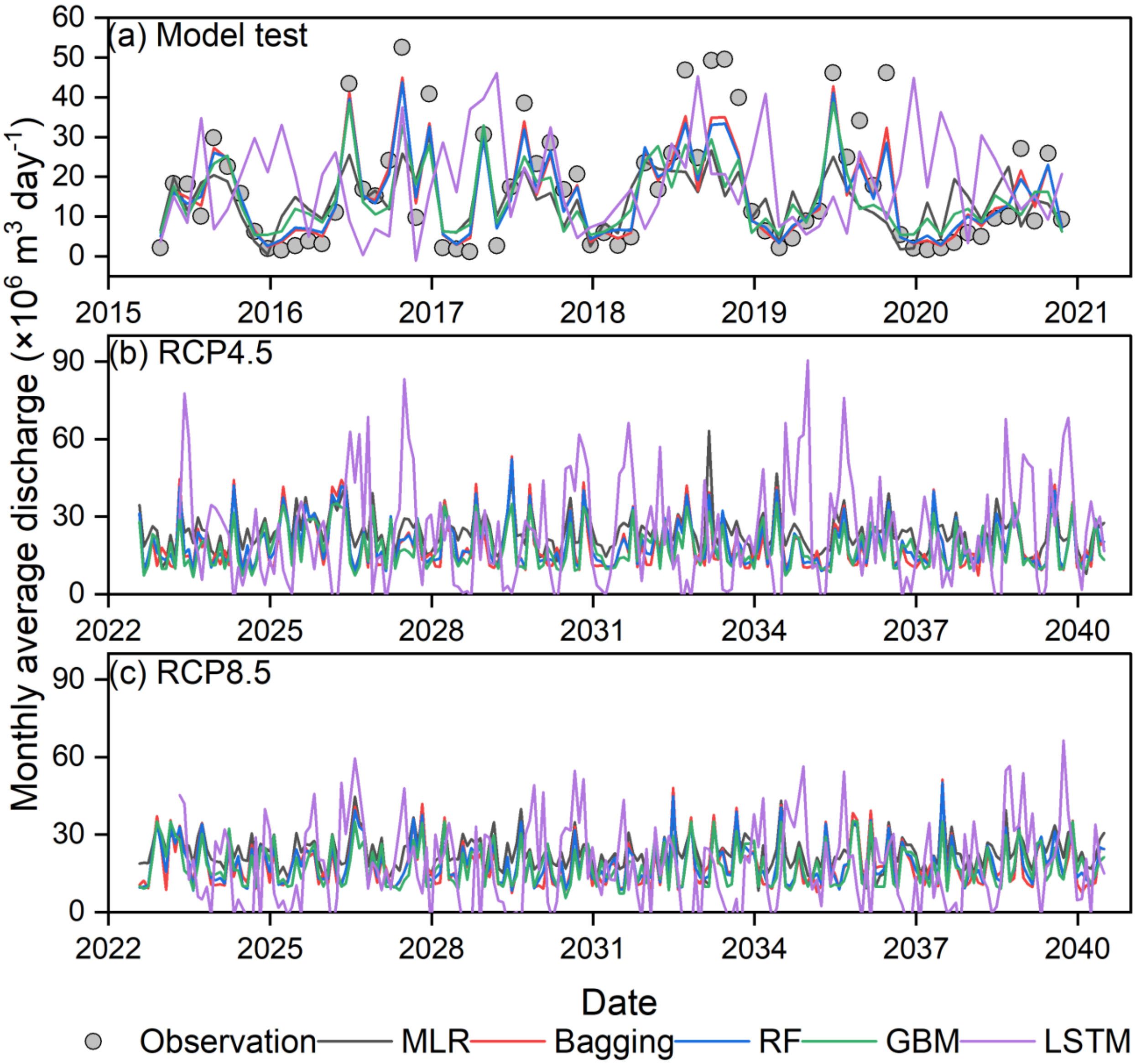

Figure 4.7 Model test and future prediction of monthly average discharge at the outlet of Maumee River watershed using different machine learning models.

4.3.2 Maumee River watershed TSS export simulation

All machine learning techniques accurately simulated the historical monthly TSS export at the outlet of the Maumee River watershed (Fis. 4.8 and 4.9). The Bagging and RF models demonstrated the best performance during testing, while the MLR model showed the worst performance (Table 4.3).

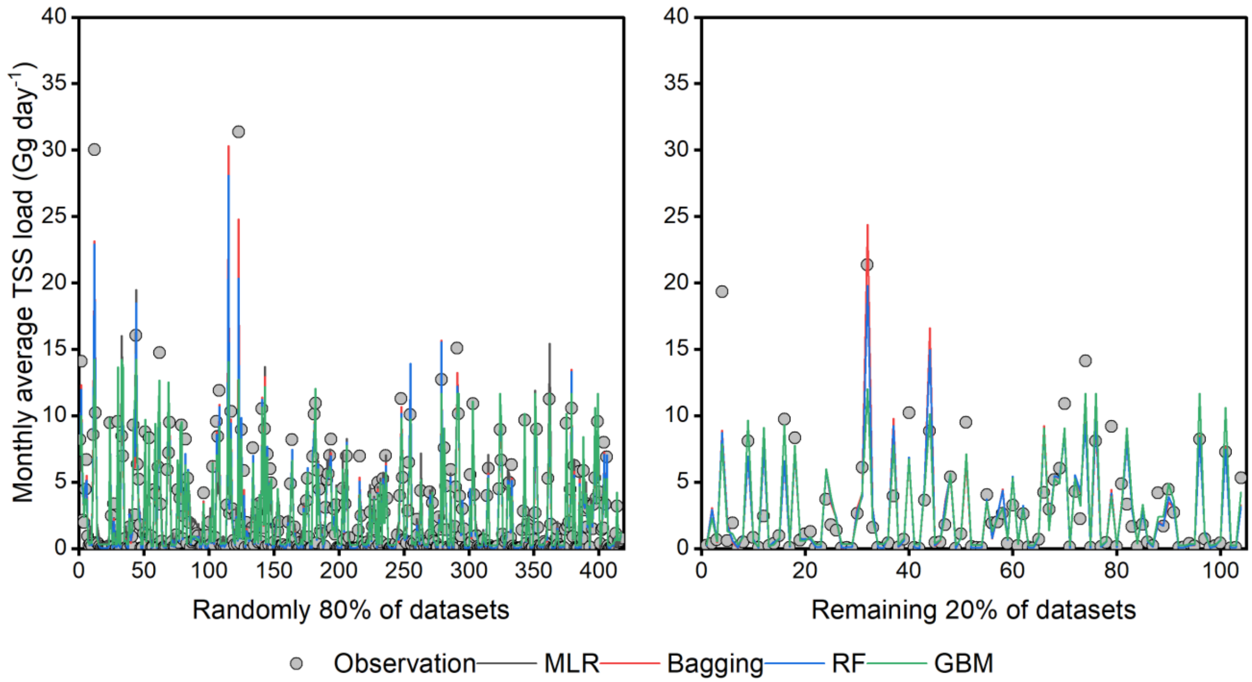

Figure 4.8 Calibration and validation of monthly average TSS export at the outlet of Maumee River watershed using different machine learning models. Model performance metrics are presented in Table 4.3.

Table 4.3 Performance of machine learning models for predicting Maumee River TSS export.

Model	Training		Validation		Testing	
	R^2	*d*	R^2	*d*	R^2	*d*
MRL	0.66	0.89	-	-	0.66	0.88
Bagging	0.95	0.98	0.74	0.93	0.91	0.97
RF	0.92	0.98	0.75	0.93	0.89	0.97
GBM	0.72	0.91	0.7	0.91	0.71	0.91

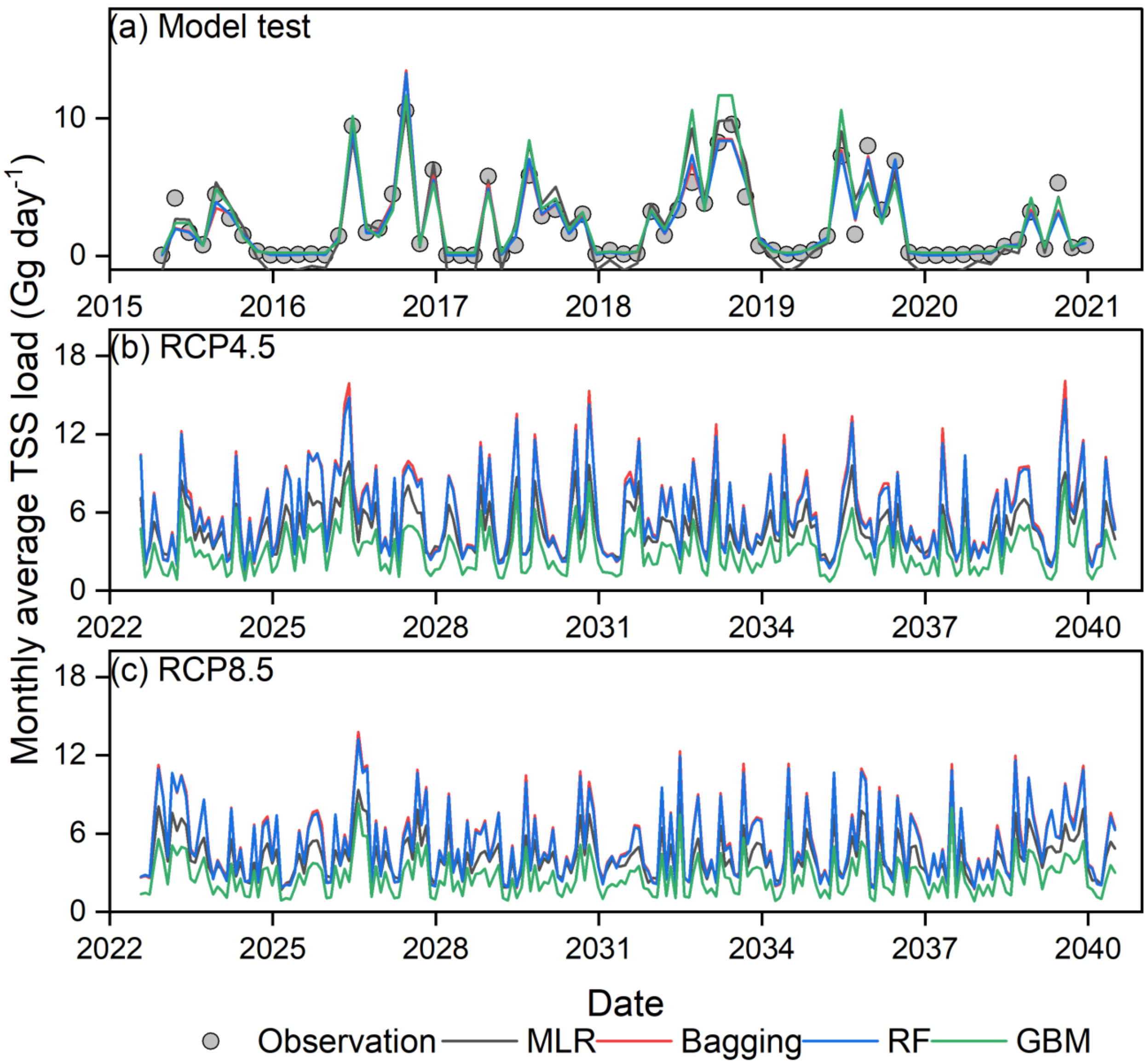

Figure 4.9 Model test and future prediction of monthly average TSS load at the outlet of Maumee River watershed using different machine learning models.

4.3.3 Maumee River watershed P export simulation

All machine learning techniques accurately simulated the historical monthly P export at the outlet of the Maumee River watershed (Fig. 4.10). The TP export simulation showed better performance than the SRP export simulation, with MLR showing the lowest values of R^2 and d at 0.83 and 0.95, respectively (Table 4.4).

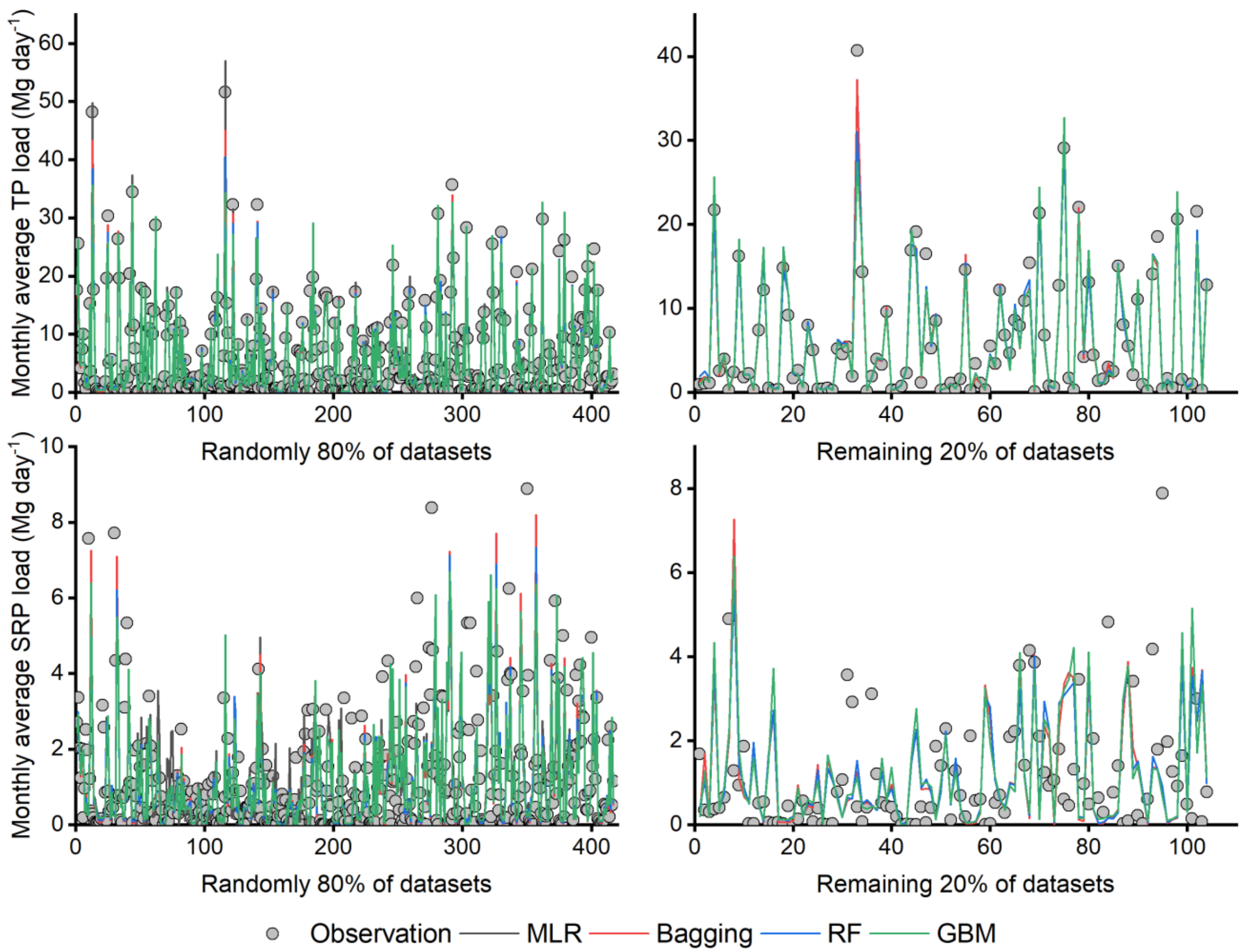

Figure 4.10 Calibration and validation of monthly average P export at the outlet of Maumee River watershed using different machine learning models. Model performance metrics are presented in Table 4.4.

Table 4.4 Performance of machine learning models for predicting P export at the outlet of Maumee River watershed.

Target	Model	Training		Validation		Testing	
		R^2	*d*	R^2	*d*	R^2	*d*
TP load							
	MRL	0.97	0.99	-	-	0.97	0.99
	Bagging	0.99	0.99	0.97	0.99	0.99	0.99
	RF	0.99	0.99	0.96	0.99	0.98	0.99
	GBM	0.96	0.99	0.93	0.98	0.95	0.99

SRP load							
	MRL	0.84	0.95	-	-	0.84	0.95
	Bagging	0.98	0.99	0.86	0.96	0.96	0.99
	RF	0.96	0.99	0.86	0.96	0.95	0.98
	GBM	0.92	0.98	0.86	0.96	0.91	0.98

The model ensemble results indicated that, under the continued implementation of current conservation management, annual TP export was projected to remain relatively constant at approximately 3000 Mg yr^{-1}, while annual SRP export was expected to increase to around 900 Mg yr^{-1} between 2023 and 2040 (Fig. 4.11). The simulations for SRP export exhibited higher levels of uncertainty, with the MLR model showing notably higher results compared to other models (Fig. 4.12). In both TP and SRP export modeling, TSS export and discharge were the most significant variables in the modeling results (Fig. 4.12).

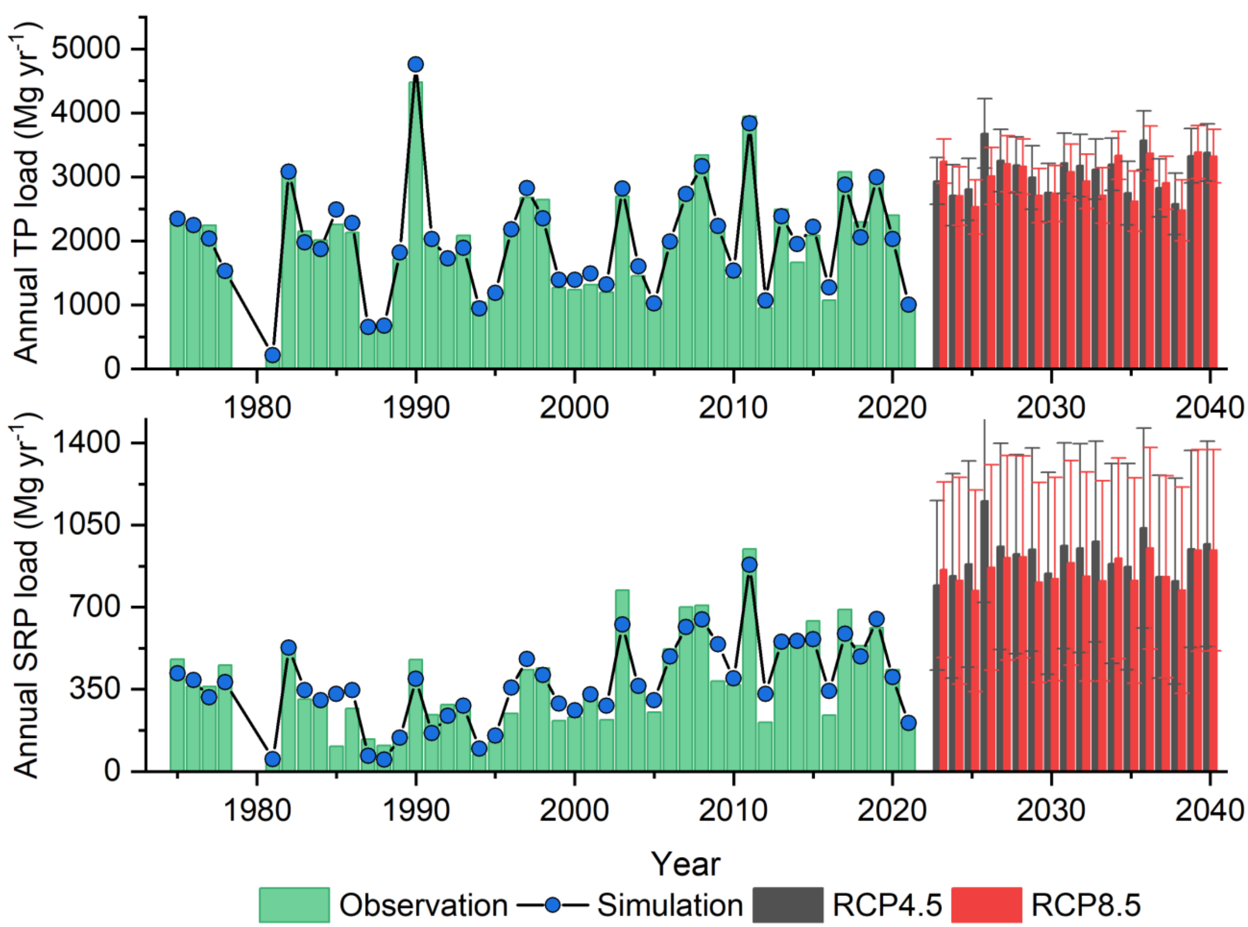

Figure 4.11 Prediction of annual P export at the outlet of Maumee River watershed. Simulation is the average value of four machine learning models. The error bar represents the standard deviation of the simulation results.

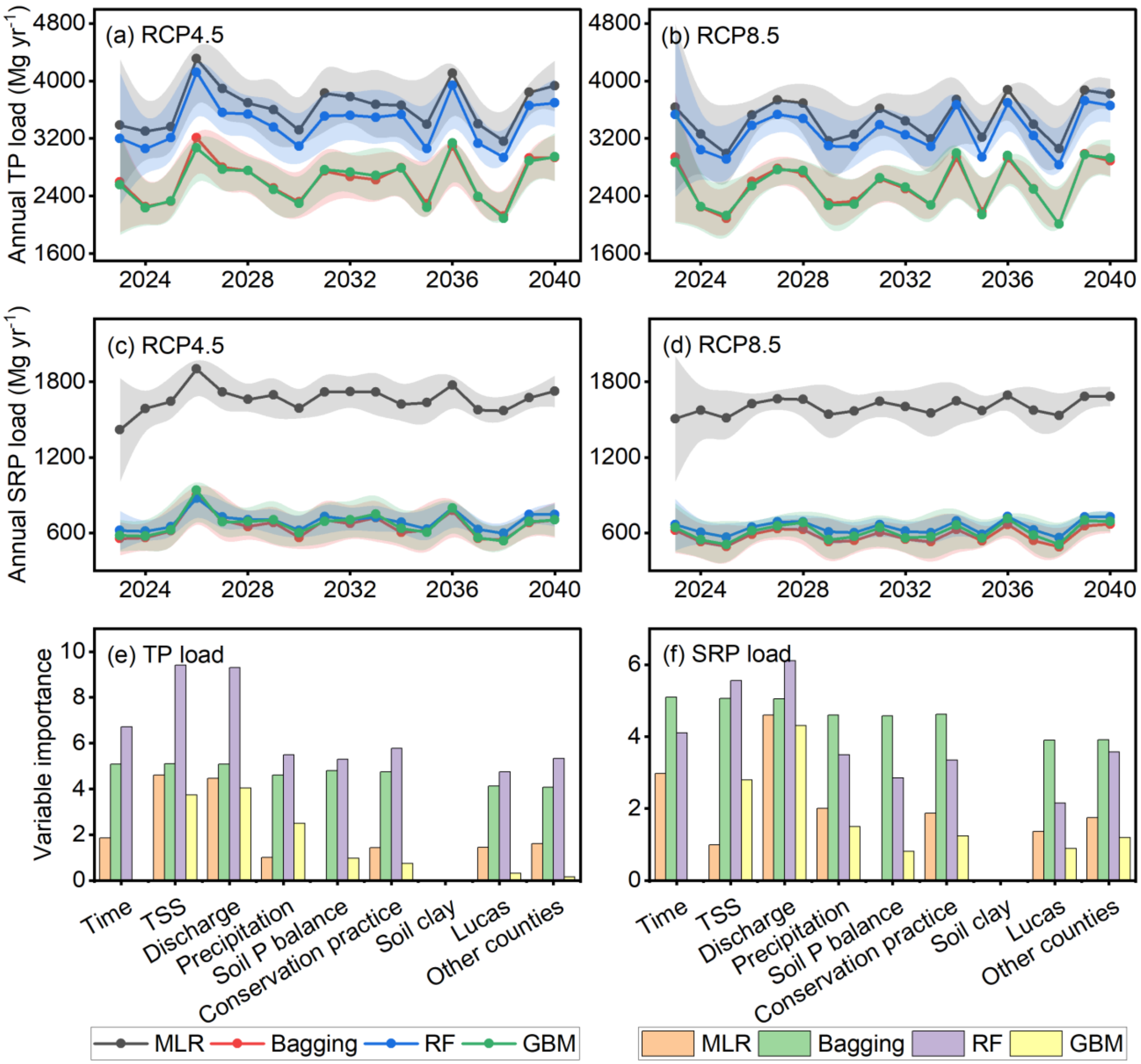

Figure 4.12 Prediction of P load under four machine learning models and the relative influence of variables on simulations. The shaded band represents the standard deviation of the simulation results.

In terms of annual spring P export simulation between 2023 and 2040, the model ensemble results suggested that spring TP export was projected to be similar to the observed levels in 2020, with an average of approximately 1260 Mg yr^{-1}, while SRP export was expected to exceed the 2020 observation, with an average of approximately 370 Mg yr^{-1} (Fig. 4.13).

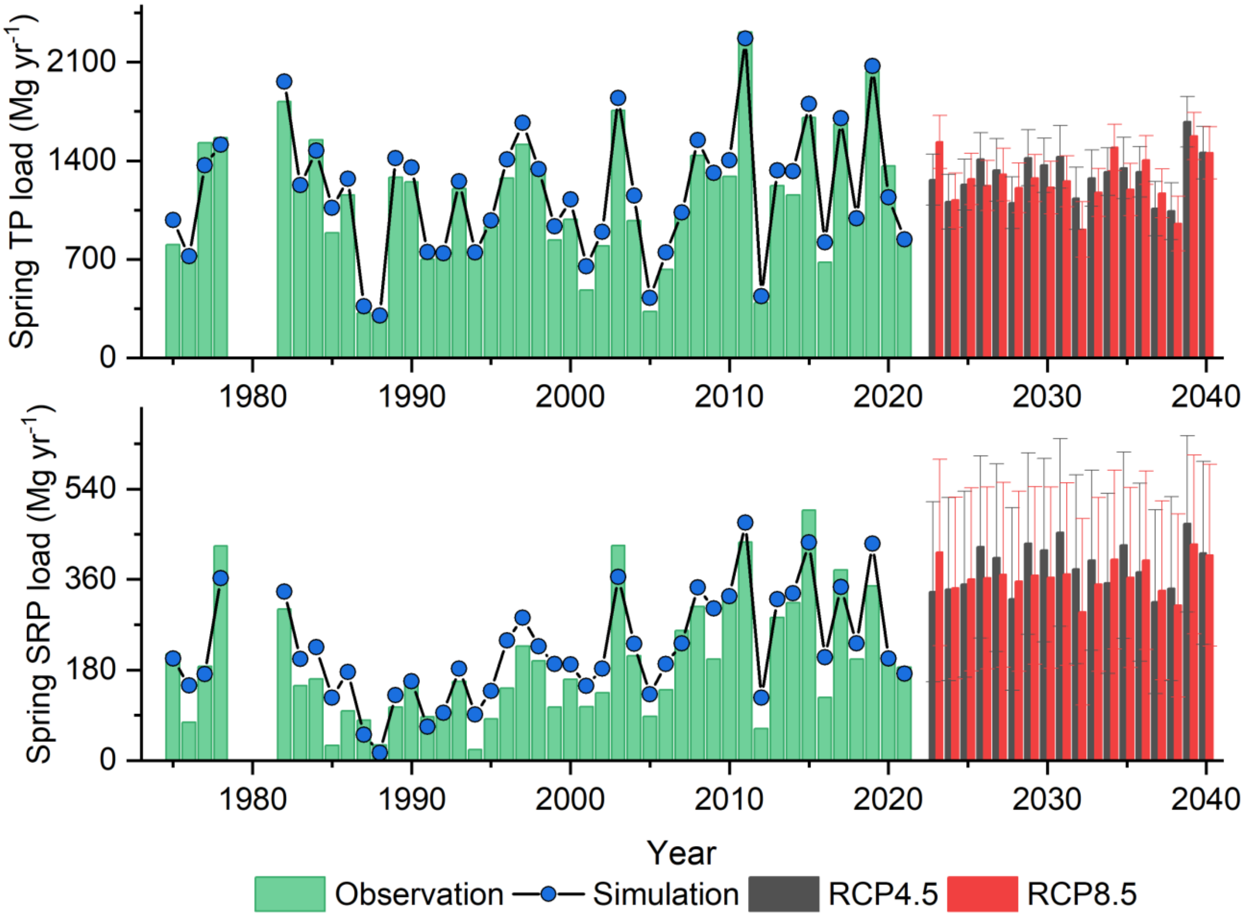

Figure 4.13 Prediction of spring P (March-July) export at the outlet of Maumee River watershed. Simulation is the average value of four machine learning models. The error bar represents the standard deviation of the simulation results.

4.4 Discussion

4.4.1 Influence of hydrology on P loading

Our analyses suggest a growing influence of hydrology on P export from the Maumee River watershed. Daily discharge events above the 80th percentile have been responsible for 81% and 71% of annual TP and SRP loads, respectively (Fig. 4.4). Both TP load and SRP load monitored at the outlet of Maumee River watershed demonstrate strong responses to daily discharge (Fig. 4.2), whereas only TP load exhibits a strong response to TSS load (Fig. 4.2). This is because sedimentary P accounts for the majority of TP loading, which is directly relevant to surface runoff into the ditch, whereas dissolved P loads are closely associated with tile drainage to the ditches via macropore flow pathways (Williams et al., 2016) and this process can be strongly influenced by the antecedent wetness conditions (Williams et al., 2022). We find that high discharge events are typically associated with exceptionally high TP and SRP loads after 1990. This finding could be relevant to the increases in spring storm events (Williams & King 2020). Furthermore, we find that the return levels of the 80th percentile discharge rate have been increasing since the late 1970s, while the reoccurrence frequency has not declined (Fig. 4.5). This finding is consistent with Choquette et al. (2019), who found that annual mean daily discharge in the upstream of Maumee River watershed had increased between 1987 and 2016. Notably, our analyses are based on calendar day totals and not as continuous 24-h events, therefore, our simulations may be conservative, because some storm runoff events occurring during a 24-h period could have spanned two calendar days and therefore been underestimated in the analysis.

4.4.2 P loading predictions

Our modeling suggests that P export from the Maumee River watershed may continue to pose a challenge to Lake Erie water quality in the coming decades. With an expected increase in annual discharge under climate change (Culbertson et al., 2016) and an associated rise in spring storm events (Cousino et al., 2015), annual TP load is projected to be comparable to previous years, while SRP load is expected to be high between 2023 and 2040 (Fig. 4.11). This contradicts the opinion that future P losses would be reduced when 48% of the Maumee River watershed area is under conservation practices (Fraker et al., 2023). One possible reason may be the different definition of conservation practices, in our work, we did not consider the implementation of cover crop or filter strips, our conservation practices only refer to conservation tillage, crop residue return, and crop rotation. A global meta-analysis by Xiao et al. (2021) confirmed that crop residue return plays a major role in controlling soil erosion rather than no tillage. However, as Jarvie et al. (2017) demonstrated, the percentage of cropland under crop residue return management in the Maumee River watershed had increased from 10% to 70% between 1980 and 2010. While an increasing trend in TP load and SRP load were still observed at the outlet of Maumee River watershed since 2000 (Stow et al., 2015). Rowland et al. (2020) analyzed 2008-2018 P concentrations near the mouth of the Maumee River and found high and relatively stable TP and SRP concentrations with no discernable annual or seasonal decreasing patterns. Besides, satellite monitoring demonstrated consistent algal blooms in western Lake Erie over the past twenty years (Sayers et al., 2019), with the Lake Erie eutrophication severity index confirming that only one year's index was below the target level since 2008 (Fig. 4.S2). Although continued algal blooms can be relevant to increased water temperature (Gibbons & Bridgeman 2020; Fig. 4.S3) and release of lake bottom sedimentary P (Wang et al., 2021), our findings force us to reconsider the impacts of current conservation management on controlling P losses. A multiple SWAT modeling for the Maumee River watershed between 2004 and 2015 also indicated that it is unlikely to reduce P loss to the 40% reduction target level (Annex 4 Objectives and Targets Task Team, 2015) under current conservation practices (Martin et al., 2021). Many studies have also demonstrated that recycled crop residues could unintentionally increase soluble P losses during snow melting, generating eutrophication risks (Baker et al., 2017; Daryanto et al., 2017; Jarvie et al., 2017; Zhang et al., 2017).

Efforts to reduce P pollution in Lake Erie appear to be an ongoing challenge. Despite a slight decline in particulate P export from the outlet of the Maumee River watershed between 1991 and 2012 (Baker et al., 2014a), both TP and SRP loads have risen to levels comparable to the 1970s over the past two decades (Stow et al., 2015). Consequently, in 2016, Canada and the United States proposed lower P loading targets. They called for a 40% reduction in TP loads entering the western basins by 2025, using 2008 as the baseline (Annex 4 Objectives and Targets Task Team, 2015; ECCC & OMECC, 2018). This proposal specifically includes springtime limits for the Maumee River for both TP (860 Mg yr^{-1}) and SRP (186 Mg yr^{-1}) loads, as spring P loads significantly impact the spatial extent of algal blooms. However, our simulations suggest that spring TP loading in the coming decades will not achieve the target reduction level of 860 Mg yr^{-1}, and even neglecting the MLR modeling results, spring SRP loading (270 Mg yr^{-1}) will still exceed the target reduction level of 186 Mg. This result indicates that additional agricultural strategies are needed to further reduce P losses. Yuan & Koropeckyj-Cox (2022) synthesized 28 SWAT modeling studies and found that cover crops and filter strips were most effective in reducing TP and SRP losses. However, surveys show that cover crops were used in 2% and 6% of cropped acres in Western Lake Erie in 2003-06 and 2012, respectively (USDA-NRCS, 2016). Cost and access to equipment are primary concerns for many farmers, not concerns or knowledge about nutrient loss or water quality (Wilson et al., 2019). Reusing soil residual P seems to be a facilitate strategy to control P applications to reduce P losses (Muenich et al., 2016). Daloğlu et al. (2012) suggested that reducing P application rates in the Sandusky River watershed by 15% could lower current SRP loads by

25%. Guo et al. (2020) showed that a 62% reduction in applied P in the Maumee River watershed in 2019 resulted in a 29% reduction in SRP losses, due to record-high precipitation that led to a record high area of unplanted agricultural fields. However, the implementation of this method may be constrained since watershed soil P balance has been consistently negative after 1990 (Jarvie et al., 2017) and 84% of counties had a negative P balance in 2014 (Dayton et al., 2020).

4.4.3 Model uncertainty

Our findings indicate a high degree of uncertainty in annual SRP loading prediction, due to the notably high SRP load simulations in MLR (Fig. 4.12). This is likely because TSS load and discharge play a significant role in MLR modeling, and MLR assumes a simple linear relationship between dependent and independent variables. However, the relationship between SRP load and TSS load is not always linear (Fig. 4.2), and the transportation of dissolved P to ditches through preferential flows to subsurface drainage is more complex than TP load (Williams et al., 2023).

Although all machine learning models adequately portrayed historical patterns of discharge, TSS load, and P load at the outlet of Maumee River watershed, there are several assumptions in our modeling that may increase the level of uncertainty. Firstly, our simulations did not split the watershed into hydraulic response units (HRUs), which prevented us from considering differences in slope and soil texture in HRUs. However, our analyses indicate that soil texture does not play a significant role in P export modeling compared to other variables. Secondly, our simulations did not consider the implementation of other strategies such as cover crop and filter strips, which may overestimate P export from the Maumee River watershed. However, we did not find this temporal information for the Maumee River watershed, and the low percentage of implementation of these strategies in western basins (USDA-NRCS, 2016) suggests that these effects will not significantly impact our simulations. In summary, our findings contribute to the growing body of knowledge about climate change-induced P export from the Maumee River watershed, although several factors may increase the level of uncertainty in our modeling results.

4.5 Conclusion

Our analyses reveal that P export from the Maumee River watershed will continue to challenge Lake Erie’s water quality between 2023 and 2040. The machine learning models reliably simulated the 1974-2021 monthly discharge and P export dynamics at the outlet of the Maumee River watershed. Our model predictions indicate that annual TP load remaining relatively stable compared to previous years, while annual SRP load is projected to increase between 2023 and 2040. Both the annual spring TP load and SRP load are anticipated to exceed the government's anticipated 40% reduction target. The implications of this study underscore the necessity for additional measures to effectively manage and mitigate the persistent issue of P pollution in Lake Erie.

4.6 Supplementary Tables and Figures

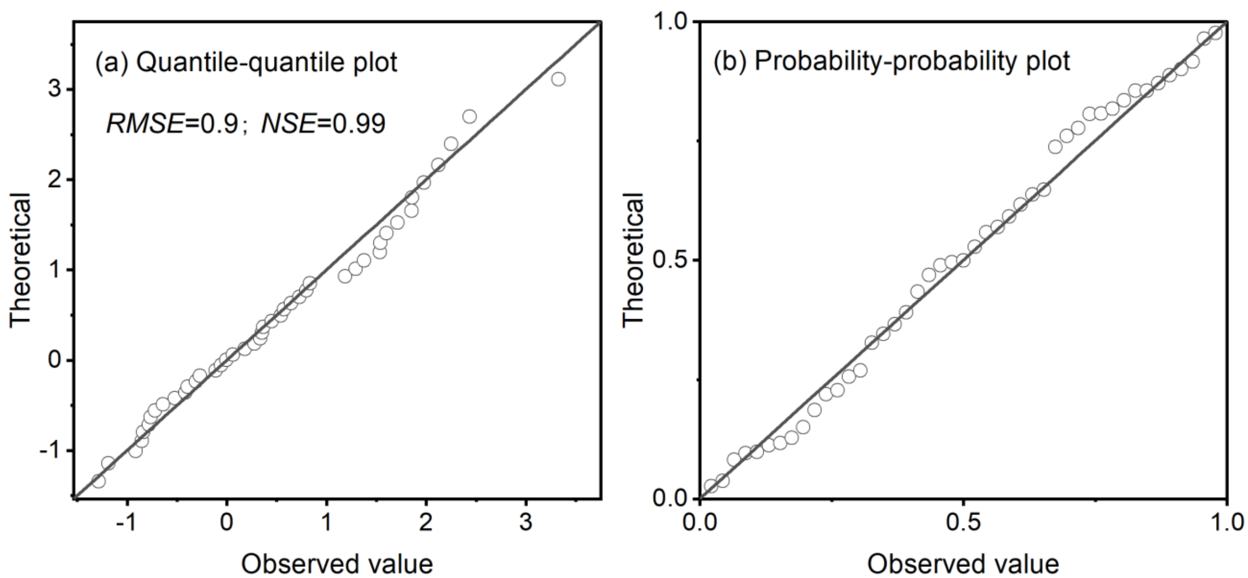

Figure 4.S1 Goodness-of-fit evaluation of the nonstationary GEV model for simulating the return level of the 80th percentile of daily discharge at the outlet of Maumee River watershed. The quantile-quantile plot and probability-probability plot are shown, where a close alignment along the unit diagonal indicates a good fit of the estimated distribution function to the observed data (Coles, 2001).

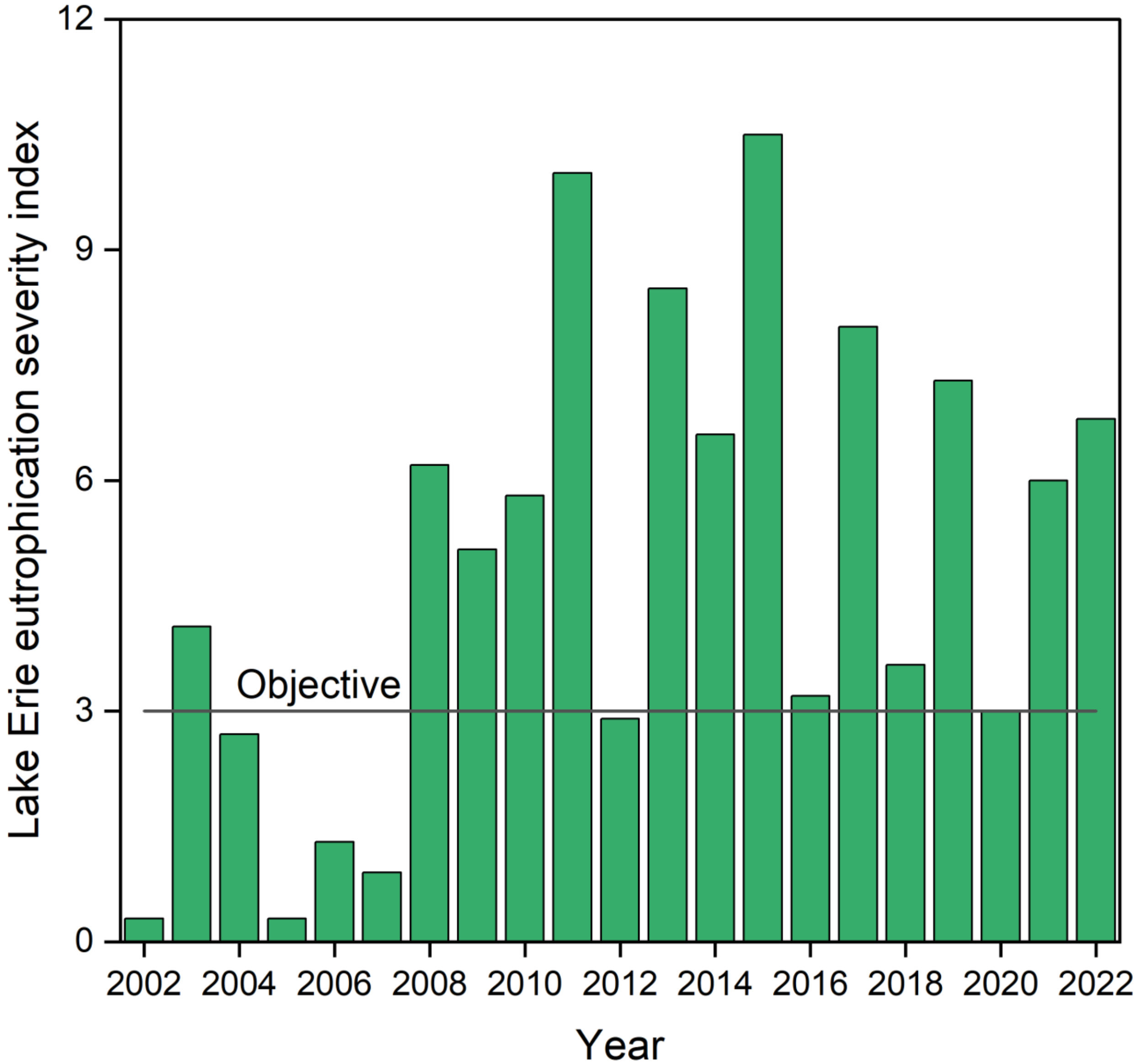

Figure 4.S2 Temporal changes of Lake Erie eutrophication severity index. This information was collected from NOAA National Ocean Service (https://coastalscience.noaa.gov/news/2022-lake-erie-algal-bloom-more-severe-than-predicted-by-seasonal-forecast/)

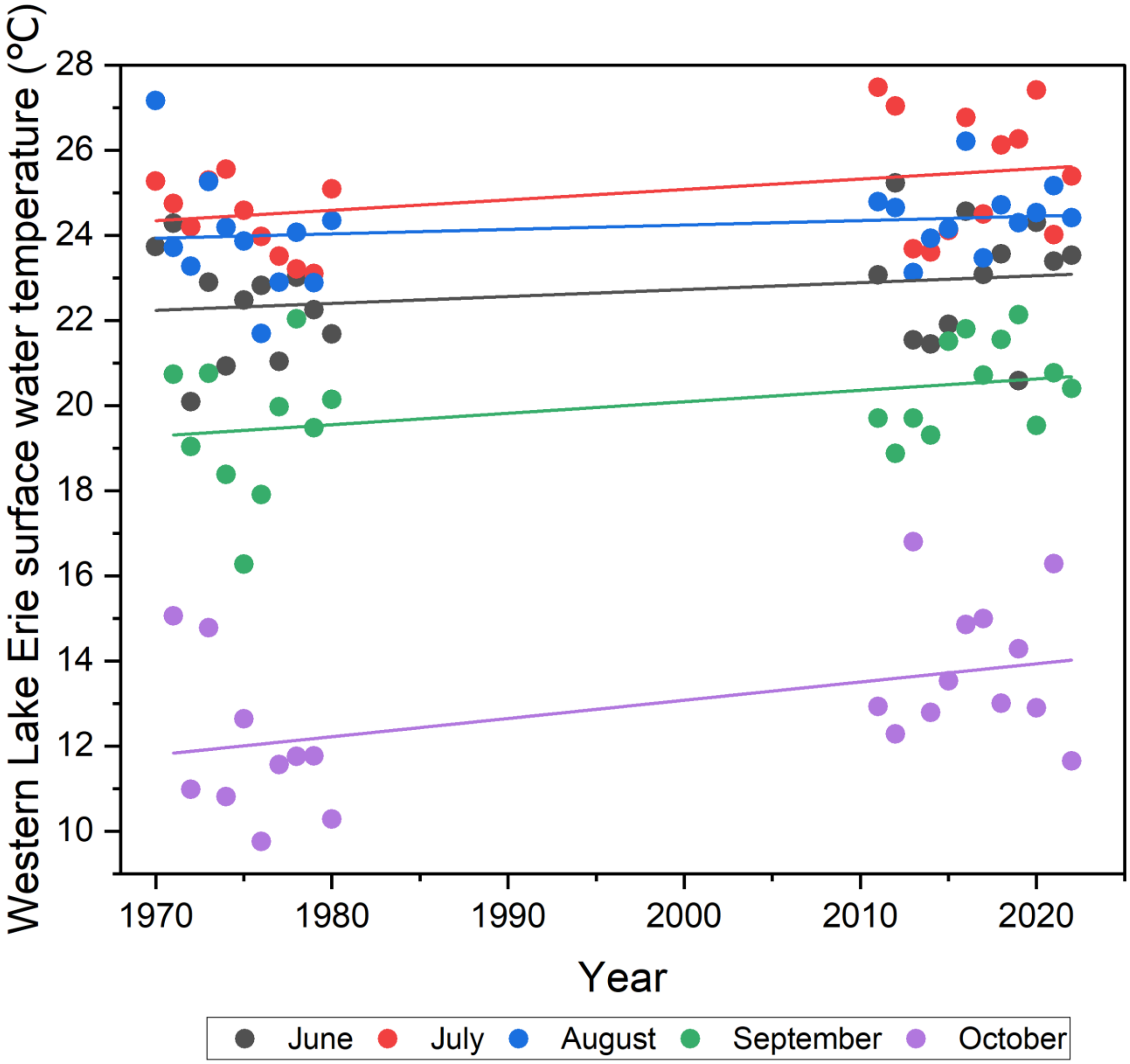

Figure 4.S3 Western Lake Erie surface water temperature. This information was collected from USGS 04199500 station (https://dashboard.waterdata.usgs.gov/app/nwd/en/?aoi=default)

Connecting text to Chapter 5

In Chapter 4, we find that the impact of hydrology on Lake Erie P pollution is increasing. Despite the growing adoption of conservatiion practices, it's unlikely that eutrophication issues driven by P loss will diminish in Lake Erie in the coming years. In Chapter 5, we focus to examining the feasibility of reducing P applications as a fundamental approach to tackle the root causes of P loss.

We develop a comprehensive P cycling model to assess P fluxes within Canada, enabling us to compute long-term agricultural soil P balances across different regions and periods, employing a mass balance approach.

The manuscript in Chapter 4 is currently undergoing the review process in the Journal of Hydrology:

Wang, J., Qi, Z., Nand, V., & Li, Z. (2023). Modeling 1974-2040 phosphorus dynamics in the outlet of Maumee River watershed

Chapter 5

Changes in Canada's phosphorus cycle 1961-2018: surplus and deficits

Jiaxin Wang, Zhiming Qi and Elena M. Bennett

Abstract

Human activities have greatly changed global phosphorus (P) cycling, posing urgent challenges related to both supply uncertainty and aquatic eutrophication. However, the long-term dynamics of P across Canada remain unquantified and under-explored. Using a material flow analysis model, we quantified temporal dynamics of P cycling in Canadian provinces from 1961 to 2018 and characterized the changes in soil P balances through the study period. We found most Canadian agricultural regions had soil P surpluses except Saskatchewan, where large P deficits (-10-0 kg ha^{-1} y^{-1}) were detected in almost all study years (except 1961). In 2018, Quebec and Atlantic provinces had the highest P surpluses (34 and 159 kg ha^{-1} y^{-1}, respectively), and low P surpluses were observed in Ontario, Manitoba, Alberta and British Columbia (9, 16, 5 and 28 kg ha^{-1} y^{-1}, respectively). P surplus was reduced in Quebec and Ontario after the nutrient management regulations were put in place in the 1980s. We demonstrated that P flows in cropland played a larger role in Canada P cycling than pasture. P use efficiency tended to be greatest in the Prairie provinces (0.74 in 2018), and least in the Atlantic provinces (0.12 in 2018). However, the rate of increase was considerably steeper in Ontario and Quebec than other provinces. Reducing inorganic fertilizer and manure application would be the most effective method to reduce remaining P surpluses.

5.1 Introduction

Human activities have greatly changed global phosphorus (P) cycling, an essential nutrient required for the growth of all crops and animals (Elser and Bennett, 2011). Globally, 80% of P extracted from finite and dwindling phosphate rock is used as fertilizer (Van Vuuren et al., 2010). Currently, the world applies 15 times more inorganic P than was applied in pre-industrial times (Smil, 2000). Since the 1940s, growing consumption of inorganic P fertilizers has contributed to major increases in crop yields around the world (Ringeval et al., 2014). At the same time, P loss from agricultural systems has resulted in serious eutrophication in freshwater and coastal systems (Schindler et al., 2008). The current rate of P flow into oceans is more than eight times greater than the pre-industrial level (Rockström et al. 2009). These changes in P flows have focused attention on evaluating P mobilization from land to aquatic systems to inform forward-looking practices and policies that can regulate long-term P sustainability (Filippelli, 2018; Alewell et al., 2020). Although several previous studies have modeled the global P cycle (Chen and Graedel, 2016; Cordell et al., 2009; MacDonald et al., 2011), there is still limited understanding of some regional P cycles.

Canada, a world-leading agricultural producer (Sarkar et al., 2018), is facing serious water pollution caused by agricultural P losses (Council of Canadian Academies, 2013). Since only about 4% of its land is arable, Canada relies heavily on agrochemicals, including P fertilizers, to maintain its elevated level of food production (Malaj et al., 2020). Yet the excess P discharged into the environment has caused serious eutrophication in Canada's rivers and lakes (Boivin-Rioux et al., 2021; Bunting et al., 2016; Seewer, 2015). Environment Canada (2011) indicated that from 2005 to 2007, 32% of surface water quality monitoring sites in Canada exceeded P guidelines more than half the time. This has devastating consequences for biodiversity, water quality and economies. Smith et al. (2019) showed that algal blooms in Lake Erie cost the Canadian government around $272 million annually.

Efforts to reduce the amount of P entering freshwater have generally focused on field level P management practices. For instance, 4R stewardship for P fertilization (right fertilizer source at the right rate, right time, and right place) (Grant and Flaten, 2019), conservative tillage practices to reduce soil erosion to thus reduce particulate P losses (Duits, 2019), control drainage to manage soil water levels to mitigate dissolved P losses (Sunohara et al., 2016), or adding soil amendments to react with soil P to mitigate P leaching (Eslamian et al., 2018). However, these efforts primarily address field P losses, and reducing P loss will become increasingly difficult the more surplus P is found in watershed soils (Carpenter 2005). All P that enters a watershed must at some point flow downhill, so understanding the P accumulation in watersheds is critical to understanding the sources, and ultimately managing P losses.

Quantifying the P cycle provides a better understanding of P disparities between inflows (e.g., fertilizer) and outflows (e.g., crop removal), supplying a stronger basis for P management strategies (Liu et al., 2016). Several previous studies have modeled part of Canada's P-associated pathways at either a watershed scale or in a single province or region, typically showing that net P inflows have resulted in regional soil P surpluses and great P losses to aquatic systems (Bittman et al., 2017; Goyette et al., 2016; MacDonald and Bennett 2009). A few global P cycle studies have developed national level P soil balances for Canadian cropland (Bouwman et al., 2009; MacDonald et al., 2011; Ringeval et al., 2017), but these low-resolution estimates limit our ability to infer anything about the spatial patterns of surpluses and deficits across the agricultural land. van Bochove et al. (2012) and Reid and Schneider (2019) have assessed Canada agricultural P balance at national scale by using the IROWC-P model; however, they have only provided static assessments when human activities had already become intensive, and there are still gaps in our knowledge of the temporal dynamics of Canada P cycling.

In this study, we build a P cycle model to systematically analyze the temporal dynamics of Canada's P cycle over the period of 1961 to 2018. We further quantify P disparities between inflows and outflows and P use efficiency at provincial scale. We thereafter characterize the changes of spatial distribution of P surplus and deficit through the study period and discuss the implications for regional P management.

5.2 Materials and methods

5.2.1 Material Flow Analysis

Material Flow Analysis (MFA) is a mass-balance model that tracks material flows within a defined system boundary. It is an efficient tool for quantifying P stocks and flows (MacDonald et al., 2011). We built an MFA model that considers the production of principal crops and livestock, and addresses two stocks (*i.e.*, cropland and pasture) at two geographic levels of jurisdiction (*i.e.*, national and provincial). Major components of the MFA model were shown in Fig. 5.1. Our analysis covered the period from 1961 to 2018, with a yearly timestep.

5.2.2 Inflows

Inflows were fertilizers, recycled manures and crop residues, crop seeds, irrigation water and imported crop yields as livestock feed. Annual national imports, mining and consumption of P mineral fertilizers (expressed as the P_2O_5 equivalent) from 1961 to 2018 were collected from the Statistics Division of the International Fertilizer Industry Association (IFASTAT) (https://www.ifastat.org/databases/plant-nutrition) and the provincial consumption was collected from Statistics Canada (https://www150.statcan.gc.ca/n1/en/type/data?MM=1). We assumed no inter-provincial trade in fertilizers since this information is not available. Atmospheric deposition, typically neglected or regarded as a constant in previous studies (Chen and Graedel, 2016; Wironen et al., 2018), was assumed to be 0.4 kg P ha^{-1} y^{-1}, which is consistent with field observations (Živković et al., 2017). Irrigation water P was estimated by multiplying monitored P concentration of source water (0.05 mg L^{-1}) (Little et al., 2010) by irrigation volume reported in Statistics Canada. Crop seed P was estimated based on a database provided by the Statistics Division of the Food and Agricultural Organization of the United Nations (FAOSTAT) (https://www.fao.org/faostat/en/#data), and temporal change of seed P concentration (*e.g.*, the effects of genetic modification) was not considered here. Datasets of imported crop yields were collected from FAOSTAT.

5.2.3 Outflows

Crop production is the main P outflow from cropland; other outputs include crop residues and runoff loss. Statistics Canada provides the provincial annual production and seeding area of 71 major crops that were all considered in our analysis (https://www150.statcan.gc.ca/n1/en/type/data?MM=1). The output pathways of the harvested crops including feed, seed and export, and were obtained from FAOSTAT. Crop residues were estimated based on the corresponding crop straw/yield mass ratio (Li et al., 2012). Crop residue P flow was assessed by multiplying straw mass by the P content in crop straw obtained from the International Plant Nutrition Institute (IPNI, 2015) (http://www.ipni.net/article/IPNI-3296). Crop residue used as animal feed was estimated based on equations proposed by Li et al. (2012) (Table 5.S3).

We also considered the outputs of 17 most important livestock types of Canada, including products sold and P uptake in grazing. Provincial livestock inventory was collected from Statistics Canada. National livestock outputs, including meat, eggs, milk and other tissues (*i.e.*, fat, offal and hides) were collected from FAOSTAT. The P content in livestock output was obtained from Chen and Graedel (2016) and Sattari et al. (2012). We estimated grazing P uptake based on livestock inventory, reported grazing time, and daily grass consumption rates assessed by government documents, literature and farmer consultations (Alberta Lamb Producers, 2013; Blood and Lovaas, 1966; Canada beef, 2015; Feeding 4-H Calves, 2021; Vachon et al., 2007). Daily grass consumption rates were different by livestock species, and set to constants (Table 5.S6). Livestock manure P was specified by livestock types (Table 5.S4), and estimated by multiplying livestock populations by their P excreta rates (Lun et al., 2018).

Runoff losses were always estimated by multiplying total soil inputs by a loss factor (Sattari et al., 2012, 2016; Bouwman et al., 2013; Lun et al., 2018; Wironen et al., 2018). In North America, the loss factor was assumed to range from 5% to 10% (Lun et al., 2018; Sattari et al., 2012; Wironen et al., 2018). Here we adopted a loss factor of 7%, a median value from these studies.

5.2.4 Interflows

Interflows included recycled P flows of sludges, crop residues and manures. Sludge P flow included detergent and human excreta P flows. The P emissions from laundry and dishwasher detergents were estimated based on detergent P consumption (0.24 and 0.04 kg P yr^{-1} per capita in laundry and dishwater, respectively before 2010; 0.1 and 0.11 kg P yr^{-1} per capita in laundry and dishwater, respectively after 2010) (van Puijenbroek et al., 2018), and resident population was provided by FAOSTAT. P-free detergent sold in Canada's market was not considered here due to data scarcity. Human excreta P was estimated based on the excreta ratio (0.43 kg yr^{-1} per capita) (Cordell et al., 2009; Van Staden, 2019). Considering the relatively slow development of wastewater recycling compared to Europe Union countries (30% in the Netherlands, Cordell and White, 2013; 25% in Germany, Ross and Omelon, 2018), and the percentage of population served by sewerage treatment in Canada was close to Germany (Hitchman, 2018), we therefore assumed 20% of P from detergent and human excreta were processed and recycled to cropland. Previous studies suggested at least 0.75 Mg ha^{-1} of straw should be left on the land for soil conservation (Sokhansanj et al., 2006; Stumborg and Townley-Smith, 2004). Li et al. (2012) reviewed previous field papers and showed 30-75% of crop residues were left on ground to protect soil from erosion, Liu and Lobb (2021) suggested 40% of crop residues would be left on the field. A government document from Ontario showed that 60% of crop residues were left in the field (Oo and Lalonde, 2012), so we assumed 50% of the crop residues were recovered to cropland. Similar assumption can also be found in previous P cycling studies (Lun et al., 2018; Macdonald et al., 2011). The rest of the residues were baled for livestock feed (Table 5.S3), or bioenergy use/burning which were not explored in this study. For each province, manure left on pasture, recycled to cropland, or lost during handling were assessed based on the proportion estimations of Huffman et al. (2008) (Table 5.S4). Harvested crops as livestock feed were collected from FAOSTAT.

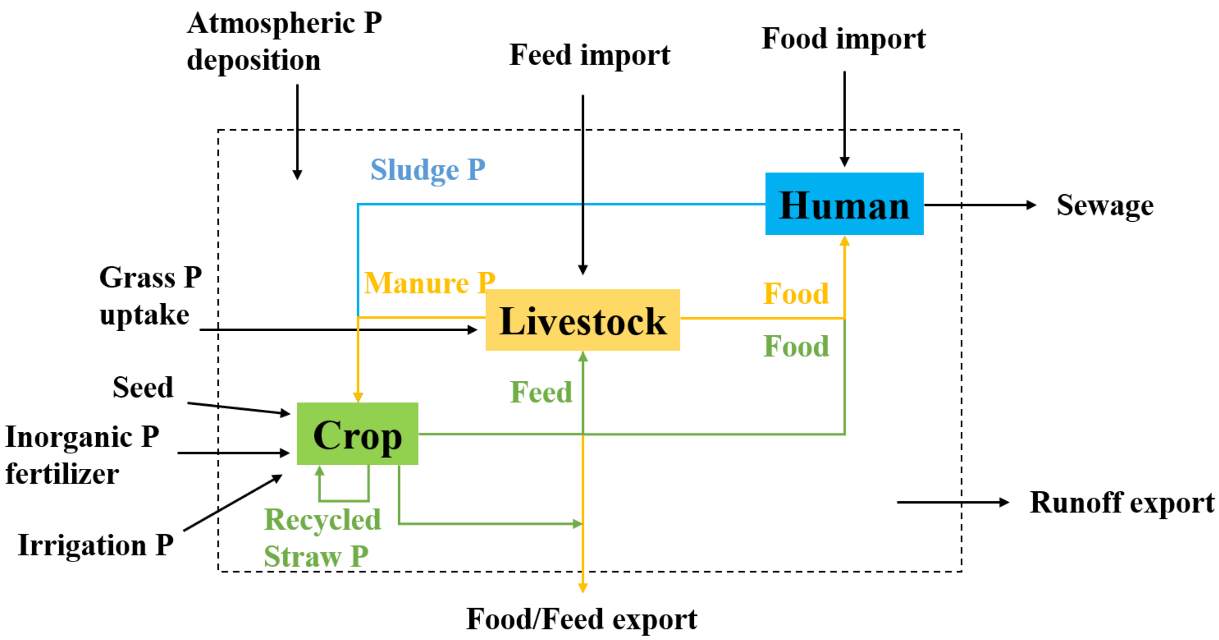

Figure 5.1 Canadian major components of the P flows analysis model at the national scale. Green solid lines refer to P flows from cropland, yellow solid lines refer to P flows from livestock production, and blue solid lines refer to P flows from human systems. For provincial scale modeling, feed import, food import and food/feed export are excluded due to data unavailable.

5.2.5 Soil phosphorus balance

The soil stock changes were based on the net P-balance (*i.e.*, the annual total P inputs minus the total outputs). We used Eqs. (1-4) to estimate soil P balance for a specific type crop in a given province, by assuming crop species with higher P removal rates required higher P fertilizer applications (Eq. 3), to finally depict national cropland P balance map.

$$P_{budget_i} = \frac{P_{Total\_input_i} - P_{Total\_output_i}}{Area_i} \quad (5.1)$$

$$P_{Total\_input_i} = P_{Fertilizer\_input_i} + P_{atmosp_i} + P_{residue2soil_i} + P_{seed_i} \quad (5.2)$$

$$P_{Fertilizer\_input_i} = \left(P_{fert} + P_{manure2soil} + P_{slud}\right) \times \frac{P_{crop_i}}{\sum_{i=1}^{n} P_{crop_i}} \quad (5.3)$$

$$P_{Total\_output_i} = P_{crop_i} + P_{resid_i} + P_{Total\_input_i} \times F_{loss} \quad (5.4)$$

where for a given province, i is the number of the specific crop, n is the total number of crops for that province, P_{budget_i} is the i^{th} crop's P balance (kg ha^{-1}), $P_{Total\_input_i}$ and $P_{Total\_output_i}$ are total P input and output for the i^{th} crop, respectively (Mg), $Area_i$ is the i^{th} crop's seeding area (hectare), $P_{Fertilizer\_input_i}$ is P application (including inorganic fertilizer, manure and sludge) in the i^{th} crop's seeding area (Mg), P_{atmosp_i} is the atmospheric deposition of P in the i^{th} crop's seeding area (Mg), $P_{residue2soil_i}$ is the P in the i^{th} crop's residues recycled to the i^{th} cropland (Mg), P_{seed_i} is the P in the i^{th} crop as seed (Mg), P_{fert}, $P_{manure2soil}$ and P_{slud} are the P in inorganic fertilizers, recycled manure and sludge applied in the given province (Mg), P_{crop_i} is the P in the i^{th} harvested crop yield (Mg), P_{resid_i} is the P in the i^{th} harvested crop residues (Mg), F_{loss} is the runoff P losses factor (7 %). Most P flows were estimated by multiplying a material quantity (e.g., Mg of wheat) by a conversion factor representing the material's P-content (% P) (Tables 5.S1 and 5.S2).

5.2.6 Phosphorus use efficiency

Phosphorus use efficiency (PUE) is an important indicator of how efficiently the agricultural system converts P inputs into P outputs. We calculated PUE as a ratio of outflows to inflows, and defined cropland total PUE ($PUE_{Cropland\_total}$), cropland PUE ($PUE_{Cropland}$, *i.e.*, excluding residues), and livestock total PUE ($PUE_{Livestock\_total}$), and livestock (excluding manure) PUE ($PUE_{Livestock}$) (Lun et al., 2018):

$$PUE_{Cropland\_total} = \frac{P_{crop}+P_{resid}}{P_{fert}+P_{atmosp}+P_{residue2soil}+P_{manure2soil}+P_{seed}+P_{slud}} \quad (5.5)$$

$$PUE_{Cropland} = \frac{P_{crop}}{P_{fert}+P_{atmosp}+P_{residue2soil}+P_{manure2soil}+P_{seed}+P_{slud}} \quad (5.6)$$

$$PUE_{Livestock\_total} = \frac{P_{milk}+P_{egg}+P_{meat}+P_{tissu}+P_{manu}}{P_{feed}+P_{graze}+P_{residue2feed}} \quad (5.7)$$

$$PUE_{Livestock} = \frac{P_{milk}+P_{egg}+P_{meat}+P_{tissu}}{P_{feed}+P_{graze}+P_{residue2feed}} \quad (5.8)$$

where P_{crop} is the P in harvested crops (Mg), P_{resid} is the P in crop residues (Mg), P_{fert} is the P in inorganic fertilizers (Mg), P_{atmosp} is the atmospheric deposition P (Mg), $P_{residue2soil}$ is the P in the crop's residues recycled to the cropland (Mg), $P_{manure2soil}$ is the P in the livestock manure recycled to the cropland (Mg), P_{seed} is the P in crop seed (Mg), P_{slud} is the P in sludge applied into cropland (Mg), P_{egg}, P_{meat}, P_{milk}, P_{tissu} are the P in eggs, meat, milk and tissues (the sum of P in fats, offals and hides), respectively (Mg), P_{manu} is the P in manure (Mg), P_{feed} is the P in domestic and imported crop yields as livestock feed (Mg), P_{graze} is pasture livestock uptake P

(Mg), $P_{residue2feed}$ is the P in crop residues used as animal feed (Mg). We defined total PUE toward understanding the ratio of total P outputs, excluding runoff P losses, compared to total P inputs from cropland (or pasture). We defined PUE excluding crop residue (manure) to assess the ratio of P in the harvested economic outputs to total P inputs. Because of lacking provincial-scale livestock production datasets, we only calculated livestock PUE at national scale. We used linear and polynomial fitting to interpret long-term PUE trend, fitting equations were shown in Table 5.S7.

5.2.7 Uncertainty analysis

Since most of the statistical datasets were collected from official or international databases, and there was no repetitive dataset available, uncertainties from the material flux data (*e.g.*, clerical errors) were excluded and we only addressed the uncertainties of the main P flows propagated when P coefficients remained within the range reported in the literature, results were shown in the Supporting Information.

5.3 Results

5.3.1 P flows at national scale

From 1961 to 2018, we found annual P surpluses consistently in both cropland and pasture at the national scale (Fig. 5.2a); however, the pastures' mean P surplus was insignificant (1.9 kg ha^{-1} y^{-1}) (Fig. 5.S1). Nationwide, cropland P inputs were mainly from inorganic P fertilizers and manure. P fertilizer consumption rate increased from 78 Gg y^{-1} in 1961 to 495 Gg y^{-1} in 2018 (Fig. 5.2b), while manure P flow remained at approximately 103 Gg y^{-1} throughout the study (Fig. 5.2c). Crop residue P remaining in soil showed an increasing trend from 24 Gg y^{-1} in 1961 to 112 Gg y^{-1} in 2018. Other inflows, including those of crop seeds, sludge, irrigation and atmospheric deposition barely changed (on average, 7.4, 3.8, 0.0 and 9.7 Gg y^{-1}, respectively), and their impacts were relatively insignificant in Canada overall P cycling.

Crop removal was the largest P outflow, increasing from 67 to 414 Gg y^{-1} over the study period (Fig. 5.2d). Crop also contributed more than 90% of the P in food supplied to the domestic market (Fig. 5.2e). Cropland contributed the largest P flux to freshwater (Fig. 5.2f), increasing from 14.2 to 48.3 Gg y^{-1} during the study period. The second largest contributor was human waste, which increased from 10.3 to 18.9 Gg y^{-1}, while P flux from pasture to freshwater systems was maintained at about 4.3 Gg y^{-1} throughout the study period.

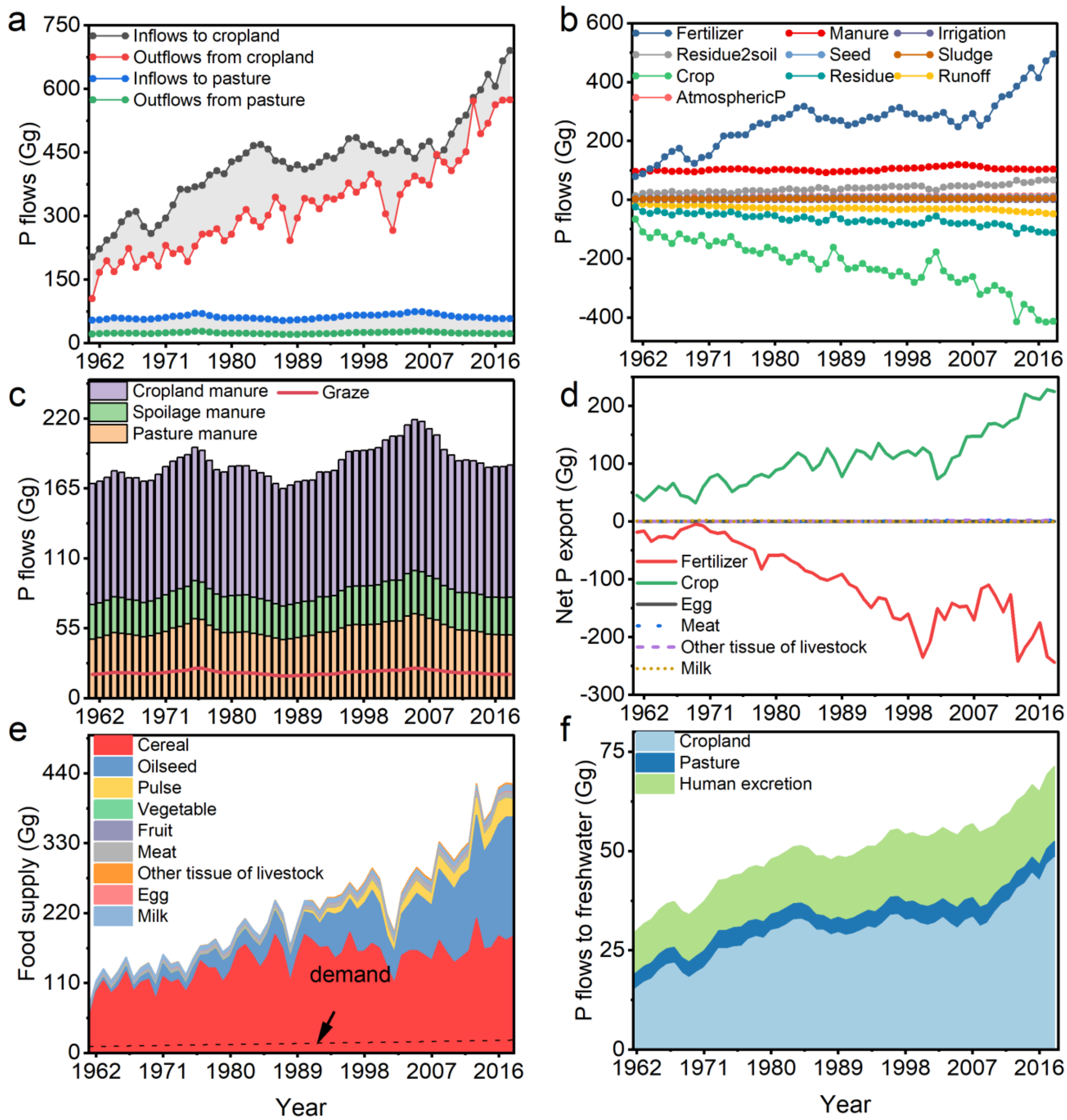

Figure 5.2 Temporal changes in the P cycle in Canada agricultural land. (a) Total P inflows and outflows of Canada agricultural land. (b) Variations of key P flows in cropland. (c) Variations of key P flows in pasture. (d) P flows embedded in internationally traded commodities, positive value represents net export and negative value represents net import. (e) Composition of food-P supply and human P demand (estimated by population multiplied by human P excreta rate). (f) P losses to freshwater.

5.3.2 P flows at provincial scale

Inorganic fertilizer and manure were the most important P inflow to provincial cropland from 1961 to 2018 (Fig. 5.3). The Prairie provinces had the highest P fertilizer consumption rates, which increased from 44 Gg y^{-1} in 1961 to 399 Gg y^{-1} in 2018. In contrast, P fertilizer consumption in Atlantic provinces, Quebec, Ontario and British Columbia were much lower (22, 26, 48 and 0 Gg y^{-1} in 2018, respectively). Manure contributed significantly to the cropland P stock of Quebec and British Columbia, in which maintained approximately 21 Gg y^{-1} (46% in total P flow) and 5 Gg y^{-1} (59% in total P flow), respectively.

There was a consistent annual net P surplus in the croplands of almost all provinces except Saskatchewan, which showed net P deficits. The annual P surplus in Atlantic provinces was comparable to the amount of fertilizer inputs. P surpluses in Quebec and Ontario changed greatly through the study period, with the highest P surpluses around 1980 (45 and 70 Gg y^{-1} respectively). Thereafter, the high P surplus in Ontario gradually decreased to 10 Gg y^{-1} in 2018, while a relatively high soil P surplus of 24 Gg y^{-1} was still observed in Quebec. P surplus in the Prairie provinces tended to be more variable but smaller, with an average of 14 Gg y^{-1} and 18 Gg y^{-1} of P surplus observed in Manitoba and Alberta respectively, while P deficit of 13 Gg y^{-1} was detected in Saskatchewan. P surplus in British Columbia was strongly affected by fertilizer application, with the highest surplus reaching 10 Gg y^{-1} between 1980 and 1990, thereafter declining to 2 Gg y^{-1} in 2018.

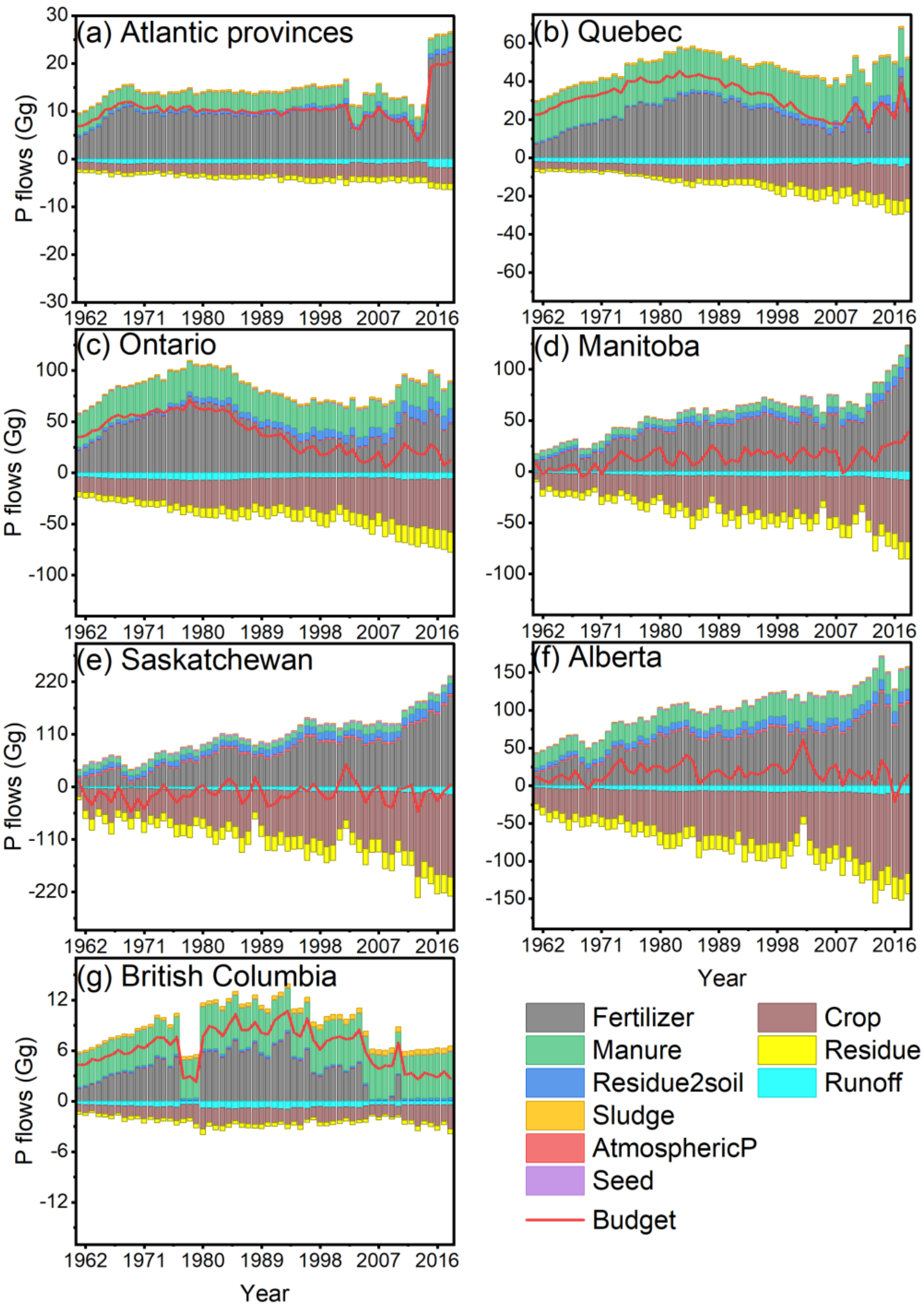

Figure 5.3 Temporal dynamics of P flows in Canada cropland from 1961 to 2018.

We found a consistent annual net P surplus in pasture of all provinces, in which manure and grazing were the major P inflow and outflow, respectively (Fig. 5.4). A consistently decreasing P surplus trend was observed in pasture of Atlantic provinces, Quebec and Ontario (reducing to 1, 2 and 2 Gg y^{-1} in 2018, respectively), while the Prairie provinces and British Columbia maintained a relatively high P surplus (approximately 8 and 3 Gg y^{-1}, respectively).

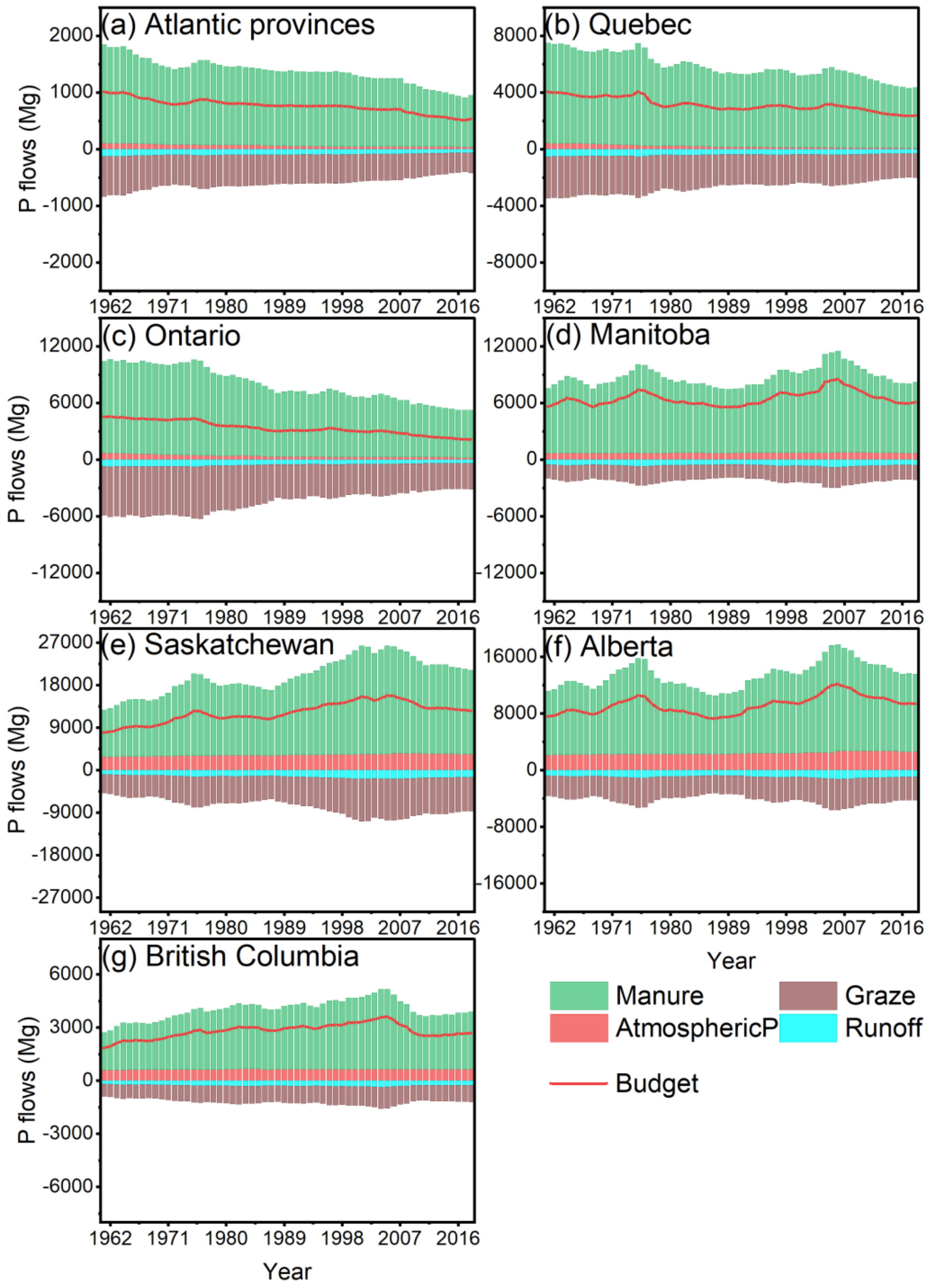

Figure 5.4 Temporal dynamics of P flows in Canada pasture from 1961 to 2018.

Most Canadian agricultural areas had a soil P surplus in most years of our study (Fig. 5.5), except Saskatchewan, where P deficits (-10-0 kg ha^{-1} y^{-1}) were detected in almost all study years except

1961. We consistently observed relatively low soil P surplus in Manitoba, Alberta and British Columbia, with the highest field P surplus in 2018 reaching 16, 5 and 28 kg ha^{-1} y^{-1}, respectively. We observed high P surplus in southern Quebec and the Atlantic provinces (34 and 159 kg ha^{-1} y^{-1}, respectively, in 2018). For Ontario, the amount of P surplus generally decreased from 1961 to 2018, reducing to just 9 kg ha^{-1} y^{-1} in 2018.

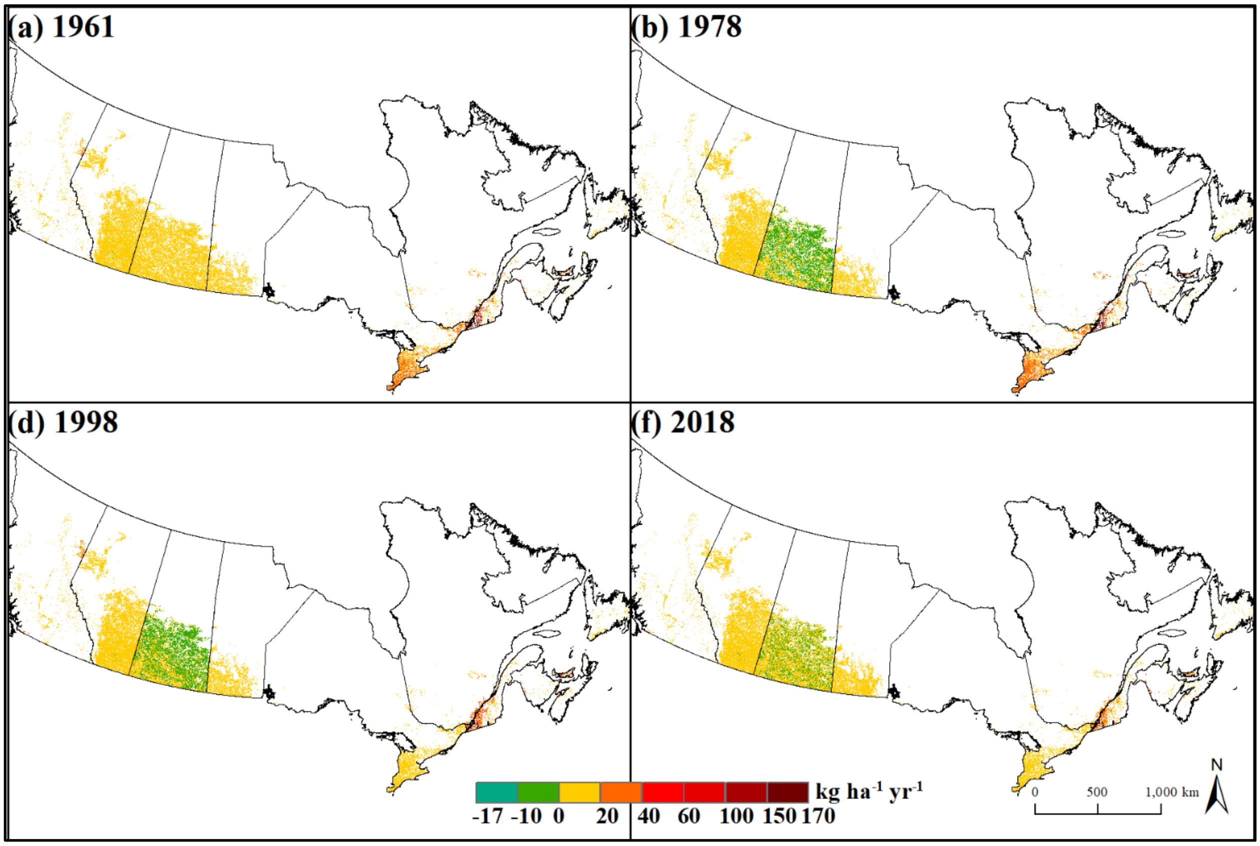

Figure 5.5 Spatial variation of Canada agricultural soil P balance throughout the study period. Data are shown for 1961, 1978 (peak of P surplus), 1998 (transition in trends) and 2018. Annual Space-based Crop Inventory (ACI) map is provided by Agriculture and Agri-Food Canada (AAFC) for 2018.

5.3.3 Phosphorus Use Efficiency

We found that all provinces except Saskatchewan showed an increasing trend in both cropland and total phosphorus use efficiency (PUE) across the study period (Fig. 5.6). The rate at which PUE increased was considerably steeper in Quebec and Ontario than in other provinces, with cropland PUE consistently increasing to 0.34 and 0.58, respectively by 2018. Manitoba and Alberta consistently maintained a relatively stable cropland PUE from 1961 to 2018 (0.49 and 0.67 in 2018, respectively). The highest cropland PUE in 2018 was observed in Saskatchewan (0.74). PUE of Atlantic provinces and British Columbia showed a relatively slow climb to 0.12 and 0.43 in 2018, and PUE of British Columbia was strongly correlated to fertilizer application.

For pasture systems, livestock total PUE values above 1 were observed before 1971, which might be related to missing early crop feed data, thereafter the values remained approximately 1. The long-term livestock PUE barely changed and showed a slow climbing trend to 0.2 in 2018 (Fig. 5.7).

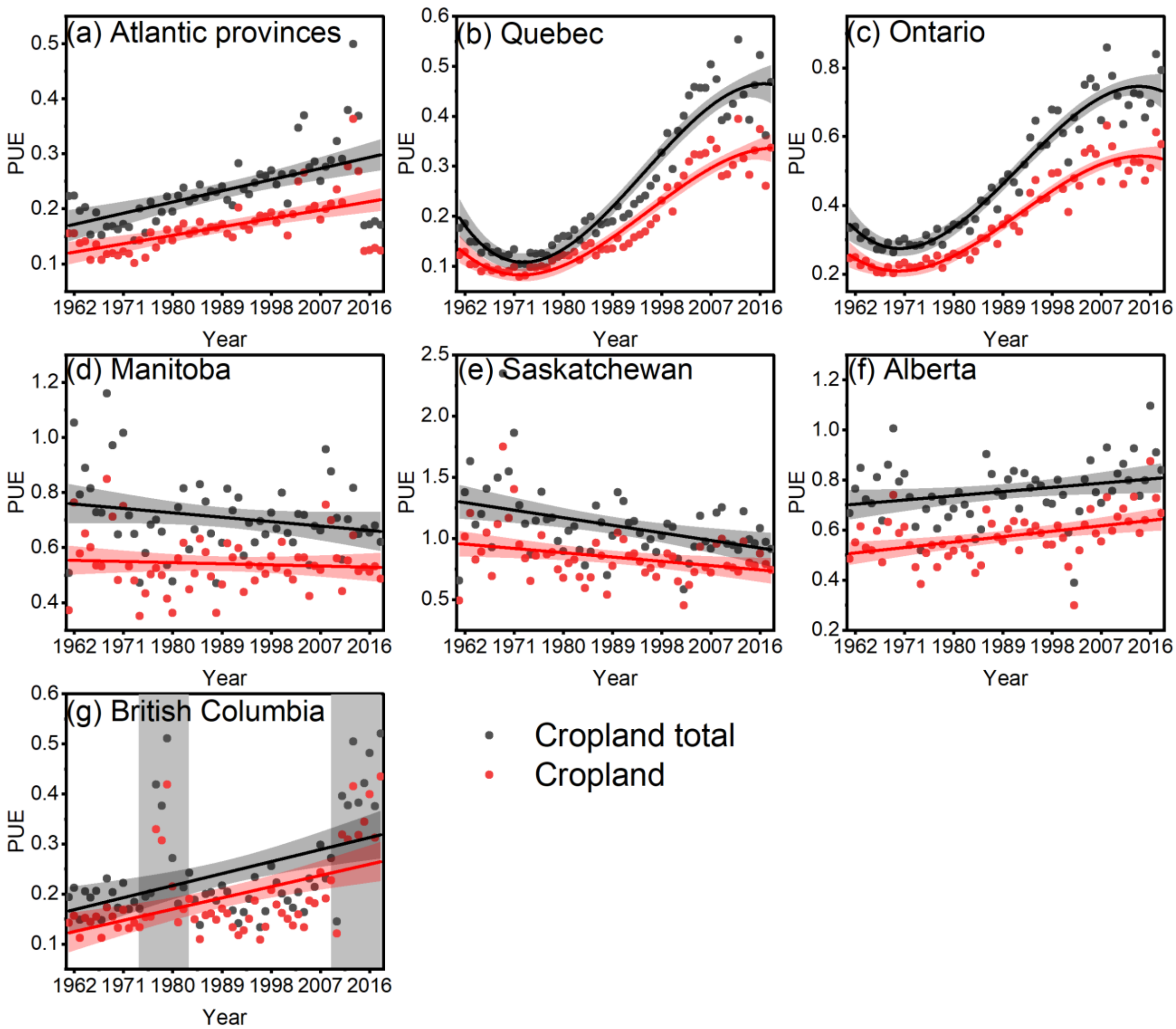

Figure 5.6 Annual changes of the calculated PUE in Canada cropland at the provincial scale from 1961 to 2018. Fitted line and 95% confidence intervals (shaded area) are presented. Cropland total PUE is the sum of P outflow of crop grain and total residue divided by the sum of P inflow of

inorganic fertilizer, recycled manure, atmospheric deposition, recycled crop residue, seed and recycled sludge, cropland PUE includes the same P inflows while only consider the P outflow of crop grain (*i.e.*, excluding residues). Gray regions bounded anomalies between 1976-1980, and 2010-2018, in British Columbia.

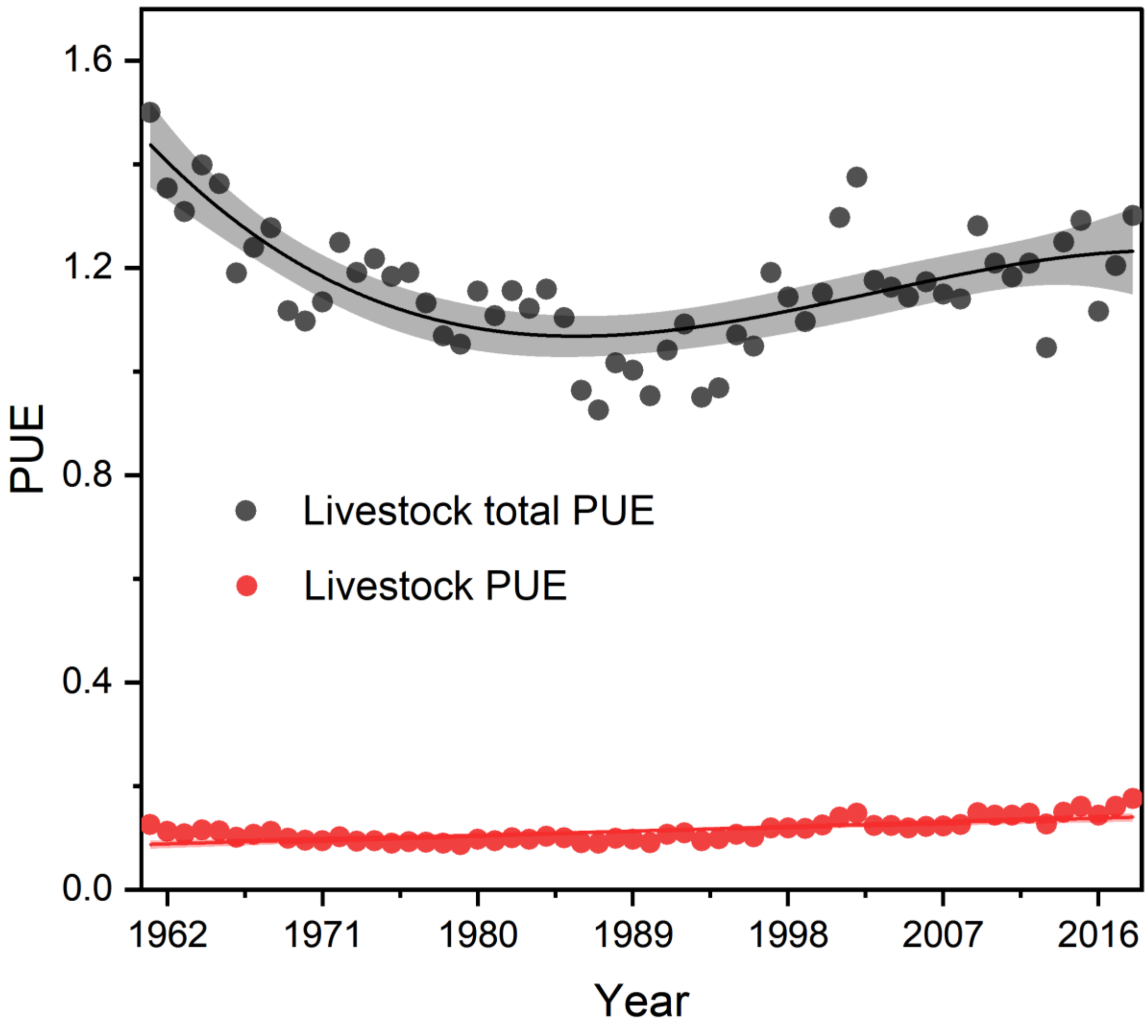

Figure 5.7 Annual changes of the calculated PUE in Canada pasture at the national scale. Fitted line and 95% confidence intervals (shaded area) are presented. Livestock total PUE is the sum of P outflow of egg, milk, livestock meat, other tissues and manure divided by the sum of P inflow of livestock feed from crop grain, crop residue and grass, livestock PUE includes the same P inflows while exclude the P outflow of livestock manure.

5.4 Discussion

5.4.1 P flows across Canada

In this study, we demonstrated that P flows within cropland played the larger role to Canada P cycling compared to pasture. We showed high annual agricultural P surplus in Quebec and found the most observable annual P surplus reduction over time in Ontario. Manure was an important contributor to cropland P surplus of Quebec and Ontario, which may partly be explained by the over-application of manure to maintain soil nitrogen level while unintended applied more P than the crops can uptake (Reid et al., 2019), as well as the geographically concentrated livestock production (Beaulieu et al., 2006; MacDonald and Bennett, 2009). Between the late 1970s and early 1980s, large quantities of mineral fertilizers and manure had been reported that applied on Quebec and Ontario cropland to obtain higher yields (Bruulsema et al., 2011; IJC, 2018; van Bochove et al., 2011). This has resulted in a high P build-up in agricultural soils (Fig. 5.3), and we found declining rates of surplus since then, which maybe mainly explained by mandatory field P management, local P regulate policies, and an increasing public awareness of P pollution (GLWQA, 2012). And the consistently obvious P surplus reduction in Ontario could be partly attributed to an increasing seeding area of oilseed crops (Fig. 5.S3) that have a relatively high P removal rate (Table 5.S1).

High agricultural P surpluses in Atlantic provinces might be explained by the rapidly growing agriculture industry (*e.g.*, intensive livestock and potato production) without effective fertilizer management. For instance, in Prince Edward Island, potato yields had consistently increased over the past 35 years, grain corn had increased 151.3% since 2006, and canola area increased from 158 acres in 2006 acres to 2962 acres in 2011 (PEI Department of Agriculture and Forestry, 2012). While continued inputs of fertilizers in excess of crop requirements had led to a build-up of soil nutrient levels, Burton (2019) had shown that residual soil nitrogen had increased to a very high level through much of Atlantic region. A recent two-year experiment in New Brunswick had showed that the current P recommendations for potatoes can be reduced without affecting yield (Nyiraneza et al., 2017), highlighting the need to progressively adjust fertilizer inputs in coming years. Additionally, Kedir et al. (2021) suggested that P accumulation in Atlantic provinces could be attributed to the conversion from forest to agricultural land that soils have a significant P adsorption capacity.

Low P surplus observed in Manitoba and Alberta might be explained by an increase in organic farmland in the three Prairie provinces (Canada Organic Trade Association, 2017), where external inputs of inorganic P fertilizer are restricted (Entz et al., 2001; Løes and Øgaard, 2001; Martin et al., 2007; Schneider et al., 2019; Welsh et al., 2009). The P surplus in British Columbia may be attributed to its limited geographical opportunity for nutrient export (Reid and Schneider, 2019), and the geographically concentrated over-application of cattle and poultry manure (Fig. 5.S4). Large area P deficits observed in Saskatchewan in 2018 was consistent with previous soil P tests conducted in 2015 that over 80% of the agricultural soils were testing deficient (Guenther, 2017). Except for the increasing of organic farmland, this might be associated with the changes in cropping systems that consistently increasing yields of high P removal crop varieties (*e.g.*, oilseed and pulse crops), against unchanged P application rates, had further depleted soil P (Barker, 2016; Booker, 2017). Besides, more focuses are on N because its deficiency symptoms are much more visible than P deficiencies, may also contribute to soil P deficiency (Fleury, 2018).

5.4.2 Implications for P Management

Our results indicated Canadian cropland still faced a great P surplus in 2018, driven primarily by mineral fertilizer and manure application. The most likely method in the short-term to stop soil P accumulating is to reduce fertilizer and manure inputs. Six-year corn experiments in Quebec suggested it was unnecessary to apply inorganic P fertilizer when manure was applied at rates complying with the field application guidance (Parent et al., 2020). A high P buildup field trial in Saskatchewan showed that wheat grew just as well with only nitrogen fertilization as when fertilized with additional P fertilizer over a 15-year period (Liu et al., 2015). Similar field experiments in Ontario showed soil residual P sustained corn and soybean yields compared to those with continuous P addition over 11 years (Zhang et al., 2020). Taken together, these results suggest that P fertilizer could be further reduced without a major detrimental impact on crop production.

P accumulation in soils could also be mitigated by increasing crop uptake, either by increasing the proportion of crops with high P uptake (*e.g.*, oilseed crops) or by adding additional crops into the rotation (Welsh et al., 2009). A review of the literature suggests winter forages as cover crops could successfully reduce soil residual N (Ketterings et al., 2015), which would have the side benefit of increasing P removal from the soil (Reid et al., 2019), while suitable species for Canada require further research because of frigid conditions (Zhang et al., 2017b). A few studies have also suggested that winter cover crops might undesirably release dissolved reactive P because of the disruption of plant cells caused by freeze-thaw cycles (Lozier and Macrae, 2017; Lozier et al., 2017; Miller et al., 1994), but it may still be effective in the areas with the greatest P surplus (Cober et al., 2019). Additionally, crop breeding to enhance crop P uptake levels might be another promising way to reduce soil P accumulation (Veneklaas et al., 2012).

Recycling excessive manure from areas of P surplus (*e.g.,* Quebec) to areas with P deficits (*i.e.,* Saskatchewan) appears to be a promising way to address these problems; however, manure freight costs over large distances seems to be a major challenge (Hadrich et al., 2010). While Metson et al. (2016) showed distances between surplus recyclable P manure and crop demands could be shorter than expected, the cost of transporting manure remains substantial. Another concern is that animal excreta often contains antimicrobial additives such as heavy metals and veterinary drugs, which could affect soil biology (Li et al., 2011). Several recent studies have focused on the role of renewable energy production as a way to overcome manure cost issues (Metson et al., 2022; Vanttinen, 2022); however, the manure transportation and fermentation process can also produce greenhouse gases, resulting environmental problems (Guo et al., 2022).

Decreasing manure P concentration might be one way to effectively reduce manure-induced soil P surplus. A previous literature review suggested that adding a phytase supplement to pigs' diet, or genetically modifying pigs (Golovan et al., 2001; Spencer et al., 2000) could increase P digestibility or retention, decreasing the need for P supplements, and therefore decreasing P excretion by 25% to 50% (Knowlton et al., 2004). Yet the opportunities for this technology might be limited because the use of phytase has already been widely adopted (Reid et al., 2019). Besides, it is feasible to reduce the P excretion by livestock through ration balancing to decrease dietary P intake. This is relatively straightforward on most swine or poultry farms, where the stock are fed a complete ration, although it may require a "phase feeding" approach, with different rations at different growth stages (Reid et al., 2019).

It should be noted that crop residue P that recycled to soil was consistently increasing, attributable to crop yields increasing (Fig. 5.2), while several studies have showed recycled crop residues unintentionally increased soluble P losses during snowmelting that generating eutrophication risks (Baker et al., 2017; Daryanto et al., 2017; Jarvie et al., 2017; Zhang et al., 2017a), hence more attention maybe needed in the future (Macrae et al., 2021).

5.4.3 Evaluation of Results and limitations

Our results are broadly comparable to others who used a similar agronomic balance approach. Soil P balance estimations in Ontario parallel those of Van Staden's long-term assessment (Van Staden, 2019). The highest P surplus in Ontario estimated by Van Staden (2019) was 37 kg ha^{-1} y^{-1} in 1981, which was slightly lower than our highest P surplus estimation for 1978 (59 kg ha^{-1} y^{-1}), but was close to our estimation for 1981 (44 kg ha^{-1} y^{-1}), thereafter our result aligns with Van Staden's that Ontario' soil P surplus decreases to 9-15 kg ha^{-1} y^{-1} in 2016. MacDonald and Bennett (2009) estimated the highest P surplus in southern Quebec watersheds in 1981 to have attained 100 kg ha^{-1} y^{-1}, which was comparable to our estimation (122 kg ha^{-1} y^{-1}). In addition, the average watershed soil P content based on 1995–2001 Quebec survey data was 117±49.1 kg ha^{-1} (MacDonald and Bennett, 2009), which was higher than our estimation (74 kg ha^{-1}), indicating that in reality Quebec's soil P surplus might be even worse than our estimations (Damar et al., 2021). Reid and Schneider (2019) indicated that > 600 kg P ha^{-1} accumulated in Atlantic provinces from 1976 to 2011, while our results suggest a possibly greater soil P accumulation (3000 kg P ha^{-1}), which might be explained by the differences between specific crop P balance calculations (Eqs. 1-4). For British Columbia, Harder et al. (2021) estimated soil P balance in the Okanagan Valley, and most census units had P surpluses, with the greatest attained 0.39 Gg, Bittman et al. (2017) assessed there was 3.65 Gg y^{-1} net P inputs to Fraser valley agricultural soils in 2011, which was similar to our geographical result (3.16 Gg y^{-1} P). We demonstrated negative soil P balance in Saskatchewan, which was consistent with Reid and Schneider (2019), and van Bochove et al. (2012) calculated soil P surpluses for Saskatchewan ranging from -2 to 2 kg ha^{-1} y^{-1} from 1981 to 2006, which concurred with our results (-4 to 4 kg ha^{-1} y^{-1}).

Due to high uncertainties in livestock weight, livestock waste production and manure P content which could have changed because of different dietary regimes and animal performance, the highest uncertainty was found in manure P flow (Fig. 5.S5), which may partly explain the livestock total PUE values higher than 1 (Fig. 5.7). Other P flows including atmospheric deposition, recycled sludge, irrigation, or livestock production were not numerically important pieces of Canada's P cycling.

A major limitation of this study was that we constantly assumed 7% of total P inputs as runoff P losses, and the variations of runoff P loss in different seasons were not explored in this study (Liu et al., 2021; Plach et al., 2019). However, our national inter-year runoff P loss results were comparable to Alewell et al. (2020), who particularly assessed river P losses in North America (Table 5.S8). Liu et al. (2021) analyzed runoff P loss data of 8 fields in Ontario, Manitoba and Saskatchewan, covering the period from 1995 to 2017, and showed total P losses ranged from 0 to 2.5 kg ha^{-1}, which were also consistent with our results (Table 5.S9).

Another limitation was that we did not consider the response of different soil P-pools (*e.g.*, manure organic P) to runoff losses (Brooker et al., 2018). We did not consider the changes of atmospheric P deposition coefficient causing by global combustion-related P emissions, while Wang et al. (2014) estimated global atmospheric P budget from 1960 to 2007 and showed the P deposition change was small. We constantly assumed 50% of crop residue recycled to field, a better representation would consist of changes of percentage of crop residue recycled. Li et al. (2012) calculated residue coverage by considering temporal changes of land percentage under different tillage practices, whereas information on the percentage of a crop's seeding area under different tillage practices was not available, and our results also suggested recycled residue P did not play an important role to provincial P balances (Fig. 5.3).

5.5. Conclusions

This study has broadened our comprehension of the temporal dynamics of Canada's P cycling with an MFA model, highlighting that P flows within cropland played the most important role to Canada P cycling compared to pasture. This study further quantifies provincial P disparities between inflows and outflows, and characterizes the temporally spatial distribution of soil P balance, suggesting that most Canadian agricultural areas have soil P surplus in 2018, except Saskatchewan, where large P deficits are observed. Cropland P use efficiency tended to be greatest in the Prairie provinces, and the rate of increase was considerably steeper in Ontario and Quebec. Finally, this work provides insight for Canada's regional P management, suggesting that research on how to reduce fertilizer and manure inputs without detrimental impacts on crop yields represents a most important way to reduce Canada's P accumulation.

5.6 Supplementary Tables and Figures

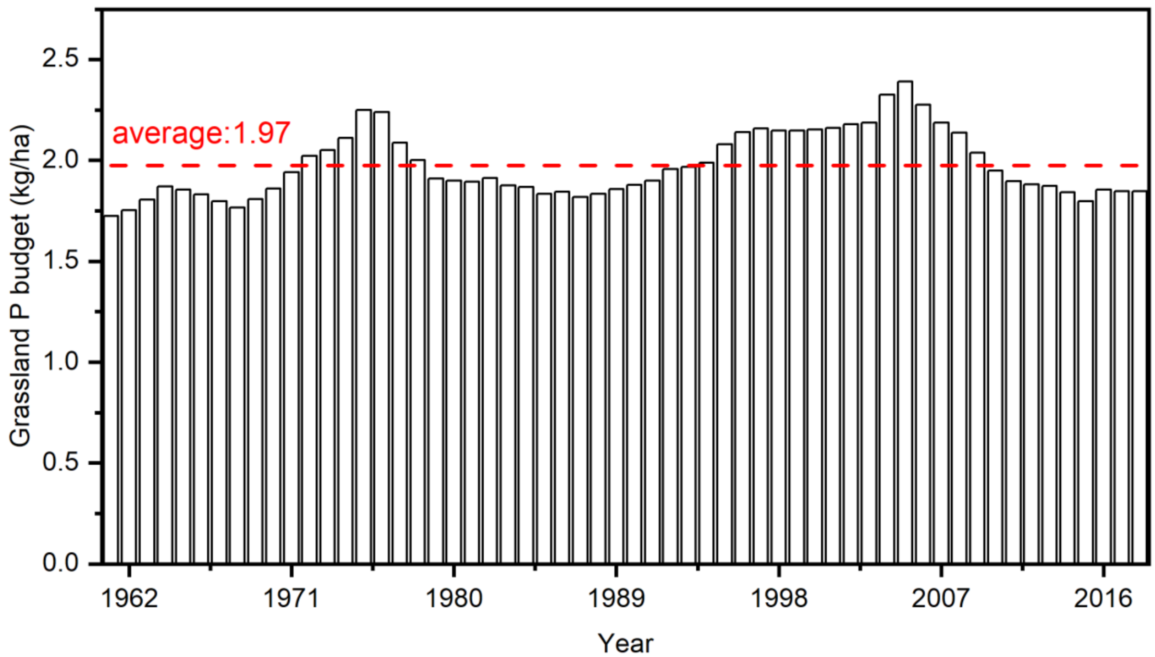

Figure 5.S1 Annual variations of Canadian grassland P budget.

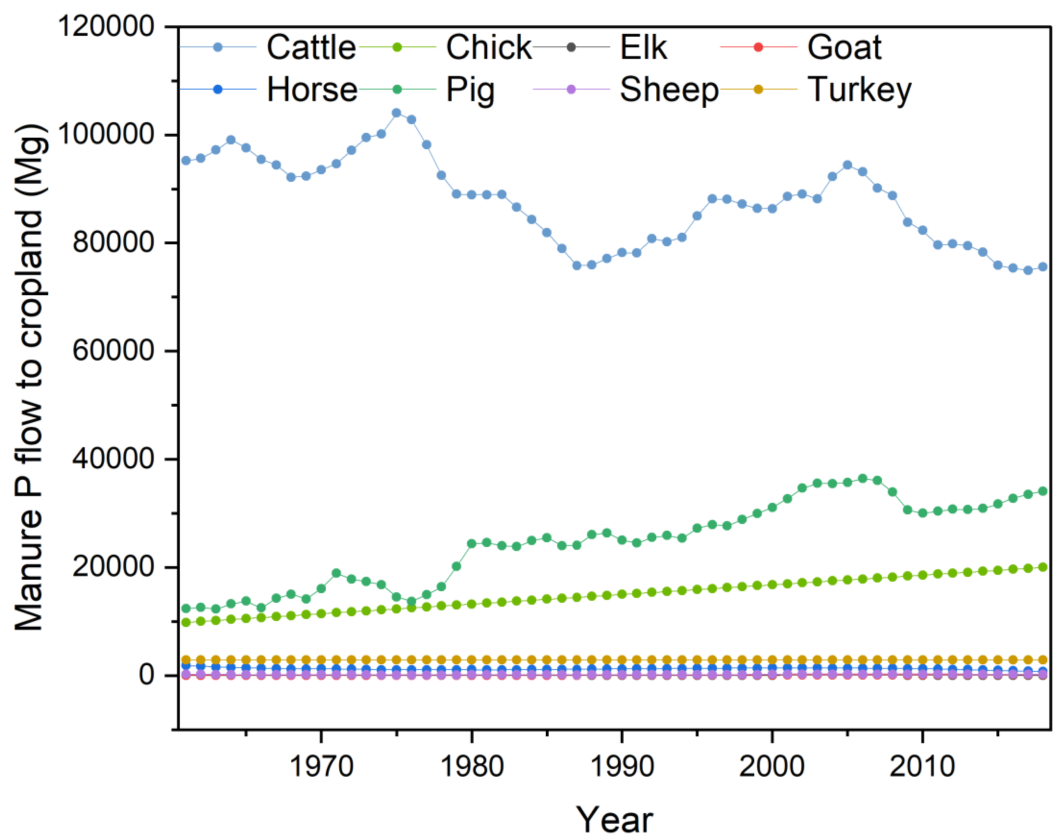

Figure 5.S2 Annual manure P flows recycled to nationwide cropland.

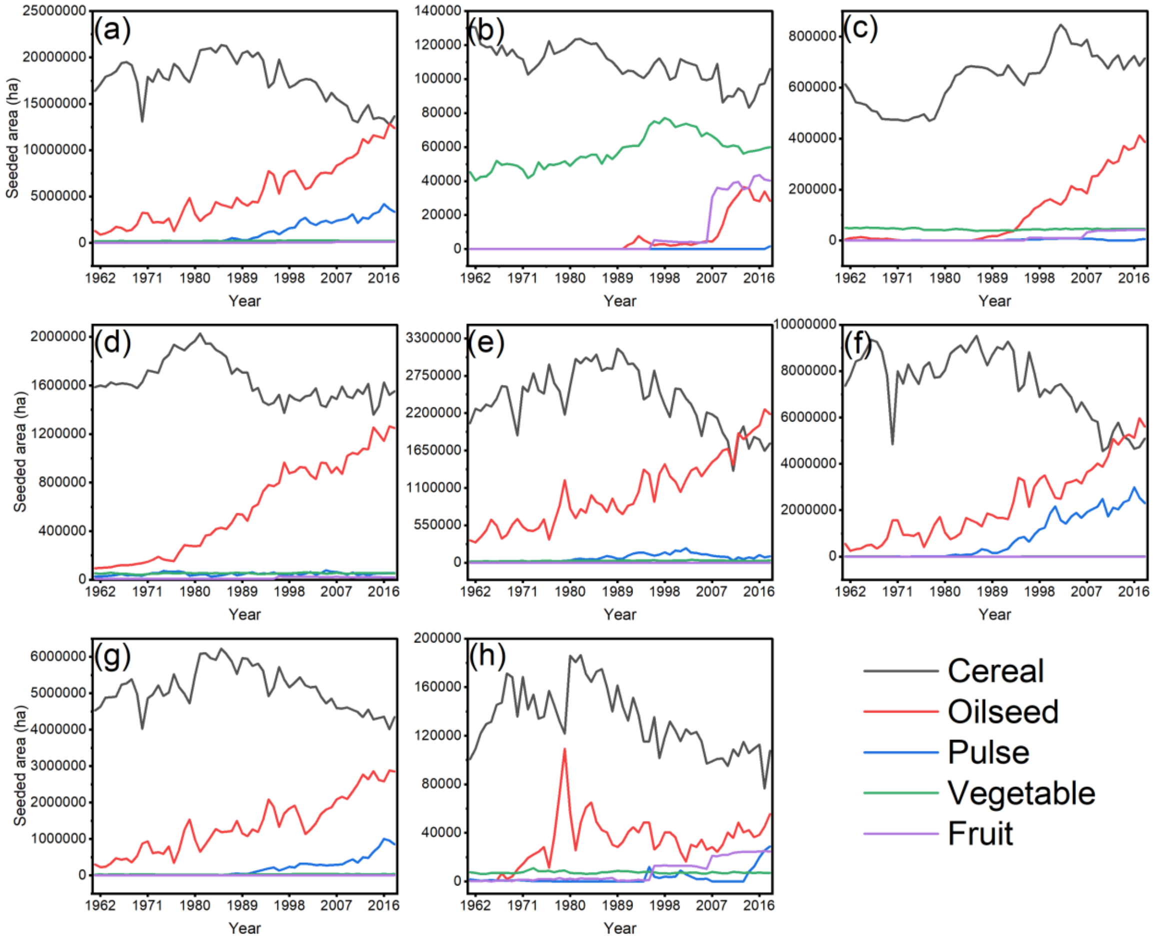

Figure 5.S3 Crop seeding area of Canadian provinces: (a) Atlantic provinces (including New Brunswick, Newfoundland and Labrador, Nova Scotia, and Prince Edward Island), (b) Quebec, (c) Ontario, (d) Manitoba, (e) Saskatchewan, (f) Alberta and (g) British Columbia.

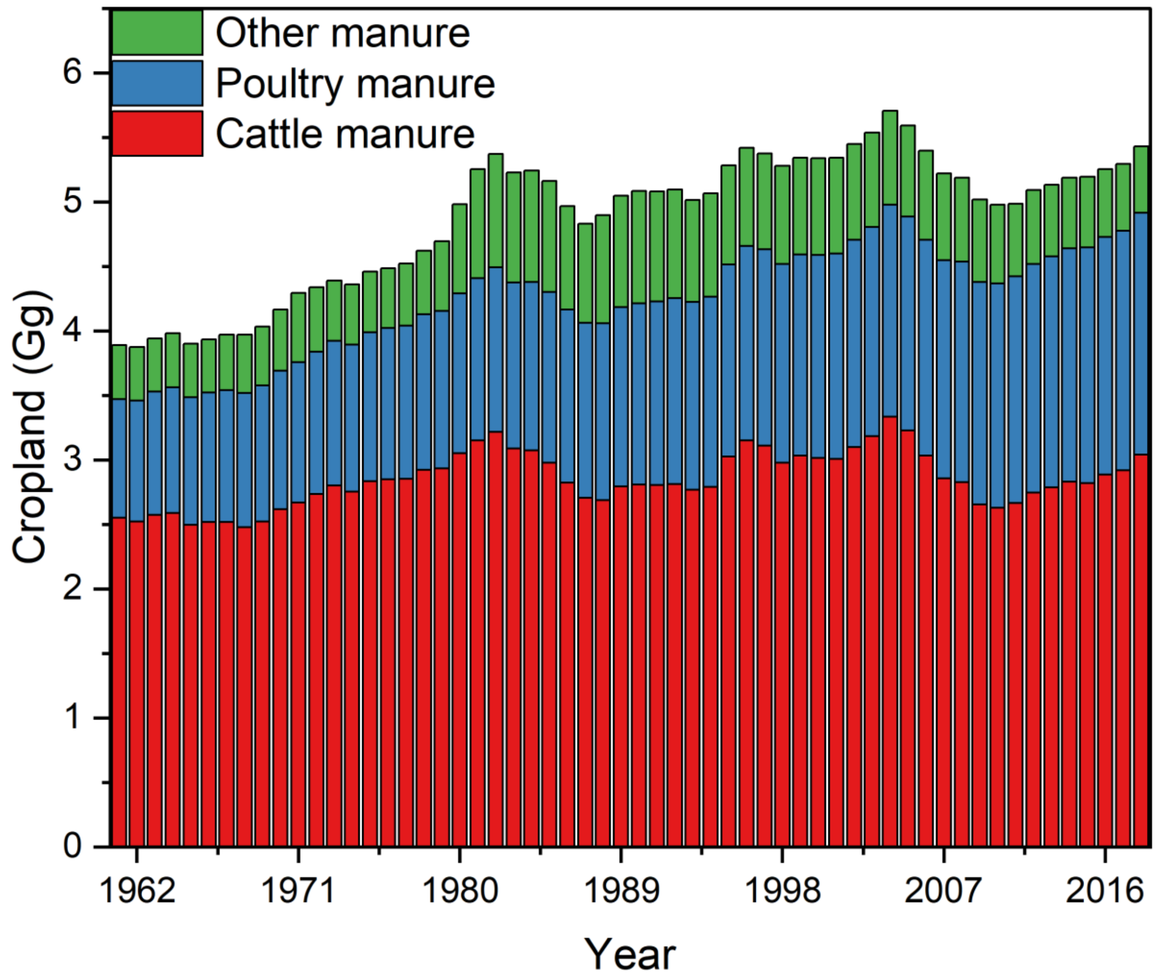

Figure 5.S4 Animal manure recycled to cropland in British Columbia from 1961 to 2018.

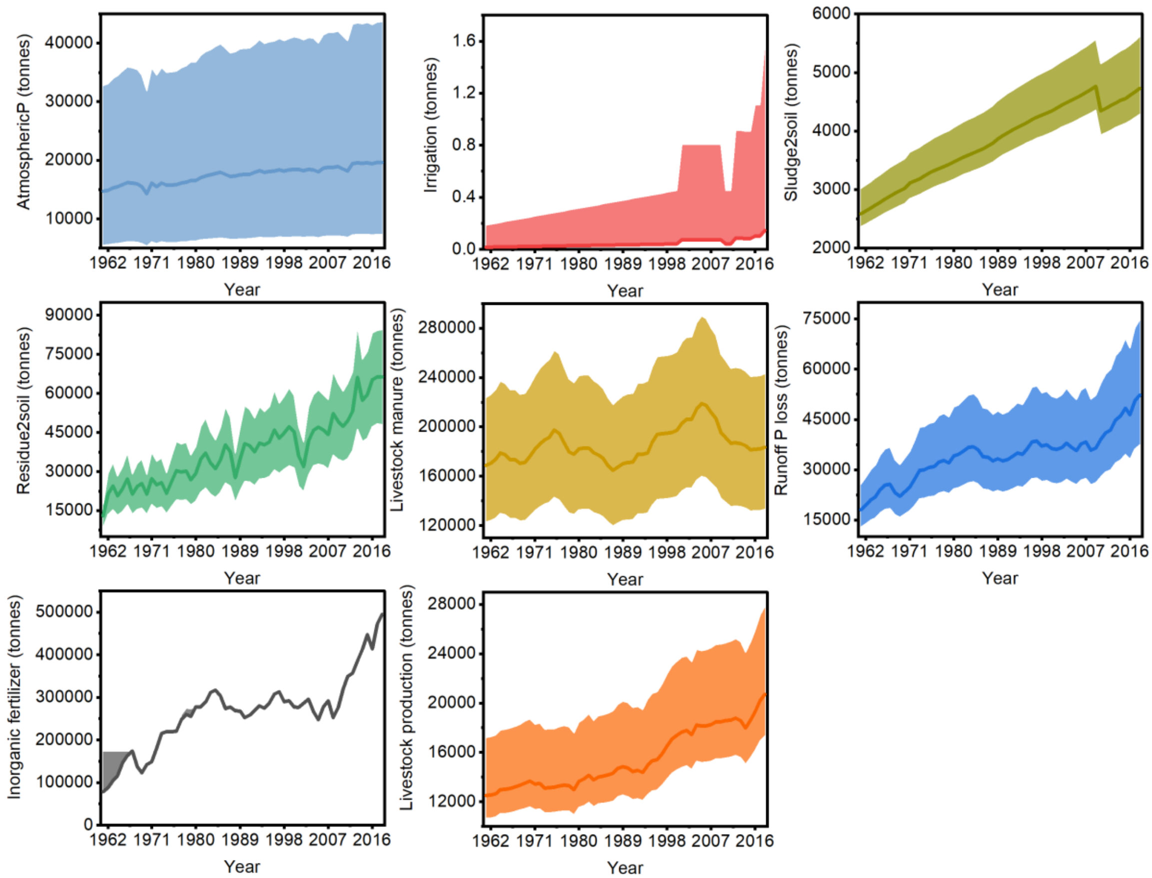

Figure 5.S5 Uncertainty of key P flows. The annual key P flows and uncertainties are shown as model input values (lines) combined with ranges depicting the area between minimum and maximum values (shaded areas).

Table 5.S1 Crop categories and their P contents.

Category	P content (%, w/w)	Items
Cereals	0.35	Winter wheat
	0.38	Spring wheat
	0.36	Durum wheat
	0.08	Wheat straw
	0.18	Corn
	0.1	Corn straw
	0.31	Oats, Barley, Rye, Mixed grains, Canary seed
	0.11	Oat straw, Barley straw
	0.07	Rye straw
	0.1	Mixed grains straw
	0.22	Buckwheat, Triticale
Oilseeds	0.57	Flaxseed
	0.1	Flaxseed straw
	0.52	Soybeans
	0.19	Soybean straw
	0.7	Canolar rapeseed
	0.1	Canolar rapeseed straw
	0.47	Mustard seed
	0.42	Sunflower seed

	0.04	Sunflower seed straw
Pulses	0.57	Dry white beans, Colored beans
	0.43	Dry peas, Faba beans
	0.11	Dry peas straw
	0.37	Chickpeas
	0.36	Lentils
Sugar beet	0.05	Sugar beet
	0.09	Sugar beet straw
Tame hay	0.25	
Vegetables and melons	0.02	Fresh asparagus, Fresh beets, Fresh broccoli, Fresh Brussels sprouts, Fresh cabbage, Fresh carrots, Fresh cauliflowers, Fresh celery, Fresh cucumbers and fresh gherkins (all varieties), Fresh dry onions, Fresh eggplants (except Chinese eggplants), Fresh French shallots and green onions, Fresh garlic, Fresh green and wax beans, Fresh leeks, Fresh lettuce, Fresh parsley, Fresh parsnips, Fresh peppers, Fresh pumpkins, Fresh radishes, Fresh rhubarb, Fresh rutabagas and turnips, Fresh spinach, Fresh squash and zucchini, Fresh sweet potatoes, Fresh tomatoes, Fresh watermelons, Other fresh melons
	0.07	Potato, Green maize
	0.03	Potato straw
Fruit	0.04	Fresh apples, Fresh grapes, Fresh strawberries, Fresh apricots, Fresh blackberries, Fresh blueberries, Fresh cranberries, Fresh currants, Fresh nectarines, Fresh

		peaches, Fresh pears, Fresh plums and prune plums, Fresh raspberries, Fresh saskatoon berries, Fresh sour cherries, Fresh sweet cherries

Data sources: IPNI, 2015; Chen and Graedel, 2016; Lun et al., 2018

Table 5.S2 P contents of livestock products.

Items	P content (%, w/w)	Source
Eggs, hen	0.204	United States Department of Agriculture, 2015
Milk	0.11	United States Department of Agriculture, 2015
Meat, cattle	0.165	United States Department of Agriculture, 2015
Meat, hog	0.202	United States Department of Agriculture, 2015
Meat, mutton	0.337	United States Department of Agriculture, 2015
Meat, poultry	0.203	United States Department of Agriculture, 2015
Meat, horse	0.17	United States Department of Agriculture, 2015
Offal, cattle	0.73	Sattari et al., 2012
Offal, horse	0.73	Sattari et al., 2012
Offal, sheep	0.73	Sattari et al., 2012
Offal, hog	0.73	Sattari et al., 2012
Fat, cattle	0.73	Sattari et al., 2012
Fat, hog	0.73	Sattari et al., 2012
Fat, sheep	0.73	Sattari et al., 2012
Fur, cattle	0.42	Sattari et al., 2012

Table 5.S3 Equations used in this study.

Pool	Flow	Calculation	Coefficient and source
Phosphate	Inorganic fertilizer (P_{fer})	$P_{fer} = P_{P_2O_5}\% \times Fer$	Fer: P minerals from IFA and Statistics Canada
Irrigation	Irrigation to cropland ($P_{irrigation}$)	$P_{irr} = P_{irrigation}\% \times Irr$	Irr: irrigation water volume from Statistics Canada $P_{irrigation}\%$: P content in irrigation water (Little et al., 2010)
Atmosphere	Deposition to cropland ($P_{atmcrop}$)	$P_{atmcrop} = Croparea \times Atm$	Atm : Annual atmospheric P deposition rate (Živković et al., 2017)
	Deposition to pasture ($P_{atmpasture}$)	$P_{atmpasture} = Pasturearea \times Atm$	
Cropland	Crop production (P_{crop})	$P_{crop} = Crop \times P_{crop}\%$	$P_{crop}\%$: crop P content collected from IPNI, 2015
	Crop as food ($P_{crop-food}$)	$P_{crop-food} = Crop - Food \times P_{crop}\%$	Crop source: FAOSTAT
	Crop as livestock feed ($P_{crop-feed}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT

	Crop as seed ($P_{crop-seed}$)	$P_{crop-seed} = Crop - Seed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop processing ($P_{crop-pro}$)	$P_{crop-pro} = Crop - Processing \times P_{crop}\%$	Crop source: FAOSTAT
	Crop losses ($P_{crop-losses}$)	$P_{crop-losses} = Crop - Losses \times P_{crop}\%$	Crop source: FAOSTAT
	Crop as other uses ($P_{crop-other\,use}$)	$P_{crop-oth} = Crop - Other\ Use \times P_{crop}\%$	Crop source: FAOSTAT
	Crop export ($P_{crop-export}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop import ($P_{crop-import}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop residues ($Residue_{crop}$)	$Residue_{crop} = Cropgrain \times Res$	Res : straw/grain ratio for Canadian crops (Li et al., 2012)
	Total crop residues ($P_{crop-res}$)	$P_{crop-res} = Residue_{crop} \times P_{crop}\%$	
	Crop residues recycled to cropland ($P_{recy-res}$)	$P_{recy-res} = P_{crop-res} \times 50\%$	Li et al. 2012

	Crop residues as feed ($P_{feed-res}$)	$P_{feed-res} = cattle\ number\ (h) \times 1\ kgh^{-1}d^{-1} \times 150\ d$	Li et al. 2012
	Crop residues to other uses ($P_{oth-res}$)	$P_{oth-res} = P_{crop-res} - P_{recy-res} - P_{feed-res}$	
	Cropland runoff ($P_{runoff-crop}$)	$P_{runoff-crop} = (P_{fer} + P_{atmcrop} + P_{irr} + P_{recy-res} + P_{crop-manure} + P_{sludge-cro}) \times\ 7\%$	Sattari et al., 2012; Wironen et al., 2018; Lun et al., 2018
Pasture	Grass as feed ($P_{grass-uptake}$)	$P_{grass-uptake} = \text{Weight} \times \text{uptakeratio} \times\ \text{time}\ \times P_{grass}$	weight: livestock average weight uptakeratio: daily grass uptake rate, expressed as percentage of body weight time: grazing time period (92 days, from June to August) P_{grass}: P content in grass (IPNI, 2015)
	Pasture runoff ($P_{runoff-pasture}$)	$P_{runoff-pasture} = (P_{atmpasture} + P_{dir-manure}) \times\ 7\%$	Sattari et al., 2012; Wironen et al., 2018; Lun et al., 2018

Livestock	Total manure (P_{manure})	$P_{manure} = livestock\ head \times N\ excretion\ rate \times P:N\ ratio$	Huffman et al., 2008; Lun et al., 2018
	Manure directly left on pasture ($P_{dir-manure}$)	$P_{dir-manure} = P_{manure} \times Dir$	Dir : Proportion of animals depositing manure directly on pasture
	Manure as waste ($P_{was-manure}$)	$P_{was-manure} = P_{manure} \times Was$	Was: Proportion of animals manure lost during handling
	Manure to cropland ($P_{crop-manure}$)	$P_{crop-manure} = P_{manure} - P_{dir-manure} - P_{was-manure}$	
	Meat (P_{meat})	$P_{meat} = Meat \times P_{meat}\%$	Product source: FAOSTAT
	Egg (P_{egg})	$P_{egg} = Egg \times P_{egg}\%$	Product source: FAOSTAT
	Milk (P_{milk})	$P_{milk} = Milk \times P_{milk}\%$	Product source: FAOSTAT
	Offal (P_{offal})	$P_{offal} = Offal \times P_{offal}\%$	Product source: FAOSTAT
	Fat (P_{fat})	$P_{fat} = Fat \times P_{fat}\%$	Product source: FAOSTAT
Humans	Detergent and cleaning ($P_{detergent}$)	$P_{detergent} = Population \times k_1 + Population \times k_2$	k_1 : Use of P in laundry detergents (0.24 kg/cap/year before 2010, 0.1

			kg/cap/year after 2010) k_2 : Use of P in dishwasher detergents (0.04 kg/cap/year before 2010, 0.11 kg/cap/year after 2010) Data source: van Puijenbroek et al., 2018
	Human excreta (P_{human})	$P_{human} = Population \times k_3 \times 365$	k_3 : Daily human excreta P (kg/cap/day) (Cordell et al., 2009; Van Staden, 2019)
	Sludge to cropland ($P_{sludge-cro}$)	$P_{sludge-cro} = (P_{detergent} + P_{human}) \times 20\%$	
	Sludge to freshwater ($P_{sludge-fre}$)	$P_{sludge-fre} = (P_{detergent} + P_{human}) \times 80\%$	

Table 5.S4 Manure P excretion rates and proportion of animals depositing manure directly on pasture, by province and livestock type.

Animal	N	P:N	Proportion of animals depositing manure directly on pasture (%)

type	excretion rate (kg N head^{-1} yr^{-1})	ratio for livestock manure	BC	AB	SK	MB	ON	QC	NB	NS	PE	NL
Broilers	0.4	0.24	0	0	2	0	0	0	0	3	0	0
Hens	0.6	0.24	0	0	10	0	0	0	0	0	0	0
Pullets	0.4	0.24	0	0	10	0	0	0	0	0	0	0
Turkeys	1.5	0.25	0	30	40	10	1	3	2	3	0	2
Calves	25.3	0.18	70	45	48	70	33	50	50	49	40	44
Steers	56.3	0.18	70	45	48	70	33	50	50	49	40	44
Heifers	52.2	0.18	5	0	25	50	17	19	22	10	40	22
Beef cattle	78.8	0.18	70	45	48	70	33	50	50	49	40	44
Dairy cows	122	0.18	5	0	25	50	17	19	22	10	40	22
Bulls	90.1	0.18	70	45	48	70	33	50	50	49	40	44
Boars	9.9	0.28	2	0	1	0	0	0	0	0	1	0
Hogs	8.5	0.28	2	0	1	0	0	0	0	0	1	0
Sows	9.6	0.28	0	0	0	0	0	0	0	0	0	0
Sheep	7	0.15	80	100	60	75	62	43	40	25	50	40
Goats	10.5	0.15	76	75	60	75	60	25	38	50	38	38

Horses	49.3	0.19	50	89	60	60	57	50	47	50	40	47
Elk,deer	25.1	0.19	50	89	60	60	57	50	47	50	40	47

Data sources: Huffman et al., 2008; Lun et al., 2018

Table 5.S5 Parameters used for uncertainty analysis.

Items	Unit	Value in this study	Value range	Source
Atmospheric deposition	kg ha^{-1} yr^{-1}	0.4	0.15-0.89	Živković et al., 2017; Chen and Graedel, 2016
Irrigation	g cm^{-3}	0.05	0.05-0.54	Little et al., 2010
Human P excretion	kg yr^{-1} per capita	0.43	0.37-0.55	Cordell et al., 2009; Van Staden, 2019
Residue recycled ratio	%	50	30-75	Li et al., 2012
P:N ratio for livestock manure				Lun et al., 2018;
Cattle	/	0.18	0.13-0.24	
Hog	/	0.28	0.23-0.35	
Sheep	/	0.15	0.09-0.23	
Goat	/	0.15	0.09-0.23	
Horse	/	0.19	0.18-0.21	
Elk, deer	/	0.19	0.18-0.22	

Chick	/	0.24	0.13-0.35	
Turkey	/	0.25	0.21-0.29	
Runoff P loss	%	7	5-10	Sattari et al., 2012; Wironen et al., 2018; Lun et al., 2018
Livestock production				Chen and Graedel, 2016
Eggs, hen	%	0.204	0.17-0.226	
Milk	%	0.11	0.95-0.158	
Meat, cattle	%	0.165	0.132-0.198	
Meat, hog	%	0.202	0.175-0.229	
Meat, poultry	%	0.203	0.147-0.312	

Table 5.S6 Parameters used for livestock grass P uptake.

Livestock type	Average weight (kg)	Daily uptake ratio of body weight	Time period (day)	P content in grass
Bull	800	2.5%	92	0.15%
Steer	800	2.5%	92	0.15%
Dairy	450	3%	92	0.15%
Beef	450	3%	92	0.15%
Heifer	345	3%	92	0.15%
Calve	145	2.5%	92	0.15%

Sheep	97	3%	92	0.15%
Lamb	45	2.5%	92	0.15%
Goat	83	4%	92	0.15%
Horse	527.5	2%	92	0.15%
Elk	315.3	3%	92	0.15%

Data sources: Alberta Lamb Producers, 2013; Blood and Lovaas, 1966; Canada beef, 2015; Feeding 4-H Calves, 2021; Vachon et al., 2007; farmer consultations

Table 5.S7 Fitting results of phosphorus use efficiency.

Region		Equation	R^2
Cropland			
Atlantic	Total PUE	$y=0.00226x-4.25327$	0.32
	PUE	$y=0.0017x-3.21662$	0.34
Quebec	Total PUE	$y=66613.52115-100.21082x+0.05025x^2$	0.92
	PUE	$y=40282.67255-60.57762x+0.03036x^2$	0.91
Ontario	Total PUE	$y=89068.93116-134.17001x+0.06736x^2$	0.93
	PUE	$y=61138.0401-92.09491x+0.04624x^2$	0.92
Manitoba	Total PUE	$y=-0.00177x+4.23924$	0.03
	PUE	$y=-4.57032E-4x+1.45046$	0.01

Saskatchewan	Total PUE	y=-0.00688x+14.78954	0.15
	PUE	y=-0.0039x+8.59667	0.1
Alberta	Total PUE	y=0.00187x-2.9664	0.1
	PUE	y=0.00241x-4.21683	0.17
British Columbia	Total PUE	y=0.00267x-5.06576	0.18
	PUE	y=0.00249x-4.7627	0.23
Pasture			
Canada	Total PUE	$y=0.00293+3.37002E-5x+0.01676x^2-2.51105E-5x^3$	0.53
	PUE	y=9.19115E-4x-1.71506	0.5

Table 5.S8 Comparison of estimated annual runoff P losses.

Year	Alewell et al. (2020), assuming 1.4 kg ha^{-1} yr^{-1} runoff P loss for North America	Canada river P loss	Unit: tonnes
1961	26143.93432	14185.86107	
1962	27469.06873	15566.69873	
1963	28042.78951	17014.26698	
1964	28594.73941	17744.11937	
1965	29166.43161	19973.04903	
1966	30404.80632	21316.04086	
1967	30259.20106	21709.15312	

1968	30519.73344	19243.3073	
1969	29279.29865	18083.62907	
1970	24980.49827	19395.28588	
1971	31275.54614	20619.32528	
1972	29577.94451	22788.59366	
1973	31120.04775	25394.97384	
1974	30044.81275	25345.30314	
1975	30766.40847	25814.46291	
1976	31215.1981	26058.20092	
1977	31192.94386	27765.63776	
1978	32852.17249	28440.70792	
1979	33058.00191	27949.86634	
1980	33263.15341	29945.82918	
1981	35290.0132	30422.48522	
1982	35945.16269	31388.59954	
1983	36419.99102	32567.18025	
1984	37869.79024	32817.49351	
1985	38604.33075	32048.50419	
1986	38590.22995	30105.87278	
1987	37695.39033	29978.34758	
1988	37928.86758	28816.44843	
1989	39083.74351	29407.83469	

1990	38231.28141	28724.9423	
1991	38097.06597	29084.44909	
1992	38184.94994	29864.5454	
1993	39310.3564	30875.75919	
1994	39580.03226	30473.41592	
1995	39715.60492	31820.5643	
1996	39741.57387	33747.9529	
1997	40682.20634	33947.75632	
1998	41011.88142	32491.0318	
1999	40009.96481	32814.96837	
2000	41613.86761	31758.14747	
2001	40163.58042	31294.77061	
2002	40006.39325	31855.56144	
2003	40518.73875	33181.58224	
2004	40015.62794	31654.59053	
2005	38901.02666	30484.48017	
2006	38774.07692	32516.77587	
2007	39999.06999	33281.89045	
2008	40685.45286	30916.47984	
2009	40777.04616	31875.14936	
2010	38095.44689	34536.91493	
2011	37553.75222	36667.6245	

2012	42306.10822	37631.26858	
2013	42867.4665	40536.75951	
2014	42517.01417	41820.70402	
2015	43447.57309	44346.56932	
2016	44365.09913	42422.88059	
2017	44469.11191	46627.4541	
2018	45163.9337	48320.58885	

Table 5.S9 Annual runoff P losses in Ontario, Manitoba and Saskatchewan.

Year	Ontario	Manitoba	Saskatchewan	**Unit: kg ha^{-1}**
1961	2.316235	0.50107	0.304385	
1962	2.402397	0.557967	0.349508	
1963	2.575166	0.578856	0.39657	
1964	2.661482	0.606425	0.383237	
1965	2.950424	0.669866	0.439488	
1966	3.099019	0.701391	0.458032	
1967	3.272463	0.744644	0.444635	
1968	3.253141	0.515024	0.315198	
1969	3.345455	0.547145	0.265355	
1970	3.33385	0.747362	0.384408	
1971	3.178973	0.645841	0.336928	

1972	3.263733	0.830259	0.432914	
1973	3.34028	0.904595	0.503327	
1974	3.016094	0.970173	0.551536	
1975	3.303972	0.93245	0.50696	
1976	3.161289	0.872398	0.520011	
1977	3.15917	1.029323	0.591782	
1978	3.345086	1.075242	0.580665	
1979	3.21936	1.055244	0.524227	
1980	3.144722	1.024265	0.614204	
1981	3.085314	0.92734	0.597803	
1982	3.032242	0.918284	0.652522	
1983	2.980043	1.037385	0.69411	
1984	3.051248	1.020424	0.643094	
1985	2.855166	1.048407	0.637101	
1986	2.657024	1.007839	0.571354	
1987	2.697708	1.12446	0.577134	
1988	2.461369	0.970244	0.501074	
1989	2.346197	1.002283	0.524237	
1990	2.447438	1.056944	0.513806	
1991	2.417143	1.039988	0.548157	
1992	2.354768	1.133247	0.572603	
1993	2.250707	1.115179	0.596996	

1994	2.136517	1.148622	0.622063	
1995	1.994014	1.191677	0.681002	
1996	1.937869	1.298809	0.764042	
1997	2.085099	1.227927	0.724816	
1998	1.934489	1.183806	0.660058	
1999	1.988208	1.299336	0.694542	
2000	1.953268	1.117082	0.659218	
2001	1.867476	1.161592	0.624718	
2002	1.80339	1.337961	0.694961	
2003	2.033165	1.315584	0.709274	
2004	1.766276	1.215379	0.708984	
2005	1.79978	1.228432	0.678683	
2006	2.044663	1.411958	0.719447	
2007	1.988613	1.382496	0.718968	
2008	1.815614	1.156401	0.679675	
2009	1.869764	1.302389	0.668725	
2010	2.25207	1.292226	0.77379	
2011	2.49601	1.536498	0.926133	
2012	2.361801	1.381222	0.830895	
2013	2.262958	1.565233	0.872439	
2014	2.224257	1.668383	0.876153	
2015	2.551009	1.769769	0.939858	

2016	2.325706	1.834575	0.919424	
2017	1.977161	1.98783	1.00329	
2018	2.152097	2.122517	1.083796	

Connecting text to Chapter 6

In Chapter 5, we introduce a P cycling model to evaluate the soil P balance within Canada's agricultural land. In Chapter 6, we integrate a soil-crop P uptake dynamics module into P cycling model to explore the advantages of recycling residual soil P in mitigating P loss and reducing the need for mineral P applications across Canada.

The manuscript in Chapter 5 has been published in the Global Biogeochemical Cycles:

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Chapter 6

Managing mineral phosphorus application with soil residual phosphorus reuse in Canada

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Abstract

With limited phosphorus (P) supplies, increasing P demand, and issues with P runoff and pollution, developing an ability to reuse the large amounts of residual P stored in agricultural soils is increasingly important. In this study, we investigated the potential for residual soil P to maintain crop yields while reducing P applications and losses in Canada. Using a P cycling model coupled with a soil P dynamics model, we analyzed soil P dynamics over 110 years across Canada’s provinces. We found that using soil residual P may reduce mineral P demand as large as 132 Gg P yr^{-1} (29%) in Canada, with the highest potential for reducing P applications in the Atlantic provinces, Quebec, Ontario, and British Columbia. Using residual soil P would result in a 21% increase in Canada's cropland P use efficiency. We expected that the Atlantic provinces and Quebec would have the greatest runoff P loss reduction with use of residual soil P, with the average P loss rate decreasing from 4.24 and 1.69 kg ha^{-1} to 3.45 and 1.38 kg ha^{-1}, respectively. Ontario, Manitoba, and British Columbia would experience relatively lower reductions in P loss through

use of residual soil P, with the average runoff P loss rate decreasing from 0.44, 0.36, and 4.33 kg ha^{-1} to 0.19, 0.26, and 4.14 kg ha^{-1}, respectively. Our study highlights the importance of considering residual soil P as a valuable resource and its potential for reducing P pollution.

6.1 Introduction

To maintain crop yields while reducing environmental impact, it is important to balance the use of crucial inputs such as phosphorus (P). P is essential for crop growth but is primarily obtained through nonrenewable and dwindling phosphate rocks in modern agriculture (Yuan et al., 2018). It is also a critical pollutant in freshwater systems, where it arrives via runoff from fertilized systems (Liu et al., 2016). The increasing global use of P fertilizers has led to buildup of anthropogenically sourced P in the soil, which can lead to excess P losses from agricultural fields (Rockstrom et al., 2009; Macdonald et al., 2011) and freshwater pollution, which pose threats to aquatic ecosystems, human health, and the economy (Smith et al., 2019). The build-up arises from using more fertilizer than crops can take up, with a small amount running off, and the remainder sorbing to agricultural soils, where it accumulates (Carpenter, 2005; Wang et al., 2022). Sometimes, the effects of this pollution are so severe as to impact swimming and drinking, such as when Toledo's drinking water supply underwent an emergency shutdown due to contamination from toxic algal blooms in Lake Erie (Stow et al., 2015). It is imperative to manage P more efficiently in the process of achieving sustainable agricultural production.

Reusing soil residual P offers a practical and cost-effective solution in reducing P pollution. Current field observations suggest that P applications exceed P removed in crop production, with 42-54% of applied P fertilizer remaining in the soil each year of application (Syers et al., 2008; de Oliveira et al., 2019). Although residual P can be bound to organic matter, precipitated in forms not readily available to crops, or adsorbed to mineral particles, it can also be released into the soil solution slowly and may become available to crops in subsequent years due to microbial activities (Aulakh et al., 2007; Liu et al., 2015; Roy et al., 2016; Liu et al., 2017; Lemming et al., 2019; Zhang et al., 2022). With concerns raised by Zou et al. (2022) regarding the exacerbation of global P pollution in 2050, which is expected to surpass the environmental threshold for P surplus (Springmann et al., 2018) under current P use strategies, the significance of reusing residual P to reduce soil P runoff and safeguard water ecosystems (Withers et al., 2014) becomes evident. Moreover, the reuse of residual P not only mitigates the depletion of high-quality P reserves but also tackles the escalating costs associated with P fertilizers, highlighting the practical and economic benefits of this approach (Filippelli, 2018; Mogollón et al., 2021; Magnone et al., 2022). Reusing soil residual P has gained significant attention in recent years. Many experiments and field trials have focused on improving the efficiency of residual P use by using soil P activators (Teng et al., 2020) or agricultural practices such as crop rotation (Rigon et al., 2022), cover crops (Soltangheisi et al., 2020), or identifying and mitigating climatic effects (Hou et al., 2018; Jarvie et al., 2020). While these efforts contribute to identifying suitable practices for stimulating the release of residual P, they fall short of providing a comprehensive understanding of the potential quantity and distribution of residual P, and do not generally address the intricate dynamics of soil P transfer among different pools and plant uptake. Some modeling studies have attempted to quantify the spatial distribution of residual P (Ringeval et al., 2017; Lou et al., 2018) or the potential impacts on runoff P load (Muenich et al., 2016; Motew et al., 2017; Kast et al., 2021; von Arb et al., 2021), mostly at a watershed scale. Only a few modeling studies have attempted to quantify the potential benefits of soil P reuse on a national scale (Sattari et al., 2014; Noë et al., 2020; Pavinato et al., 2020), partly due to the high uncertainty in spatially distributed modeling or the limited availability of related P data. Liu et al. (2018) applied a grid-based crop model that considers the remobilization of residual P sources to estimate global P losses, although they only simulated three of the most produced crops: corn (*Zea mays* L.), rice (*Oryza sativa* L.), and wheat (*Triticum aestivum* L.). Sattari et al. (2012, 2016) developed a large-scale soil P dynamics model to assess the potential contribution of residual P to global P application to cropland and grassland by 2050, respectively, and suggested that residual P could potentially reduce 17% of mineral P applications in North America (Sattari et al., 2012). However, since their simulations were conducted on a continental extent, there is still limited understanding of the reuse of residual P at the regional extent.

Canada is a leading agricultural producer that is grappling with the issue of P pollution. The combination of decades of widespread fertilizer uses and the growing geographic concentration of livestock production has led to “hotspots” of P accumulation (MacDonald & Bennett, 2009; Reid et al., 2019) and increased P runoff loss (Wang et al., 2022), hindering the achievement of water quality goals (Environment Canada, 2011), and placing pressure on the government to reduce P loss (Saxe, 2017). Field trials have explored the potential of using residual P to feed crops, and long-term experiments conducted across Quebec, Ontario, Manitoba, and Saskatchewan have shown that residual P can sustain crop yields while reducing runoff P loss (Liu et al., 2015; Liu et al., 2019; Parent et al., 2020; Zhang et al., 2020). However, a comprehensive evaluation of the national-scale benefits of using residual P to mitigate P applications and losses is lacking, which is crucial when implementing sustainable P management and national policies.

In this study, we aim to fill this knowledge gap by using a combination of a national-scale P cycling model and the soil P dynamics model developed by Sattari et al. (2012) to comprehensively examine the accumulation and transformation of residual P and its potential benefit towards reducing mineral P applications and soil P losses in Canada's agricultural land. Our study focuses on addressing the following key questions: (a) What is the extent of residual P accumulation across Canada's agricultural land and where are the regions with the highest residual P buildup? (b) How much mineral P applications can be potentially reduced by using residual P? (c) To what extent can the reuse of residual P help reduce runoff P loss?

6.2 Material and methods

6.2.1 Overview

We used a P cycling model to quantify P inputs to outputs from Canada's agricultural land, spanning the period from 1908 to 2022. Building upon these P flow estimations, we used a soil P dynamics model to estimate the temporal changes in residual soil P across Canada's agricultural land over this same time period. We collected projected agricultural statistics from 2023 to 2030 to estimate the anticipated P applications and crop P uptake using our P cycling model. Using the target P uptake as an input variable, we determined the amount of P fertilizers required to grow crops in this future simulation, and the corresponding consumption of soil P pools assuming that no new mineral fertilizer is added to the soil. This approach enabled us to evaluate the potential contribution of reusing soil P in reducing mineral P applications and, consequently, the associated reduction in soil P loss.

6.2.2 P cycling model

6.2.2.1 Soil P surplus calculation

P cycling models are a reliable method for estimating large-scale soil P balance. We used the P cycling model developed by Wang et al. (2022) to calculate P-flows across Canada. This model considers 71 major crop production types and 17 types of primary livestock inventory in Canada. It considers P inputs and outputs to the landscape with P surplus being defined as the difference between P inputs and P withdrawals in the form of crop harvest and grass consumption by livestock:

$$N_{Crop}(i,t) = FERT_{p,crop}(i,t) + SLU_p(i,t) + MAN_{p,crop}(i,t) + RRES_p(i,t) + IRR_p(i,t) + ATM_{p,crop}(i,t) + WEA_{p,crop}(i,t) - Crop_p(i,t) \quad (6.1)$$

$$N_{Past}(i,t) = FERT_{p,past}(i,t) + MAN_{p,past}(i,t) + ATM_{p,past}(i,t) + WEA_{p,past}(i,t) - GRAZ_p(i,t) \quad (6.2)$$

where i refers to the i^{th} province and t is time unit (yr). $N_{Crop}(i,t)$ and $N_{Past}(i,t)$ represent surplus P applied at the soil surface to cropland and pastureland, respectively. $FERT_{p,crop}(i,t)$ and $FERT_{p,past}(i,t)$ refer to annual mineral P fertilizer applied to cropland and pastureland (Gg P yr^{-1}), respectively. $SLU_p(i,t)$ represents recycled sludge applied to cropland (Gg P yr^{-1}). $MAN_{p,crop}(i,t)$ and $MAN_{p,past}(i,t)$ refer to manure P applied to cropland and pastureland (Gg P yr^{-1}), respectively. $RRES_p(i,t)$ refers to crop residues P returned to cropland (Gg P yr^{-1}). $IRR_p(i,t)$ refers to irrigation water P applied into cropland (Gg P yr^{-1}). $ATM_{p,crop}(i,t)$ and $ATM_{p,past}(i,t)$ are atmospheric deposition P on cropland and pastureland (Gg P yr^{-1}), respectively. $WEA_{p,crop}(i,t)$ and $WEA_{p,past}(i,t)$ are weathering P on cropland and pastureland (Gg P yr^{-1}), respectively. $Crop_p(i,t)$ represents crop P removal (Gg P yr^{-1}). $GRAZ_p(i,t)$ refers to grass P consumption by grazing livestock (Gg P yr^{-1}). Further information about P-flow calculations can be found in Supporting Information.

6.2.2.2 Percentage of crop residue P returned to the field

Wang et al. (2022) assumed that 50% of crop residues were recycled to the field among provinces. We have improved the calculation of recycling crop residue P flow by considering provincial cropland area under baling. We divided the crop species into two groups based on: (i) residues fully left in the field, and (ii) residues partly returned to the field, according to investigation by Li et al. (2012). For crop species in which the residues are partially recycled to the field, we determined the percentage of crop residues returning to field based on crop residue baled area, which we collected from Statistics Canada (https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3210036601). Briefly, we first calculated the proportion of cropland area that is under baling among provinces. Within the baling area, we assumed that approximately 60% of crop residue was removed from the field by balers for other purposes (*e.g.*, bioenergy) based on the work of Liu et al. (2019). Then, we determined the ratios of removed residues by multiplying the percentage of baled area by 60%. These calculated ratios were finally applied to the specific crop type areas, with further details provided in Tables 6.S1 and 6.S2.

6.2.2.3 Soil P dynamics model

To account for the accumulation and transformation of soil residual P, we integrated a large-scale soil P dynamics model developed by Sattari et al. (2012) into our P cycling model. This model has proven to be a robust tool for estimating the transfer of soil P and the removal of P on a large scale (Mogollón et al., 2018, 2021; Magnone et al., 2019, 2022; Zou et al., 2022). By inputting the target P removal as an input variable, the model is capable of performing inverse simulations to determine the necessary P fertilizers and the consumption of soil P pools (Sattari et al., 2012, 2016; Mogollón et al., 2021; Magnone et al., 2022). This model divides the soil P stock into labile and stable P pools. And considers the annual transformation between these two pools based on field observations by Janssen et al. (1987). The model assumes that plants absorb P from labile P pool, and it can be expressed as:

$$\frac{dL_{Crop}(i,t)}{dt} = f \times \left(FERT_{p,crop}(i,t) + SLU_p(i,t) + MAN_{p,crop}(i,t) + RRES_p(i,t) + IRR_p(i,t)\right) + \mu_{SL,crop}(i) \times S_{Crop}(i,t) + ATM_{p,crop}(i,t) - \mu_{LS,crop}(i) \times L_{Crop}(i,t) - \alpha_{crop}(i) \times L_{Crop}(i,t) - k_{run}(i,t) \times L_{Crop}(i,t) \quad (6.3)$$

$$\frac{dS_{Crop}(i,t)}{dt} = (1-f) \times \left(FERT_{p,crop}(i,t) + SLU_p(i,t) + MAN_{p,crop}(i,t) + RRES_p(i,t) + IRR_p(i,t)\right) - \mu_{SL,crop}(i) \times S_{Crop}(i,t) + WEA_{p,crop}(i,t) + \mu_{LS,crop}(i) \times L_{Crop}(i,t) - k_{run}(i,t) \times S_{Crop}(i,t) \quad (6.4)$$

$$\frac{dL_{Past}(i,t)}{dt} = f \times \left(FERT_{p,past}(i,t) + MAN_{p,past}(i,t)\right) + \mu_{SL,past}(i) \times S_{Past}(i,t) + ATM_{p,past}(i,t) - \mu_{LS,past}(i) \times L_{Past}(i,t) - \alpha_{past}(i) \times L_{Past}(i,t) - k_{run}(i,t) \times L_{Past}(i,t) \quad (6.5)$$

$$\frac{dS_{Past}(i,t)}{dt} = (1-f) \times \left(FERT_{p,past}(i,t) + MAN_{p,past}(i,t)\right) - \mu_{SL,past}(i) \times S_{Past}(i,t) + WEA_{p,past}(i,t) + \mu_{LS,past}(i) \times L_{Past}(i,t) - k_{run}(i,t) \times S_{Past}(i,t) \quad (6.6)$$

where $L_{Crop}(i,t)$ and $L_{Past}(i,t)$ refer to soil labile P pool in cropland and pastureland (Gg P yr^{-1}), respectively. $S_{Crop}(i,t)$ and $S_{Past}(i,t)$ refer to soil stable P pool in cropland and pastureland (Gg P yr^{-1}), respectively. f refers to the percentage of P applications that transfers to soil labile P pool (%) (previous studies assumed to 80%, Liu et al., 2018; Demay et al., 2023). $\alpha_{crop}(i)$ and $\alpha_{past}(i)$ refer to coefficient of crop P removal and grass P grazing (%), respectively. $\mu_{LS,crop}(i)$ and $\mu_{SL,crop}(i)$ are the rates of annual soil P transfer from labile P to stable P and vice versa in cropland (%), respectively. $\mu_{LS,past}(i)$ and $\mu_{SL,past}(i)$ are the rates of annual soil P transfer from labile P to stable P and vice versa in pastureland (%), respectively. $k_{run}(i,t)$ refers to runoff P loss coefficient (%).

Soil P transfer rates between soil P pools are always considered as constants in previous studies (Van Meter et al., 2021; Mogollón et al., 2021; Demay et al., 2023). This study considered the soil properties (*i.e.*, Fe and Al oxide concentrations, soil organic carbon, and soil taxonomy) in Canada's agricultural surface soils to incorporate the influence of soil chemical composition on the transfer of soil P between the labile and stable pools. These soil properties were selected due to their significant role in P transfer between the labile and stable P pools (Wang et al., 2022). Wang et al. (2022) had proposed multiple linear and nonlinear regression equations to estimate P transfer rates. Here, we used multiple linear equations to estimate these rates and assigned priority weights to Fe and Al oxide concentrations, soil organic carbon, and soil silt, according to Wang et al. (2022). The equations can be expressed as follows:

$$\mu(i) = a \times (Fe_{ox}(i) + Al_{ox}(i)) + b \times SOC(i) + c \times Soil_{silt}(i) + d \times Soil_{sand}(i) + e \times Soil_{clay}(i) \quad (6.7)$$

where $\mu(i)$ refers to soil P transfer rate (*i.e.*, $\mu_{LS,crop}(i)$, $\mu_{SL,crop}(i)$, $\mu_{LS,past}(i)$, and $\mu_{SL,past}(i)$). $Fe_{ox}(i)$ and $Al_{ox}(i)$ refer to surface soil oxalate-extractable Fe and Al concentration (%), respectively. $SOC(i)$ refers to surface soil organic carbon (%). $Soil_{silt}(i)$, $Soil_{clay}(i)$, and $Soil_{sand}(i)$ refer to surface soil silt, clay, and sand percentage (%), respectively. a, b, c, d, and e are dimensionless constants. Details of surface soil properties among Canada's provinces were summarized in Table 6.S3.

6.2.2.4 Soil P loss modeling

Many P cycling studies have assumed a constant percentage of total P inputs for runoff P loss (Sattari et al., 2012, 2016; Bouwman et al., 2013; Lun et al., 2018; Wironen et al., 2018). This study calculated the spatial runoff P loss based on the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997), which enables to estimate soil P loss by considering landscape, rainfall-runoff impact, and cover-management effect. The equation is expressed as:

$$k_{run}(i,t) = k_{eros}(i,t) \times k_{cove}(i,t) \times \frac{Prec(i,t)}{Q_{mean}(i)} \quad (6.8)$$

where $k_{eros}(i,t)$ refers to soil erodibility factor (ranges between 0 and 1). $k_{cove}(i,t)$ refers to cover management factor. $Q_{mean}(i)$ is mean annual discharge (mm yr^{-1}), and $Prec(i,t)$ is annual precipitation (mm yr^{-1}). We determined the values of cover management factor based on the percentage of crop residues returned to cropland and the review paper by Benavidez et al. (2018), and the values were summarized in Table 6.S4.

6.2.2.5 Soil P accumulation and P use efficiency

To represent soil P accumulation on the map, we used following equations to estimate the P accumulation for a specific crop type field within a given province. This approach assumes that crop species with higher P removal rates would necessitate larger amounts of P fertilizer application.

$$IN_{Crop}(i,t,j) = \left(FERT_{p,crop}(i,t) + SLU_p(i,t) + MAN_{p,crop}(i,t)\right) \times \frac{crop_p(i,t,j)}{\sum_{j=1}^{71} crop_p(i,t,j)} \tag{6.9}$$

$$LO_{Crop}(i,t,j) = (IN_{Crop}(i,t,j) + rres_p(i,t,j) + atm_{p,crop}(i,t,j) + wea_{p,crop}(i,t,j) - crop_p(i,t,j)) \times k_{run}(i,t) \tag{6.10}$$

$$P_{Crop}(i,t_{0\to n},j) = \frac{\sum_{t=t_0}^{t_n}\left(IN_{Crop}(i,t,j) + rres_p(i,t,j) + atm_{p,crop}(i,t,j) + wea_{p,crop}(i,t,j) - crop_p(i,t,j) - LO_{Crop}(i,t,j)\right)}{Area_{Crop}(i,t_n,j)} \tag{6.11}$$

where j refers to the jth crop species (ranges between 1 and 71). $IN_{Crop}(i,t,j)$ refers to P applications for a specific crop type field. $crop_p(i,t,j)$ is the jth crop species' P removal rate (Gg P yr^{-1}). $rres_p(i,t,j)$ refers to the jth crop species' residues P returned to cropland (Gg P yr^{-1}). $atm_{p,crop}(i,t,j)$ and $wea_{p,crop}(i,t,j)$ are atmospheric deposition P and weathering P in the jth crop species' field (Gg P yr^{-1}), respectively. $LO_{Crop}(i,t,j)$ is soil P loss for a specific crop type field. $P_{Crop}(i,t_{0\to n},j)$ is the estimated cumulative P balance for a specific crop type field during the time period from t_0 to t_n (kg ha^{-1}). $Area_{Crop}(i,t_n,j)$ is the jth crop species' seeding area (hectare) in the $t_n th$ year.

Due to limited information regarding pasture crop removal and fertilizer application, this study applied the provincial-scale pastureland P balance method to estimate the soil P accumulation:

$$LO_{Past}(i,t) = N_{Past}(i,t) \times k_{run}(i,t) \tag{6.12}$$

$$P_{Past}(i,t_{0\to n}) = \frac{\sum_{t=t_0}^{t_n}(N_{Past}(i,t) - LO_{Past}(i,t))}{Area_{Past}(i,t_n)} \tag{6.13}$$

where $LO_{Past}(i,t)$ is soil P loss for pastureland (Gg P yr^{-1}). $P_{Past}(i,t_{0\to n})$ is the estimated cumulative P balance for pastureland during the time period from t_0 to t_n (kg ha^{-1}). $Area_{Past}(i,t_n)$ is the provincial pastureland area (hectare) in the $t_n th$ year.

Eventually, we calculated the provincial-scale cropland P use efficiency (PUE) by the following equation:

$$PUE_{Crop}(i,t) = \frac{Crop_p(i,t)}{FERT_{p,crop}(i,t)+SLU_p(i,t)+MAN_{p,crop}(i,t)+RRES_p(i,t)+IRR_p(i,t)} \quad (6.14)$$

6.2.3 Data sources

6.2.3.1 1908-2022 historical data

We collected agricultural statistics from Statistics Canada, covering the period from 1908 to 2022, including population, mineral P fertilizer consumption, crop yield and seeding areas, as well as livestock inventory. Due to limited information about mineral P application in pastureland, and some farms do not consistently apply mineral P every year (Cade-Menun et al., 2013), we assumed 15% of provincial-scale mineral fertilizer consumption was used in pastureland based on previous watershed-scale study (Van Meter et al., 2021). In our P cycling model and soil P dynamics model, crop P removal is the sum of crop yield and total crop residues. We calculated the total P removal rate for crop residues based on the crop-specific straw-to-yield mass ratio (Wang et al., 2022). We estimated grazing P uptake based on livestock inventory, reported grazing time, and daily grass consumption rates assessed by government documents, literature, and farmer consultations. The percentage of livestock manure P applied to cropland and pastureland was specified by livestock types and provinces based on investigation by Huffman et al. (2008), further details can be found in Wang et al. (2022). Since recording of provincial-scale mineral P fertilizer consumption began in 1926 (https://publications.gc.ca/site/eng/9.853784/publication.html), we used linear interpolation to extend mineral P consumption data back to 1908. For cropland mineral P application, we interpolated based on the growth rate of crop P removal. We used two methods (*i.e.*, least square growth rate and average growth rate) to quantify the growth rate of crop-specific P removal among provinces, as described in Supporting Information. However, our simulation for historical pastureland soil P dynamics only covered the period from 1961 to 2022 due to limited information on P applications.

To calculate soil P loss, we collected the average annual discharge in Canada from 1971 to 2013 (Table S5), as reported by Statistics Canada (Fig. 6.S1). We then collected field precipitation from Environment and Climate Change Canada, the monitoring stations were summarized in Fig. 6.S2. We used the mean precipitation value (1908–2022) for all years of the future simulation runs, according to Van Meter et al. (2021).

6.2.3.2 2023-2030 projection

We collected projected agricultural statistics to estimate the potential benefits of soil residual P reuse in reducing P application for Canada. However, given the great variety of crop yields and livestock productions in our model, it is probably impractical to use crop models to predict yields for all of them in the short term. While a few crop model studies have projected yields for a single or three typical Canadian crops (Chipanshi et al., 2015, Ma et al., 2021), there is no national-scale predictions for other crop yields. To address this, we used projected statistics from 2023 to 2030 collected from a report by Agriculture and Agri-Food Canada, which forecasted increases in major crop yields, crop seeding areas, and primary livestock inventory for the ten-year period (2021-2030) based on economic models (MTO, 2021) (Fig. 6.S3). However, projected mineral P demand is not available for Canada. Although Mogollón et al. (2018) estimated global mineral P demand in 2050 based on the projected crop P uptake, mineral P projections are unavailable for Canada. Van Vuuren et al. (2010) had projected P consumption in Canada under different ecosystem scenarios, while they only provided static prediction for 2100. In this study, we assumed that cropland mineral P applications in each province between 2023 and 2030 would increase linearly at the same growth rate as the projected increase in crop P removal according to the MTO scenario. However, for pastureland, we assumed that mineral P applications would remain the same as 2022 due to the relatively stable inventory of cattle, sheep, and hog (Fig. 6.S3). Fig. 6.S4 summarized the projections of mineral P application, and the uncertainty associated with the mineral P projection was described in section 2.4. Based on the MTO scenario, mineral P application in Canada is projected to increase from 0.5 Tg (2020) to 0.59 Tg (2030). This increase aligns with the result of Mogollón et al. (2021), who predicted an increase of 0-0.5 Tg in mineral P application in Canada from 2005 to 2050 under various socioeconomic scenarios, and the major increase occurred between 2005 and 2035.

6.2.4 Sensitivity and uncertainty analyses

Prior to modeling, we applied a one-factor-at-a-time approach (Wang et al., 2021) to test the sensitivity of soil P dynamics model parameters (see Supporting Information). Because most of the datasets were collected from official or international agencies, and there was no repetitive datasets available to cross-validate them, uncertainties from the datasets (*e.g.*, clerical errors) were not analyzed and as a consequence we only addressed the uncertainties of parameters of the P cycle model. We established a Monte Carlo simulation assuming the parameters followed continuous uniform distributions. This approach was used in previous P cycling studies (Liu et al., 2016; Yuan et al., 2019). We randomly ran the model 10,000 times and used the 5th and 95th percentiles to represent the range of outcome uncertainty (Table S6). We determined the ranges of P flows' coefficients according to a previous P cycling work (Wang et al., 2022). We reran the modeling by inputting ±10% of the projected mineral P values to consider the uncertainty of mineral P applications.

6.2.5 Model validation

Although we have recalculated the recycled crop residue P flow in the present work (see section 2.2.2), Wang et al. (2022) had shown that recycled crop residue P flow did not play a significant role in soil P balance, and our revision did not see a substantial change in recycled crop residue P flow (Fig. 6.S5). Our estimated soil P balance during the 1961-2018 period was comparable to other national-scale (van Bochove et al., 2012; Reid et al., 2019), provincial-scale (Van Staden, 2019), or watershed-scale P balance calculations (MacDonald & Bennett, 2009; Bittman et al., 2017; Harder et al., 2021), as well as watershed soil P surveys (MacDonald and Bennett, 2009), details can be found in Wang et al. (2022). To further validate our modeling results, we compared soil labile P simulations with McDowell et al. (2023) who integrated 33000 soil test P samples (Table S7). Simultaneously, we broadly compared soil P loss simulations with annual edge-of-field P loss rates collected from field studies (Table S8). And the simulated crop P removal rates by the soil P dynamics model were validated by actual crop P removal rates obtained through the P cycling model (Fig. 6.S7 and Table 6.S9).

We applied a 10-fold cross-validation to calibrate the parameters used in the soil P dynamics model (Fig. 6.S6). The initial values of the model parameters were selected based on previous studies (Sattari et al., 2012; Van Meter et al., 2021; Wang et al., 2022). Table 6.S10 summarized the soil P dynamics model parameters used in this study. We used the coefficient of determination (R^2) and the index of agreement (d) (Wang et al., 2021; Li et al., 2022) to assess the modeling accuracy, expressed as:

$$R^2 = \left(\frac{n*\sum_{i=1}^{i=n}(Sim_i*Obs_i)-\sum_{i=1}^{i=n}Sim_i*\sum_{i=1}^{i=n}Obs_i}{\sqrt{n*\sum_{i=1}^{i=n}{Sim_i}^2-(\sum_{i=1}^{i=n}Sim_i)^2}*\sqrt{n*\sum_{i=1}^{i=n}{Obs_i}^2-(\sum_{i=1}^{i=n}Obs_i)^2}}\right)^2 \tag{6.15}$$

$$d = 1-\frac{\sum_{i=1}^{i=n}(Sim_i-Obs_i)^2}{\sum_{i=1}^{i=n}(|Sim_i-\overline{Obs}|+|Obs_i-\overline{Obs}|)^2} \tag{6.16}$$

where n is the number of paired observed and simulated values, Obs_i is the ith observed value, $\overline{Obs}$ is the mean observed value, Sim_i is the ith simulated value. R^2 and d are both statistical measures used to assess the goodness of fit between observed and predicted values in a model. R^2 measures the proportion of variance explained by the model, while d evaluates the similarity between observed and predicted values. The R^2 and d values range from 0 to 1. If the evaluated model accurately depicts the datasets, R^2 and d should be close to 1.

6.3 Results

6.3.1 Projected soil P balance

From 2023 to 2030, a majority of Canada's agricultural land was projected to experience soil P accumulation, with the highest buildup anticipated in the Atlantic provinces, Quebec, Ontario, and British Columbia (Fig. 6.1). Average soil P accumulation rates in these regions were projected to be 612 kg ha^{-1}, 187 kg ha^{-1}, 89 kg ha^{-1} and 138 kg ha^{-1}, respectively (Fig. 6.1a). In contrast, Manitoba, Saskatchewan, and Alberta were projected to have lower average soil P accumulation rates of approximately 68 kg ha^{-1}, 19 kg ha^{-1} and 41 kg ha^{-1}, respectively (Fig. 6.1a).

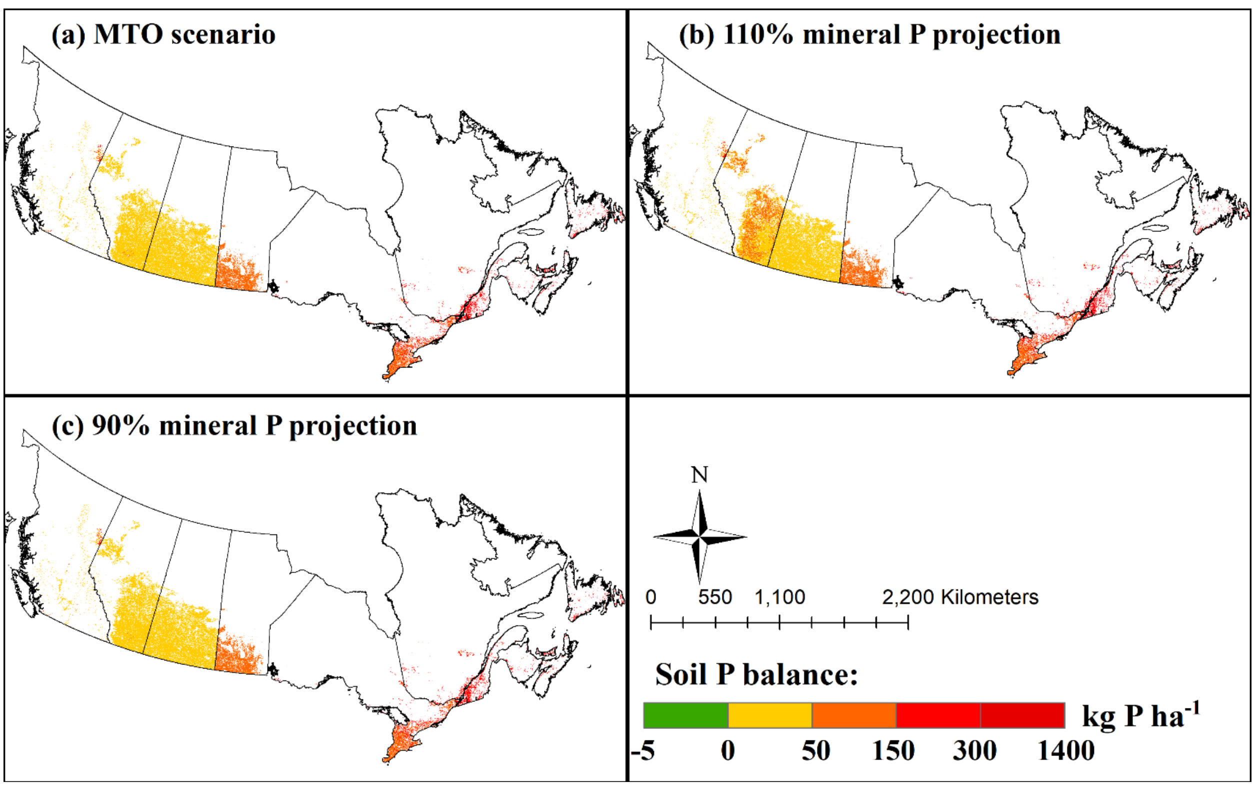


Figure 6.1 Spatial distribution of soil P balance in Canada’s agricultural land during the 2023-2030 period, with warmer colors indicating net P gain and green color indicating P loss: (a) MTO projections with the projected mineral P application, (b) MTO projections assuming 110% of the projected mineral P application, and (c) MTO projections with only 90% of the projected mineral

P application.

Table 6.1 Temporal changes in Canada's cropland area, P application rates, crop P removal, and soil P loss rates.

Province	Area, 10^6 ha^{-1}		P application rate, fertilizer and manure, kg ha^{-1}		P removal rate, kg ha^{-1}		P loss rate, kg ha^{-1}		Soil P surplus, Gg
	2021	2030	2015-2020*	2030	2015-2020*	2030	2015-2020*	2030	2023-2030**
Cropland									
Atlantic**	0.2	0.2	96	92.9	13.1	13.4	5.36	3.72	164
Quebec	1.2	1.3	39.3	43.1	20.8	21.2	2.1	1.62	302
Ontario	3	3.4	25.1	27.5	23.5	23.8	0.68	0.42	322
Manitoba	4.1	4.4	22.1	23.1	18.1	18.8	0.44	0.31	345
Saskatchewan	15	16.2	11.3	12.7	14.2	14.9	0.12	0.09	253
Alberta	8.7	9.1	15.5	17.2	16.1	16.7	0.82	0.57	389
British Columbia	0.2	0.2	31.7	41.6	13.3	9.5	5.86	4.45	64
Pastureland									
Atlantic	0.1	0.1	32.1	32.1	3.6	3.5	1.23	0.95	22
Quebec	0.2	0.2	30.8	34.5	7.3	6.9	0.82	0.72	51
Ontario	0.5	0.5	19.1	23.6	5.2	5.3	0.69	0.59	81
Manitoba	1.7	1.7	9.3	9.8	0.9	0.8	0.58	0.51	143
Saskatchewan	6.5	6.5	4.5	5.1	0.6	0.6	1.06	0.78	303
Alberta	8.6	8.6	3.6	3.9	1	1	0.2	0.17	298
British Columbia	1.6	1.6	2.2	2.1	0.6	0.6	0.24	0.16	39

*2015-2020 average annual rate

⁑2023-2030 accumulative rate

**Atlantic provinces (New Brunswick, Newfoundland and Labrador, Nova Scotia, and Prince Edward Island)

6.3.2 1908-2022 soil P dynamics

Our model accurately captured the historical patterns of soil P removal in both cropland and pastureland in most provinces, with the exception of Quebec and Ontario, where simulated crop P uptake exceeded observations between 1950 and 1980 (Fig. 6.S7 and Table 6.S9). In cropland, significant soil P accumulation occurred in the Atlantic provinces, Quebec, and Ontario between 1908 and 1990 (Fig. 6.2). Labile P levels increased from 3, 9, and 3 kg ha^{-1} to 112, 164, and 108 kg ha^{-1}, respectively. In 2022, the Atlantic provinces, Quebec, and Ontario exhibited the highest levels of soil P accumulation, with labile P of 102, 96, and 83 kg ha^{-1}, and stable P of 1115, 462, and 288 kg ha^{-1}, respectively. Manitoba and British Columbia showed relatively lower levels of P accumulation, with labile P of 39 and 34 kg ha^{-1}, and stable P of 165 and 185 kg ha^{-1}, respectively. Saskatchewan and Alberta exhibited the lowest levels of P accumulation, with labile P of 22 and 27 kg ha^{-1}, and stable of 49 and 55 kg ha^{-1}, respectively.

In terms of pastureland, soil P accumulation was generally lower compared to cropland in most provinces, with the exception of Quebec and Ontario (Fig. 6.3). The Atlantic provinces, Quebec, and Ontario consistently experienced soil P accumulation between 1961 and 2022, with labile P levels increasing from 33, 19, and 29 kg ha^{-1} to 87, 84, and 78 kg ha^{-1}, respectively. Other provinces did not exhibit clear trends in soil P accumulation, with soil labile P reaching 32, 16, 21, and 22 kg ha^{-1} in Manitoba, Saskatchewan, Alberta, and British Columbia, respectively, in 2022.

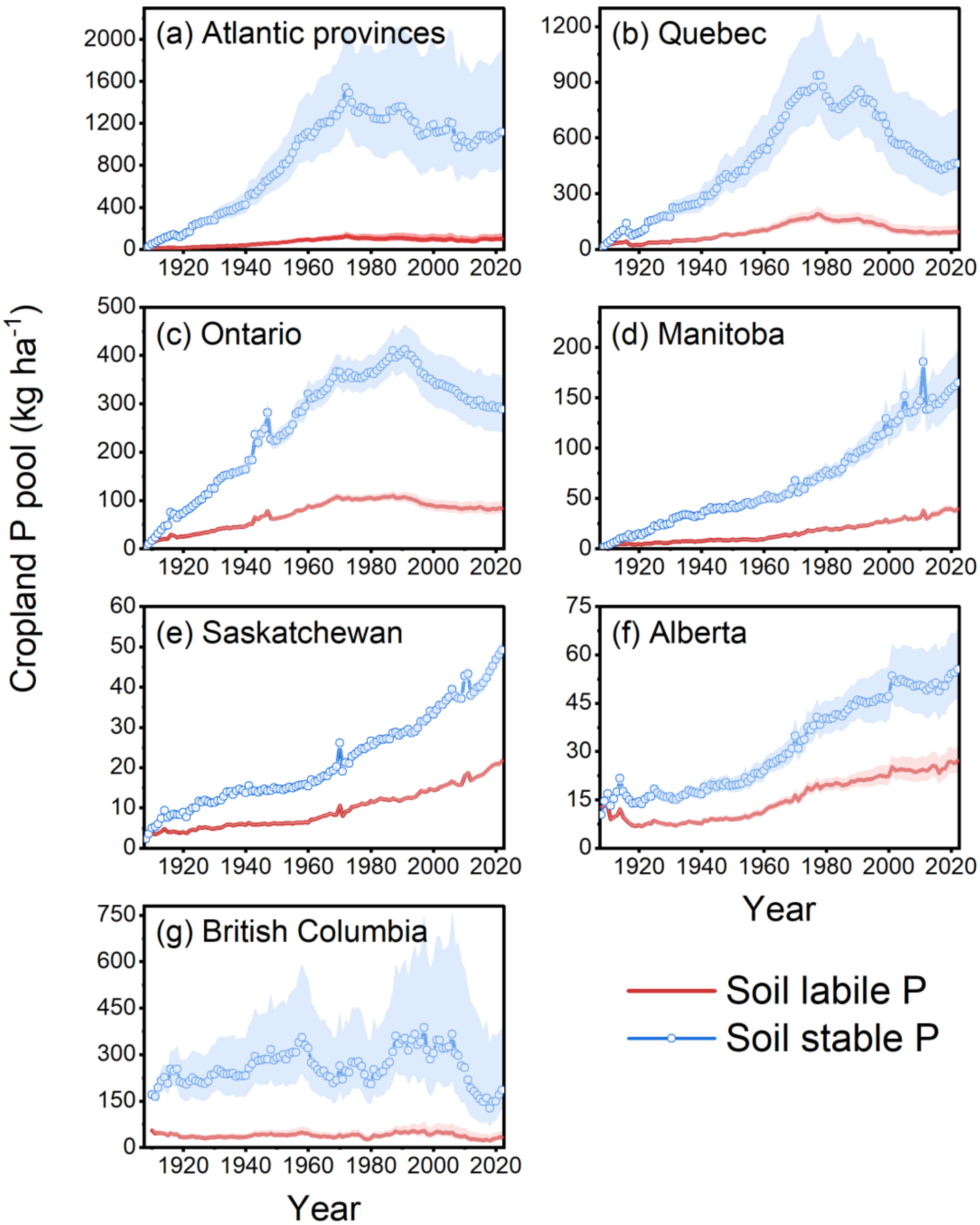


Figure 6.2 Simulation of cropland soil P dynamics among Canada's provinces from 1908 to 2022. Blue dot line and red line represent simulated soil labile P and stable P across Canada’s agricultural land, respectively. The shaded area represents the calculation uncertainty propagated from the P cycle model parameters (the 5th and 95th percentiles).

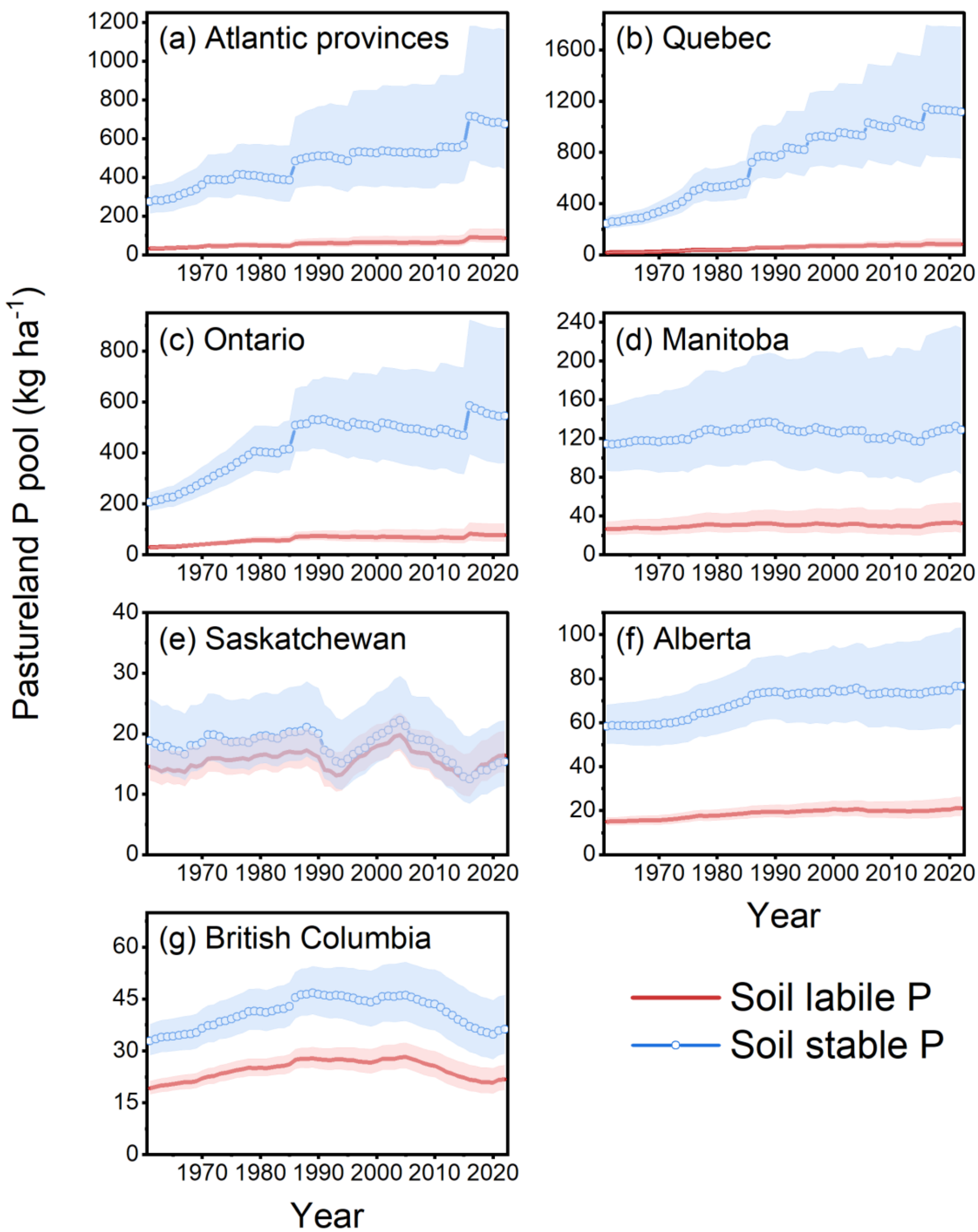


Figure 6.3 Simulation of pastureland soil P dynamics among Canada's provinces from 1961 to 2022. Blue dot line and red line represent simulated soil labile P and stable P across Canada’s agricultural land, respectively. The shaded area represents the calculation uncertainty propagated from the P cycle model parameters (the 5th and 95th percentiles).

Our simulated soil P loss rates from 1908 to 2022 align closely with field observations across provinces (Table S8). In general, almost all provinces exhibited an upward trend in soil P losses in both cropland and pastureland, with the exception of British Columbia where cropland P loss demonstrated a decreasing trend from 1908 to 1940 (Figs. 6.4 and 6.5). Among the provinces, the Atlantic provinces, Quebec, and British Columbia recorded the highest P loss rates in cropland in 2022, reaching 8, 2.3, and 3.9 kg ha^{-1}, respectively. Conversely, Ontario and Manitoba reported relatively lower P loss rates of 0.6 and 0.7 kg ha^{-1}, respectively. In terms of pastureland, the Atlantic provinces, Quebec, and Saskatchewan had relatively higher P loss rates in 2022 (1.7, 0.9, and 1 kg ha^{-1}, respectively), while Manitoba and Ontario exhibited comparatively lower P loss rates (0.9 and 0.6 kg ha^{-1}, respectively).

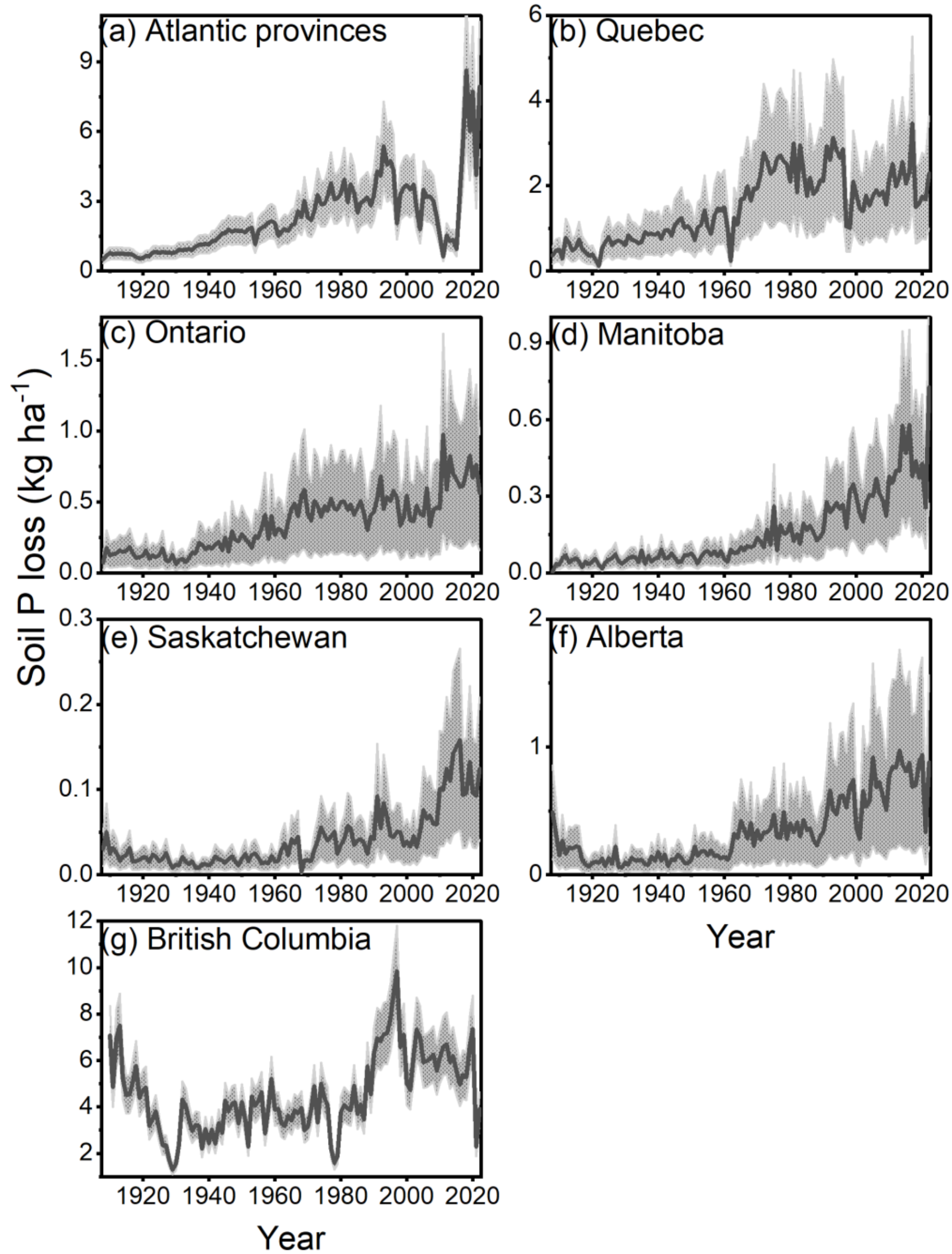


Figure 6.4 Simulation of cropland soil P loss among Canada's provinces from 1908 to 2022. The shaded area represents the calculation uncertainty propagated from the P cycle model parameters (the 5th and 95th percentiles).

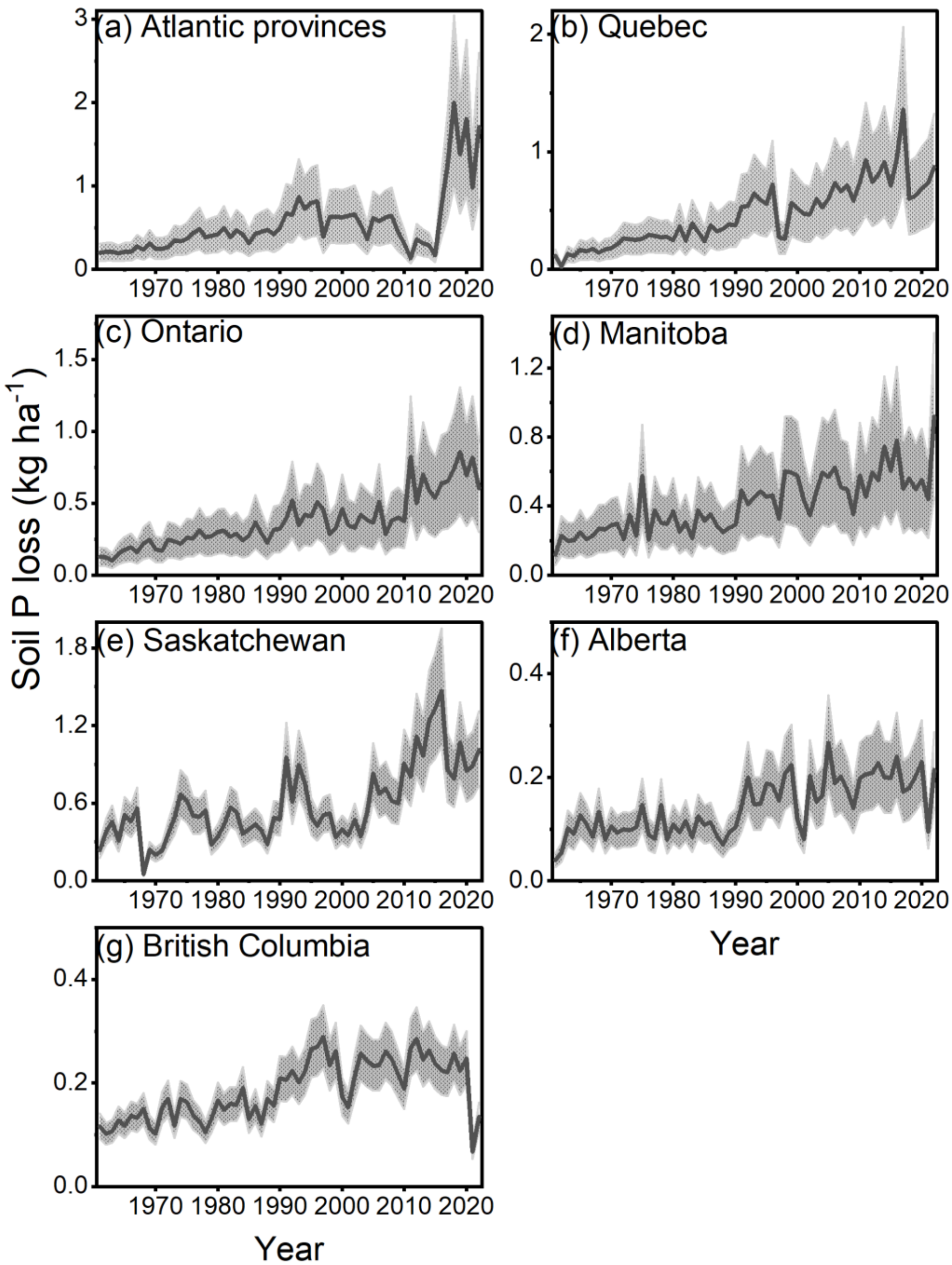


Figure 6.5 Simulation of pastureland soil P loss among Canada's provinces from 1961 to 2022. The shaded area represents the calculation uncertainty propagated from the P cycle model parameters (the 5th and 95th percentiles).

6.3.3 Cropland P application reduction

To estimate the impact of using residual soil P, we re-ran our model assuming no mineral P applications to Canada's cropland between 2023 and 2030 (Fig. 6.6). In Ontario, this led to a continuous decrease in soil labile P from 83 to 59 kg ha^{-1} over the seven-year period. The prairie provinces, specifically Saskatchewan and Alberta, experienced a rapid decline in soil P pools. Both provinces started with lower soil labile P levels compared to the recommended labile P level in the first year (2023) of the simulation. Additionally, in Manitoba, the soil labile P pool only supported the target crop P removal for the first year of the simulation, after which the value dropped below the recommended level. However, the Atlantic provinces and Quebec did not exhibit a significant decrease in soil P pools, and British Columbia showed an increasing trend over the study period through organic P application.

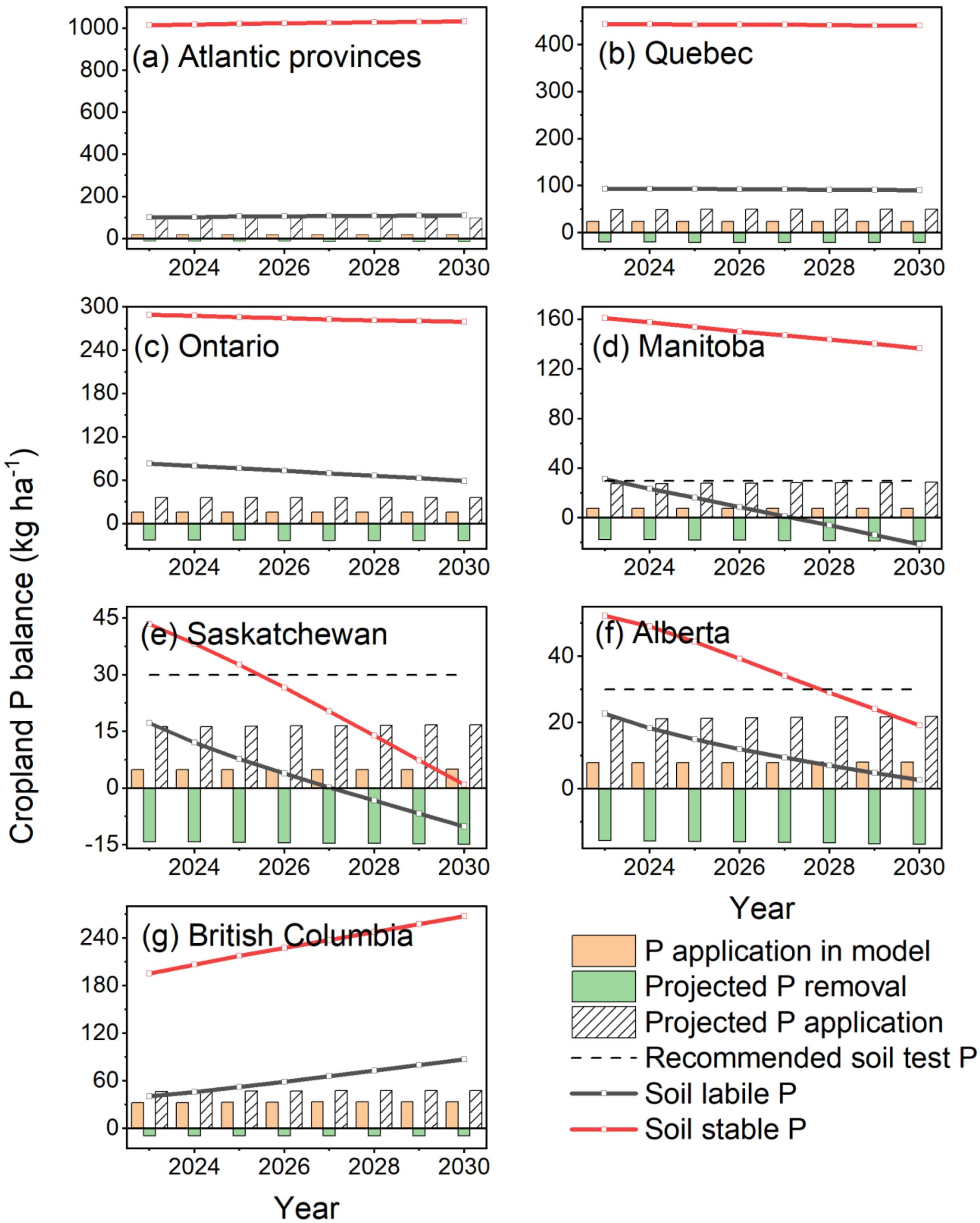


Figure 6.6 Simulation of soil P dynamics during the 2023-2030 period when reducing mineral P fertilizer applications in cropland. The green bar represents crop P removal (*i.e.*, MTO projection) in the soil P dynamics model, the orange bar represents P applications (*i.e.*, no mineral P

application) in the soil P dynamics model, while the blank bar represents the P application projection based on the MTO scenario. The dot lines represent the soil labile P and stable P pools. The dashed line represents the recommended soil labile P level in Canadian prairie provinces as cited from Grant & Flaten (2019).

We proceeded to calculate the provincial-scale cropland PUE when considering the absence of mineral P application in the Atlantic provinces, Quebec, Ontario, and British Columbia between 2023 and 2030, and reducing the one-year mineral P application in Manitoba (Fig. 6.7a). Overall, this adjustment would result in a 21% increase in Canada's cropland PUE. Specifically, PUE in the Atlantic provinces, Quebec, Ontario, and British Columbia was projected to rise from 0.13, 0.42, 0.68, and 0.21 to 0.73, 0.91, 0.96, and 0.3, respectively. Additionally, the average mineral P application in Canada between 2023 and 2030 would be reduced from 590 to 458 Gg P yr^{-1}, resulting in approximately 29% savings in annual mineral P application (Fig. 6.7b).

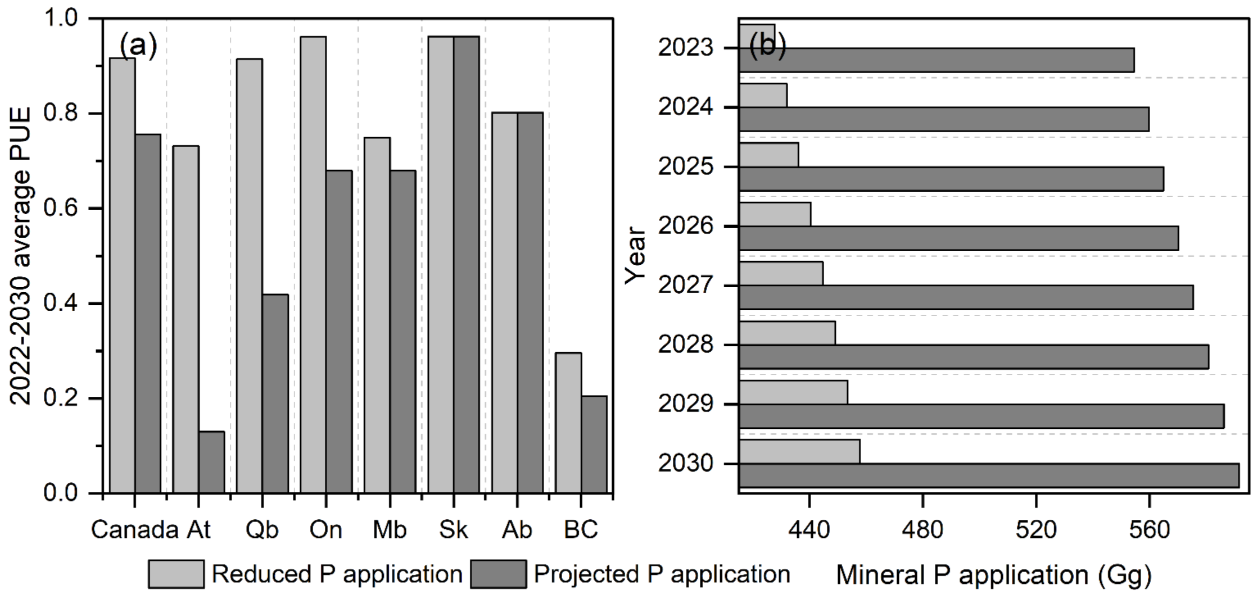


Figure 6.7 (a) Canada’s average PUE over the 2022-2030 period. (b) Potential contribution of consuming soil P pool to reduce mineral P application to meet the target crop P removal of Canada. At, Atlantic provinces; Qb, Quebec; On, Ontario; Mb, Manitoba; Sk, Saskatchewan; Ab, Alberta; BC, British Columbia.

6.3.4 Soil P loss reduction

We then reanalyzed 2023-2030 cropland soil P loss considering the mineral P application reduction, as demonstrated in Fig. 6.8. The Atlantic provinces and Quebec were expected to have the greatest soil P loss reduction, with the average P loss rate decreasing from 4.24 and 1.69 kg ha^{-1} to 3.45 and 1.38 kg ha^{-1}, respectively. Ontario, Manitoba, and British Columbia experienced relatively lower reductions in P loss, with the average soil P loss rate decreasing from 0.44, 0.36, and 4.33 kg ha^{-1} to 0.19, 0.26, and 4.14 kg ha^{-1}, respectively.

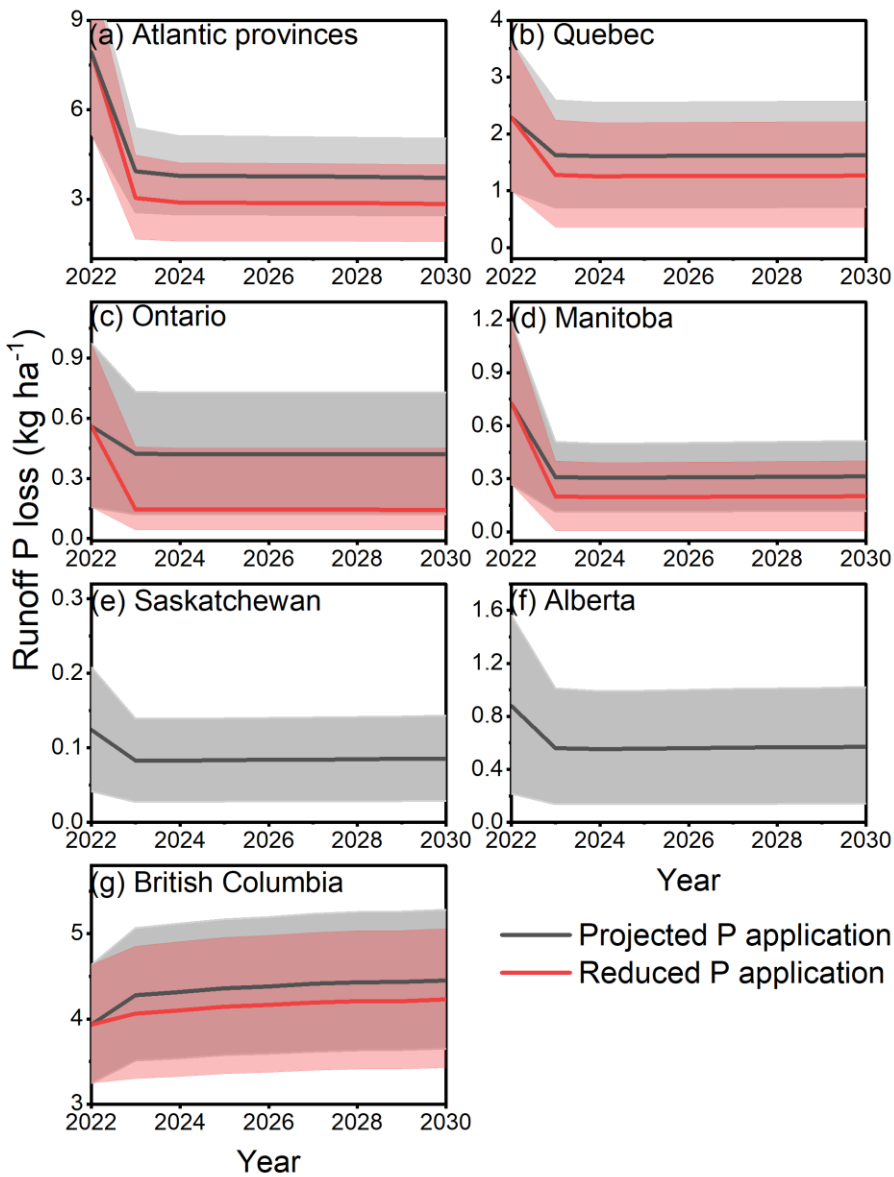


Figure 6.8 Cropland soil P loss rate in Canada from 2022 to 2030. Black line and red line represent simulated soil P loss based on MTO scenario and reduced mineral P application by using soil

residual P, respectively. The shaded area represents the calculation uncertainty propagated from the P cycle model parameters (5% and 95% percentiles).

Table 6.2 Previous field trials of reuse soil residual P to reduce P applications in Canada.

Source	Province	Result
Nyiraneza et al., 2017	New Brunswick	P application can be reduced from a general application of 105 to 35 kg P ha^{-1} yr^{-1} while sustaining potato yields
Sanderson et al., 2006	Prince Edward Island	Maximum carrot yield was achieved at 110 kg P ha^{-1} while 95% of maximum yield could be reached with 22 kg P ha^{-1}
Parent et al., 2020	Quebec	370 field trials that sustained crop yields over six years without mineral P application where the $(P/Al)_{M3}$ exceeded 5%
Zhang et al., 2004	Quebec	Ten years without P application
Zhang et al., 2020	Ontario	Fourteen years without P application
Liu et al., 2019	Manitoba	Low application (6.1-6.3 kg P ha^{-1} yr^{-1}) while sustained crop yield over eight years
Gervais, 2009	Manitoba	Three years without P application
Gao et al., 2010	Manitoba	One year without P application
Liu et al., 2015	Saskatchewan	Fifteen years without P application
McKenzie et al., 2008	Alberta	Three years without P application
Hubbard and Mason (1967)	British Columbia	Six years without P application

6.4 Discussion

6.4.1 Overview

Although there is controversy over how long global phosphate reserves will last (Cordell et al., 2009; Zou et al., 2022), there is a consensus that P use efficiency should be improved (Scholz & Wellmer, 2019). This study provides evidence of how much residual soil P could be potentially reused in Canada, and the likely impacts on soil P losses. This is a timely endeavor given the fact that P is consistently accumulated in Canada's most agricultural soils (Wang et al., 2022). Based on our previous P cycling work (Wang et al., 2022), here, we coupled a soil P dynamics model to further evaluate the potentials for reusing soil P. We showed that mineral P projections can be reduced by 29% in Canada to meet the target crop P removal, with consistent applications of organic P fertilizers (*i.e.*, manure, recycled sewage sludge, crop residues, and irrigation). Although surprisingly large, this finding is consistent with previous estimate of 17% mineral P reduction for North America (Sattari et al., 2012). In contrast, we found soil P in the prairie provinces are unlikely to support the target crop P removal without mineral P applications. This finding aligns with previous field trial in Manitoba (Gao et al., 2010), and is supported by previous government report in Alberta and the soil survey in Saskatchewan in 2015, which suggests the most agricultural soils in Alberta and Saskatchewan are under threshold P levels (Paterson et al., 2006; Guenther, 2017). Several reason may explain this result including an expansion in organic farming, an increase in high P removal crop yields against low P application rates, and a greater emphasis on addressing crop N deficiencies (Wang et al., 2022).

Global runoff P loss has increased over eightfold since preindustrial times (Rockström et al., 2009), and this alarming trend tends to exacerbate the future global P shortage (Alewell et al., 2020). In Canada, annual mineral P consumption has increased by nearly sevenfold over the past 60 years (Wang et al., 2022), this has resulted in the increases of soil P loss across all provinces (Figs. 6.4 and 6.5). Environment Canada (2011) revealed that 32% of surface water quality monitoring exceeded P guidelines more than half the time between 2005 and 2007, with provinces like Quebec, Ontario, Manitoba, and British Columbia suffering from long-term freshwater P pollution issues (Canada-Ontario Lake Erie Action Plan, 2018; Environment and Climate Change Canada, 2021). Previous work has emphasized the urgent need to regulate mineral and manure P inputs in these provinces (Bittman et al., 2017; Benjannet et al., 2018; Reid et al., 2019). Our study is the first attempt to evaluate the potential benefits of reusing residual soil P to reduce P losses across Canada's agricultural soils. We expect that the Atlantic provinces and Quebec will have the greatest P loss reductions. This will result in an overall 21% increase in Canada's cropland PUE.

Achieving sustainable P management requires scientifically guided P management plans, as highlighted in earlier analyses (Michalak et al., 2013; Schindler et al., 2016). A range of agricultural practices can reduce runoff P loss, including conservative tillage (Duits, 2019), cover crops (Zhang et al., 2017), and vegetated buffer strips (Roberts et al., 2012), but effective P loss control requires careful management of P fertilizer application to account for the release of residual P (Jarvie et al., 2013). It is crucial to recognize that continued P inputs to watersheds with residual P buildup can result in more rapid P loss in runoff, and it may take centuries to millennia for soil P levels to return to below-threshold conditions (Goyette et al., 2018). Therefore, the regulation of residual P is an essential goal in achieving sustainable P management.

6.4.2 Evaluation of results and limitations

We find that the Atlantic provinces, Quebec, Ontario, and British Columbia have the greatest potential to reuse soil residual P. This finding is cross validated with previous experiments and field surveys (Table 2). However, considering the field heterogeneity and management, we find that fields in Alberta and Saskatchewan can also sustain crop yields by using soil residual P. This suggests that our province-scale projections need to be down-scaling to make them watershed-appropriate. We do not consider the effects of agricultural practices in our soil P dynamics modeling. This could result in a bias in the potential contribution of residual P to P applications. However, a global meta-analysis suggests that soil properties have a greater impact on the release of residual P compared to climate and agricultural practices (MacDonald et al., 2012). Previous experiments in Canada further support the significance of soil properties in soil P release (Laverdière & Karam, 1984; Lafond & Ziadi, 2018; Messiga et al., 2021; Kedir et al., 2021). Moreover, a field trial conducted in Quebec suggests that even in high P-fixing soils, a large initial application of P can be sufficient to achieve high crop yields for several years due to the release of residual P (Kamprath, 1967).

Crop P removal modeling in Quebec and Ontario shows relatively low accuracy for the period between 1950 and 1980. This can be attributed to the extensive use of mineral fertilizers and manure in these regions during that time to achieve maximum crop yields (Bruulsema et al., 2011; IJC, 2018; van Bochove et al., 2011). As our model simulates soil P removal based on P applications (Equations 3 and 5), it tends to overestimate crop P removal when large P applications are employed. This observation aligns with a recent global-scale study that also encountered challenges in reproducing temporal trends in 29% of the countries using the same model (Demay et al., 2023). This may also be ascribed to the methodology employed for initializing the initial soil labile P pool. In our study, the labile pool size was initialized based on available information on P input and harvest in 1908, while Ringeval et al. (2017) initialized their labile pool size using data on natural soil P derived from Hedley fractionation measures by Yang et al. (2013). Additionally, our study did not consider inter-provincial trade in fertilizers due to the unavailability of data, which may lead to an overestimation of P applications. However, it is worth noting that the crop P removal modeling in Quebec and Ontario aligns better with observations after 1990 (Fig. 6.S7), and the comparison between simulated soil labile P and P loss rates, as well as field observations, remains reasonable (Tables S7 and S8). These findings indicate that our estimated soil P pool consumption between 1950 and 1980 may have been overestimated.

In addition, we assume that mineral P would increase linearly at the same rate as the increase in crop P removal, this could be the potential caveats in our estimates, because mineral P application can be influenced by climate and fertilizer prices (Cordell et al., 2009). While our projected mineral P applications between 2023 and 2030 appear to be reasonable compared to Mogollón et al. (2021), and our national-scale average P surplus rate of 3.8 kg ha^{-1} for the period between 2023 and 2030 is also comparable to estimate of Zou et al. (2022). Furthermore, the time series of observational datasets and parameters, collected as much as possible from national statistics, government reports, literatures and field experiments may still contain temporal and geographical uncertainties, notwithstanding the thorough uncertainty assessment conducted to bolster the robustness of our findings. Further improvement in the accuracy of this study can be achieved through the acquisition of more precise activity data and parameters. In addition, our analyses do not include economic analysis as suggested in Yuan et al. (2018), therefore further investigations are warranted to improve the understanding of the value of residual P.

6.4.3 Moving forward

Maintaining agricultural production while reducing environmental impacts is a critical challenge that calls for innovative solutions. Our study highlights the potential of reusing residual P to reduce reliance on mineral P fertilizers and mitigate soil P losses in Canada. We find that the Atlantic provinces, Quebec, Ontario, and British Columbia have the greatest potential to reduce P applications though the use of residual P. Hence, more attention should be paid to the reuse of residual P in these provinces for policy decisions pertaining to optimal fertilizer use. However, it is important to recognize that the use of residual P alone provides a temporary solution unless the recycling of organic-sourced P, such as manure and sewage sludge, is increased. Further investigations are warranted to explore the possibilities of enhancing organic P recycling to decrease the need for additional P applications. Besides, more field experiments are required to assess the reuse of residual P in the Atlantic provinces, Quebec, Ontario, and British Columbia. Strategies that promote the release of residual P in field crop production are crucial and increasingly significant. Previous field experiments have suggested that intercropping or crop rotation can enhance the release of residual P by promoting the secretion of organic acids and phosphatase (Hinsinger et al., 2011; Darch et al., 2018). Other agricultural practices, such as crop straw return to the field and reduced tillage, have also been found to improve soil phosphatase activity and increase the release of residual P (Monreal et al., 2000; Calonego et al., 2013). However, some studies have reported that these practices may lead to an increase of soluble P losses (Jarvie et al., 2017), thus warrant site-specific investigation (Macrae et al., 2020). Additionally, biofertilizers could be a promising technology for solubilizing insoluble P to soluble forms, as various soil microorganisms and agents have been documented to effectively solubilize insoluble P (Edwards et al., 2016; Ichriani et al., 2018). Furthermore, breeding new cultivars with enhanced P absorption abilities represents a potential strategy (Lyu et al., 2016), but further research is needed. The efficient utilization of soil P is crucial for a sustainable global P cycle in the 21st century.

6.5 Conclusion

Our study attempts to evaluate the spatial and temporal changes in residual soil P across Canada's agricultural landscape. We provide the conclusive evidence of how much residual soil P can be potentially reused in Canada, and the likely impacts on soil P losses. It will contribute to the growing body of knowledge regarding the sustainable P use. We highlight that the Atlantic provinces, Quebec, Ontario, and British Columbia have the greatest potential to reduce P applications, with the greatest reduction in soil P loss projected in the Atlantic provinces and Quebec. This will enhance the understanding of the role of residual P in achieving a more sustainable P cycle throughout Canada. Our research could also support policy decisions pertaining to optimal fertilizer use within the agricultural sector of Canada. Strategies that promote the release of residual soil P in field crop production are crucial and increasingly significant. Improvements in the precision of activity data and parameters, and further investigation into the economic implications, offer opportunities to expand our understanding of the value in reutilizing residual soil P.

6.6 Supplementary Information

1 P cycling model

Material Flow Analysis (MFA) is a mass-balance method that tracks material flows within a defined system boundary. It is an efficient tool for quantifying P stocks and flows (Wang et al., 2022). We built a P cycling model based on MFA that considers the production of principal crops and livestock, and addresses two stocks (*i.e.*, cropland and pasture) at two geographic levels of jurisdiction (*i.e.*, national and provincial). Table 1 summarized the primary equations in our P cycling model.

1.1 Inflows

Inflows were fertilizers, irrigation water, atmospheric deposition, and weathering. Annual national imports, mining and consumption of P mineral fertilizers (expressed as the P_2O_5 equivalent) were collected from the Statistics Division of the International Fertilizer Industry Association (IFASTAT) (https://www.ifastat.org/databases/plant-nutrition), Statistics Canada (https://www150.statcan.gc.ca/n1/en/type/data?MM=1), and government report (https://publications.gc.ca/site/eng/9.853784/publication.html). We assumed no inter-provincial trade in fertilizers since this information is not available. Atmospheric deposition, typically neglected or regarded as a constant in previous studies (Chen and Graedel, 2016; Wironen et al., 2018), was assumed to be 0.4 kg P ha^{-1} y^{-1}, which is consistent with field observations (Živković et al., 2017). Irrigation water P was estimated by multiplying monitored P concentration of source water (0.05 mg L^{-1}) (Little et al., 2010) by irrigation volume reported in Statistics Canada.

1.2 Outflows

Crop production is the main P outflow from cropland; other outputs include crop residues and runoff loss. Statistics Canada provides the provincial annual production and seeding area of 71 major crops that were all considered in our analysis (https://www150.statcan.gc.ca/n1/en/type/data?MM=1). Crop P removal was estimated by crop yield multiplying by corresponding P content (Table 2). Crop residues were estimated based on the corresponding crop straw/yield mass ratio (Li et al., 2012). Crop residue P flow was assessed by multiplying straw mass by the P content in crop straw obtained from the International Plant Nutrition Institute (IPNI, 2015) (http://www.ipni.net/article/IPNI-3296).

We also considered the P outflows of 17 most important livestock types of Canada (*i.e.*, grass P uptake and manure). Provincial livestock inventory was collected from Statistics Canada. We estimated grazing P uptake based on livestock inventory, reported grazing time, and daily grass consumption rates assessed by government documents, literature and farmer consultations (Alberta Lamb Producers, 2013; Blood and Lovaas, 1966; Canada beef, 2015; Feeding 4-H Calves, 2021; Vachon et al., 2007). Daily grass consumption rates were different by livestock species, and set to constants (Table 3). Livestock manure P was specified by livestock types (Table 4), and estimated by multiplying livestock populations by their P excreta rates (Lun et al., 2018).

1.3 Interflows

Interflows included recycled P flows of sludges, crop residues and manures. Sludge P flow included detergent and human excreta P flows. The P emissions from laundry and dishwasher detergents were estimated based on detergent P consumption (0.24 and 0.04 kg P yr^{-1} per capita in laundry and dishwater, respectively before 2010; 0.1 and 0.11 kg P yr^{-1} per capita in laundry and dishwater, respectively after 2010) (van Puijenbroek et al., 2018), and resident population was provided by FAOSTAT (https://www.fao.org/faostat). P-free detergent sold in Canada's market was not considered here due to data scarcity. Human excreta P was estimated based on the excreta ratio (0.43 kg yr^{-1} per capita) (Cordell et al., 2009; Van Staden, 2019). Considering the relatively slow development of wastewater recycling compared to Europe Union countries (30% in the Netherlands, Cordell and White, 2013; 25% in Germany, Ross and Omelon, 2018), and the percentage of population served by sewerage treatment in Canada was close to Germany (Hitchman, 2018), we therefore assumed 20% of P from detergent and human excreta were processed and recycled to cropland. For each province, manure left on pasture, recycled to cropland, or lost during handling were assessed based on the proportion estimations of Huffman et al. (2008) (Table 4). Harvested crops as livestock feed were collected from FAOSTAT.

Table 1. Equations used in Canada's P cycling model.

Pool	Flow	Calculation	Coefficient and source
Phosphate	Inorganic fertilizer (P_{fer})	$P_{fer} = P_{P_2O_5}\% \times Fer$	Fer: P minerals from IFA and Statistics Canada
Irrigation	Irrigation to cropland ($P_{irrigation}$)	$P_{irr} = P_{irrigation}\% \times Irr$	Irr : irrigation water volume from Statistics Canada

			$P_{irrigation}\%$: P content in irrigation water (Little et al., 2010)
Atmosphere	Deposition to cropland ($P_{atmcrop}$)	$P_{atmcrop} = Croparea \times Atm$	Atm : Annual atmospheric P deposition rate (Živković et al., 2017)
	Deposition to pasture ($P_{atmpasture}$)	$P_{atmpasture} = Pasturearea \times Atm$	
Cropland	Crop production (P_{crop})	$P_{crop} = Crop \times P_{crop}\%$	$P_{crop}\%$: crop P content collected from IPNI, 2015
	Crop as food ($P_{crop-food}$)	$P_{crop-food} = Crop - Food \times P_{crop}\%$	Crop source: FAOSTAT
	Crop as livestock feed ($P_{crop-feed}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop as seed ($P_{crop-seed}$)	$P_{crop-seed} = Crop - Seed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop processing ($P_{crop-pro}$)	$P_{crop-pro} = Crop - Processing \times P_{crop}\%$	Crop source: FAOSTAT
	Crop losses ($P_{crop-losses}$)	$P_{crop-losses} = Crop - Losses \times P_{crop}\%$	Crop source: FAOSTAT
	Crop as other uses ($P_{crop-other\ use}$)	$P_{crop-oth} = Crop - Other\ Use \times P_{crop}\%$	Crop source: FAOSTAT
	Crop export ($P_{crop-export}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop import ($P_{crop-import}$)	$P_{crop-feed} = Crop - Feed \times P_{crop}\%$	Crop source: FAOSTAT
	Crop residues ($Residue_{crop}$)	$Residue_{crop} = Cropgrain \times Res$	Res: straw/grain ratio for Canadian crops (Li et al., 2012)
	Total crop residues	$P_{crop-res} = Residue_{crop} \times P_{crop}\%$	

	($P_{crop-res}$)		
	Crop residues recycled to cropland ($P_{recy-res}$)	$P_{recy-res} = P_{crop-res} \times 50\%$	Li et al. 2012
	Crop residues as feed ($P_{feed-res}$)	$P_{feed-res} = cattle\ number\ (h) \times 1\ kgh^{-1}d^{-1} \times 150\ d$	Li et al. 2012
	Crop residues to other uses ($P_{oth-res}$)	$P_{oth-res} = P_{crop-res} - P_{recy-res} - P_{feed-res}$	
	Cropland runoff ($P_{runoff-crop}$)	$P_{runoff-crop} = (P_{fer} + P_{atmcrop} + P_{irr} + P_{recy-res} + P_{crop-manure} + P_{sludge-cro}) \times 7\%$	Sattari et al., 2012; Wironen et al., 2018; Lun et al., 2018
Pasture	Grass as feed ($P_{grass-uptake}$)	$P_{grass-uptake} = \text{Weight} \times \text{uptakeratio} \times \text{time} \times P_{grass}$	weight: livestock average weight uptakeratio: daily grass uptake rate, expressed as percentage of body weight time: grazing time period (92 days, from June to August) P_{grass} : P content in grass (IPNI, 2015)
	Pasture runoff ($P_{runoff-pasture}$)	$P_{runoff-pasture} = (P_{atmpasture} + P_{dir-manure}) \times 7\%$	Sattari et al., 2012; Wironen et al., 2018; Lun et al., 2018
Livestock	Total manure (P_{manure})	$P_{manure} = livestock\ head \times N\ excretion\ rate \times P{:}N\ ratio$	Huffman et al., 2008; Lun et al., 2018
	Manure directly left on pasture ($P_{dir-manure}$)	$P_{dir-manure} = P_{manure} \times Dir$	Dir : Proportion of animals depositing manure directly on pasture
	Manure as waste	$P_{was-manure} = P_{manure} \times Was$	Was : Proportion of

	($P_{was-manure}$)		animals manure lost during handling
	Manure to cropland ($P_{crop-manure}$)	$P_{crop-manure} = P_{manure} - P_{dir-manure} - P_{was-manure}$	
	Meat (P_{meat})	$P_{meat} = Meat \times P_{meat}\%$	Product source: FAOSTAT
	Egg (P_{egg})	$P_{egg} = Egg \times P_{egg}\%$	Product source: FAOSTAT
	Milk (P_{milk})	$P_{milk} = Milk \times P_{milk}\%$	Product source: FAOSTAT
	Offal (P_{offal})	$P_{offal} = Offal \times P_{offal}\%$	Product source: FAOSTAT
	Fat (P_{fat})	$P_{fat} = Fat \times P_{fat}\%$	Product source: FAOSTAT
Humans	Detergent and cleaning ($P_{detergent}$)	$P_{detergent} = Population \times k_1 + Population \times k_2$	k_1: Use of P in laundry detergents (0.24 kg/cap/year before 2010, 0.1 kg/cap/year after 2010) k_2 : Use of P in dishwasher detergents (0.04 kg/cap/year before 2010, 0.11 kg/cap/year after 2010) Data source: van Puijenbroek et al., 2018
	Human excreta (P_{human})	$P_{human} = Population \times k_3 \times 365$	k_3 : Daily human excreta P (kg/cap/day) (Cordell et al., 2009; Van Staden, 2019)
	Sludge to cropland ($P_{sludge-cro}$)	$P_{sludge-cro} = (P_{detergent} + P_{human}) \times 20\%$	

	Sludge to freshwater ($P_{sludge-fre}$)	$P_{sludge-fre} = (P_{detergent} + P_{human}) \times 80\%$	

Table 2. Crop categories and their P contents.

Category	P content (%, w/w)	Items
Cereals	0.35	Winter wheat
	0.38	Spring wheat
	0.36	Durum wheat
	0.08	Wheat straw
	0.18	Corn
	0.1	Corn straw
	0.31	Oats, Barley, Rye, Mixed grains, Canary seed
	0.11	Oat straw, Barley straw
	0.07	Rye straw
	0.1	Mixed grains straw
	0.22	Buckwheat, Triticale
Oilseeds	0.57	Flaxseed
	0.1	Flaxseed straw
	0.52	Soybeans
	0.19	Soybean straw
	0.7	Canolar rapeseed
	0.1	Canolar rapeseed straw
	0.47	Mustard seed
	0.42	Sunflower seed
	0.04	Sunflower seed straw
Pulses	0.57	Dry white beans, Colored beans
	0.43	Dry peas, Faba beans
	0.11	Dry peas straw
	0.37	Chickpeas
	0.36	Lentils
Sugar beet	0.05	Sugar beet
	0.09	Sugar beet straw
Tame hay	0.25	

Vegetables and melons	0.02	Fresh asparagus, Fresh beets, Fresh broccoli, Fresh Brussels sprouts, Fresh cabbage, Fresh carrots, Fresh cauliflowers, Fresh celery, Fresh cucumbers and fresh gherkins (all varieties), Fresh dry onions, Fresh eggplants (except Chinese eggplants), Fresh French shallots and green onions, Fresh garlic, Fresh green and wax beans, Fresh leeks, Fresh lettuce, Fresh parsley, Fresh parsnips, Fresh peppers, Fresh pumpkins, Fresh radishes, Fresh rhubarb, Fresh rutabagas and turnips, Fresh spinach, Fresh squash and zucchini, Fresh sweet potatoes, Fresh tomatoes, Fresh watermelons, Other fresh melons
	0.07	Potato, Green maize
	0.03	Potato straw
Fruit	0.04	Fresh apples, Fresh grapes, Fresh strawberries, Fresh apricots, Fresh blackberries, Fresh blueberries, Fresh cranberries, Fresh currants, Fresh nectarines, Fresh peaches, Fresh pears, Fresh plums and prune plums, Fresh raspberries, Fresh saskatoon berries, Fresh sour cherries, Fresh sweet cherries

Data sources: IPNI, 2015; Chen and Graedel, 2016; Lun et al., 2018

Table 3. Parameters used for livestock grass P uptake.

Livestock type	Average weight (kg)	Daily uptake ratio of body weight	Time period (day)	P content in grass
Bull	800	2.5%	92	0.15%
Steer	800	2.5%	92	0.15%
Dairy	450	3%	92	0.15%
Beef	450	3%	92	0.15%
Heifer	345	3%	92	0.15%
Calve	145	2.5%	92	0.15%
Sheep	97	3%	92	0.15%
Lamb	45	2.5%	92	0.15%
Goat	83	4%	92	0.15%

Horse	527.5	2%	92	0.15%
Elk	315.3	3%	92	0.15%

Data sources: Alberta Lamb Producers, 2013; Blood and Lovaas, 1966; Canada beef, 2015; Feeding 4-H Calves, 2021; Vachon et al., 2007; Farmer consultations.

Table 4. Manure P excretion rates and proportion of animals depositing manure directly on pasture, by province and livestock type.

Animal type	N excretion rate (kg N head^{-1} yr^{-1})	P:N ratio for livestock manure	Proportion of animals depositing manure directly on pasture (%)									
			BC	AB	SK	MB	ON	QC	NB	NS	PE	NL
Broilers	0.4	0.24	0	0	2	0	0	0	0	3	0	0
Hens	0.6	0.24	0	0	10	0	0	0	0	0	0	0
Pullets	0.4	0.24	0	0	10	0	0	0	0	0	0	0
Turkeys	1.5	0.25	0	30	40	10	1	3	2	3	0	2
Calves	25.3	0.18	70	45	48	70	33	50	50	49	40	44
Steers	56.3	0.18	70	45	48	70	33	50	50	49	40	44
Heifers	52.2	0.18	5	0	25	50	17	19	22	10	40	22
Beef cattle	78.8	0.18	70	45	48	70	33	50	50	49	40	44
Dairy cows	122	0.18	5	0	25	50	17	19	22	10	40	22
Bulls	90.1	0.18	70	45	48	70	33	50	50	49	40	44
Boars	9.9	0.28	2	0	1	0	0	0	0	0	1	0
Hogs	8.5	0.28	2	0	1	0	0	0	0	0	1	0
Sows	9.6	0.28	0	0	0	0	0	0	0	0	0	0
Sheep	7	0.15	80	100	60	75	62	43	40	25	50	40
Goats	10.5	0.15	76	75	60	75	60	25	38	50	38	38
Horses	49.3	0.19	50	89	60	60	57	50	47	50	40	47
Elk,deer	25.1	0.19	50	89	60	60	57	50	47	50	40	47

Data sources: Huffman et al., 2008; Lun et al., 2018

2 Calculation of crop P removal growth rate

2.1 The least-squares growth rate

The least-squares growth rate represents an average rate and is reflective of the available observations over the entire period. This method can be applied to any type of variable, as it does not assume any specific growth pattern (Javorsek, 2015). The time trend equation is derived through a logarithmic transformation:

$$X_{t_n} = X_{t_0} * (1 + r)^n \quad (1)$$

$$lnX_{t_n} = lnX_{t_0} + nln(1 + r) \quad (2)$$

where n is the number of time periods (yr); X_{t_0} is the value of the variable X (*i.e.*,71 species crop yield) at time t_0; X_{t_n} is the value of the variable X at time t_n; r is the growth rate over the n-period time series; and ln is the natural logarithm. Then the regression model can be expressed as:

$$lnX_{t_n} = \alpha + \beta n + \varepsilon \quad (3)$$

$$r = \exp(\hat{\beta}) - 1 \quad (4)$$

where $\alpha = lnX_{t_0}$, $\beta = ln(1 + r)$.

2.2 The average growth rate

The average growth rate is a frequently used method for estimating the growth rate of various variables (Javorsek, 2015). The equation for the average growth rate is expressed as:

$$r_{ave} = \left(\frac{X_{t_n}}{X_{t_0}}\right)^{\frac{1}{n}} - 1 \quad (5)$$

where r_{ave} is the average growth rate over the n-period time series.

We used the above two methods to calculate the growth rate of P removal for a specific crop type in a given province, and then adopted the average of the results from these two approaches to interpolate cropland mineral P applications for the specific crop type. Finally, the estimated P applications were summed to determine the provincial-scale P application. Specifically, for the period of 1908-1926, the mineral P interpolation was conducted with the following parameters: X: time series crop yield of 71 species in a given province, t_0: 1908, t_n: 1926, n: 19; For the period of 2022-2030, the mineral P interpolation was performed with the parameters: X: time series crop yield of 71 species in a given province, t_0: 2022, t_n: 2030, n: 9.

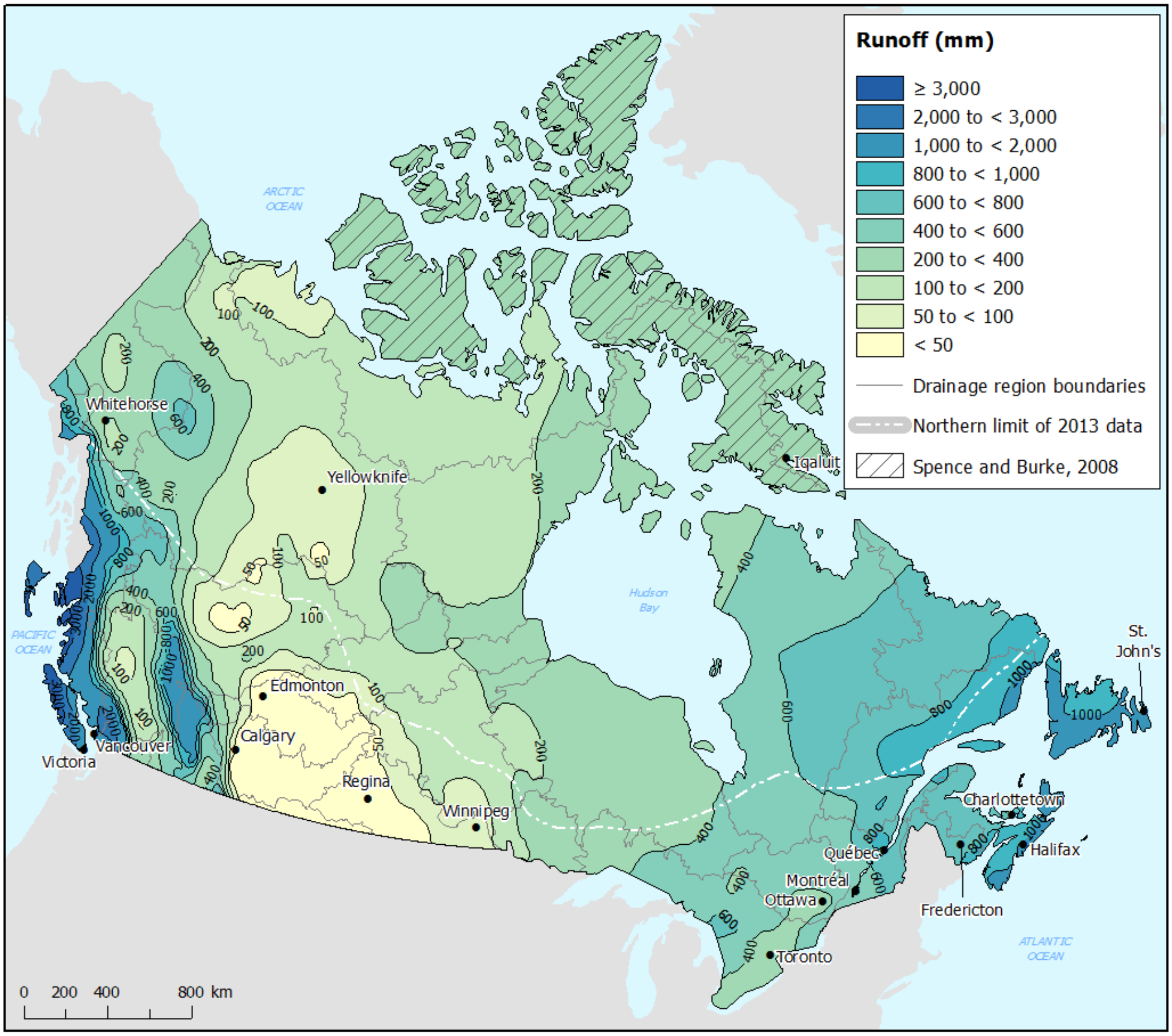
3 Sensitivity analysis

Prior to modeling, we applied a one-factor-at-a-time approach (Arunrat et al., 2018) to test the sensitivity of soil P dynamics model parameters:

$$A_i = \frac{\left|PUP_{1.1X_i} - PUP_{X_i}\right| + \left|PUP_{0.9X_i} - PUP_{X_i}\right|}{0.2PUP_{X_i}} \quad (6)$$

where A_i is the sensitivity coefficient of parameter X_i for soil P removal, ranging from 0 (non-sensitivity) to 1 (extreme-sensitivity); PUP_{X_i} is the simulated soil P removal obtained by setting all parameters to default values; and $PUP_{1.1X_i}$ and $PUP_{0.9X_i}$ are simulated soil P removal obtained by setting parameter X_i to 110% and 90% of its default value, respectively, with all other parameters set to default values. Results of sensitivity analysis were summarized in Table 6.S10.

6.7 Supplementary Tables and Figures



Note(s): Runoff data were derived from discharge values from hydrometric stations with natural flows for the period 1971 to 2013 below the boundary delineated on the map and 1971 to 2004 above the boundary line with the exception of the Arctic Islands where estimates were taken from Spence and Burke, 2008.

Source(s): Statistics Canada, Environment, Energy and Transportation Statistics Division, 2017, based on data from Environment and Climate Change Canada, 2015, *Water Survey of Canada, Archived Hydrometric Data (HYDAT)*, www.ec.gc.ca/rhc-wsc/default.asp?lang=En&n=4EED50F1-1 (accessed December 3, 2015); Spence, C. and A. Burke, 2008, "Estimates of Canadian Arctic Archipelago runoff from observed hydrometric data," *Journal of Hydrology*, Vol. 362, pp. 247–259.

Figure 6.S1 Long-term (1971-2013) average annual runoff across Canada. Source: Statistics Canada (https://www150.statcan.gc.ca/n1/daily-quotidien/170321/mc-b001-eng.htm).

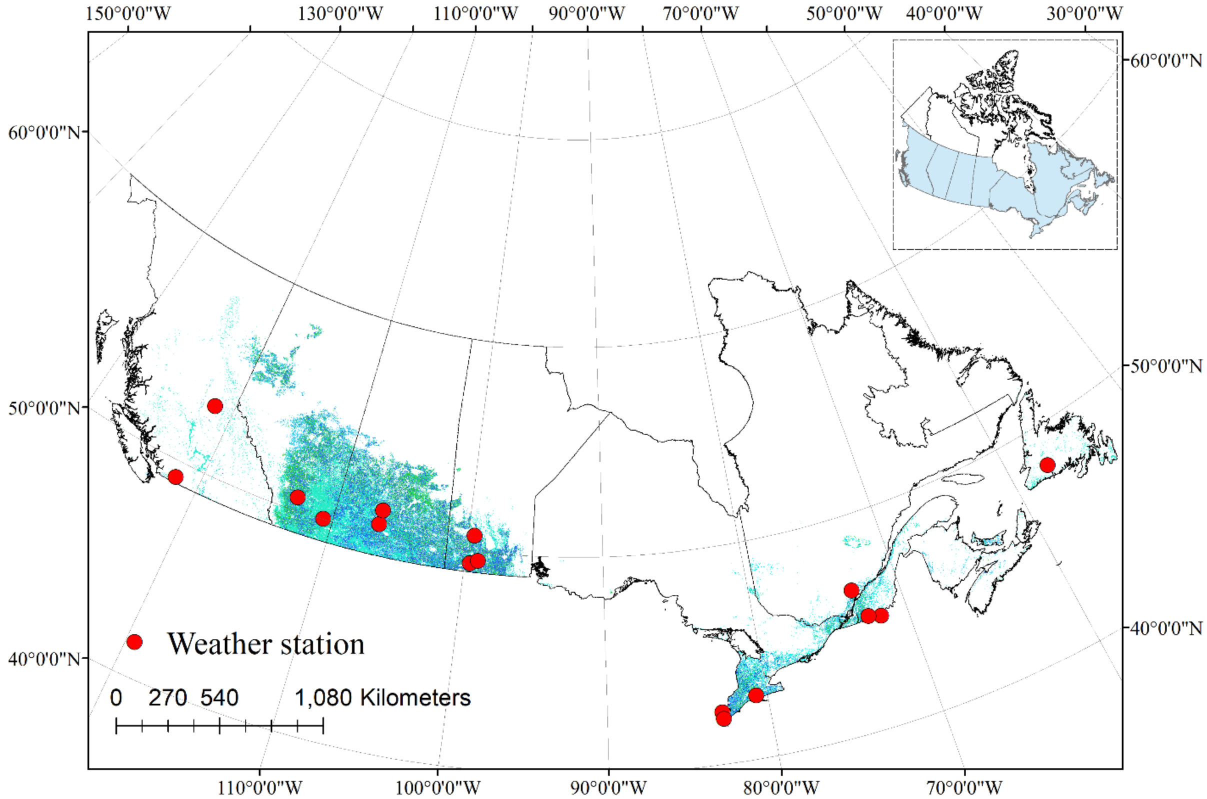


Figure 6.S2 Precipitation monitoring station selected across Canada's agricultural land. Colourful area in the map represents Canada's agricultural land, while red dot represents monitoring station. Source: Environment and Climate Change Canada (https://climate.weather.gc.ca/historical_data/search_historic_data_e.html). Station ID: the Atlantic provinces (station: BURNT POND (ID: 8400812); STANHOPE (ID: 7028240)), Quebec (station: BROME (ID: 7020840); ST ALEXIS DES MONTS (ID: 7016816)), Ontario (station: TILLSONBURG WWTP (ID: 6138270); WINDSOR RIVERSIDE (ID: 6139520); HARROW CDA (ID: 6133360)), Manitoba (station: NINETTE (ID: 5022040); CYPRESS RIVER (ID: 5010640); MCCREARY (ID: 5043158)), Saskatchewan (station: CHAPLIN (ID: 4021520); ELBOW CS (ID: 4022359)), Alberta (station: MEDICINE HAT A (ID: 3034480); QUEENSTOWN (ID: 3035340)), and British Columbia (station: AGASSIZ CDA (ID: 1100120); BARKERVILLE (ID: 1090660)).

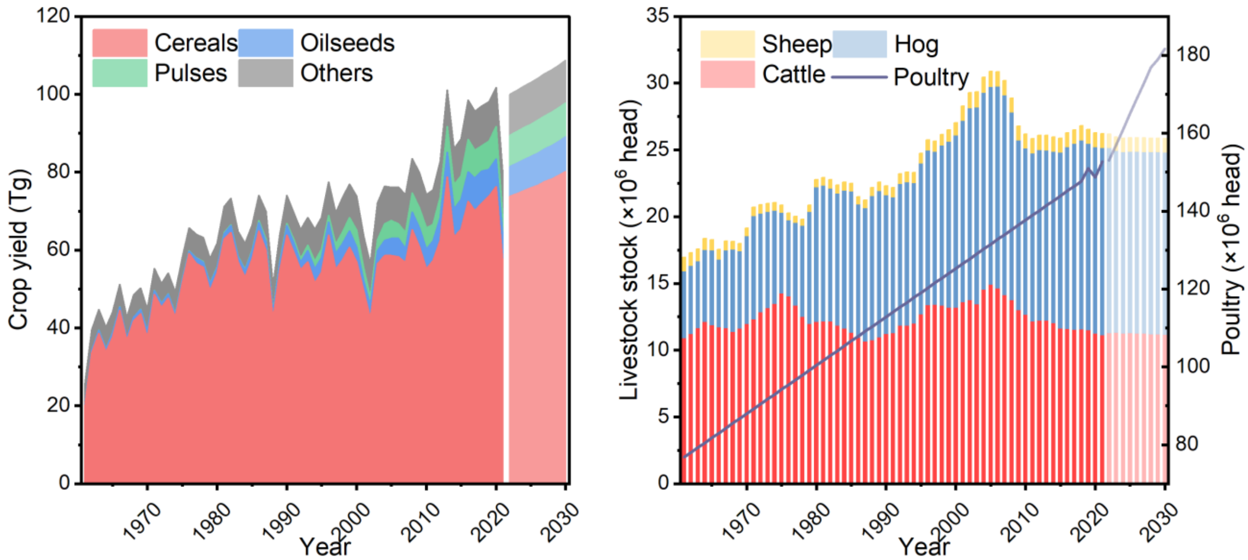


Figure 6.S3 Canada's annual crop yields and livestock inventory from 1961 to 2030. Historical 1961-2021 statistics can be assessed from Statistics Canada (Wang et al., 2022). While 2022-2030 projected statistics (faded colors) are collected from a report by Agriculture and Agri-Food Canada (MTO, 2021).

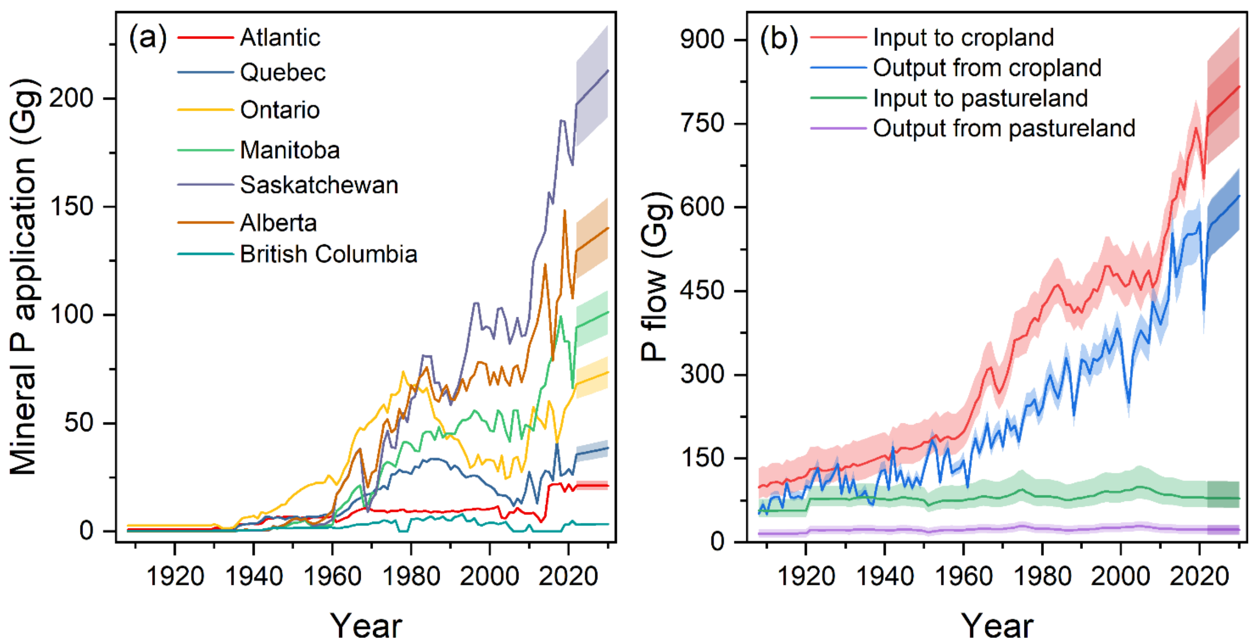


Figure 6.S4 (a) Canada's annual mineral P fertilizer consumption from 1908 to 2030. (b) Estimation of Canada's P balance over the period from 1908 to 2030. Shaded area represents an uncertainty of ±10% mineral P fertilizer projections. The light shaded area represents the uncertainty of P cycling model parameters (5% and 95% percentiles), while the heavy shaded area

represents the uncertainty for ±10% mineral P fertilizer projection.

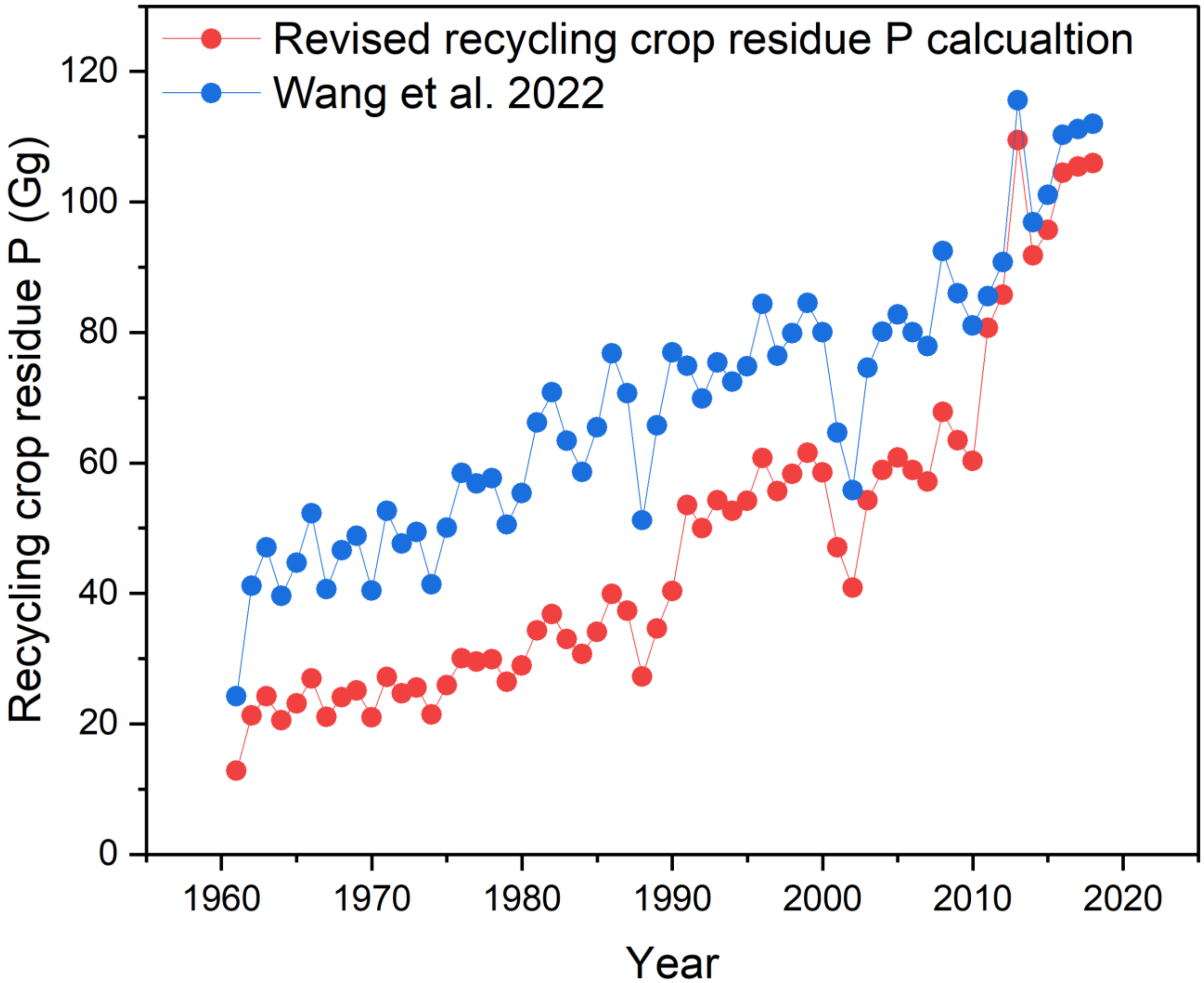


Figure 6.S5 Comparison between revised crop recycling residue P in our model and Wang et al. (2022).

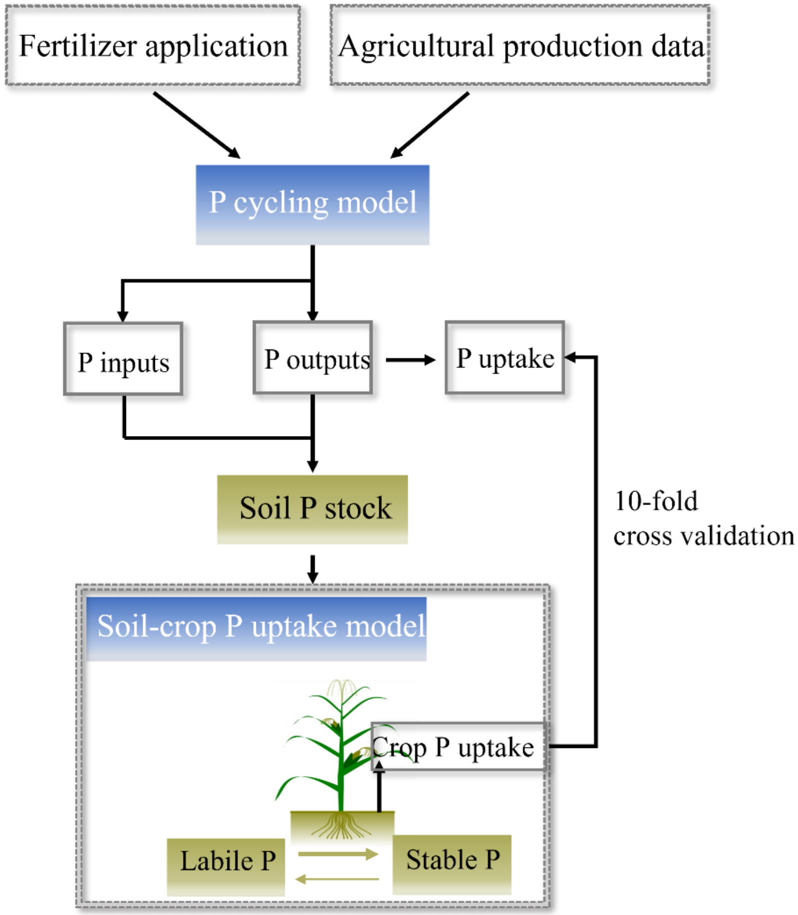


Figure 6.S6 The modeling framework. We calculated P flows by P cycling model, then we calculated soil internal P recycling by soil P dynamics model, and the simulated crop P removal rates by the soil P dynamics model were validated by actual crop P removal rates obtained through the P cycling model.

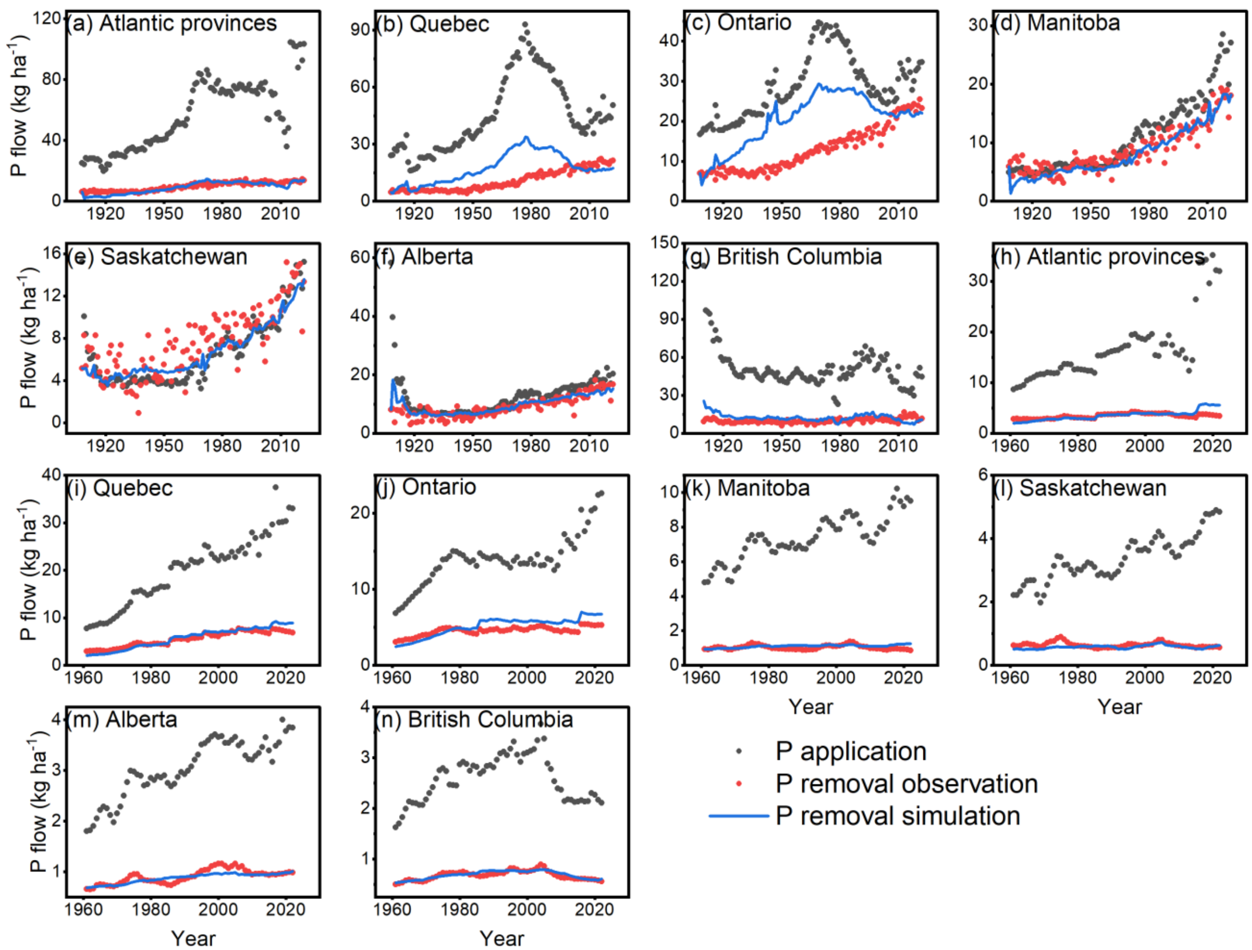


Figure 6.S7 Simulation of Canada's historical (1908-2022) annual crop P removal rate and historical (1961-2022) pastureland grazing P removal rate. Modeling performance indices were presented in Table 6.S9.

Table 6.S1 Proportion of crop residue baled area in Canada.

Item	Year	Canada	Atlantic provinces*	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia
Crop seeded area (ha)	2011	26824107	218084	1075098	2712737	2851419	12192763	7598024	175981
	2016	31689356	226442	1176878	2896596	3975956	14791808	8418763	202912
	2021	32325569	230086	1170456	2937068	4093832	15115709	8578034	200383
Crop residue baled area (ha)	2011	2380809	39045	221917	353339	302359	537013	905206	21930
	2016	2816118	39150	218480	386714	357339	672104	1117511	24821
	2021	2858127	46667	235573	404911	470977	699959	968558	31323
Proportion of crop residue baled area	2011	9%	18%	21%	13%	11%	4%	12%	12%
	2016	9%	17%	19%	13%	9%	5%	13%	12%
	2021	9%	20%	20%	14%	12%	5%	11%	16%

* The Atlantic provinces refer to New Brunswick, Newfoundland and Labrador, Nova Scotia, and Prince Edward Island

Table 6.S2 Percentages of residue recycling to crop field.

Time period*	Atlantic provinces	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia
1908-1990	50%	50%	50%	50%	50%	50%	50%
1991-2010	70%	70%	70%	70%	70%	70%	70%
2011-2015	89%	88%	92%	94%	97%	93%	93%

2016-2020	90%	89%	92%	95%	97%	92%	93%
2021-2030	88%	88%	92%	93%	97%	93%	91%

*Since statistics Canada only provides crop residue baled area in 2011, 2016 and 2021 (Table S1), we assumed 50% of crop residues recycled to cropland in the 1908-1990 period, and assumed 70% of crop residues recycled to cropland in the 1991-2010 period. Crop species that residues are partly recycled to the field including barley, canola, durum wheat, flaxseed, corn, mixed grains, oat, rye, spring wheat, and winter wheat (Li et al., 2012).

Table 6.S3 Information of surface soil properties across Canada's agricultural land.

Province	Soil type*	Fe_{ox} ** concentrations (%)	Al_{ox} ** concentrations (%)	SOC⁑ (%)	Silt⁑ (%)	Sand⁑ (%)	Clay⁑ (%)
Atlantic provinces	Brown soil	0.05-2.6	0.05-1.38	4.21	25	45	30
Quebec	Sainte-Rosalie Soil	0.08-0.45	0.07-0.27	3.78	26	46	18
Ontario	Guelph Soil	0.5-2.57	0.33-2.43	1.73	31	40	19
Manitoba	Newdale Soil	0.02-0.52	0.01-0.19	2.84	28	46	26
Saskatchewan	Weyburn Soil	0.12-0.4	0.07-0.22	1.84	32	43	25
Alberta	Breton Soil	0.56-4.7	0.13-0.68	2.51	43	37	20
British Columbia	Branham Soil	0.22-1.15	0.14-2.52	3.08	39	48	13

* Agricultural soil type is cited from https://agriculture.canada.ca/en/agricultural-production/soil-and-land/our-home-and-native-land-significant-agricultural-soils-across-canada

** Sources: Atlantic provinces (McKeague & Day, 1965), Quebec (Leclerc et al., 2000), Ontario

(Evans & Wilson, 1985), Manitoba (Ige et al., 2005), Saskatchewan (Stonehouse & Arnaud, 1971), Alberta (Dudas, 1986), British Columbia (Yuan & Lavkulich, 1994)

⁑ Source: Cited from the National Soil Database of Canada (https://sis.agr.gc.ca/cansis/nsdb/index.html)

Table 6.S4 Cover management factor values.

Percentages of crop residue recycled to cropland	values of cover management factor ($k_{cove}(i,t)$)
50%	0.1
70%	0.14
80%-97%	0.18

Table 6.S5 Long-term (1971-2013) average annual runoff across Canada's agricultural land.

Province	Mean annual runoff (mm yr^{-1})
The Atlantic provinces	1000
Quebec	600
Ontario	500
Manitoba	300
Saskatchewan	150
Alberta	50
British Columbia	1200

Table 6.S6 Parameters in the P cycling model used for Monte Carlo simulation.

Parameter	[min, max]	Default
Crop P content		
Oat	[0.29%,0.38%]	0.31%
Rye	[0.29%,0.36%]	0.31%
Canary	[0.29%,0.34%]	0.31%
Mixed grain	[0.29%,0.34%]	0.31%
Maize	[0.09%,0.27%]	0.18%

Spring wheat	[0.35%,0.44%]	0.38%
Winter wheat	[0.32%,0.38%]	0.35%
Soybean	[0.2%,0.62%]	0.52%
Vegetable	[0.01%,0.04%]	0.02%
Fruit	[0.02%,0.06%]	0.04%
P:N ratio for livestock manure		
Cattle	[0.13,0.26]	0.18
Pig	[0.21,0.32]	0.28
Sheep	[0.08,0.23]	0.15
Goat	[0.08,0.23]	0.15
Horse	[0.17,0.21]	0.19
Elk	[0.18,0.22]	0.19
Chick	[0.13,0.35]	0.24
Turkey	[0.21,0.29]	0.25
Other		
Atmospheric deposition	[0.15,0.89]	0.4 kg ha^{-1}
Human excreta P	[0.37,0.55]	0.43 kg y^{-1}
Soil erodibility factor ($k_{eros}(i,t)$)		
Atlantic	[0.03,0.09]	0.06
Quebec	[0.01,0.03]	0.02
Ontario	[0.005,0.015]	0.01
Manitoba	[0.005,0.015]	0.01
Saskatchewan	[0.005,0.015]	0.01
Alberta	[0.005,0.015]	0.01
British Columbia	[0.03,0.09]	0.06

Table 6.S7 Simulated soil labile P compared to field soil Olsen P samples.

Source	Region	Time period	Soil labile P (kg ha^{-1} yr^{-}	Estimates in this work (kg

			¹)	ha⁻¹ yr⁻¹)
	Cropland			
McDowell et al. (2023)	Atlantic provinces	2000-2019	84	91
	Quebec	2000-2019	108	95
	Ontario	2000-2019	78	86
	Manitoba	2000-2019	31	32
	Saskatchewan	2000-2019	22	17
	Alberta	2000-2019	29	25
	British Columbia	2000-2019	36	36
MacDonald and Bennett, (2009)	Quebec (n=56)	1995-2001	117 ± 49.1*	126
Zhang et al. (2020)	Ontario (n=1)	2009, 2016	90	83
	Pastureland			
McDowell et al. (2023)	Atlantic provinces	2000-2019	78	69
	Quebec	2000-2019	78	75
	Ontario	2000-2019	72	71
	Manitoba	2000-2019	31	31
	Saskatchewan	2000-2019	22	16

	Alberta	2000-2019	29	20
	British Columbia	2000-2019	31	25
Chen et al. (2001)	Manitoba (n=2)	1995-1998	36	32
Cade-Menun et al. (2013)	Saskatchewan (n=5)	2009	15	17
Evans et al. (2012)	British Columbia (n=2)	1998	20	27

n is the number of sampled fields

* Mean values±standard error.

We transferred unit mg kg^{-1} of soil Olsen P to kg ha^{-1} by assuming soil bulk density 1.2 t m^{-3}, the equation can be expressed as: 1 ha × soil bulk density×sampling depth×Olsen P content (mg kg^{-1}) = soil Olsen P level in kg ha^{-1}. In field samples, soil sampling depth included 15 cm and 20 cm.

Table 6.S8 Simulated soil total P loss compared to edge-of-field P loss observations.

Source	Region	Time period	Field P loss (kg ha^{-1} yr^{-1})	Estimates in this work (kg ha^{-1} yr^{-1})
	Cropland			
Kinley et al. (2007)	Northwestern Nova Scotia (n=39)	2002-2003	3.43	3.19
Rees et al. (2011)	Northwestern New Brunswick (n=3)	2000-2003	2.67	3.39
Eastman et al. (2010)	Pike River basin (n=4)	2005-2006	1.88±1.63*	1.83
Deslandes et al. (2007)	Pike River basin (n=1)	2000-2003	1.08±1.26*	1.62
Plach et al. (2019)	Midwestern Ontario (n=2)	2012-2016	0.49	0.67
	Southwestern Ontario (n=1)	2013-	0.85	0.7

		2016		
Kim et al. (2016)	Bay of Quinte watershed, Ontario (n=70)	1965-2005	0.3	0.46
Liu et al. (2021)	The Great Lakes region, Ontario (n=3)	2013-2017	0.55	0.68
Tan and Zhang, 2011	Southwestern Ontario (n=2)	2000	0.5	0.43
Liu et al. (2021)	Manitoba (n=24)	2013-2017	0.4	0.48
Rattan et al. (2017)	Red River Valley, Manitoba (n=11)	2010, 2013-2014	0.48	0.45
Liu et al. (2021)	Saskatchewan (n=3)	2013-2017	0.03**	0.13
Nicholaichuk and Read, 1978	Swift Current, Saskatchewan (n=4)	1971	<0.1	0.02
Riemersma et al. (2006)	North-central Alberta (-)	1987	0.28	0.27
	Lake Wabamun watersheds, Alberta (-)	1985	0.35	0.35
Richard, 1988	Fraser Valley, British Columbia (n=14)	1985-1986	3.87	3.9
	Pastureland			
Sinclair et al. (2015)	Thomas Brook watershed, Nova Scotia (n=5)	2004-2008	0.67	0.56
Chow et al. (2011)	Northwestern New Brunswick (n=1)	2003-2007	0.3**	0.54
Deslandes et al. (2007)	Pike River basin (n=1)	2000-2003	0.39±0.22*	0.51
Kim et al. (2016)	Bay of Quinte watershed,	1965-	0.25	0.31

	Ontario (n=71)	2005		
Hargrave, (1992)	Manitoba (n=3)	1985-1987	0.43	0.32
Smith, 2011	Near Lanigan, Saskatchewan (n=8)	2008-2009	0.83	0.61
Riemersma et al. (2006)	Haynes Creek, Alberta (-)	1998	0.21	0.21
Bittman et al. (2017)	Fraser Valley, British Columbia (n=14)	2011	403⁑	430

n is the number of sampled fields

* Mean values±standard error.

** Measured dissolved reactive P

⁑ Estimated by P cycling model

Table 6.S9 Model performance for simulating soil P removal rate.

Province	Evaluation metrics	
	R^2	*d*
Cropland		
Atlantic	0.24	0.67
Quebec	0.45	0.71
Ontario	0.55	0.71
Manitoba	0.93	0.98
Saskatchewan	0.88	0.96
Alberta	0.92	0.98
British Columbia	0.61	0.86

Pastureland		
Atlantic	0.45	0.61
Quebec	0.42	0.62
Ontario	0.55	0.74
Manitoba	0.40	0.58
Saskatchewan	0.27	0.66
Alberta	0.82	0.92
British Columbia	0.79	0.94

The R^2 and d values range from 0 to 1. If the evaluated model accurately depicts the datasets, R^2 and d should be close to 1. Calculation of R^2 and d refer to Equations 15-16 of the main text.

Table 6.S10 Calibrated soil P dynamics model parameters and sensitivity analysis.

Parameter	Atlantic provinces	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia	Sensitivity (A_i)
f	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.42
$k_{eros}(i,t)$	0.06	0.02	0.01	0.01	0.01	0.01	0.06	0.4
Fe_{ox}	1.3	0.27	1.54	0.27	0.26	2.63	0.69	0.14
Al_{ox}	0.7	0.17	1.38	0.1	0.15	0.41	1.33	0.21
Cropland								
$a_{\mu_{LS,crop}}$	0.056	0.006	0.0056	0.0087	0.0114	0.06	0.2229	0.4
$b_{\mu_{LS,crop}}$	0.051	0.004	0.003	0.0067	0.0077	0.0149	0.0067	0.12
$c_{\mu_{LS,crop}}$	0.0069	0.0004	0.0003	0.001	0.0012	0.0011	0.0002	0.05
$d_{\mu_{LS,crop}}$	1E-11	0.005	0.006	0.0029	0.005	0.0003	0.0002	0.06

$e_{\mu_{LS,crop}}$	1E-11	0.002	0.001	0.001	0.0011	0.0011	0.001	0.06
$\mu_{LS,crop}$	0.5	0.3	0.3	0.2	0.3	0.3	0.5	0.68
$a_{\mu_{SL,crop}}$	0.0035	0.0058	0.0053	0.0082	0.0112	0.0164	3E-11	0.4
$b_{\mu_{SL,crop}}$	0.004	0.0036	0.003	0.0042	0.0074	0.0127	0.0048	0.12
$c_{\mu_{SL,crop}}$	0.0029	0.0004	0.0003	0.0005	0.001	0.001	0.0002	0.05
$d_{\mu_{SL,crop}}$	1E-11	1E-11	0.001	1E-11	0.0017	0.0002	0.0002	0.06
$e_{\mu_{SL,crop}}$	1E-11	0.0013	0.001	0.0005	0.001	0.001	0.0007	0.06
$\mu_{SL,crop}$	0.02	0.05	0.08	0.04	0.15	0.15	0.04	0.56
$\alpha_{crop}(i)$	0.2	0.3	0.2	0.3	0.4	0.35	0.15	0.37
Pastureland								
$a_{\mu_{LS,past}}$	0.0347	0.0057	0.03	0.0082	0.011	0.0311	0.0396	0.4
$b_{\mu_{LS,past}}$	0.014	0.003	0.008	0.0042	0.0067	0.02	0.0048	0.12
$c_{\mu_{LS,past}}$	0.0029	0.0003	0.0013	0.0005	0.001	0.0016	0.0002	0.05
$d_{\mu_{LS,past}}$	0.004	0.012	0.009	0.0078	0.001	0.0003	0.0002	0.06
$e_{\mu_{LS,past}}$	1E-11	0.001	0.006	0.0005	0.001	0.0014	0.0007	0.06
$\mu_{LS,past}$	0.4	0.6	0.6	0.4	0.1	0.25	0.12	0.67
$a_{\mu_{SL,past}}$	0.006	0.0057	0.0087	0.0081	0.0097	3E-11	0.0072	0.4
$b_{\mu_{SL,past}}$	0.0042	0.003	0.0067	0.0041	0.0048	0.0067	0.0041	0.12

$c_{\mu_{SL,past}}$	0.0004	0.0003	0.001	0.0004	0.0003	0.0002	0.0001	0.05
$d_{\mu_{SL,past}}$	1E-11	1E-11	1E-11	0.001	0.0001	0.0002	0.0002	0.06
$e_{\mu_{SL,past}}$	1E-11	0.001	0.001	0.0005	0.0004	0.0009	0.0007	0.06
$\mu_{LS,past}$	0.4	0.6	0.6	0.4	0.1	0.25	0.12	0.67
$\alpha_{past}(i)$	0.05	0.08	0.07	0.03	0.03	0.04	0.03	0.4

Chapter 7
Discussion and conclusions

7.1 General overview

Through meta-analysis, we found that conservation practices are often feasible and effective methods of sustainable P management. Subsequently, we applied ML techniques to assess the impacts of conservative measures on P export from the Maumee River Basin under climate change. The results of this work suggest that additional practices are still needed to address P loss induced pollution in Lake Erie. Subsequently, we assessed the potential for residual soil P reuse to reduce p losses from Canadian agricultural lands. By developing a P cycle model and combining it with a soil-crop P uptake model, we found that the use of residual P could reduce mineral P demand in Canada, with the Atlantic Provinces, Quebec, Ontario, and British Columbia having the greatest potential to reduce P applications. We expect that the use of residual soil P in the Atlantic Provinces and Quebec could minimize runoff P loss, while the amount of P loss that could be reduced by the use of residual soil phosphorus in Ontario, Manitoba, and British Columbia would be relatively low.

7.2 Discussion

This work will advance the understanding of long-term P balance in Canada agricultural production. By evaluating the effectiveness of BMPs in controlling P loss, this work will provide insights into how to manage P use more sustainable within the context of climate change. Specifically, this research is expected to offer crucial evidence for policymakers, farmers, and environmentalists to minimize soil P loss, thereby reducing the negative impact of agriculture production on the ecosystem. This research will serve as a valuable reference for other countries grappling with P loss-induced pollution. This work will also promote progress on Sustainable Development Goal (SDG) 12 (‘Responsible consumption and production’). Future research can build upon several established findings. For example, Chapter 3 demonstrates a negative correlation between "Growing Season Rainfall" and "Soil Total P". This result is partly attribute to the negative effects on soil TP loss found in previous buffer strip and controlled drainage field experiments (Fig. 3.S1). Such negative effects may be due to field observation biases (Tan and Zhang, 2011; Pu, 2013).

Our studies reveal that while vegetative buffer strips are instrumental in environmental conservation and mitigating nutrient runoff, they may also inadvertently lead to a reduction in crop yields (as illustrated in Fig. 3.7). The land required for these strips could otherwise be used for growing crops, resulting in a direct decrease in the area available for cultivation. Additionally, these strips may compete with crops for vital resources such as water, nutrients, and sunlight, particularly if their management is not optimized. In some cases, buffer strips might also inadvertently serve as habitats for pests or pathogens, which can negatively impact nearby crops and contribute to yield losses.

When managing P loss in agricultural systems, the decision to prioritize TP or particulate P over soluble P should be informed by a careful evaluation of several critical factors. Key considerations include the environmental impact of P forms, where the bioavailability of soluble P is a particular concern. Additionally, the effectiveness of management practices such as tillage and erosion control measures on the release of various P forms is paramount. Local conditions must also be taken into account, including soil and hydrological characteristics, as well as regional regulations and guidelines for P management, which can significantly vary and thus demand tailored approaches to monitoring and controlling P levels. A comprehensive assessment of these factors is essential to make an informed decision on prioritizing one form of P over another. This strategic approach ensures effective P management that not only addresses agricultural needs but also protects and preserves water resources.

Analyzing extreme rainfall events based on calendar day rather than continuous 24-hour monitoring introduces several limitations and uncertainties. Firstly, extreme rainfall events can occur within shorter time intervals than a calendar day, meaning that relying solely on daily data may underestimate the intensity and frequency of extreme events. Secondly, using daily data may not capture the temporal distribution of rainfall within a day, potentially leading to inaccuracies in characterizing the onset, duration, and intensity of extreme events. Additionally, extreme events may span multiple days or occur intermittently within a day, making it challenging to accurately identify and analyze them using only daily data. Continuous 24-hour monitoring provides more granular data that better captures the dynamics of extreme rainfall events, allowing for more precise characterization and assessment of their impacts. Therefore, while calendar day data may offer some insights into extreme rainfall events, continuous monitoring provides a more comprehensive and accurate understanding, reducing uncertainties in analyses and decision-making related to extreme precipitation.

Cover crops and filter strips can potentially reduce soil P loss, but their effectiveness can vary depending on various factors, as highlighted by meta-analyses of previous field work. Cover crops, planted during fallow periods between cash crop seasons, can mitigate soil erosion and nutrient leaching by offering protective ground cover, enhancing soil structure, and boosting nutrient retention. They have the capacity to slow surface runoff and encourage water infiltration, which in turn can minimize the displacement of sediment-bound P. However, the success of cover crops in curbing soil P loss hinges on various elements, including the choice of species, planting and termination schedules, climatic conditions, soil characteristics, and agricultural practices. Our collected previous experiments present a spectrum of outcomes, with some studies noting substantial reductions in soil P loss and others observing less pronounced or inconsistent effects due to these influencing factors. Similarly, filter strips—vegetated zones established along field edges or near water bodies—serve to trap sediment and nutrients, thereby preventing their entry into waterways. They function by capturing P-bound sediment and acting as natural filters. Nevertheless, the performance of filter strips in reducing soil P loss is contingent on several variables, such as the width of the strips, the type of vegetation used, the slope of the land, soil properties, and hydrological patterns. Meta-analyses have yielded diverse results, with certain studies showing significant decreases in P transport and others reporting lesser or variable impacts. While both cover crops and filter strips offer promise in the reduction of soil P loss, their actual effectiveness is contingent upon specific site conditions and management practices. To optimize the benefits of these practices, they should be integrated into a comprehensive nutrient management plan, complemented by other conservation measures. It is crucial to tailor these practices to local factors and conduct targeted assessments to ensure they are as effective as possible in minimizing soil P loss and enhancing water quality.

According to the variable importance analysis conducted using machine learning techniques (Fig. 4.12), soil texture does not emerge as a significant predictor in P export modeling compared to other variables. This finding may seem surprising, as soil texture, which refers to the proportions of sand, silt, and clay in the soil, is traditionally considered a critical factor influencing nutrient transport in the environment. Soil texture affects factors such as water infiltration rates, surface runoff, and soil water holding capacity, all of which can influence nutrient movement and export. However, several factors could contribute to this result. Firstly, machine learning techniques analyze the interactions among multiple variables simultaneously and may identify other predictors that have a stronger influence on P export compared to soil texture (i.e., discharge and TSS load, Fig. 4.12), which may overshadow the influence of soil texture in the modeling process. Secondly, the absence of a significant effect of soil texture on P export in the machine learning analysis could also be attributed to the complexity and variability of soil-landscape interactions. Additionally, the scale and scope of the study, as well as the specific modeling approach and dataset used, can influence the outcomes of variable importance analysis. While soil texture may not emerge as a significant predictor in this work, its importance in P export modeling may vary depending on regional differences, watershed characteristics, and the specific objectives of the study.

While our analyses were conducted using data from the US side of Lake Erie, it's important to consider the applicability of the results to the Canadian side and broader Canadian situations. Access to comprehensive datasets covering both sides of Lake Erie is essential for conducting integrated assessments and developing cross-border nutrient management strategies. Future work should focus on enhancing data sharing, collaboration, and integration efforts between US and Canadian agencies, researchers, and stakeholders to support more robust and comprehensive analyses.

The estimation of P emissions from laundry and dishwasher activities in Canada on a per capita basis offers valuable insight into nutrient inputs, yet not incorporating the implementation of P-free detergents in the Great Lakes region since the 1972 agreement may introduce significant variation into predictions. This oversight could lead to overestimation of P emissions, failing to capture the reductions achieved through the adoption of P-free detergents. Regional variations in adoption rates, population growth, consumption patterns, and policy advancements further contribute to the complexity of predicting P emissions accurately. Future assessments should account for these factors to provide more precise predictions and inform effective nutrient management strategies tailored to specific regions and contexts.

While excluding runoff P losses from PUE calculations may overlook a portion of P inputs to the system, it allows for a more targeted evaluation of crop P utilization efficiency and management practices aimed at improving nutrient uptake and productivity. However, it's essential to consider runoff P losses in overall nutrient management strategies to minimize environmental impacts and promote sustainable agricultural practices. Therefore, a comprehensive approach that considers both crop utilization and P loss mitigation strategies is necessary for effective nutrient management and environmental stewardship.

Our calculated soil P accumulation of 3000 kg P ha^{-1} significantly exceeds the reported range of >600 kg P ha^{-1} from other source (Reid and Schneider, 2019). Several factors could contribute to this discrepancy and influence the estimation confidence. The first factor is in Reid and Schneider (2019), they estimated mineral P as P recommendation based on soil test minus manure P, while our mineral P is collected from Statistics Canada (i.e., P_2O_5). The second factor is in our P cycling model, except mineral and manure P, we also considered P inputs from crop seed, weathering, atmospheric deposition, and sludge. The third factor may be different P coefficients.

In Canada, the agricultural sector plays a significant role in the P cycle, with livestock production being a key contributor to the availability of this essential nutrient. Recycled sludge P inputs, particularly from meat production, do contribute to the overall P cycling within the country. However, when compared to the quantities of P found in manure, the numerical importance of sludge P inputs is relatively small. While sludge P inputs may be smaller in scale, they still represent a valuable component of the P cycle, particularly when considering the sustainability of agricultural practices. The economic benefits of recycling sludge for P fertilizer applications are a topic that warrants further investigation. Moreover, the study of animal manure P characteristics and its implications for cleaner environmental management is an area of active research in Canada. Understanding the forms and availability of P in manure is crucial for optimizing its use as a fertilizer and minimizing its environmental impact.

The RUSLE is a widely used empirical model designed to predict soil erosion caused by water in agricultural fields. However, when applied to tile-drained areas, such as those on the Canadian side of Lake Erie, its applicability and reliability for predicting soil P loss may be affected by the unique hydrological dynamics introduced by tile drainage systems. The RUSLE equation is:

$$A = R * K * LS * C * P$$

Where A is the annual average erosion (t ha^{-1} yr^{-1}). R is the rainfall-runoff erosivity factor (MJ mm ha^{-1} h^{-1} yr^{-1}), which describes the effect of rainfall and run-off on erosion and is defined by the energy intensity of rainfall events. K is the soil erodibility factor (t ha h ha^{-1} MJ^{-1} mm^{-1}), which is affected by soil properties, including particle size fractions, organic matter content, soil structure, soil permeability, and soil freezing. LS is the topographic factor (dimensionless), which describes the effect of slope length (L) and steepness (S) on erosion. C is the cover-management factor (dimensionless), which considers the effects of different cropping and tilling practices on erosion. P is the support practice factor (dimensionless), which accounts for the effect of various support practices on erosion, including contouring, strip cropping, terracing, and subsurface drainage. At the experimental field sites, the effect of subsurface drainage on erosion was considered in the P factor, and the P factor value of 0.6 was suggested by Renard et al. (1997).

The predicted soil P loss rates from both cropland and pastureland in Ontario highlight key considerations for P management in the region. The discovery that pastureland may experience similar or even higher soil P loss rates than cropland, despite greater soil P accumulation in the latter, indicates the complexity of P dynamics in pasture systems. This could be due to several factors, including the modelling uncertainty, intensity of grazing, soil erosion rates, the extent of vegetation cover, and nutrient cycling processes (i.e., manure left on pastureland) that are unique to pastureland and can affect P transport and loss. The predicted loss rates, which are 0.42 to 0.68 kg ha^{-1} for cropland and 0.59 to 0.69 kg ha^{-1} for pastureland, emphasize the need for strategic P management across different land uses. It's important to note that these rates are based on provincial scale simulations that may not fully represent field-scale conditions due to variations in regional climate, land management practices, and agricultural strategies. Therefore, further research at regional and field scales is essential for both crop and pastureland to refine P management strategies and protect water quality in Ontario’s ecosystems. The observed decline in both stable and labile soil P levels in Ontario since the adoption of the balance approach is indicative of enhanced P management and soil conservation efforts. The balance approach is designed to synchronize nutrient inputs with crop needs, thereby avoiding surplus applications that could lead to soil P accumulation and environmental risks. The reduction in soil P levels points to a more efficient nutrient management system, where inputs are more precisely matched to crop demands, reducing the likelihood of P saturation and potential runoff into water bodies. The success of the balance approach in promoting sustainable agricultural practices and safeguarding water quality in Ontario underscores its importance as a model for other regions facing similar challenges. However, to sustain this progress and refine P management further, continuous monitoring of soil P levels and adaptive strategies are crucial. This will ensure that soil fertility is preserved while minimizing the environmental impact of agricultural activities, maintaining the delicate balance between agricultural productivity and ecological health.

7.3 Future work

P reuse involves recovering and utilizing P-rich materials from various waste streams or secondary sources for beneficial purposes, such as agriculture, industry, or environmental remediation. This process requires identifying suitable P sources, characterizing and treating the materials to enhance P availability and quality, determining optimal application methods based on crop nutrient requirements and environmental considerations, ensuring regulatory compliance, establishing monitoring protocols to track performance and environmental impacts, and engaging stakeholders through education and outreach efforts. By adopting a responsible and holistic approach to P reuse, stakeholders can maximize the benefits of recycling P resources from livestock manure, food waste and city sludge, enhance nutrient cycling efficiency, reduce dependency on mined P fertilizers, and promote sustainable agriculture and environmental stewardship.

Understanding the practical challenges farmers face, particularly regarding economics, is crucial for informing agricultural research and policy decisions that effectively support sustainable farming practices. Farmers grapple with market volatility, rising input costs, limited access to credit and financing, resource management complexities, labor shortages, regulatory compliance burdens, and market access issues. Balancing profitability with sustainability requires addressing these challenges through collaborative efforts involving policymakers, researchers, agricultural extension services, financial institutions, and farmer organizations. By developing targeted solutions that address the real-world concerns of farmers, such as improving market access, reducing input costs, enhancing resource efficiency, and supporting labor availability, agricultural initiatives can foster economic resilience, environmental sustainability, and social equity in the agricultural sector.

Figure 4.6 illustrates the results from multiple machine learning models, indicating no significant differences among the models in their predictive performance of discharge. This finding suggests that the various machine learning algorithms evaluated produced similar outcomes when applied to the discharge dataset. This difference may be due to the relatively small input variable pools that all of them recognize the same significant factors. While individual models may exhibit subtle differences in their predictive capabilities, the overall consensus among the models is that they perform comparably in terms of their ability to predict the target variable. This result has implications for model selection and deployment, indicating that researchers may have flexibility in choosing among the evaluated machine learning algorithms without sacrificing predictive accuracy. Future work on the tile drainage effect on P loss through machine learning modeling would likely emphasize the need for tailored model development, comprehensive data integration, and rigorous evaluation to elucidate the intricate relationships between tile drainage characteristics and P loss dynamics. This would involve incorporating tile drainage parameters as predictor variables, integrating diverse datasets on soil properties, land use, hydrology, and P loss measurements, and employing feature selection and engineering techniques to enhance model performance.

While our analysis is conducted at a provincial scale, it may indeed be feasible to conduct the analysis at a more regional level, such as the county level, to provide a more detailed understanding of Canada's P cycle dynamics. Analyzing P cycle changes at the county level would allow for a more localized assessment of agricultural practices, land use patterns, and environmental impacts, providing valuable insights for targeted management interventions and policy decisions. By disaggregating data and conducting spatially explicit analyses, it becomes possible to capture regional variations in P inputs, outputs, and transformations, as well as identify hotspots of P accumulation or loss. This scale analysis could enhance the precision and applicability of findings, enabling stakeholders to tailor strategies for nutrient management, soil conservation, and water quality protection to specific regional contexts. However, conducting analyses at the county level may require access to detailed data on agricultural practices, land cover, soil characteristics, and hydrological conditions, as well as careful consideration of data quality, consistency, and spatial resolution. Collaboration with local stakeholders, government agencies, and research institutions may also be valuable for data collection, validation, and interpretation. Overall, while conducting the analysis at the county level presents logistical and data challenges, the potential benefits in terms of improved understanding and targeted interventions justify the effort and investment required.

While residual P was identified as a potential strategy for reducing mineral P demand in Canada, it is acknowledged that other management practices may offer greater effectiveness in mitigating P demand. Indeed, it would be valuable to explore the potential impacts of implementing these more effective practices, such as crop straw return, cover cropping, intercropping, efficient irrigation in Western Canada, reduced tillage, and others, on reducing P demand. By conducting scenario analyses or modeling exercises, it becomes possible to assess the cumulative effects of implementing multiple management practices simultaneously and quantify their contributions to reducing mineral P demand across different regions of Canada. This approach would provide a more comprehensive understanding of the potential synergies and trade-offs among various management practices, as well as their implications for agricultural productivity, environmental sustainability, and economic viability. Additionally, considering the regional context and specific challenges faced by different provinces or agricultural regions would enable the identification of tailored strategies for optimizing nutrient management and promoting sustainable agricultural intensification. Collaborative efforts involving researchers, policymakers, agricultural stakeholders, and extension services would be essential for integrating scientific evidence, stakeholder perspectives, and practical considerations into decision-making processes aimed at enhancing nutrient stewardship and environmental resilience in Canadian agriculture.

7.4 Conclusions

Objective 1: To apply a meta-analysis to assess the effectiveness of BMPs in mitigating soil P loss by synthesizing results from peer-reviewed experimental trials.

Our findings indicate that the most effective P loss management practices do not necessarily result in the greatest improvement in crop yield. We show that efficient irrigation, crop straw return, buffer strip, and intercropping are the most effective in reducing soil P loss, achieving an average reduction of -94.2%, -87.7%, -87.2%, and -61%, respectively. Soil amendment, intercropping, and conservation practices demonstrated the largest increase in crop yields, attaining an average increase of 188.8%, 80%, and 72.9% respectively. Our regression analyses suggest that soil available P level, crop growing season rainfall, and P addition amount are important factors that influence the effectiveness of P management practices. High soil available P and rainfall tend to reduce the effectiveness of these practices, while high P additions are correlated with more effective reduction of P loss. Based on our findings, we recommend prioritizing conservation practices when implementing P loss control practices.

Objective 2: To evaluate the effectiveness of the best practice identified through the meta-analysis in reducing P loss under climate change.

Our findings indicate that the hydrology has a growing influence on P export from the Maumee River watershed. The ML models accurately simulated the P export dynamics from 1974 to 2021. By assuming that the implementation area of conservation practices stays unchangeable, ML models suggested that the P load would continue to deteriorate the water quality of western Lake Erie between 2023 and 2040. The annual TP load was projected to remain consistent, while the annual SRP load was predicted to increase. This may be attributed to inaccuracies in the modeling results or inaccurate information on the implementation area of conservation practices. Despite the large uncertainty in SRP loading prediction, both the annual spring TP and SRP load were unable to meet the government's target of a 40% reduction. These results emphasize the need for additional practices to manage ongoing P pollution in Lake Erie.

Objective 3: To calculate the long-term spatial soil P balance across Canadian agricultural land.

Our results indicate that the majority of agricultural regions in Canada have soil P surpluses, except for Saskatchewan, where large P deficits were detected in almost all years. In 2018, we find that Quebec and the Atlantic provinces had the highest P surpluses, with low P surpluses observed in Ontario, Manitoba, Alberta, and British Columbia. We find that P flows in cropland play a larger role in Canada's P cycling than pasture. P use efficiency tended to be greatest in the Prairie provinces, and least in the Atlantic provinces. However, the rate of increase in P use efficiency was significantly steeper in Ontario and Quebec than in other provinces. To reduce remaining P surpluses, we recommend reducing inorganic fertilizer and manure application.

Objective 4: To explore the potentials for using residual soil P to reduce P applications and losses.

Our findings indicate that using soil residual P may reduce mineral P demand as large as 132 Gg P yr^{-1} (29%) in Canada, with the highest potential for reducing P applications in the Atlantic provinces, Quebec, Ontario, and British Columbia. Using residual soil P would result in a 21%

increase in Canada's cropland P use efficiency. We expected that the Atlantic provinces and Quebec would have the greatest runoff P loss reduction with use of residual soil P, while Ontario, Manitoba, and British Columbia would experience relatively lower reductions in P loss. Our study highlights the importance of considering residual soil P as a valuable resource and its potential for reducing P pollution.

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