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From food to feed: Historical shifts in fertilizer allocation and efficiency trade-offs in global food systems

Fernando Coello Sanz

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Fernando Coello Sanz
PhD thesis



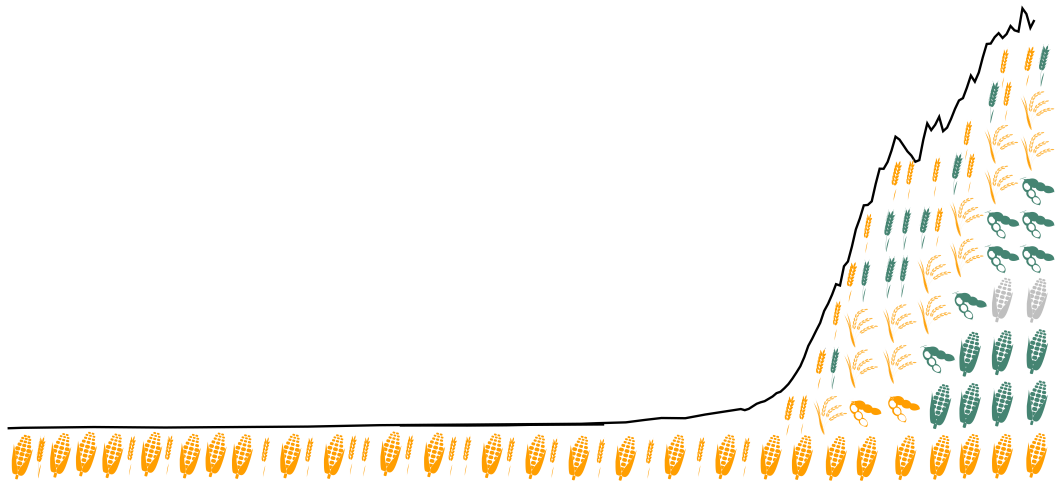
Fernando Coello Sanz

From food to feed: Historical shifts in fertilizer allocation and efficiency trade-offs in global food systems

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Cover image: Cereal field and dairy farm in Tona (Osona, Catalonia, Spain). Photograph by Fernando Coello, 2026.

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Abstract

Global fertilizer use has more than tripled since the second half of the 20th century, enabling the sustained population growth of the past century. More than half of this consumption has been allocated to the four main crops worldwide: wheat, maize, rice, and soybean. However, not all of the production of these crops has been used for direct human consumption; other uses, such as livestock feed and bioethanol production, have gained importance during this period. Despite this, the relationship between fertilizer use and its ultimate purpose, determined by the end use of crops, has not yet been fully characterized.

This thesis aims to explore these dynamics since the second half of the 20th century, focusing on the four main crops and identifying the periods and crops in which the main inefficiencies in fertilizer use are concentrated.

First, historical datasets have been compiled and machine learning (ML) techniques have been applied to construct a global-scale database. Second, temporal trends in fertilizer use over the past century have been analyzed. Third, the allocation of fertilizer use across the four main crops has been examined according to their final use (direct human consumption, animal feed, or other uses). Finally, the interaction between fertilizer use and crop utilization has been evaluated in terms of its impact on overall efficiency, measured as kilograms of protein or energy produced per kilogram of fertilizer.

Overall, the results show that modern machine learning techniques have demonstrated the potential of ML to resolve chronic data fragmentation in historical nutrient accounting, and that patterns of growth in fertilizer use are crop- and country-specific, with highly diverse underlying drivers depending on the context. Moreover, for the four main crops, fertilizer use has increased both for direct human food production and for animal feed and other uses, although the relative importance of the latter two has grown in recent decades. Finally, the combination of these factors, together with the expansion of livestock production, particularly monogastrics, suggests that improvements in crop-level fertilizer use efficiency driven by technological gains are effectively being neutralized at the food-system level, as they are not fully translated into overall efficiency because of the inefficiencies of the livestock sector.

These results suggest that demand-side policies may constitute a key tool for advancing towards more sustainable food production in terms of fertilizer use,

contributing to reducing overall fertilizer consumption and its associated impacts.

Keywords: Fertilizer use, agricultural intensification, crop allocation, international trade, fertilizer use efficiency, partial factor productivity, machine learning, data imputation, historical reconstruction, bayesian statistics.

Resum

L'ús global de fertilitzants s'ha més que triplicat des de la segona meitat del segle XX. Més de la meitat del seu consum s'ha destinat als quatre principals conreus a escala mundial: blat, blat de moro, arròs i soja. Tanmateix, no tota la producció d'aquests cultius s'ha destinat al consum humà directe; altres usos, com l'alimentació del bestiar o la producció de bioetanol, han guanyat rellevància durant aquest període. Malgrat això, la relació entre el consum de fertilitzants i la seva finalitat última, determinada pel destí dels conreus, encara no ha estat completament caracteritzada.

Aquesta tesi té com a objectiu explorar aquestes dinàmiques centrant-se en els quatre principals cultius i identificant en quins períodes i per a quins conreus es concentren les principals ineficiències en l'ús de fertilitzants.

En primer lloc, s'han recopilat bases de dades històriques i s'han emprat tècniques de *machine learning* per construir una base de dades a escala global. En segon lloc, s'han analitzat les tendències temporals en el consum de fertilitzants durant l'últim segle. En tercer lloc, s'ha examinat, per als quatre principals cultius, quin ha estat el destí de l'ús de fertilitzants (alimentació humana directa, animal o altres usos). Finalment, s'ha avaluat com la interacció entre el consum de fertilitzants i l'ús dels cultius ha repercutit en la seva eficiència global, mesurada com els quilograms de proteïnes o energia produïts per quilogram de fertilitzant.

En conjunt, els resultats mostren que les tècniques modernes de *machine learning* constitueixen una eina eficaç per a la imputació de grans bases de dades a escala global, i que els patrons de creixement en l'ús de fertilitzants són específics de cada país i cultiu, amb causes potencials molt diverses segons el context. Així mateix, per als quatre principals cultius, l'ús de fertilitzants ha augmentat tant per a la producció d'aliments de consum humà directe com per a l'alimentació animal i altres usos, si bé la importància relativa d'aquests dos darrers s'ha incrementat en les darreres dècades. Finalment, la combinació d'aquests factors, juntament amb l'augment de la producció ramadera, especialment de monogàstric, ha provocat que les millores en l'eficiència de l'ús de fertilitzants a nivell de cultiu no s'hagin traslladat plenament al sistema alimentari en el seu conjunt.

Aquests resultats suggereixen que polítiques orientades a la demanda poden constituir una eina clau per avançar cap a una producció alimentària més sostenible en termes d'ús de fertilitzants, contribuint a reduir-ne l'ús total i els impactes associats.

Resumen

El uso global de fertilizantes se ha más que triplicado desde la segunda mitad del siglo XX, permitiendo el crecimiento poblacional del último siglo. Más de la mitad de su consumo se ha destinado a los cuatro principales cultivos producidos a nivel mundial: trigo, maíz, arroz y soja. Sin embargo, no toda la producción de estos cultivos se ha destinado al consumo humano directo; otros usos, como la alimentación del ganado o la producción de bioetanol, han ganado relevancia durante este periodo. A pesar de ello, la relación entre el consumo de fertilizantes y su finalidad, determinada por el destino de los cultivos, aún no ha sido caracterizada.

Esta tesis tiene como objetivo explorar estas dinámicas centrándose en los cuatro principales cultivos e identificando en qué periodos desde la segunda mitad del siglo XX se concentran las principales ineficiencias en el uso de fertilizantes.

En primer lugar, se han recopilado bases de datos históricos y se han empleado técnicas de *machine learning* para construir una base de datos global. En segundo lugar, se han analizado las tendencias temporales en el consumo de fertilizantes durante el último siglo. En tercer lugar, se ha examinado, para los cuatro principales cultivos, cuál ha sido el destino del uso de fertilizantes (alimentación humana, animal u otros usos). Por último, se ha evaluado cómo la interacción entre el consumo de fertilizantes y el uso de los cultivos ha repercutido en su eficiencia global, medida como unidad de proteínas o energía producidas por unidad de fertilizante.

En conjunto, los resultados muestran que las técnicas de *machine learning* constituyen una herramienta eficaz para la imputación de grandes bases de datos, y que los patrones de crecimiento en el uso de fertilizantes son específicos de cada país y cultivo, con causas potenciales muy diversas según el contexto. Asimismo, para los cuatro principales cultivos, el uso de fertilizantes ha aumentado tanto para la producción de alimentos de consumo humano directo como para la alimentación animal y otros usos, si bien la importancia relativa de estos dos últimos se ha incrementado en las últimas décadas. Finalmente, la combinación de estos factores, junto con el aumento de la producción ganadera, especialmente de animales monogástricos, ha provocado que las mejoras en la eficiencia del uso de fertilizantes a nivel de cultivo no se hayan trasladado plenamente al sistema alimentario.

Estos resultados sugieren que políticas orientadas a la demanda constituyen una herramienta para avanzar hacia una producción alimentaria más sostenible en términos de uso de fertilizantes, reduciendo su uso y los impactos asociados.

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List of Acronyms

CJS_{dist} cumulative Jensen–Shannon distance. 72, Ap.16

R^2 Bayesian Coefficient of Determination. 71–73, 75, 77, Ap.46

δ Cliff's delta. 87, 103, 122

$\hat{R}$ potential scale reduction factor. 71–73, 75, Ap.16

K_2O potassium oxide. xii–xiv, xvii, 7, 8, 15, 18–30, 32–37, 40, 41, 44, 46, 47, 51–55, 61, 64–69, 72–80, 85, 101, Ap.40

KCl potassium chloride. 7

N_2O Nitrous oxide. 13, 106

NH_3 Amonnia. 13, 106

NOx nitrogen oxides. 13, 106, Ap.1

Nr reactive Nitrogen. 11, 12, Ap.1

P_2O_5 phosphorus pentoxide. xii, xvii, 5, 6, 15, 18–30, 32–37, 40, 41, 44, 46, 47, 49–51, 53–55, 59–61, 64–69, 72–79, 81, 85, 101, Ap.2

AS ammonium sulfate. 2

BCE Before Common Era. 3, 64

BNF Biological Nitrogen Fixation. 11, 12, 14, Ap.1

C Carbon. 2

CB Commodity Balances. 100

CEC cation exchange capacity. 38

CI Credible Interval. 72, 75, Ap.25

CO_2e CO_2 equivalent. 11

CV cross validation. 43, 61

DDGS distillers dried grain with soluble. Ap.65

DEFRA Department for Environment, Food & Rural Affairs. 56, 61

DMC Dry matter content. 100, Ap.75

DTM Detailed Trade Matrix. 86, 99, 100, 103, 119, Ap.76

ESS effective sample size. 71–73, 75, Ap.24

EU European Union. 21, 22, 28, 30, 34, 35, 81, 97

FAO Food and Agriculture Organization. xviii, 3, 20–22, 26–30, 36–38, 65, 67, 88, 100, 101, 127, Ap.88

FAOSTAT Food and Agriculture Organization Corporate Statistical Database. xvii, 11, 21, 23, 32, 38–40, 44–46, 86, 99–101, 103, 118, 119, Ap.3

FB Food Balances. xvi, 86, 98–101, 118, 119, Ap.75

FCR Feed Conversion Ratios. 95, 107, 119, 120, Ap.87

FE Fertilizer Europe. 22, 30

FFR fertilizer used for *feed* relative to *food*. 86, 87, 89, 94–96, Ap.53

FPS Fertilizer Potential Savings. 107, 114, 116, 117, Ap.97

FR Feed Rations. 119, Ap.80

FUBC fertilizer use by crop. 20–23, 30, 38, 44, 98, Ap.69

GDP gross domestic product. 39, 41, 54

GHG Greenhouse gases. 11, 13

GR Green Revolution. 4, 84, 94, 95, 123, 126

HGB HistGradientBoosting. 19, 42, 43, 46, 53, 61, 118

ICC Indicative Crop Classification for agricultural census. 20

IFA International Fertilizer Association. 20, 21, 26, Ap.69

IFDC International fertilizer Development Center. 20–22, 27, 30

IQR Interquartile Range. 122

K Potassium. xiii, xv, 1–3, 7–9, 11–14, 18, 19, 27, 40, 41, 64, 65, 77, 80, 85–89, 91, 92, 94, 96–98, 101, 103, 106, 108, 110, 112, 114, 116, 118, 121, 123–126, 129, Ap.59

kcal kilocalories. 4

LCU local currency units. 39

LM Law of Minimums. 3

LMDI Logarithmic Mean Divisa Index. 103

LS Livestock Systems. 119, Ap.80

MAE mean absolute error. 28–30, 32, 43, 44, 53, 56, 59, 60, 103

MAP mean annual precipitation. 38

MAPE mean absolute percentage error. 44, 56, 102, 122

MAT mean annual temperature. 38

MC Monte Carlo. 87, 103, 122, Ap.71

ML machine learning. iii, 19, 20, 23, 37, 41–44, 53, 61, 62, 118, 123, Ap.70

MLH Multiple Limitation Hypothesis. 3

MMTOE million metric tonnes of oil equivalent. 84, Ap.60

MSE mean squared error. 43

Mt Mega tonnes. 11

N Nitrogen. xii–xv, xvii, 1–3, 8–15, 18–37, 40, 41, 44, 46–49, 51, 53–56, 61, 62, 64–69, 72–81, 85–89, 91, 92, 94–98, 101, 103, 106, 108, 110, 112, 114, 116–118, 121, 123–127, Ap.26

NUE Nutrient Use Efficiency. 13, 15

NUTS No-U-Turn Sampler. 71

OCS organic carbon stock. 54

OHE one-hot encoded. 41, 43

P Phosphorus. xii, xiii, xv, 1–5, 8, 9, 11, 12, 14, 18, 19, 27, 40, 41, 64, 65, 77, 78, 80, 85–92, 94–98, 101, 103, 106, 108, 110, 112, 114, 116, 118, 120, 121, 123–127, 129, Ap.53

PET potential evapotranspiration. 38

PFP Partial Factor Productivity. xiii, 106–113, 117, 121–127

PR phosphate rock. 4–7, 11, Ap.2

RMSE root mean squared error. 43

S Sulfur. 1

SDG Sustainable Development Goals. 117

SFR Social Federal Republic. 34

SHAP SHapley Additive exPlanations. 17, 19, 42, 43, 53, 54, 61

SOC soil organic carbon. 38

SOP potassium sulfate. 2

SSP single superphosphate. 2, 4, 5, Ap.2

TSP triple superphosphate. 5

UK United Kingdom and Northern Ireland. xii, xv, 4, 7, 22, 33, 44, 56, 58–60, 124, Ap.66

UN United Nations. 4

USA United States of America. xii, 4, 5, 7, 20, 22, 44, 47, 51, 56, 57, 59–61, 84, 87, 94–97, 106, 112, 114, 116, 124, Ap.61

USAID United States Agency for International Development. 94

USD United States dollars. 39

USDA United States Department of Agriculture. 56, 61

USGS United States Geological Survey. Ap.2

USSR Union of Soviet Socialist Republics. 5, 34, 35, 42, 67, 114, 125, Ap.71

WW World War. 5, 7, 96

xAI eXplainable artificial intelligence. 43

XGB eXtreme Gradient Boosting or XGBoost. 19, 42, 43, 53

Chapter 1

General introduction

Humanity is rooted in the harvests of crops, yet each harvest depends on a set of chemical elements that sustain plant growth. Until the 19th century, however, the role of elements in plant nutrition was unknown. The discoveries by Carl Sprengel and Justus von Liebig demonstrating that plants require a combination of mineral elements established the mineral theory of plant nutrition [1, 2]. These findings provided one of the main cornerstones for modern agriculture, and inorganic fertilizers became the tool that put this principle into practice. Over the last two centuries the use of inorganic fertilizers has boosted crop yields and thus helped avert Malthus' prediction of population-driven food shortages [2]; nevertheless, their widespread application has disrupted natural biogeochemical cycles [3–5], a disruption now regarded as one of the major global-change concerns [6]. Today, almost two hundred years after the first commercialization of an inorganic fertilizer, agriculture faces the dual challenge of feeding a growing population while reducing the impacts associated with fertilizer use. In this thesis, we address this challenge by delving into historical development of fertilizer use intensification at global, national, and crop levels, with the aim of understanding the changing purposes of their use, shedding light on past and current utilization to assess how crop demand has driven its use.

Inorganic fertilizers, also referred to as mineral or synthetic fertilizers, are manufactured, refined or mined materials that provide one or more essential plant nutrients in a mineral form [7]. Nowadays, their commercialization covers the supply of the 14 essential mineral elements required for plant nutrition, as well as some elements while not essential, can be beneficial [7]. However, the production and use of inorganic fertilizers is clearly dominated by three of these elements: Nitrogen (N), Phosphorus (P) and Potassium (K) [8]. In 2020, global agricultural use of inorganic N, P and K fertilizers together surpassed 200 Tg, whereas Sulfur (S), the next most supplied nutrient through inorganic fertilizers, accounted for only

about 7-10 Tg [1]. The primacy of N, P and K in inorganic fertilizer use reflects their fundamental roles in plant growth and the frequent scarcity in soils.

Why are N, P and K important for crop production?

N, P, and K are three of the six mineral elements commonly referred to as macronutrients which occur at the highest concentrations in plants. After carbon Carbon (C), captured from the air, N is the element required in the largest amounts by plants, typically accounting for 1 to 5% of total plant dry matter [7, 11]. It is a structural element of proteins, nucleic acids, chlorophyll, co-enzymes, phytohormones and secondary metabolites, and is therefore indispensable for photosynthesis, growth and reproduction among other plant functions [11]. The availability of N affects biomass production, organ size and structure, and leaf area development, thereby determining photosynthetic capacity [12]. Consequently, its supply influences all components of crop yields: the number of plants per hectare (ha), the number of bearing organs per plant, and the mass of yield per bearing organ [12]. N availability in soils also influences the nutritional quality of most crops as higher N availability tends to increase the protein concentration of grains and other seeds [13].

P occurs in lower concentrations in plants than N, approximately 0.05-0.5% of the plant dry matter [14]; however, it is a structural component of nucleic acids and is abundant in the phospholipids of the biomembranes [11]. Phosphate esters and energy-rich phosphates serve as essential molecules for cellular energy metabolism [14]. Other P forms, such us inorganic phosphates, phytates or inorganic polyphosphate control key enzyme reactions, play a key role in C portioning between the chloroplast and the cytosol, store energy, or function as a cation exchanger [14]. Therefore, deficiencies in P reduce crop productivity because they underpin several biochemical processes that power plants to growth [15].

K is the second most demanded mineral element for plants after N, accounting for 1 to 5% of plant dry matter [7]. Unlike N or P, it is not a structural element; however, K^+ is the most suitable cation for regulating vital functions due to its ionic stability [5], and it is, consequently, the most abundant cation in plants [16, 17]. K^+ plays a central role in plant homeostasis, solute and energy transport, enzymatic regulation, growth, and stress responses among other functions [11, 16]. A deficit of K^+ leads to morphological and physiological changes that reduce both crop yield and quality [17, 18]. For example, major crops such as maize or wheat can benefit

[1]The estimate of 7 Tg was based on total consumption of ammonium sulfate (AS), single superphosphate (SSP), and potassium sulfate (SOP) [9], together with their sulfur content [10]. Most agricultural sulfur is applied through fertilizers that supply sulfur in combination with other nutrients, with AS, SSP, and SOP among the most widely used [7, 8]. Previous estimates for 2015 indicate that these three products accounted for about 70% of the agricultural sulfur supplied by inorganic fertilizers [8], and this ratio was used to derive the 10 Tg figure.

from adequate K^+ supply through increased yields via reduced stalk lodging, and improved quality through higher protein and amino acid content in seeds [17].

These three elements, N, P and K are fundamental for plants; therefore, their availability is a key factor that limit terrestrial ecosystem productivity [19–22], and crop production [23, 24]. Currently, two debated main hypotheses explain how nutrients limit plants growth: the Law of Minimums (LM) proposed by Sprengel [25] and popularized by von Liebig [26] in the 19th century and the Multiple Limitation Hypothesis (MLH) proposed at the end of the 20th [27]. LM states that plant's growth is limited by the element in least supply relative to the plant's requirement with potential release of the nutrient in excess [25, 26, 28, 29]. MLH states that plants adjust their growth patterns to changes in resource availability to reduce extreme exchange ratios and thus they are co-limited by multiple nutrients simultaneously [27–29]. Whether nutrients limitation follows LM or the MLH remains a central scientific debate [29]. Although the global estimates of nutrients limitation to productivity vary depending on the methodology and paradigm applied, N, P and K limit or co-limit natural ecosystems and croplands. For example, based on LM paradigm and global data on leaf N and P reabsorption efficiency, it has been estimated that 18% of natural terrestrial lands are N limited and 43% P limited [20]. In contrast, a recent metanalysis grounded in the MLH framework and using fertilization experiments found that more than 80% of the studies included were co-limited by the three nutrients [21]. In croplands, some studies have concluded that nutrient inputs should be increased in more than three-fourths of cereal-growing areas to close their yield gaps [23], or that 30% of croplands were P -limited [24].

From traditional to modern agriculture

Since the dawn of agriculture nutrient limitations promoted management practices for enhancing plant nutrition. The use of natural substances rich in N, P and K to dates back to at least 6500 Before Common Era (BCE), when the application of manure and middening were common practices in the agricultural production of northern Mesopotamian urban centers [30]. These practices, and others such as the utilization of guano, developed independently in several human cultures [31, 32]. Before the establishment of mineral theory and the development of the inorganic fertilizer industry, beyond the recycling of crop residues, the main sources in agricultural soils of N were legume-based crop rotations and animal, human and green manures [2]; of P were animal and human manures, and bones [33]; and of K were animal and human manures, and ashes from wood [34]. The most productive traditional systems, where some of these management practices were implemented and continuous cultivation was possible, were able to feed based on largely vegetarian diets more than 10 person per ha of agricultural land, and 5 persons per ha in regions or countries with a less hospitable clime [2].

Conversely, current figures, based on Food and Agriculture Organization (FAO)

from United Nations (UN) energy recommendations, estimate that global croplands produce enough kilocalories (kcal) to feed 10.1 person per ha, and, based on current diets and crop utilization, deliver sufficient energy to feed 6.1 person per ha [35]. That global averages have reached the same levels as the most productive traditional systems is the result of the development and widespread implementation of modern agriculture technologies around the world. Improvements in mechanization, modern seed varieties, nutrient supply, pathogens control, and management practices began in the high-income regions; Europe, North America, Australia and Japan, during the late 19th century and the beginning of the 20th [2, 36, 37].

Inorganic fertilizers (hereinafter 'fertilizer') were the pillar for improving plant nutrition in the transition towards modern agriculture by replenishing the nutrients removed from soil during crop harvesting. This transition began with the establishment and promotion of mineral theory and continued with the creation and growth of the modern fertilizer industry, leading to today's global situation. These innovations started in a small cluster of high-income countries; nevertheless, they became global after the Second World War. International programs promoted by the FAO, by national organizations such as the U.S. Technical Cooperation Administration, and by private foundations such as the Rockefeller Foundation in the period commonly known as the Green Revolution (GR) (1960s-1980s) promoted worldwide the utilization of fertilizers and other technologies [38, 39]. A full historical description of this process is beyond the scope of this thesis; however, the following section will summarize the key milestones in the development of the fertilizer industry, its supply, and its current challenges.

Fertilizer Industry Development and Current Situation

Phosphate Mining History and current Supply

Modern fertilizer industry began with in 1841 in the United Kingdom and Northern Ireland (UK) with the first sale of a fertilizer: phosphate of lime (commercially known as SSP), produced following the von Liebig's idea of treating bones with sulfuric acid [40]. Two years later John Bennett Lawes's factory at Deptford on Thames applied this idea to produce ordinary superphosphate SSP using phosphate rock (PR), specifically coprolites [40]. PR was first mined in England in 1847, followed by smaller operations in Norway, France, Canada, and the United States of America (USA) [41]. However, beyond the use of manure, it was not until the 1870s that PR-based fertilizers became the main source of P for producing fertilizers [2]. During the 1850s and 1860s, most P- fertilizers were derived from guano [41, 44]. Nevertheless, since 1870s PR-based fertilizers have been the main source of P-fertilizers. The

[2]Based on UK import data of Peruvian guano [42], taking into account that the UK held a monopoly on guano imports [42], which were the main alternative to PR [43], as well as on the significance of USA PR production in South Carolina relative to global production during the 1870s and 1880s [43].

invention of triple superphosphate (TSP) that contained between two and three times more P than SSP [40]; and the discovery of the Florida phosphorite deposits in the 1880s (today the principal production site in the USA, the world's third-largest phosphate producer [44]) marked the beginning of this new phase in P-fertilizer production.

Since then, PR has completely dominated the P-fertilizers market only with interruptions in the increases during periods such as the years between the two World War (WW) ([40], Fig. 1.1 a), the decades following the collapse of the Union of Soviet Socialist Republics (USSR) ([40], Fig. 1.1 a), and the recent Russian invasion of Ukraine ([45], Fig. 1.1 a). Its production has growth almost continuously to the 240 Mt of PR produced in 2024 (Fig. 1.1 a), of which approximately 85% are consumed as fertilizers [46] (~ 45 Mt of phosphorus pentoxide (P_2O_5)) [3] . Several milestones have marked the past 150 years of PR production and P-fertilizer supply, most of them in the early decades: in 1912, the discovery of the marine phosphorite deposits of in Morocco, the largest known reserves of phosphates [40, 44, 47]; in 1930, the discovery of the apatite deposits in the Kola Peninsula (today in the Russian Federation), the most important igneous PR deposits [41]; or in 1960s, the development of phosphate mining industry in China [48], currently the world top producer [44].

Today, current production is dominated by a few countries (Fig. 1.1 b), and phosphate reserves are even less evenly distributed (Fig. 1.1 c). How long the PR supply can be sustained has been one of the heated debates in food security of this century [33, 40, 49–52], although such concerns date back almost to the earliest days of phosphate mining [53]. There is no clear consensus on the lifetime of global PR reserves, owing to discrepancies in: 1) the definition and calculation of current resources, reserves, and potential resources, and 2) the methods used to estimate future demand [49, 51]. Nonetheless, the order of magnitude of PR reserves lifetime appears to be between decades and centuries, rather than millennia according to both academia [50] and fertilizer companies [46]. Short-term supply concerns are related with other factors such as the imbalanced location of the reserves with a few countries, principally in Morocco, controlling global future supply [54], or prices spikes occurring as a result of multiple socioeconomic and geopolitical factors [45].

[3]The figures about phosphate production [44] and fertilizer consumption matched approximately considering that according to fertilizer companies [46]: i) mining recovery to convert in situ tonnage to run-of-mine ore is on average 82%, ii) beneficiation, run-of-mine ore to concentrate efficiency, is 84% on average and iii) 85% of global P_2O_5 is used for fertilizers.

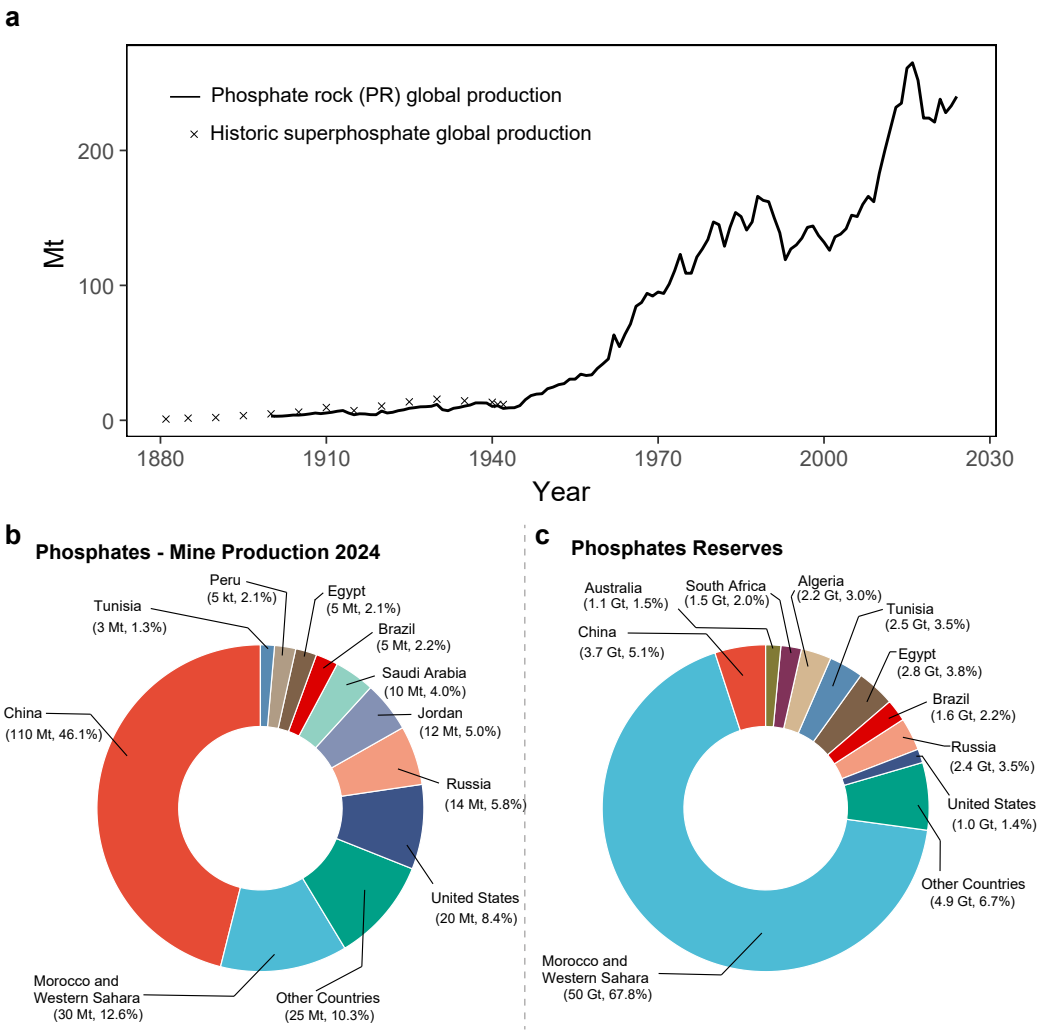


Figure 1.1. (a) Phosphate rock (PR) (in P_2O_5) production since 1900, and historic single superphosphate (SSP) production during the early years of the industry [44]. Data are reported as produced quantities, not converted to P_2O_5 equivalents. (b) Share and quantity of phosphate rock produced in 2024 by the major producing countries [44]. (c) Share and quantity of national PR reserves among the countries with the largest reserves [44].

Potash Mining History and current Supply

The inception of potash mining and fertilizer production occurred in Germany two decades after the start of the development of the phosphate industry in the UK. In 1861, the first mine was established in Staßfurt (Saxony-Anhalt), following the discovery of potash salts, specifically carnallite, in two salt shafts five year earlier [55]. One year later, in 1862, the Vorster & Grüneberg company began processing carnallite using the thermal dissolution process, which remains one of the most common methods for producing potassium chloride potassium chloride (KCl) [55]. These discoveries were followed by the discovery of richer K-content minerals as kainite, and the opening of new mines and factories in Germany [55]. These events mark the start of the potash fertilizer industry and by 1919, before the end of WW1, the German Empire operated more than 200 plants across six regions, including mines in Alsace, and also controlled other important known deposits, such as those in Catalonia [34] monopolizing the global potash market.

Since the start of mining in Germany, potash rocks became the main source of K-fertilizers, completely replacing earlier products such as wood and kelp ashes [34]. Before WW1, German and Alsatian mines produced 1.1 Mt of potassium oxide (K_2O), more than 90% of which was used in agriculture, with Germany itself accounting for over half of this consumption [56]. This monopoly was transformed to a French German cartel when the French government took control of the Alsatian mines after WW1; however, global production did not substantially change until the end of WW2 (Fig. 1.2 a). The devastation in Europe, and the discovery of potash deposits, first in the Dead Sea (now Palestine/Israel and Jordan, 1930), then in the Urals (now Russian Federation, 1933), Soligorsk (now Belarus, 1958), and finally in Saskatchewan (Canada, 1962) completely reshaped the global potash market and boosted production [34, 55] (Fig. 1.2). In the recent decades only the emergence China as an important actor in global markets have modified global markets with, both through its domestic production [57] and its potential international investments, particularly in Laos [58].

Today current reserves are controlled by a few countries (Fig. 1.2 c). Six of them, Canada, Laos, Russian Federation, Belarus, Israel and Jordan account for more than 90% of known potash reserves. Like PR, the lifetime of potash reserves for K-fertilizer production has raised scientific concerns, with estimates suggesting depletion within the next century [59]. However, because these estimates place depletion at least a hundred years into the future [59] and given the potential for future economic extraction from silicate rocks or seawater [55, 60], such concerns are generally viewed as less urgent than the K depletion debate of the beginning of this century. Short-term supplies are linked to the uneven geographical distribution of the resources. Recent events, such as the Russian invasion of Ukraine, or the trade conflict initiated by the USA in 2025 imposing tariffs to Canada, have highlighted the fragility of the K-market and how disruptions involving major producers can trigger sharp global and regional price spikes [61, 62].

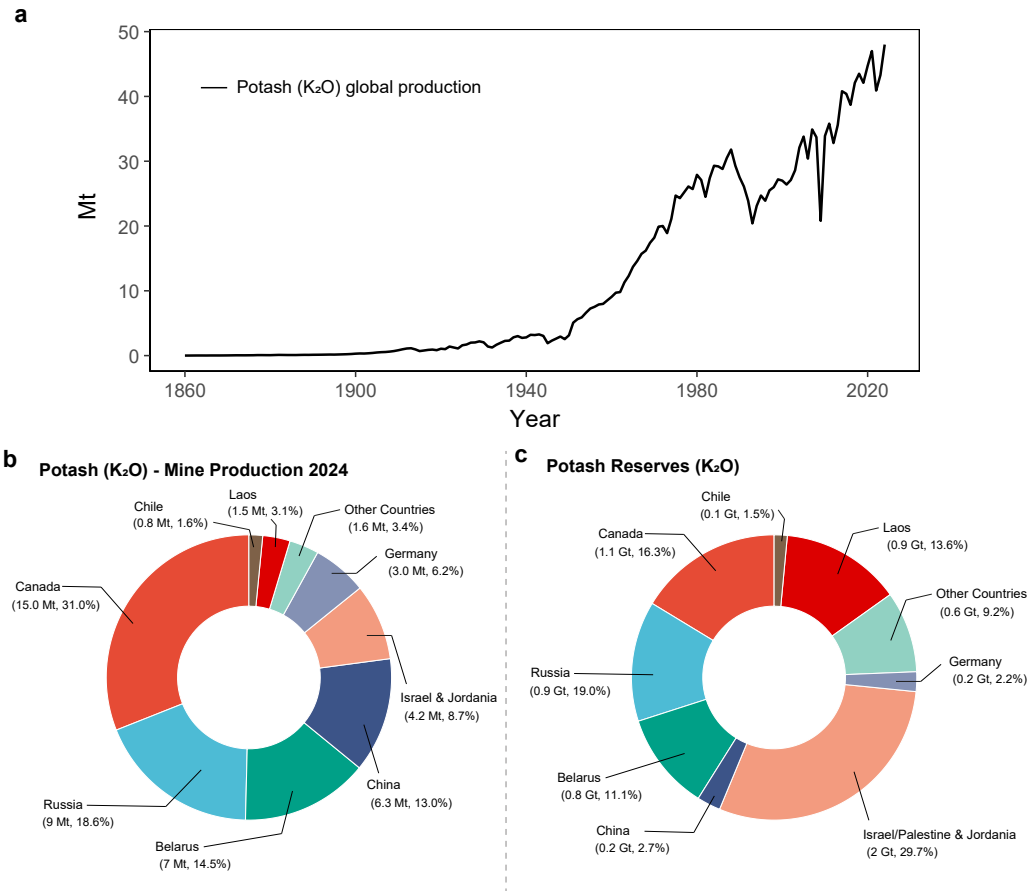


Figure 1.2. (a) Potash rock production (K_2O) since 1861 [56, 57]. Data prior to 1920 were estimated by assuming K_2O production equal to 10% of potash rock extracted, based on data and proportion between extraction and annual use [56]. (b) Share and quantity of potash rock (K_2O) produced in 2024 by the major producing countries [57]. (c) Share and quantity of national potash rock (K_2O) reserves among the countries with the largest reserves. Israel and Jordan were together because of they share the deposits of the Dead Sea [57].

Nitrogen Supply History

Conversely to P and K, N supply does not rely on mining resources. The history of N production was fundamentally shaped by the invention of the Harber-Bosch process in 1908. Before this invention, N supply was dominated by naturally derived mineral sources: first by guano, which accounted for 87.5% of total N production in 1860 [2] and then by Chilean calcium nitrate (86.6% of total N production in 1890 [2]). These natural resources, together with early industrial processes such as the recovery of ammonium sulfate as a by-product of coke oven and the fixation of atmospheric N_2 through calcium cyanamide synthesis from carbonate, were the primary means of N supply at the beginning of the 20th century [2]. Collectively, these sources provided about 610 kt of N globally in 1910 (Fig. 1.3); 20 years later, total N production was more than four times higher (Fig. 1.3), with ammonia from the Haber–Bosch process

accounting for two-thirds of global output [2].

The Haber-Bosch process, the synthesis of ammonia (NH_3) from its elements (N_2) and (H_2) has been one of the most important scientific advances of the last centuries, as it has sustained approximately half of the human growth population since its invention [63]. Fritz Haber in his 1918 Nobel Prize lecture, acknowledged the importance of the discovery, recognizing that agriculture was already limited by nitrogen supply: "Agriculture, always the main consumer, is not satisfied with a supply of nitrogen alone - potash and phosphates are equally indispensable - but the world possesses far fewer natural resources for meeting nitrogen requirement" [64]. He also noted that the Chilean calcium nitrate deposits would eventually be insufficient: "it became clear that towards the middle of the present century a major emergency would be unavoidable, unless the chemistry found a way out" [64]. Nevertheless, he did not foresee the profound environmental consequences that would follow from the large-scale deployment of his discovery.

Today, more than 99% of the N supply relied in the Harber-Bosch process [2]. Most of the feedstuff of the H_2 used in this process came from fossil fuels, 96.6% in total [65], with approximately 71% obtained from natural gas and 25% from coal [65]. As the source of N, atmospheric N_2 is available everywhere, the geographic distribution of ammonia production is largely determined by access to cheap H_2 feedstock. Consequently, the major ammonia producers tend to be those with significant natural gas production (Fig. 1.3 b). This explains why, although N market is less geographically concentrated than P or K market, it is still dependent on a relatively small group of 20-30 countries. It also explains why disruption in natural gas supply or spikes in gas prices directly affects ammonia production, as illustrated by the reduction in output and sharp price increases observed in Germany following natural gas shortages after the Russian invasion of Ukraine [66].

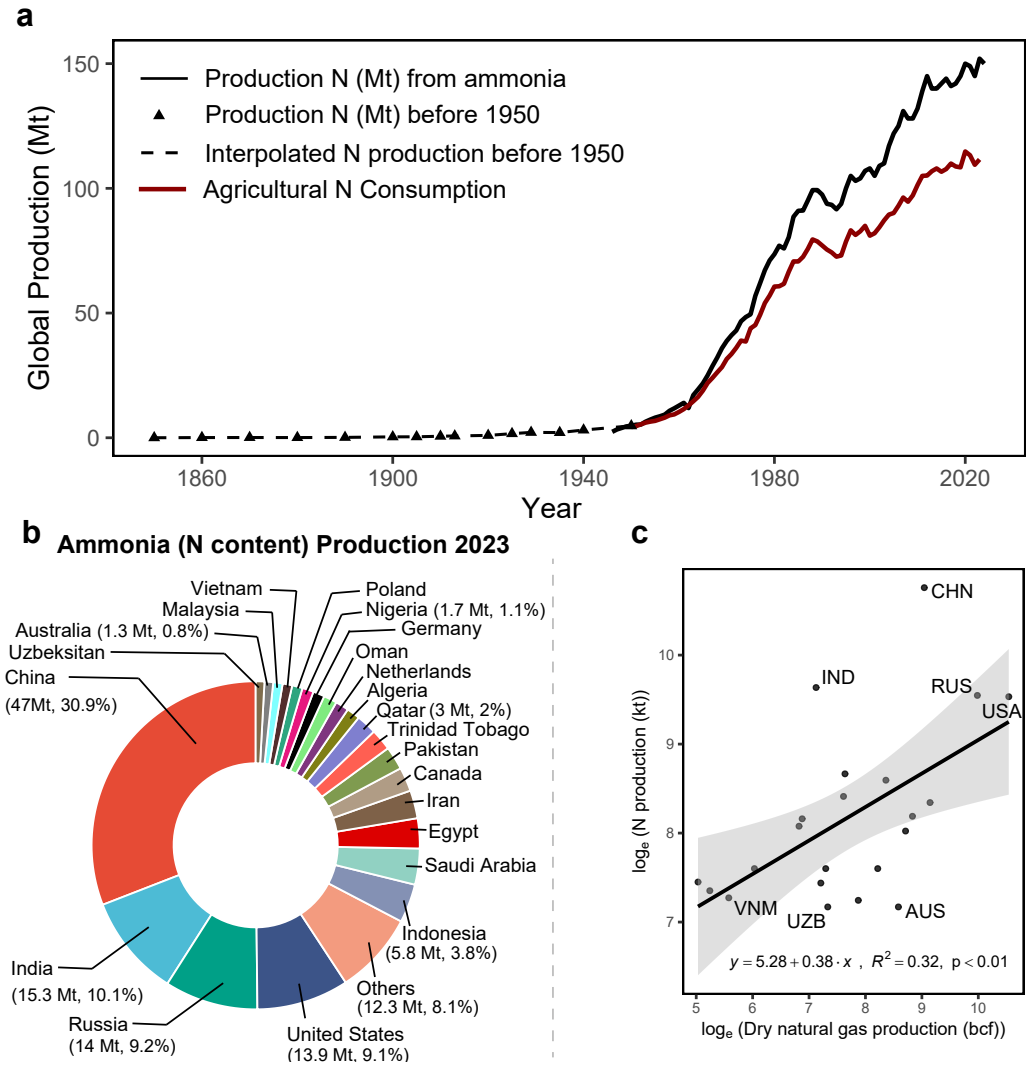


Figure 1.3. (a) Global nitrogen N production since 1860 [2, 67]. Data prior to 1943 were linearly interpolated (dashed line) based on decadal data compiled in Smil [2] The solid black line indicates production data since 1943 from fixed atmospheric N_2 [67], and the solid red line represents agricultural N use [68]. (b) Share and quantity of ammonia production (expressed as N content) in 2023 by the major producing countries [67]. (c) Linear relationship between ammonia production in kilotonnes (kt) [67] (log scale) and dry natural gas production in billion cubit feet (bcf) [69] (log scale).

Impacts of Fertilizer Production and Alteration of Natural Biogeochemical Cycles

The production of fertilizers has generated local impacts and contributed globally to climate change. Moreover, their utilization has altered the natural NPK biogeochemical cycles [3–5], a disruption now regarded as one of the major global-change concerns [6] due to its environmental impacts. Most of the documented impacts and social concerns of fertilizer production and use relate to N and P; however, in this introduction we also incorporate the knowledge on the environmental impacts associated with K production and utilization.

Impacts from fertilizer production

The production of fertilizers, including manufacturing, extraction of raw materials, and transportation is responsible for approximately 1% of global Greenhouse gases (GHG) emissions. In 2020, according to Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) [70], energy use in fertilizer manufacturing emitted 450 Mega tonnes (Mt) of CO_2 equivalent (CO_2e) ($\sim$ 0.75% of total GHG emissions [70, 71]). These figures increase further when accounting for emissions from potash mining and beneficiation ($\sim$ 6 Mt of CO_2e [57, 72, 73]), PR extraction and beneficiation ($\sim$ 15 Mt of CO_2e [44, 73, 74]), the extraction and transport of fossil fuels used to produce the H_2 required for the Haber–Bosch process ($\sim$ 0.8 Mt of CO_2e [65]), and the transport of fertilizer products (>30 Mt of CO_2e [65, 75]).

At the local scale, potash mining has been associated with water pollution and salinization [76], with potential consequent impacts on biodiversity [77]; it has also been linked to microseismic events [78], and in some cases, the collapse of large underground mines [79]. Phosphate mining has likewise been associated with environmental and human-health impacts. Air and water contamination of trace elements and radioactive materials has been documented in areas affected by phosphate extraction [80, 81], and some studies have reported potential human-health risks, including increased prevalence of cancer in populations living near mining operations [82]. Aboveground phosphate mining has been responsible for important landscape degradation as the case of Nauru, probably the nation with the most altered natural landscape [83].

Impacts from fertilizer use

Nevertheless, the major impact of fertilizer use has been the disruption of natural biogeochemical cycles. Fertilizers inputs have reached, and in some cases surpassed the natural inputs of N, P and K to continental lands (Fig. 1.4). For N, the fixed N_2 used as fertilizers already exceeds the natural sources of reactive Nitrogen (Nr) (i.e., lightning, rock weathering and Biological Nitrogen Fixation (BNF) in unmanaged

lands). Moreover, the N fixed for fertilizer use is greater than all other anthropogenic inputs combined, including BNF in agricultural lands and Nr generated through industrial activities and fossil-fuel combustion (Fig. 1.4 a). For P, the amount mined for agricultural use surpassed natural P weathering in the 1970s, while for K the amount mined has now reached comparable levels to the natural K weathering (Fig. 1.4 b-c).

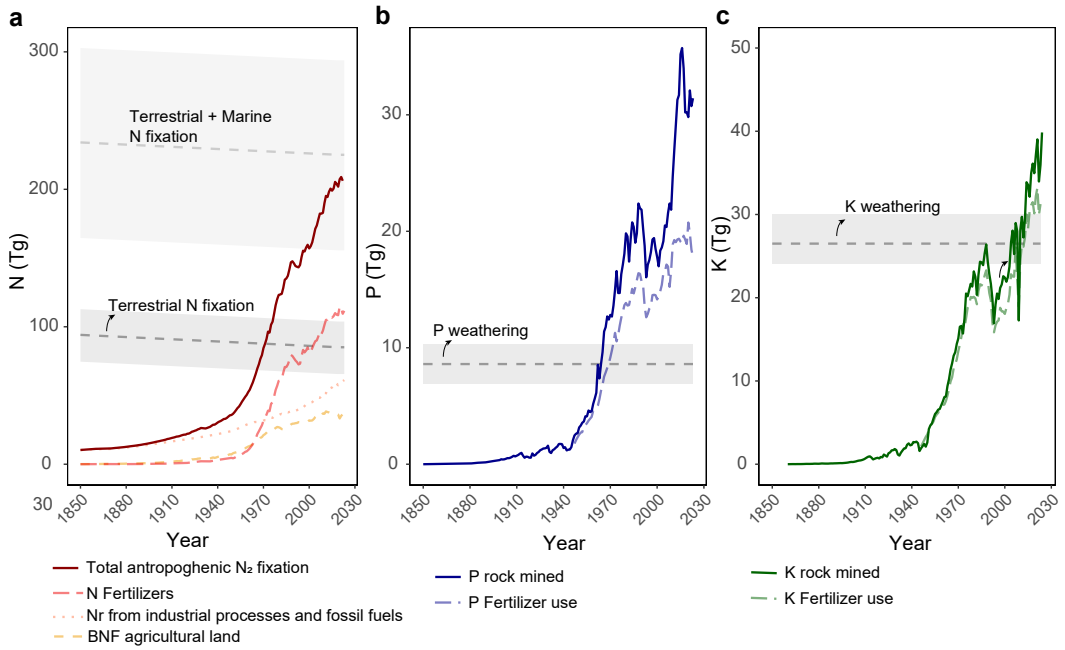


Figure 1.4. (a) Global reactive nitrogen (Nr) production since 1850. The dark grey line and shaded area represents mean and sd of natural terrestrial biological nitrogen fixation (BNF) [84] lightning-fixed N [85] and terrestrial N from weathering [86] together. The light grey line and shaded area represent the marine BNF and the previous terrestrial sources [87]. The long dashed red line shows fertilizer N use [2, 68], while the dashed yellow line represents BNF in agricultural lands [84, 88, 89]. The dotted orange line represents Nr fixed from fossil fuels and industrial activities [90, 91]. All anthropogenic inputs are indicated by the solid red line. (b) Global phosphorus (P) production since 1850. The dark grey line and shaded area represent the terrestrial P from weathering [92]. The dashed blue line shows P fertilizer used in agriculture since 1945 [68], and the solid blue line represents the annual P mined [44, 93]. (c) Global potassium (K) production since 1850. The dark grey line and shaded area represent terrestrial mean, minimum and maximum estimated K weathering from dissolved riverine transport [94, 95]. The dashed green line shows K fertilizer use since 1945 [68], and the solid green line represents the annual K mined [56, 57]. See Appendix A for further methodological details on the figure creation.

Not all the anthropogenic N, P and K inputs to croplands are ultimately taken by crops. A substantial fraction end up in watersheds through leaching contributing to: i) water eutrophication causing harmful algal blooms, hypoxia and loss of biodiversity [96–98], ii) surface and groundwater pollution with nitrates,

nitrites, heavy metals, and radioactive elements, leading to health problems such as stomach cancer or methemoglobinemia [99], iii) groundwater salinization linked to K utilization, and other forms of groundwater pollution [100, 101].

In the case of N, another significant fraction is emitted to the atmosphere [89] contributing to GHG as Nitrous oxide (N_2O) [102], promoting acidification and eutrophication with Amonnia (NH_3) deposition [103] and affecting the tropospheric ozone dynamics via nitrogen oxides (NOx) emissions [104]. In addition, sustained fertilizer application can trigger local impacts on soil health; as it has been associated with soil acidification [105] and the accumulation of heavy metals and radioactive compounds [106, 107].

Utilization of Fertilizers and Existing Knowledge Gaps

Fertilizers have acted as a central lever linking gains in food security with global environmental impacts. This coupling exposes a structural trade-off: maintaining high crop yields tend to intensify the environmental burdens arising from fertilizer manufacture, field application and nutrient losses. Nevertheless, a wide range of strategies and technologies have been developed to bend this lever for reducing the magnitude of these pressures while preserving or even enhancing food security.

Most of these efforts converge on a single general aim: improving Nutrient Use Efficiency (NUE). In its simplest definition, NUE describes the relationship between nutrient inputs and outputs within a given context (e.g., plant, soil, farm level or food system). Consequently, the evaluation of NUE varies with the system considered, the inputs and outputs included, and the way these flows are related. Much of the research on NUE has focused on improving NUE at plant scale through advancements in fertilization products and application techniques [108], precision agriculture [109], crop management practices [110], plant physiological attributes [111], conventional breeding, and molecular approaches [110].

At the farm or food-system level, evaluations comparing nutrient inputs with nutrients available for human consumption are far less common [112, 113]. Moving from plant-level efficiency to farm and food system level requires accounting for additional processes such as crop utilization, international crop products trade, the performance of livestock systems or the nutrient losses occurring at multiple stages along the chain.

Most of the assessments done are for N [112, 114–120], and they provide valuable insights. For example, estimates for Europe have shown that NUE from the crop level to the cropping system level declined from 31% to 18%. However, previous research differs regarding the most effective pathway toward sustainability. While some studies clearly highlight changes in demand patterns, such as shifts in human diets, as the most powerful means of improving food-system NUE [117, 118], others dismiss these measures and instead emphasize improvements at the plant level [114, 115].

One of the major gaps of previous assessments is the lack of crop level analysis with broad temporal and spatial coverage. This limitation is critical because it restricts our capacity to identify inefficiencies across the farm-food system. It affects the evaluation of all major inputs to croplands, including fertilizers, manure, atmospheric deposition, nutrients supplied through irrigation, and BNF.

Another of the major gaps of previous assessments is the absence of K in global analysis. Global assessments have been usually focused on N, and P, as the environmental impacts associated with their use and concerns about their supply have been more evident and pressing.

In this thesis, we aim to narrow this broad problem by focusing on the main anthropogenic input of nutrients: fertilizers. By isolating fertilizers, we address a key component of total nutrient inputs directly linked to both agricultural intensification and environmental impacts. Although this focus limits the scope of our conclusions to fertilizer-derived nutrients, it provides a necessary and tractable first step towards resolving the wider knowledge gap in crop-nutrient use efficiency across the farm-food system.

Scope and Goals of the Thesis

The overarching aim of this thesis is to quantify and characterize the spatiotemporal evolution of fertilizer use and how their nutrients have flowed across the farm-food system to the final human-edible resources identifying the main crops, drivers, regions and periods involved in every step. To achieve this objective, the thesis addresses four complementary, sequential objectives, each examined in a dedicated chapter (Fig. 1.5).

First, we develop a new crop-level database of fertilizer use with longer temporal coverage than previous assessments and harmonized information for the three major nutrients (N, P, and K). This dataset address two critical gaps in existing literature: the absence of global consistent crop-specific input data with large temporal resolution and the omission of K in most global assessments.

Second, we employed the technology diffusion framework to systematically identify and classify different phases of fertilizer intensification across crops, countries, and nutrients over the past century by identifying when fertilizers were adopted, and when their application stagnated or even declined for each crop-country-nutrient combination.

Third, we investigate the underlying drivers of change in total fertilizer consumption for major crops. By distinguishing among end uses of each crop production; human food, livestock feeding or other uses; we identify the main purposes of crop production and associated fertilizer application. By disentangling the contributions of cropland expansions, changes in fertilizer rate, and shifts in crop utilization patterns, we determine the main factors shaping fertilizer demand.

Fourth, and finally, we extend conventional agronomic NUE to the entire food-system (crop-to-fork) scale by focusing on a single main input, fertilizers, and a single main output, the nutrients ultimately delivered to humans through food. This whole system perspective quantifies cascade efficiencies, identifies major nutrient loss pathways allows us to quantify how efficiently fertilizer-derived nutrients are converted into human nutrition and to identify where major losses occur along the chain as for example during livestock feeding.

Goal Chapter 1:
Global fertilizer database
Development a harmonized a crop disaggregated database of N, P_2O_5, K_2O fertilizer use database with extended temporal and geographical coverage.

Goal Chapter 2:
Temporal adoption trajectories
Analysis of diffusion technology framework to identify temporal phases of adoption, stagnation, and decline by crop–country–nutrient.

Goal Chapter 3:
Drivers of change for major crops
Quantify the relative contributions of cropland expansion, changes in fertilizer application rates, and end uses to total fertilizer consumption.

Goal Chapter 4:
Food-system NUE for major crops
Quantify crop-to-fork fertilizer use efficiencies by comparing fertilizer inputs vs nutrients delivered to humans.

Figure 1.5. Overview of thesis goals and corresponding chapters.

Chapter 2

Global crop-specific fertilization dataset (1961–2019)

This chapter is based on:

Coello F.[1,2,3,*], **Decorte T.**[4,*], **Janssens I.**[5], **Mortier S.**[5], **Sardans J.**[2,3], **Peñuelas J**[2,3]**. and Verdonck T.**[4] (2025). Global Crop-Specific Fertilization Dataset (1961–2019). *Scientific Data*, **12**, 40. https://doi.org/10.1038/s41597-024-04215-x

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Author contributions. J.P., J.S., and T.V. designed the study. F.C. constructed the dataset. I.J. and S.M. developed the models and generated the SHapley Additive exPlanations (SHAP) values. T.D. and F.C. created the spatial maps and performed the model validation. I.J., F.C., S.M., and T.D. drafted the chapter. All authors analysed the data, discussed the results, and reviewed and approved the final chapter.

Abstract

As global fertilizer application rates increase, high-quality datasets are paramount for comprehensive analyses to support informed decision-making and policy formulation in crucial areas such as food security or climate change. This study aims to fill existing data gaps by employing two machine learning models, eXtreme Gradient Boosting and HistGradientBoosting algorithms to produce precise country-level predictions of nitrogen (N), phosphorus pentoxide (P_2O_5), and potassium oxide (K_2O)) application rates. Subsequently, we created a comprehensive dataset of 5-arcmin resolution maps depicting the application rates of each fertilizer for 13 major crop groups from 1961 to 2019. The predictions were validated by both comparing with existing databases and by assessing the drivers of fertilizer application rates using the model's SHapley Additive exPlanations. This extensive dataset is poised to be a valuable resource for assessing fertilization trends, identifying the socioeconomic, agricultural, and environmental drivers of fertilizer application rates, and serving as an input for various applications, including environmental modeling, causal analysis, fertilizer price predictions, and forecasting.

Background & Summary

Inorganic fertilizers are essential for replenishing the nutrients that are removed from soils during crop harvesting. The three main nutrients provided by fertilizers, Nitrogen (N), Phosphorus (P) and Potassium (K), play a key role in plant functions. While N and P, which are basic components of nucleotides, proteins and membrane lipids, are essential in energy metabolism [121, 122], K is essential for the transportation of water, metabolites, and nutrients across plant tissues, for defense against oxidative stresses, and for the maintenance of osmotic homeostasis [5, 16]. Although the first commercial inorganic fertilizers were developed in 1843, they were not the main anthropogenic inputs in the N, P, and K biochemical cycles until the second half of the 20th century [89]. Today, inorganic fertilizers dominate as the primary nutrient input in croplands, surpassing the second human input, manure, by over double [89], and also serve as one of the main N input for grasslands [123]. This substantial surge during the 20th century not only facilitated the rapid growth in

human population, but also had ecological and socioeconomic ramifications, such as water eutrophication, soil degradation, climate change, and mineral resource depletion [124, 125]. In the remainder of this chapter, the term 'fertilizer' will refer to inorganic fertilizers, and all data and results regarding P and K will be presented in their oxidative forms (P_2O_5 and K_2O, respectively), in accordance with common references in international standards and regulations.

Given their food security, socioeconomic and environmental implications, considerable research has been conducted to discern the temporal and regional trends in the use of N, P_2O_5, and K_2O [24, 123, 126–128]. Nevertheless, limited availability of temporal global spatial information regarding their application across various crops have restricted these analyses to a few global and regional studies that primarily focused on N [126, 129, 130]. These studies initially estimated consumption at the country- and state-level using simple equations, based on a few crop-specific fertilization features and changes in crop surface area [126, 129, 130], or using Bayesian Markov Chain Monte Carlo modeling [131]. A global, crop-specific fertilization dataset is crucial for understanding crop nutrient management practices worldwide, identifying past trends and current gaps in fertilization, guiding agricultural policies to improve crop yields while minimizing environmental impacts, and providing input data for modeling [126]. Therefore, we aim to address this knowledge gap by providing insights into the application rates of P_2O_5 and K_2O while also seeking to improve estimates for N.

In order to accomplish this objective, we began by updating the panel datasets on cropland fertilization; enhancing the most comprehensive database developed by Ludemann et al. (2022) [132] by incorporating global datasets covering data from the 1970s and 1980s [133, 134], country-specific data for European countries from 2001 to 2014 [135–138]. This compilation process led to a 35% expansion of the Ludemann et al. (2022) [132] database. Second, the dataset was expanded with data of various potential socioeconomic, environmental, and agricultural drivers of cropland fertilization. Third, two machine learning (ML) regression models - eXtreme Gradient Boosting or XGBoost (XGB) [139] and HistGradientBoosting (HGB) [140], both capable of handling the prevalent missing values within the dataset [140]- were applied to predict N, P_2O_5, and K_2O fertilizer application rates for the different crop classes over 60 years. Since these models are considered black-box models, feature importance was incorporated using SHAP [141] values to identify the global socioeconomic, agricultural, and environmental drivers of cropland fertilization and to validate the ML models. Fourth, the predictions were validated on national databases. However, since the ML models were trained on global data, which show a discrepancy with the national data, the model predictions were first adjusted to match the total annual country-level N, P_2O_5, and K_2O use in agricultural land, similar to previous studies [24, 126–128, 142]. Crucial in this adjustment was the fraction of total country-level fertilizer use allocated to grasslands and fodder crops, as an important portion of total fertilizer use in some countries is devoted to these areas, and little previous estimates existed [89, 142–

144], especially for K_2O [89]. Therefore, these fractions were estimated by reviewing scientific and technical information from 75 countries. The adjusted predictions were then validated using national databases of fertilizer application rates at the crop-level. Finally, the results were spatially allocated using crop maps of the year 2000, developed by Monfreda, Ramankutty and Foley (2008) [145]; the annual harvested area of each crop class in each country; and the spatial changes in cropland surface based on the Hyde v3.3. project [146].

Methods

The following section outlines the comprehensive methodology that was adopted in this study. The methodology encompasses various stages, including the collection and aggregation of different datasets and the compilation into a unified dataset, as well as all preprocessing steps that were carried out. Additionally, we introduce the ML models used in this study, as well as the respective training and evaluation procedures. Furthermore, we discuss the measures that were undertaken to explain the predictions made by the ML models. Following this, we describe how we used the predictions to create detailed maps of global fertilizer application rates. Finally, we explain how we assessed the validity and plausibility of the dataset derived from our study.

Data collection and preprocessing

Data collection

Fertilizer application rate by crops To compile a consistent and detailed dataset of fertilizer application rates for different crops, countries, and years, 14 global datasets [132–138, 147–153] were used. We discarded national databases, such as the United States of America (USA) [154] and India [155–161], to construct a homogeneous database. This approach avoids multiple year-nutrient-crop-country entries from both global and national databases, and allows us to retain external databases for validating the ML model predictions . To standardize all these datasets and minimize data loss, we classified all crop types into 13 crop groups (wheat, maize, rice, other cereals, soybean, palm fruit, other oilseeds, vegetables, fruits, roots and tubers, sugar crops, fiber crops and other crops) (Table B.1), in alignment with the Indicative Crop Classification for agricultural census (ICC) Version 1.1 [162].

During the 80s, the International fertilizer Development Center (IFDC) published two reports [133, 134] regarding crop-specific data of fertilizer use by crop (FUBC) (hereinafter referred to as FUBC-IFDC). After the crop grouping, these publications included data for 459 country-crop-years combinations (kg ha^{-1} of N, P_2O_5, and K_2O) from 83 countries for 1973-1988. During the 90s, the Food and Agriculture Organization (FAO), in collaboration with the fertilizer industry (IFDC and International Fertilizer Association (IFA)), published five crop-specific

datasets of fertilizer application rate (hereinafter referred to as FUBC-FAO). After grouping the data, these publications included data for 1693 fertilizer application rate specific to years and crops (kg ha^{-1} of N, P_2O_5, and K_2O) from 108 countries for 1984–2002, although most of the data (98%) covered 1988–2002. The data were collected using questionnaires from governmental agencies, members of industry companies, agronomists, and economic experts. In both datasets (FUBC-IFDC and FUBC-FAO), the use of fertilizer for each combination of nutrient, crop, country, and year was provided two ways: (a) as the average application rate of a fertilizer over total cropland area, and (b) as the percentage of fertilized cropland area and the application rate in that area. We transformed all data to the average application rate by multiplying the percentage of fertilized area by the application rate in that area. The data were either from a year (e.g., 1996) or a season (e.g., 1996/97). For seasonal data, we considered the starting year of the season as the year of the data in the analyses. For data for nutrient, crop, country, and year that were in more than one report, the data was selected from the most recent report. Data for crop, country, and year that were divided into crop varieties or management practices (e.g., irrigated or rain-fed rice, or soft or durum wheat) were aggregated and weighted by the area of the crop class included in the report. Data for sweet maize, or corn, were excluded, assuming that it referred to *Zea mays* var. *saccharata* and the data for silage maize, because Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) reports only the harvested area for maize grain. Values for the crop groups were derived from individual crops when either more than 90% of the harvested area (based on FAOSTAT data[163]) was dedicated to the production of a single crop, or when a combination of crops was available in the data, their weighted average was assigned to the entire group.

Since the last FAO publication, IFA has released five reports detailing the total amount of N, P_2O_5, and K_2O used for various crop classes, providing yearly or seasonal data spanning from 2006 to 2018 [132, 152, 153, 164] (hereinafter referred to as FUBC-IFA). Initially covering 11 crop types, these reports expanded to 14 types in the fourth report. They encompassed information for the European Union (EU) together as well as 27 other countries. In 2022, Ludemann et al. (2022) [132] published a more comprehensive dataset covering data for 66 countries, featuring EU data at the country scale, and information for 20 crop classes [132]. This publication also included the FUBC-FAO data for the 1990s and prior data from IFA. However, small discrepancies between the FUBC-FAO original data and the one compiled by Ludemann et al. (2022) [132] prompted us to retain the original FUBC-FAO information. To estimate the average application rate for each combination of crop, country, and year, we divided the total used amount of each fertilizer by the harvested area provided by FAOSTAT [163]. As previous research we assumed the harvested area as a proxy for the crop's annual surface on each country [126, 127]. It is worth noting that the average application rate for maize was slightly overestimated because FUBC-IFA included the amount discharged to silage maize. According to Maiz'Europ' [165], the current area of forage maize crops is 17.3 million ha (approximately 1% of the

total area of maize crops in 2020) with the European Union as the most important producer of silage maize, with 6 million ha. We utilized the available raw data from Ludemann et al. (2022) [132], adopting FAO-IFDC datasets methods for grouping, and omitted certain countries where values were estimated based on the previous report and changes in crop surface. For the EU countries, Norway and the United Kingdom and Northern Ireland (UK), four unpublished datasets from Fertilizer Europe (FE) spanning 2001–2015 (referred to as FUBC-EFMA) [135–138] were used. These datasets offered similar information to the FUBC-FAO publications for the EU countries, the UK and Norway and allowed us to exclude the fertilizer application to silage maize, which is important in the EU [165]. However, FUBC-EFMA datasets lacked individual crop classes for rice and soybeans, resulting in missing data at the country-level for these crops since 2000 in EU countries.

The resulting dataset included data for the average fertilizer application for 3712 combinations of 13 crop classes, 114 countries, and years from 1973 to 2018. For most of the combinations of countries and crops, data were available for only a few years (on average, a country-crop combination had data for 4.1 ± 2.9 years, and 64% of the combinations had five or fewer years with available data).

In order to later validate our estimations, we compiled a series of national databases. National data was quite limited, as only a few countries conduct surveys to study fertilizer management across different crops. The two countries with most available data were the USA [154], and the UK [166], which collected long time series on cropland fertilization for the three primary nutrients. The USA dataset [154] contains fertilization information for four crops -cotton, maize, soybean, and wheat- dating back to 1964. To compare with our predictions, we converted all data to average kg ha^{-1}. Additionally, based on the same surface threshold used for global datasets, we assumed that the application rate for cotton was equivalent to that of all fiber crop classes. The UK dataset [166] provides data for four crop classes -roots and tubers, other oilseeds, sugar crops, and wheat- starting from 1998 for the three nutrients across all Great Britain. We also compiled existing information from several Asian countries, including India, the Philippines, and Pakistan [155–161, 167, 168]. The datasets from India [155–161] and Pakistan [167] did not require additional preprocessing, as they provided the data in average kg ha^{-1}. However, the dataset from Pakistan presented the information for all three nutrients combined [167]. For the dataset from the Philippines, which covers rice and maize, we converted the raw data on the regional number of 50 kg bags per hectare of different fertilizers to N and P_2O_5 using the country-specific fertilizer nutrient information [169]. Finally, we also compiled existing data from Sweden [170–173] and New Zealand [174]. The data for P_2O_5 and K_2O in the Sweden dataset, initially present in their pure nutrient form, were transformed to their oxidized forms by multiplying by the molecular weights of these elements.

Fertilizer use in other agricultural lands An important step in the methods involves adjusting ML model predictions to national-level fertilizer use. We used the FAOSTAT database regarding fertilizer annual use at the country level for making this adjustment [68]. This database includes data on all fertilizer use for agricultural lands, covering both croplands and grasslands [68]. However, the crops included in the ML models, as well as in the FAOSTAT harvested area data [163] do not cover grasslands -whether permanent or temporary- nor fodder crops such as silage maize or fodder beet. Therefore, the primary goal of this section is to estimate the fraction of total fertilizer used for these types of agricultural lands.

Data regarding fertilizer application rate for grasslands and fodder crops is even more scarce than fertilization for other croplands. Additionally, FAOSTAT lacks information about the surface of the majority of the fodder crops [163]. Therefore, the methods used for estimation may not be as accurate as those used for other agricultural lands. Here, we reviewed technical information, such as the FUBC compiled reports [132–138, 147–151, 153], and scientific information from countries where the fertilization of grasslands was considered to be higher than 1% of the total fertilizer consumption in previous research [89, 123, 142–144]. Previous research typically focused only on permanent grassland fertilization, as their goal was to distinguish agricultural fertilizer usage between arable -croplands and temporary grasslands- and non-arable land -permanent grasslands- [89, 143, 144] . However, we included in the estimation the proportion of fertilizer used for temporary grasslands and fodder crops for two main reasons: 1) our main goal was to distinguish agricultural fertilizer usage between all croplands included in the thirteen crop classes defined in the previous section and the rest of the agricultural land, 2) the majority of data available in the compiled global reports give information about all grasslands and fodder crops together [132–138, 147–153]. The information estimated was the annual country proportion of N, P_2O_5, K_2O fertilizers used for agriculture for grasslands and fodder crops. Depending on the available information, we have assessed at the country- or regional-level. In total, we reviewed scientific and technical reports for 75 countries. As in previous research [89, 142–144], the methods used for estimating the share of N, P_2O_5, and K_2O usage for grasslands and fodder crops varied between countries and regions depending on the available information. Therefore, for every country, we argued the decisions taken based on the available data for providing at least as transparent as possible the estimations made. Moreover, we included a summary table (Table 2.1) with the sources used for estimating the range of values used for each country. The results of this compilation are available online [175].

Table 2.1. Fraction of N, P_2O_5, and K_2O allocated to grasslands and fodder crops. Values are unique values or ranges for the entire period.

Country	N share	P_2O_5 share	K_2O share	Sources
Argentina	0-9.8	0-28.0	0	[133, 134, 147–151, 176–185]
Canada	12.0	14.5	25.3	[132, 186, 187]
Chile	1.2-22.9	1.5-35.0	1.2-26.9	[132–134, 147–151, 153, 188]
Dominican Republic	0-3.1	0-3.0	0-2.5	[147, 149, 150, 189]
Mexico	0	2.6	0	[147, 151]
United States of America	6.6-16.6	4.0-17.2	6.8-19.1	[147, 149, 153, 187, 190]
Uruguay	2.0-12.4	21.5-42.9	0	[132, 134, 147, 151, 191]
Australia	6.4	38.4	41.6	[132, 134, 147–151, 153]
New Zealand	91.1	93.0	88.8	[132, 149, 151, 153]
Austria	20.8-31.4	27.1-30.3	19.5-21.8	[133, 134, 144, 147–151]
Belgium and Luxembourg	52.7-66.9	35.5-62.3	41.2-52.3	[132, 133, 135–138, 144, 147–151]
Czech Republic	16.7-19.7	13.6-16.0	13.9-16.3	[132, 137, 138, 144, 151]
Slovakia	10.4-13.6	6.6-8.6	5.9-7.7	[132, 137, 138, 144, 151]
Czechoslovakia	20.8-31.4	27.1-30.3	19.5-21.8	[132, 137, 138, 144, 151]
Denmark	10.0-62.0	10.0-74.0	9.0-61.0	[132, 133, 135–138, 147–151, 192]
Finland	37.0-49.0	22.0-37.0	21.0-64.0	[132, 133, 135–138, 147–151]
France	7.0-39.0	9.0-48.0	12.0-52.0	[132, 135–138, 144, 147–151, 187, 193–197]
Germany	11.0-43.0	10.0-42.0	9.0-39.0	[133, 135–138, 144, 147–151, 187]
Greece	0-10.0	0-13.0	0-10.0	[132, 135–138, 144, 147–151]
Hungary	1.0-20.0	1.0-18.0	1.0-20.0	[132, 133, 136–138, 144, 147]
Ireland	24.0-90.0	20.0-82.0	19.0-83.0	[132, 135–138, 147–151, 198–209]
Italy	9.0-11.0	7.0-8.0	6.0-8.0	[132, 135–138, 144, 148–151, 187]
The Netherlands	52.8-77.6	9.2-58.3	10.5-26.2	[132, 133, 135–138, 144, 149–151, 210]
Poland	1.0-43.0	1.0-40.0	1.0-33.0	[132, 135–138, 144, 147, 150, 151, 211]
Portugal	2.0-23.0	3.0-23.0	2.0-29.0	[132, 133, 135–138, 144, 147, 148, 150, 151]
Romania	4.3-5.6	4.2-5.4	2.2-2.8	[136–138, 144, 147, 149]

Continued on next page

Country	N	P_2O_5	K_2O	Sources
Spain	4.0-4.6	1.4-12.1	0-7.9	[132, 133, 135–138, 144, 147, 148, 150, 151, 212]
Sweden	12.7-45.1	2.1-36.7	0-7.9	[132, 134–138, 147, 148, 150, 151, 187]
United Kingdom and Northern Ireland	32.4-60.8	17.6-48.8	21.7-39.7	[132, 135–138, 147, 149, 166, 213, 214]
Iceland	97.5	97.5	97.5	[215, 216]
Switzerland	32.7-56.5	36.3-51.0	10.8-38.2	[133, 147–151]
Norway	64.0	50.0	66.0	[132, 135–138, 148–151, 187]
Yugoslav SFR	15.4	16.1	14.9	[135, 144, 148, 217]
Croatia	8.8-22.4	8.7-25.9	8.8-37.8	[132, 135–138, 144, 148, 151]
Montenegro and North Macedonia	10.2-25.1	10.5-28.2	10.4-36.0	[132, 135–138, 144, 148, 151]
Serbia	11.6-27.7	12.2-31.1	12.1-37.6	[132, 135–138, 144, 148, 151, 218]
Slovenia	45.6-70.9	43.2-77.9	35.1-76.5	[132, 135–138, 144, 148, 151]
USSR	0-34.0	0-34.0	0-32.0	[147, 219–221]
Armenia, Georgia and Azerbaijan	4.0	7.0	9.0	[151]
Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan	2.0	2.0	1.5	[153]
Estonia	5.0-40.0	3.0-32.0	21.0-64.0	[132, 135–138, 151]
Latvia	7.0-81.0	6.0-60.0	6.0-65.0	[132, 135–138, 151]
Lithuania	18.0-59.0	16.0-45.0	16.0-63.0	[132, 135–138, 151]
Belarus	27.0	14.0	26.0	[132, 153]
Republic of Moldova	7.0	6.0	3.0	[149]
Ukraine	2.0	1.0	1.0	[132, 153]
Russian Federation	6.5-43.4	1.8-19.4	2.8-33.4	[148, 149, 153]
Islamic Republic of Iran	0-3.2	0-3.7	0-1.1	[147, 148, 153]
Japan and Republic of Korea	17.3	16.9	15.6	[132, 133, 147–151, 153]
Turkey	0-1.2	0-2.4	0-2.1	[132, 133, 147–151, 153]
Egypt	4.0	8.6	1.0	[134, 150]
Morocco	14.8	10.5	6.1	[147, 150, 222]
South Africa	12.4	13.3	9.2	[132, 147–151, 153]

Argentina: In the 1960s, fertilizer application rate in Argentina was primarily directed towards sugar cane and citrus [176], with minimal application to grasslands, nearly zero in 1964 [176]. Throughout the 1970s and 1980s, the fertilizer application rate remained low, although there was a notable increase in P_2O_5 application to grasslands, reaching 28% country consumption in 1979 [133]. The substantial expansion in N and P_2O_5 fertilizer

occurred during the 90s, leading to a slight rise in the share of N used for grasslands, and to a significant decrease in P_2O_5 share for grasslands [147–151]. To fill data gaps, we adopted a methodology similar to Lassaletta et al. (2014) [143], utilizing linear interpolation of national [177–185] and global datasets for the years lacking data, with grasslands' fertilizer share assumed as 0 in 1965 [176]. Despite potential limitations, setting the share to 0, as done in FAO nutrient budgets [89], may underestimate fertilizer application rate, particularly for P_2O_5. K_2O fertilizer application rate in Argentina remains minimal due to soil composition, with all reports except one considering it as 0 in the use for grasslands and fodder crops [133, 134, 147–151, 177–185].

Brazil: According to several sources, the use of fertilizer in Brazil's grasslands has been very low [223, 224]. The most recent values reported by IFA in 2014 and 2018 indicate that less than 1% of the fertilizer used in Brazil is used in grasslands [132, 153]. However, Lassaletta et al. (2014) [143] and FAO [89] considered higher percentages for N and K_2O based on regional averages [143] or previous research [89]. For P_2O_5 and K_2O, only FAO includes an estimation, considering 0 for P_2O_5, while they estimate the K_2O consumption by calculating the average between N and P_2O_5 consumption [89]. We have decided to consider 0 as the share used for grasslands and fodder crops due to the latest reported values and considering that no information is reported in previous reports [132–134, 147–151, 153].

Canada: Most of the compiled reports do not provide information about the use of fertilizers for fodder crops and grasslands [133, 134, 147–151]. The latest report, with 2018 data, indicated that 0.5% of N, 0.9% of P_2O_5, and 0.6% of K_2O fertilizers were allocated to permanent grasslands, which increased to 12%, 14.5%, and 25% respectively when considering tame hay and silage maize as well. Regarding N, FAO [89] and the 2014 estimation by Lassaletta et al. (2014) [143] are consistent with the 2018 estimation for all forages. However, the values for P_2O_5 and K_2O for all forages in the latest report differ significantly from those used by FAO [89] (0% for P_2O_5 and 5% for K_2O). This discrepancy in P_2O_5 may be due to FAO's reliance on Heffer, Gruère and Roberts (2017) [153] which does not consider nongrass perennial crops 0% [186], and the discrepancy for K_2O because FAO considered the average value between N and P_2O_5 [89]. We decided to utilize the percentage for all forages included in the last report [132] for the entire period. We maintained the same values throughout the period due to insufficient data to estimate any trends. Additionally, in 1974, Beaton and Berger (1974) [187] noted that a significant share of fertilizer used in Canada was for forages, estimating 45% of total use in 1970 was for hay and grazing grasslands [187]. They suggested that their estimation might be overestimated; however, it is unlikely that the fraction of fertilizers used for forages was 0 between 1960 and 1990.

Chile: Based on the estimations of the FAO and IFA reports, Lassaletta et al. (2014) [143] and FAO [89] considered a significant share of fertilizer used for grasslands. For N Lassaletta et al. (2014) [143] suggested an increasing percentage from 0% in 1960 to 20% in 2005, while FAO maintained a constant percentage of 20% [89]. For P_2O_5 and K_2O, the values used by FAO were also high, at 30% and 25% respectively. However, for Chile, using a constant value for the period overestimated the early years as the share used for grasslands for N and P_2O_5 was only 1% at the beginning of the 1960s [188]. We therefore decided to make a reconstruction similar to the one demonstrated by Lassaletta et al. (2014) [143], by considering 1% as the starting share for each nutrient, and incorporating the reported values for all grasslands [132–134, 147–151, 153].

Dominican Republic: The values reported in global studies from the 1990s indicate that during this decade, the percentage of fertilizer application rate on grasslands and fodder crops ranged between 2% and 4% [147, 149, 150]. Considering these findings, Lassaletta

et al. (2014) [143] allocated values ranging from 0% to 2% for N. We have chosen to utilize the average values from the three reports [147, 149, 150] for the period 1990-2020. This decision was influenced by the lack of available data since 1997, and by the emergence of fertilizer application rate for pasture as a new and increasing practice during the 90s [189].

Mexico: The use of fertilizer for grasslands and fodder crops appears to be nearly zero, as indicated by previous research [89, 143] and reported values [132, 147, 151, 153]. The only relevant fertilizer used for grasslands and fodder crops in Mexico appears to be related with P_2O_5 related with alfalfa production [147, 151, 225]. Due to limited available information, and the longstanding presence of alfalfa production in Mexico since the Spanish colonization, we opted to consider the average percentage (2.5%) used in the two reports with data for alfalfa [147, 151].

United States of America: According to global and national estimates from previous research, the share of N used for grasslands during the period ranged from 0% to 20% of the total [89, 129, 143]. For P_2O_5 and K_2O, the most recent estimation from FAO indicated a constant share of 0% for P and 10% for K [89]. To estimate the total fertilizer use for permanent and non-permanent grasslands from 1959 to 2014, we used all the available data [147, 149, 153, 187, 190]. In many sources, the information for grasslands is combined, encompassing both permanent and non-permanent grasslands. We used linear interpolation to estimate the share used for all grasslands together, replicating the method from the most recent estimation [129]. However, we included data from three additional years (1974, 1992, 1996) [147, 149, 187], and also extended the estimation to cover P_2O_5, and K_2O.

Uruguay: Grassland fertilization was actively promoted by the Uruguayan government during the 60s [191]. As early as 1963, one-third of the fertilizer used in the country was applied to pastures, with a focus on P_2O_5 due to the low P content of the Uruguayan soils [191]. These trends are reflected in the first IFDC report, which allocated 45% of the P_2O_5 used in the country for grasslands and fodder in the year 1986 [134]. However, this share decreased to 22% by 2018. In contrast, the percentage of N used for grasslands has shown an increasing trend, from almost 0% in 1986 [134] to 12% in recent years [132, 151]. K_2O is not used for these agricultural lands in the country [132, 134, 147, 151]. Given the significant variation in percentages between decades and nutrients, we performed linear interpolation considering 33% for P_2O_5 in 1960, and 0% for N as starting points, and all the values included in the reports [132, 134, 147, 151].

Venezuela: Information regarding grassland and fodder crop fertilization in Venezuela is limited. Due to the scarcity of data and discrepancies between reported values [149, 151], FAO has considered a fertilization rate of 0% for grasslands during the specified period. Conversely, Lassaletta et al. (2014) [143] proposed different rates between 0% and 9% from 1960 to 2009 for N. Given the challenge of determining the most appropriate criteria, we opted to adhere to the FAO considerations. This decision is influenced by low government optimal use recommendations for grasslands compared to croplands [226], along with scientific evidence suggesting minimal fertilization for warm-climate grasslands [226, 227].

Australia: According to Lassaletta et al. (2014) [143], the share of N used for grasslands never exceeded 8.5% [143], which is similar to the 10% used by FAO in their nutrient budgets assessments [89]. Despite an intensification in the use of N in Australian grasslands over the past three decades [228], it is noted that these grasslands were already being fertilized in the late 1950s, primarily with K_2O [229]. For instance, in 1956, 15% of the K_2O used in South Australia was directed towards pastures, a figure that rose to 42% by 1966 [229]. Therefore, we have opted to consider a constant share of 6.4% for N use since 1960 derived from the mean value of the reports [132, 134, 147–151, 153]. Regarding P_2O_5 and K_2O fertilizer, it

appears that the FAO estimations [89] may have underestimated their use, particularly for K_2O. Thus, we decided to use the average value of all reports, because even with fluctuations, the variation in the reported values since 1985 is not too high, resulting in figures of 38.4 ± 4.1% for P_2O_5 and 41.6 ± 6.9% for K_2O [132, 134, 147–151, 153].

New Zealand: Previous global research presented contradictory estimates of fertilizer application rate for grasslands in New Zealand [89, 143], with figures ranging widely from 0% to 90%. However, both global and national reports consistently support the notion that the majority of the fertilizer application rate in the country is directed towards grasslands and fodder crops [132, 149, 151, 153, 174]. Therefore, we have adopted a constant percentage throughout the entire period as grasslands have been the primary type of agricultural land developed in the country since the British colonization, their fertilization has been relevant since the early 20th century [230], and the fraction used for grassland has remained constant at least in the last 30 years [132, 149, 151, 153]. The percentages selected were derived from the average of global reports [132, 149, 151, 153]: 91.1 ± 1.4% for N, 93.0 ± 3.3% for P_2O_5, and 88.8 ± 4.4% for K_2O.

Europe: Between 1980 and 2000, Europe accounted for at least half of the N fertilizer used for grasslands and fodder crops, while consuming less than one-third of the total global fertilizer consumption [123]. Consequently, the available information was broader, and the methods applied could be more comprehensive. Einarsson et al. (2021) [144] provided the most comprehensive estimation for N in most European countries [144]. They compiled and estimated the surfaces of croplands, including fodder crops, as well as temporary and permanent grasslands for the EU countries spanning from 1960 to 2019. Using their compiled data and the fertilizer application rate information from our study, we employed a similar methodology to estimate the fraction of N, P_2O_5, and K_2O used in these areas.

However, we extended the analysis to include fodder crops and all types of grasslands together, while also estimating P_2O_5, and K_2O. First, we used Eq. (2.1) to estimate the ratio (R_{f-a}) between the fertilization intensity of grasslands and fodder combined, and the fertilization intensity of all agricultural land for the years with available data:

$$\frac{Q_f}{Q_a} = \frac{R_f \times A_f}{R_a \times A_a} \rightarrow \frac{Q_f \times A_a}{Q_a \times A_f} = \frac{R_f}{R_a} = R_{f-a} \tag{2.1}$$

where Q_f is the amount of fertilizer (N, P_2O_5, or K_2O) used for grasslands and fodder crops, Q_a denotes all the fertilizer of the same nutrient used in the country, A_f represent the grassland and fodder surface, and A_a represents the total agricultural land, and R_{f-a} the ratio of fertilizer application rate per area between fodder and grasslands (R_f), and all agricultural land (R_a). Therefore, R_{f-a} represents the fertilizer application relationship between fodder and grassland in comparison to all agricultural lands.

After estimating the annual R_{f-a}, we used two different procedures and equations depending on the years for which R_{f-a} data was available. If scientific literature and the observed variation in R_{f-a} indicated significant differences across the years, we performed a linear interpolation of the available values and then applied Eq. (2.2). Otherwise, we applied (2.3). To assess the variation in R_{f-a} we estimated the mean absolute error (MAE) of the results derived from Eq. (2.3) compared with all the reported values. When the variation of R_{f-a} occurred only in some decades within the period, we combined Eq. (2.2) and Eq. (2.3). Detailed explanations were provided for each country individually. For non-EU countries, we applied similar procedures as those used for the other continents. In Eqs. (2.2) and (2.3) presented below, $\overline{R_{f-a}}$ is the average R_{f-a} of all reports with data, and i is the year.

$$\frac{Q_{f_i}}{Q_{a_i}} = R_{f-a\,i} \times \frac{A_{f_i}}{A_{a_i}} \tag{2.2}$$

$$\frac{Q_{f_i}}{Q_{a_i}} = \overline{R_{f-a}} \times \frac{A_{f_i}}{A_{a_i}} \tag{2.3}$$

Austria: The methodology used by Einarsson et al. (2021) [144] results in an almost constant percentage of N used for permanent grasslands of ≈10% for the 1960-2019 period. This result led FAO to consider that 10% of fertilizer used in agricultural lands was used for permanent grasslands [89]. The intensification of grassland management began in the 1970s and 1980s [231], and the share used for grasslands was higher in the late 1970s than in the 1990s [133, 147]. For P_2O_5 and K_2O, FAO considered a constant 10% allocation for permanent grasslands [89], based on previous estimations for P_2O_5 [142] and the average value between the fraction used for N for K_2O. While historical data suggest fluctuations in the percentage of fertilizers used for grasslands and fodder crops over time [133, 134, 147–151], the application of Eq. (2.3) using constant $\overline{R_{f-a}}$ values of 0.33 for N, 0.46 for P_2O_5, and 0.32 for K_2O, and surfaces changes [144], provided an MAE of 2.33 ± 3.09%, 3.87 ± 3.47%, 3.31 ± 2.29% respectively. Only two errors higher than 10% occurred, both underestimations, namely -11.8 % for N in 1977 [133], and -10.2% for P_2O_5 for 1990 [147], suggesting higher R_{f-a} during the 1970-1990 period. Based on these results, we decided to utilize the mentioned $\overline{R_{f-a}}$ values for the period from 1991 to 2020 as well as for the period from 1961 to 1969. For the years from 1970 to 1990, we calculated the average R_{f-a} from 1977 and 1990 reports [133, 147] to minimize the errors during the period.

Belgium and Luxembourg: Belgium and Luxembourg often share statistics as a single entity in historical statistics. Consequently, we adopted the same estimation for both countries. According to Einarsson et al. (2021) [144], the percentage of fertilizer application rate for permanent grasslands ranged from 53% in the 1980s to 40% in the last years. They deem the N fertilization of permanent grasslands significant throughout the period based on the little available information they found [144]. The same literature confirmed the use P_2O_5, K_2O for grasslands as early as 1955, although with slightly lower applications [144] as in the actual reports. The use of constant R_{f-a} values of 1.03 for N, 0.91 for P_2O_5, and 0.81 for K_2O based on the technical reports values [132, 133, 135–138, 147–152] resulted in MAE values of 2.18 ± 1.82% for N, 5.46 ± 4.04% for P_2O_5, 3.62 ± 2.51% for K_2O. Only two instances of overestimations exceeding 10% were observed for P_2O_5 in the two last reports [132, 138]. This may be linked with the enforcement of limits on P_2O_5 application in the Flanders region since 2011 [232]. Therefore, for P_2O_5 we decided to use the average R_{f-a} for the 1960-2010 period, and use a linear interpolation of the R_{f-a} values since 2011.

Czech Republic, Slovakia, and Czechoslovakia: Information regarding grasslands and fodder crops before the disintegration of the Czechoslovak Republic is very limited [144]. Following assumptions made by Einarsson et al. (2021) [144], we extended the average $\overline{R_{f-a}}$ reported for the Czech Republic and Slovakia since 1993 [132, 137, 138, 151] through the period 1960-1992, considering surfaces changes, and the agricultural land of each country [144]. Potential overestimations could occur for the early years, as the fertilization of these areas compared to other croplands might have been lower than in the 1990s, like in neighboring countries such as Hungary or Germany [233, 234]. After 1993, there are four years with available data for both countries [132, 137, 138, 151]. The R_{f-a} values for all years are similar for each nutrient in each country, so we used Eq. (2.3) to estimate the 1993-2020 period. This approach resulted in low deviations from the reported values for the Czech Republic (MAE

= 2.08 ± 1.58% for N, 2.57 ± 1.30% for P_2O_5, 1.69 ± 1.47% for K_2O) and Slovakia (MAE = 1.49 ± 1.47% for N, 2.02± 2.87% for P_2O_5, 1.79 ± 2.13% for K_2O).

Denmark: Danish grasslands and fodder crop fertilization have a long history with N, with average rates of 45 and 17 kg ha^{-1} for temporary and permanent grasslands respectively in the early 1960s [192]. The usage of Eq. (2.3) for the whole period for the three nutrients resulted in large deviations (MAE = 8.89 ± 4.40% for N, 5.36 ± 3.71% for P_2O_5, 8.42 ± 5.67% for K_2O). Therefore, as the amount of available data was large in the compiled technical reports we used Eq. (2.2), and linear interpolation of all R_{f-a} values for the period 1980-2020 [132, 133, 135–138, 147–151]. For the 1960-1980 period, we utilized N data from 9 years within that timeframe [192]. Additionally, we considered the 1980-2020 relationship between N $\overline{R_{f-a}}$ and P_2O_5 or K_2O $\overline{R_{f-a}}$, and the available N data for estimating the 1960-1980 timeframe regarding the P_2O_5 or K_2O values. We regard this assumption as the only available information for the period spanning 1960-1980 for P_2O_5 and K_2O [187] suggests a similar relationship in the application rates for all forages between N and the other nutrients, at least in the reported values since 1980 [132, 133, 135–138, 147–151].

Finland: Einarsson et al. (2021) [144] did not consider significant fertilization on permanent grasslands in Finland, as they mainly use arable land for forage production [235]. However, fodder crops and temporary grasslands are key parts of the agricultural production in the country [235], and they are commonly fertilized [132, 133, 135–138, 147–151]. Using Eq. (2.3) for the entire period across the three nutrients resulted in minimal deviations for N and P_2O_5 (MAE = 1.57 ± 2.99%, 2.10 ± 3.34% respectively), but substantial deviations for K_2O (7.51 ± 7.38%). Given the substantial deviation for K_2O, and the large bias for R_{f-a} in 1979 [133] for N and P_2O_5, the first year with available data, we opted to use Eq. (2.2), and the linear interpolation of the R_{f-a}. However, potential deviations may arise for the 1960s, as fertilizers were predominantly utilized for high-value crops during the early part of the decade [236], yet no data are available for that period.

France: Data regarding grasslands and fodder crop fertilization is less limited than in the majority of EU countries, although large differences exist between the available data. Two recent publications estimated the share of N and P_2O_5 used for permanent grasslands since 1960 [144, 193] based on country surveys at the region-level [194–197]. However, the results obtained by them differ from the FUBC-FAO and FUBC-FE reports [132, 135–138, 147–151]. For example, for 2006, Noë et al. (2018) [193] report a share of P_2O_5 used for permanent grasslands of 27% whereas the FE reports a value for all grasslands of 20%. Considering other years with comparable data, such as 1990 or 2017, Einarsson et al. (2021) [144] estimate a share of 16% and 7% respectively for N used for permanent grasslands, while FAO only reports 6% for 1990, and the national survey reports 4.7% for 2017 [197]. Therefore, as it is difficult to discern the more accurate value between the two estimations, we opted to use the average between the R_{f-a} linear interpolated data from the global datasets [132, 135–138, 147–151], and from the national surveys [194–197], considering for both as 0 the share in 1955 [193] and the single estimate for the 70s [187].

Germany: The availability of data since the German reunification is substantial in global reports [135–138, 147–151]. These reports suggest a decline since 1990 in fertilizer use for all forages compared to the rest of croplands, with the drop being particularly notable for N and P_2O_5. As a result, we decided to use Eq. (2.2), and interpolate the R_{f-a} values, instead of $\overline{R_{f-a}}$ for the 1990-2020 period. For the 1960-1989 period, data on grassland and fodder fertilization is scarce and primarily pertains to West Germany [187]. Most of the data available for the period are relative to N, except the 1982 IFDC-FUBC report. For the 1960-1989 period, We decided to use the linear interpolation assuming, similar to the case

of France, zero fertilization of grasslands and fodder crops in 1955, as fertilization of these areas in Western Germany, where most of this agricultural land is located, was minimal before 1960 [234], using the only report with available data for the three nutrients [133]. We extrapolate the data from Western Germany for the entire country due to data availability [133, 144, 187], the prevalence of these agricultural areas in Germany [144], and because grassland fertilization in East Germany was similar to that in West Germany, at least in the late 1970s [237]. Using these approaches, we deviate by approximately 3.9% from the N estimated data for the year 1974 [187]. Additionally, we deviated by about 10% from the N value for permanent grasslands reported by Einarsson et al. (2021) [144] for 1966 (based on real data) [144]. This deviation is reasonable, considering that the average difference between Q_f/Q_a only using information for permanent grasslands or all forages for N is 7.9% [135–138, 147–151].

Greece: Fertilization has not been considered for permanent grasslands in either previous research [89, 143, 144] or technical reports [132, 135–138, 147–151]. However, since we are also considering fertilization for fodder crops, the technical reports have allocated fertilization for them, especially for alfalfa and sillage maize [132, 135–138, 147–151], which constitute the two main actual fodder crops in the country [144]. Therefore, we used Eq. (2.2) and the linear interpolation of R_{f-a} because the values of the 1990s are lower than the actual ones, and we have assumed a zero level of fodder fertilization in 1960, as it was only experimental in the country [238].

Hungary: Einarsson et al. (2021) [144] did not consider fertilization for permanent grasslands due to the scarcity of the data and because grassland fertilization is not a common practice nowadays [144]. Reported values suggest that a significant fraction, approximately 5% of the fertilizer used since 1990 in the country was allocated to grasslands and fodder crops [132, 136–138, 147], with an even higher proportion during the 1980s [133]. Scientific information confirms that the change in the political regime in 1989 was a key driver of fertilization practices in the country, reducing the fertilizer use by five-fold in the country, and limiting fertilization of these areas to managed grasslands [239]. Furthermore, fertilization in the country commenced in the 1960s and remained stagnant during the 1980s [233]. Therefore, for the period 1960-1989, we applied Eq. (2.2), and the linear interpolation of R_{f-a} from a 0 value in 1960, to the 1980 reported value [133]. For the 1990-2020 period, we used Eq. (2.3), and the average $\overline{R_{f-a}}$, as there is no deviation larger than 10% from the reported values using this method.

Ireland: Ireland is likely one of the countries that use a larger proportion of fertilizers for grasslands and fodder crops [89, 143, 144], and also has more available information. Since 1972, six national surveys have been conducted, providing data for 22 years [204–209]. Moreover, the global datasets also include information from ten different years since 1987 [132, 135–138, 147–151]. For the 1986-2020 period, we used the average of the linear interpolation of the R_{f-a} values based on national surveys [204–209], and surfaces data [199–203], along with the R_{f-a} values based on the global datasets [132, 135–138, 147–151] and the Einarsson et al. (2021) [144] surface compilation [144]. We excluded R_{f-a} values based on the global datasets [132, 135–138, 147–151] and the Einarsson et al. (2021) [144] surface compilation for the 2006-2010 period due to a change in the criteria for temporary grassland surface, which resulted in overestimations ($Q_f/Q_a > 1$). For the 1960-1985 period, we only considered the linear interpolation of the available data, all from the national surveys R_{f-a} [204–206], and surfaces [199, 200]. In cases where there was no available surface data [199] in the national databases, like 1972, we used the closest year with available data (e.g., 1970). For 2008, which has two available national surveys [208, 209], we took the average of both.

We considered the share of fertilizer used for grasslands and fodder crops as zero in 1955 because almost all fertilizer was used for tillage crops in that year [198], with grassland fertilization increasing during the 1960s [240].

Italy: Einarsson et al. (2021) [144] used a constant $\overline{R_{f-a}}$ for permanent grasslands for all years, as similar values are given in various reports and scientific information [144]. When considering grasslands and fodder crops together, the R_{f-a} were also consistent for each nutrient over all years [132, 135–138, 148–151, 187], even including the 1974 data [187]. The MAE using Eq. (2.3) for the entire period across the three nutrients resulted in minimal deviations comparing with the reported values [132, 135–138, 148–151, 187] (MAE = 2.24 ± 1.55% for N, 2.00 ± 1.37% for P_2O_5, and 3.21 ± 1.21% for K_2O). Therefore, we used the the $\overline{R_{f-a}}$ for the three nutrients. However, there could be potential overestimations for the 1960s decade because nearby countries like France or Germany did not use fertilizers for these agricultural lands before 1955 [193].

The Netherlands: Information regarding grassland fertilization in the country is abundant [144, 210]. However, before the development of global datasets, information regarding P_2O_5 and K_2O is very limited. For the period 1979-2019, we used Eq. (2.2) considering the linear interpolation of the eleven R_{f-a} data derived from the global datasets [132, 133, 135–138, 149–151] and the agricultural surfaces changes [144]. We used the global datasets instead of the national data available because they provide information regarding the three nutrients. For the years 1960 to 1979, we used the available compilation of N application rates [210], and the total N fertilizer consumption [68] to estimate the Q_f/Q_a values for N. For P_2O_5 and K_2O, we used the ratio between the Q_f/Q_a used for N and these two nutrients for the most recent year with available data, 1979 [133], to extrapolate the results for the 1960-1979 period.

Poland: The available data in reports from the period 1988-2018 [132, 135–138, 147, 150, 151] did not show a constant R_{f-a} for any nutrient N, P_2O_5 and K_2O. Data on fertilization before 1989, during the communist government, is sparse [144, 147]. However, similar to other Eastern European countries like Hungary, it appears that fertilizer intensification in the country started during the 1960s [211], with a significant drop following the regime change [68]. As a result, we adopted the same criteria used for other Eastern European countries, setting the 1960 value to zero, and applying two distinct linear interpolations of R_{f-a}: one for the 1960-1989 period, and another for the 1990-2020 period. For the 1990-2020 period, there are seven years with available data, whereas for the 1960-1989 only 1989 has data. Despite this limited data for the earlier period, survey estimates [211] combined with FAOSTAT totals [68] suggest that the combined share of the three nutrients was between 14% and 15% in the late 1960s, which aligns with the individual nutrient shares calculated by the linear interpolation which are between 10% and 13%.

Portugal: Einarsson et al. (2021) [144] did not consider fertilization of permanent grasslands, citing the relatively low surface area in the country [144]. However, recent technical reports suggest that Q_f/Q_a exceeds 20% for the three major nutrients [132, 135–138, 149–151]. We chose to apply Eq. (2.2) and to interpolate the 1977-2020 data [132, 133, 135–138, 147, 148, 150, 151] because using Eq. (2.2) led to discrepancies greater than 10% in some years. For the years before 1977, we retained the R_{f-a} 1977 values [133] (which resulted in $Q_f/Q_a < 2\%$) as there is no information for the earlier period.

Romania: As with other Eastern European countries, there is no available information regarding grassland and fodder crop fertilization before the political regime change in 1989. However, between 1990 and 2020, data from five years suggest that about 5% of fertilizer is used for grasslands and fodder crops [136–138, 147, 149]. For Romania, we applied Eq. (2.3),

using the average $\overline{R_{f-a}}$ value and the grassland and cropland surface data [144]. Potential overestimations occurred during the first decades, although the estimated Q_f/Q_a are less than 5% for the first decades.

Spain: Previous research has not considered the fertilization of permanent grassland because this practice in the country is very uncommon [89, 144]. However, when considering temporary grasslands and fodder crops, this assumption changes, as forage crops occupy about 8% of the arable land in the country and consume nearly the same percentage of fertilizers [212]. To estimate the share of fertilizer use in these areas, we created a linear interpolation of the R_{f-a} data from the ten years with available data, ranging from 1979 to 2014, and applied Eq. (2.2). Using Eq. (2.3) resulted in estimations that were twice the reported values for the earlier years. Given the fraction used for these areas in 1979 was minimal (Q_f/Q_a < of 2%), potential overestimations for the first years are also likely minimal.

Sweden: In the country, fertilization of forage production areas is closely linked to the transition from natural permanent grassland to temporary grassland production on arable land that occurred during the first part of the 20th century, especially during the 1940s and 1950s [241]. Moreover, based on the available data, fertilizer intensification of these areas compared to other croplands R_{f-a} was lower during the 1970s than at the end of the century [150, 151, 187]. Therefore, we applied Eq. (2.2) and performed the linear interpolation of the R_{f-a} of each nutrient of the 11 years with available data since 1974 [132, 134–138, 147, 148, 150, 151, 187]. A slight overestimation might occur for the earlier years, as the intensification of these areas was increasing before the first year with available data [241], but no data for the period was found.

United Kingdom and Northern Ireland (UK): The UK has the world's longest and most complete dataset on the fertilization of grasslands and croplands [166]. Annual time series data on fertilizer use for permanent and temporary grasslands are available for England and Wales since 1969 and for Great Britain since 1982 [166]. Northern Ireland is not included in these surveys. Additionally, there are surveys for the years 1957, 1962, and 1966 for England and Wales [213]. Two problems arise for the estimation of Q_f/Q_a from this data. The first one is that the surveys only include fertilization on permanent and temporary grassland, excluding rough grazing. The second challenge is that there is no information for Northern Ireland - which accounts for about 6% of the country's fertilizer consumption [166], and from 1960 to 1982, there is also no data for Scotland, who are responsible for about 14% of the country's fertilizer consumption [166]. For the period 1982-2019, we used the annual fertilizer application rates for Great Britain's tillage crops [166] and the corresponding cropland surface area [242] (excluding temporary grasslands) to estimate the total fertilizer use for croplands. We considered grassland fertilization to be the complement of the value obtained, assuming the same application rates for Northern Ireland. To include these estimations in the fraction used for fodder crops, we add the average share used for them, which is less than the 3% for all nutrients [132, 135–138, 147, 149]. For the period 1960-1981, we applied the same methodology but using the application rates [166, 213] and surfaces [214] from England and Wales, adjusted by -2.5% for N, +2.8% for P_2O_5, and +0.9% for K_2O. These adjustments are based on the observed differences between the application rates in Great Britain and those in England and Wales during the 1980s decade. Moreover, for the 1960s decade for which there are no data available for all years, we applied the linear interpolation of the years with data. We used the national databases instead of the global datasets because they provide annual information covering almost the entire period for the three nutrients, and the values between them were quite similar.

Iceland: Iceland's agriculture sector is primarily focused on livestock production, with

about 90% of its agricultural land being permanent grasslands [215]. Additionally, most of the arable land is used for forage crops [215]. While grassland fertilization is a common practice in Iceland [216], there is limited information on application rates for different types of agricultural land, and no specific estimates on the proportion of fertilizer used for forage crops in the country. When we applied Eq. (2.3) using the average R_{f-a} from other Nordic countries—Denmark, Sweden, and Finland, it resulted in a Q_f/Q_a ratio greater than 100%. To address this, we allocated a mid-value between 100% and the proportion of agricultural land occupied by grasslands and fodder crops, ensuring it does not exceed 100%.

Switzerland: Data on fodder crop and grassland fertilization in the country from the period 1979-1999 suggest that between 30 and 50% of the fertilizer used in the country is applied to these lands [133, 147–151]. However, whereas the data of the first two years indicate that almost 50% of N is used for grasslands and fodder crops [133, 147], only about 30% was used in 1999 [151]. Since 2000, the areas of artificial grasslands and silage maize (the two main forages that receive fertilizers [147]) have remained almost constant [243]. As there is no information available regarding grassland fertilization before 1979 or after 2000, we used the 1979 data for the period 1960-1979 and the 2000 data for the period 2000-2020. For the period from 1979 to 2000, we applied linear interpolation to the six years with available data [133, 147–151].

Norway: Fodder crops and grasslands (both temporary and permanent) play a key role in the agricultural sector of the country [244, 245]. Technical reports and scientific studies data indicate a nearly constant share of Q_f/Q_a for N, P_2O_5, and K_2O [132, 135–138, 148–151, 187]. Therefore, we used the average of all the available Q_f/Q_a data [132, 135–138, 148–151, 187], covering the period 1974-2018 for N, and from the period 1990-2018 for P_2O_5 and K_2O. The resulting values, with a share of 64.02% ± 1.76% for N, 50.02% ± 2.25% for P_2O_5, and 65.59% ± 6.07% for K_2O, were comparable to those estimated for other Scandinavian countries.

Yugoslav Socialist Federal Republic, and actual former countries: Fodder crops and grasslands played a significant role in the agricultural production of the Yugoslav Social Federal Republic (SFR) [217]. Pastures and meadows occupied 33% of the country's land, while fodder crops took up 20% of the arable land [217]. However, to the best of our knowledge, no information is available regarding fertilization for different agricultural lands before the dissolution of the country. After the dissolution, information became available in global reports for Croatia and Slovenia, but not in the other countries [132, 135–138, 148, 151]. To estimate the Q_f/Q_a values for Yugoslav SFR during the period 1961-1991, we used the weighted average by agricultural land surface [144] of the earliest R_{f-a} values from Croatia and Slovenia [135, 144, 148], given that their R_{f-a} values have changed significantly in recent years [132, 135–138, 148, 151]. We also considered the cropland, grasslands, and fodder crop surfaces of Yugoslavia SFR from the 1990s [217] to estimate the Q_f/Q_a used for the 1961-1991 period. For the period 1990-2019, for actual EU former countries, we performed the linear interpolation of the R_{f-a} values [132, 135–138, 148, 151] to estimate Q_f/Q_a considering the annual surfaces values [144]. In Serbia, the largest country, forage production is a crucial component of its agricultural sector, with about two-fifths of the agricultural land dedicated to this purpose [218]. However, as no specific information on fertilization rates has been found. We considered the average weighted R_{f-a} ratio of Croatia and Slovenia along with the 2004-2008 surfaces of agricultural lands, grasslands, and fodder crops [218]. For smaller countries like Montenegro of North Macedonia, we assumed the average annual Q_f/Q_a values of Serbia and Croatia.

Union of Soviet Socialist Republics (USSR) and Former USSR Countries: Quantitative and qualitative information about fertilization of grassland and fodder crops before the collapse

of the USSR is quite scarce [147, 219, 220]. Some publications suggest that the use of fertilizers in these areas was minimal before 1975 [219, 220]. However, data from 1990-1991, just before the collapse, from certain republics (Russia, Latvia, Estonia, or Belarus) indicate that a significant share of fertilizers was used for fodder crops and grasslands [147] (e.g., 40% for N in the Russian Federation [147]). For the period 1960-1991, we estimated the R_{f-a} for the entire USSR in 1990, weighing the value of each republic R_{f-a} [147, 221] in 1990-1991 by the total fertilizer use of each republic [147, 221]. The four republics with available data for this year (Russian Federation, Belarus, Latvia, and Estonia) account for 40% of the agricultural land of the country and 62% of its fertilizer consumption [221]. After estimating R_{f-a} for each nutrient in 1990, we used linear interpolation to estimate the annual R_{f-a} values, considering the value in 1975 as zero [219, 220]. Finally, similar to the EU countries, we considered the annual cropland, grassland, and fodder crop surfaces [221], along with the calculated R_{f-a}, to estimate the annual Q_f/Q_a. For the period from 1992 to 2020, we considered individual country information where some data was available. However, for the following actual countries, there is no information in the global reports [132, 135–138, 147–152]: Armenia, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, and Turkmenistan. For all these countries, we considered a constant Q_f/Q_a ratio during the 1992-2020 period due to the limited information. For Armenia and Georgia, we assumed the Q_f/Q_a value in 1998 for Azerbaijan, the other Caucasian country [147]. For the Central Asian countries, we used the ratio for grasslands derived from Uzbekistan's 2014 data [153], which is significantly lower than the USSR's share in 1990. This reduction seems reasonable given the significant decrease in fertilizer use, temporary grasslands, and fodder crop surfaces in the region since the USSR collapse [246].

Estonia, Latvia, Lithuania: The Baltic countries are the three former USSR countries with the most available data in global datasets [132, 135–138, 151]. Fertilizer intensification in these areas has changed significantly over the last three decades due to the abandonment of intensively managed areas [144]. This trend is reflected in the changing R_{f-a} values. Therefore, we used Eq. (2.2) and the linear interpolation with the six years with available data R_{f-a} from the 1991-2018 period [132, 135–138, 151] to estimate the Q_f/Q_a values since the collapse of the USSR.

Belarus, Moldova, and Ukraine: For these three countries, limited data is available regarding fodder crops and grasslands, but some information can be found in global reports [132, 149, 153]. Thus, for each country, we used the average of the Q_f/Q_a values from the 1992-2020 period. In the case of Belarus, where two sets of data were available for grasslands and one for fodder crops [132, 153], we took the average for grasslands from both reports and the ratio that accounts for the share of grasslands and the share including fodder crops.

Russian Federation: There are three years with available data between 1992 and 2020 [148, 149, 153]. In the first two years, the data showed that an average of approximately 25% of the country's fertilizer was used on grasslands and fodder crops [148, 149]. However, in the latest report from 2014, only about 4% was attributed to these areas (excluding fodder crops not used for hay or silage) [153]. Therefore, we decide to use the linear interpolation of the Q_f/Q_a values for the years with available data. For the late years, we likely underestimated the value because some fertilizer is used for fodder crops, like fodder beet, that are not intended for silage or hay. However, these fodder crops only accounted for about the 8% of the total fertilizer used for fodder crops and grasslands in 1990 [147].

China: Fertilization of China grasslands remains low at present [153]. Among the compiled reports, only the latest one considers a proportion of the total fertilizer application rate in China, allocating 2% for N, 4% for P_2O_5, and 3% for K_2O. Other information

on grassland fertilization in China is scarce, with the few authors that provided some information describing it as sparse [247]. FAO, [89] considers this proportion as 0% for all three nutrients throughout the entire period, which differs from Lassaletta et al. (2014) [143], who, based on regional averages, estimated a percentage ranging between 0 and 4.7% from 1960 to 2014. However, any global report or national more detailed information considers any fertilization. We have decided to adopt the same criteria as FAO [89], albeit potentially underestimating values for the last decades.

Iran: Fertilization of Iran's grasslands and fodder crops appears to be minimal, with few reports providing data, and only since 1990, indicating values between 2% and 6% for all three nutrients [147, 148, 153]. Other information is scarce and focused on experimental trials rather than broader country-wide applications. Considering that the first fertilization trials were developed during the 70s, and the first report with data is for 1990 [147], which reported 2% of N and 6% for P_2O_5, we considered as 0% the share for the period 1960-1990, and the average of the reports for the period 1990-2020.

Japan: Since the first report with data, in 1979, almost all reports have underscored the importance of grassland and fodder fertilization in Japan. FAO attributed a constant share of 20% for N, 0% for P_2O_5, and 10% for K_2O for the 1960-2020 period [89]. Conversely, Lassaletta et al. (2014) [143] suggested a growing percentage of 20% for N, starting from 0% in 1960, and increasing to 20% in 2009. Although data before 1979 is unavailable, the reported data for N use in 1979 was 15.7%, higher than the 5.2% estimated by Lassaletta et al. (2014) [143]. Additionally, due to the lack of data, it is challenging to determine the inception of grassland fertilization in Japan, though it appears to coincide with the transition from semi-natural grasslands to more intensive pasture during the 60s [248]. Therefore, we opted to adhere to FAO's criteria, maintaining the same percentage throughout the period, despite the potential overestimated values for the initial years. We considered the average of all available reports with data [132, 133, 147–151, 153], because FAO criteria appears to underestimate the P_2O_5, and K_2O used for grasslands, resulting in percentages of 17.3% for N, 16.9% for P_2O_5, 15.6% for K_2O.

Korea Republic: Grassland fertilization appears to be a common practice in the country nowadays [249]. However, there is no available data on the fertilization of these areas in global reports [133, 147, 149, 151], nor scientific publications. We used the same assumption as Lassaletta et al. (2014) [143], which is to consider the same proportion as in Japan, the geographically and socioeconomically closest country [143]. This assumption also aligns with the observation that the sum of this percentage, and the fertilizer used for the main crops [133, 147, 149, 151] is less than the total for the country [68].

Turkey: Information about fertilization of grasslands and fodder crops in Turkey is scarce, suggesting that it is not a common practice. Lassaletta et al. (2014) [143] considered percentages as high as 4.8% for N in 2009, whereas FAO considered 0% for all nutrients. All the available data since 1990 except for 2014 considered some amount of fertilizer used for grasslands, and forages [132, 133, 147–151, 153]. Therefore, we used the average percentage of all reports for the period 1990 - 2020 [132, 133, 147–151, 153].

Other Asian Countries: Cambodia, Indonesia, Malaysia, The Philippines, Thailand, Vietnam, India, and Pakistan: In Asian Southeast countries, only Lassaletta et al. (2014) [143] considered that some fertilizer is used on grasslands, based on regional averages used for grasslands and other crops (including fruits, tea, vegetables, and forage and grasslands) [143]. However, no global report [132–134, 147–151, 153] or country-level sources [250] mentioned fertilizer application to grasslands as significant in these countries. Therefore, we have chosen to align with FAO's criteria, which assumes no fertilizer application rate for grasslands in

this region [89]. We applied the same criteria for India and Pakistan, despite previous research considering a certain percentage used for grasslands [123, 143]. The data reports [132–134, 147–151, 153], the scientific literature [251, 252], and FAO [89] support the idea of non-fertilization of grassland in these two countries.

Egypt: Data regarding grassland and fodder crop fertilization in Egypt are scarce [134, 150]. As is common for many African countries, there is no fertilization of grasslands [253]. However, the few available data about the fertilization of Egyptian clover [134, 150], the main fodder crop in the country [225], suggests that a significant portion of N and P_2O_5 is utilized for fodder production, aligning with country recommendations [254]. Previous research, focused solely on grasslands, has either considered 0% allocation for the three nutrients [89] or a range between 0% and 4% for N [143]. Here, we opted to consider the average of the two reports (1986, 1997) with data [134, 150] for the entire period as Egyptian clover production has been significant since the beginning of the period [255], and the available data is not sufficient to discern any trend.

Morocco: Previous research has indicated various fractions of N fertilizer used for grasslands in the country, ranging from 0% to 11% [89, 143, 253]. With the available information, it is impossible to discern if any application for permanent grasslands occurred in the country, but not for forages such as alfalfa, Egyptian clover, or vetch [222, 256]. Additionally, due to the scarce available data in the reports, discerning any trend is challenging [147, 150, 222], although the presence of improved pastures, usually linked to fertilizer application rate, doubled during the 80s decade [256]. Here, we have opted to use the same percentage, the average of all reports, to estimate the percentage of N, P_2O_5, and K_2O, despite the potential overestimations in the first decades.

South Africa: Fertilization of grasslands and fodder crops such as alfalfa appeared to be significant throughout the study period in South Africa. Both previous scientific research [89, 143] and various technical reports [132, 147–151, 153] indicated percentages ranging 0% and 22.3% for N. For all three nutrients, the share used for grasslands and fodder crops during the 90s was higher than in the last decades [132, 147–151, 153]. This percentage appears to be higher due to larger fertilizer application rates to croplands compared to grasslands and fodder crops [132, 147], and not due to the relationship between cropland and grassland surface [257]. While information regarding grassland fertilization prior to 1990 is limited, several factors support the hypothesis of early fertilizer application rate for grassland and fodder production. These include the fraction used for grasslands and fodder in 1990 [147], substantial research conducted on improved grasslands since 1920s [258], and the early introduction of alfalfa in 1858 [225] which is a significant consumer of P_2O_5 and K_2O in the country. Given the challenge of identifying any discernible trend and the likelihood of significant consumption at the beginning of the period, we have chosen to adopt the same percentage for the entire duration, aligning with FAO assumptions [89], despite potential slight over- and underestimations throughout the period. The average of all reports [132, 147–151, 153], resulted in percentages of 12.4% for N, 13.3% for P_2O_5, and 9.2% for K_2O.

Potential drivers To develop our ML models, we compiled a series of datasets that contain information on features that were identified in previous research as drivers or correlates of cropland fertilization. In this section and the next two, we clarify our rationale for the variable selection, the data sources and the methods used for estimating some of these variables. The list of all considered features can be found in Table 2.2 and further details about their estimation are provided below.

Environmental data Environmental variables related to climate and soil characteristics have

been identified as factors that influence fertilization management in farm-level studies [259] and regional panel data [260, 261]. Therefore, we selected several potential factors, some of which have previously been shown to correlate with fertilization, such as mean annual precipitation (MAP) [260], or soil organic carbon (SOC) [261], as well as newer potential factors such as the aridity index. Data for these factors were sourced from two main databases: the CRU v.4. databases [262], for climatic factors, and the SoilGrids v.2. database [263], for soil characteristics. Obtaining values at the country-level while considering variations in climatic and soil conditions within a country can be imprecise. However, our fundamental unit of analysis is the country-level, as the FUBC values are measured on this scale. To mitigate this limitation, we used spatial information for climatic and soil characteristics along with information about the location of crops [145]. All environmental variables were estimated using Eq. (2.4), but preprocessing differed across variables.

$$Env_{jic} = \frac{\sum_{g \in G}(Env_{ig} \times HArea_M2000_{gcj})}{HArea_M2000_{cj}} \tag{2.4}$$

Here, Env_{jic} represents the mean value of the environmental variable for country j, in year i, where crop c is located in the country; Env_{ig} is the value of the environmental variable in year i, for grid cell g; $HArea_M2000gc$ denotes the area of grid cell g for crop c in country j; $HArea_M2000_{cj}$ is the total surface of crop c in country j based on Monfreda, Ramankutty and Foley (2008) [145] crop maps [145]; and G denotes the set of cells where the crop is located based on Monfreda, Ramankutty and Foley (2008) [145] crop maps. For the MAP, the Env_{ig} values of Eq. (2.4) are calculated by summing the precipitation from all months in the CRU v.4. dataset [262] for each grid cell g, and year i. For the mean annual temperature (MAT), the Env_{ig} values are calculated as the average of the monthly temperatures from the CRU v.4. dataset [262], weighed by the number of days of each month. The potential evapotranspiration (PET) values are derived by multiplying the daily month average from CRU v.4. [262] by the number of days in each month and summing the results. For the aridity index, we used the United Nations (UN) definition [264] of the ratio between MAP and total PET for each grid cell. As soil variables do not have temporal resolution, we simplified Eq. (2.4) by removing the temporal factor. Additionally, for some soil variables like the soil cation exchange capacity (CEC), we aggregated the information by calculating the average for the first three depth layers from SoilGrid v.2. (0-5, 1-15 and 15-30 cm) [263].

Agrological data We selected agrological features that were previously identified as factors potentially related to or driving fertilizer intensification, such as holding size [265], crop area [261], or irrigation implementation [260], as well as features that should be connected to crop fertilization at the country-level, such as country fertilizer use per cropland area [68]. Most of the agrological variables used are taken directly from the sources indicated in Table 2.2. However, some required preprocessing. For holding size, we applied the methodology used by Zou, Zhang and Davidson (2022) [266], which involves standardizing the information based on the average holding size according to the total agricultural area. We used holding size data from the FAOSTAT agricultural censuses [267] and previous research [268]. To estimate the annual nutrient removal for each crop class based on annual production, we used the recent compilation by FAO [89] on nutrient removal in kilograms per tonne of crop produced, along with the annual country production data from FAOSTAT [163]. Additionally, we used this compilation alone as a proxy for fertilizer recommendations, since these recommendations are generally based on the nutrient requirements of each crop [269].

Socioeconomic data Economic factors, particularly those related to the profitability of fertilizer use, have been widely studied to understand fertilizer adoption at the farming-level [270, 271]. Both input prices (fertilizers) and output prices (crops) determine profitability and can be key factors influencing fertilization decisions. However, assessing inputs at the country-level is challenging, primarily due to a lack of standardized data. The only available dataset, FAOSTAT [272], does not cover all periods and lacks standardization. To address this, we used two variables as proxies of fertilizer prices: a) global real prices for Urea, phosphate rock, and muriate of potash, as compiled by the World Bank [273]; and b) the distance from the production sites or mines, following the methodology proposed by McArthur and McCord (2017) [274]. This methodology uses gravity models of trade, based on the premise that fertilizers are produced in a few specific countries [274]. The underlying hypothesis is that countries closer to fertilizer plants or mines are more sensitive to price variations because transport costs are a significant factor for farmers [274]. We applied a similar approach, estimating the minimum cost-adjusted distance by using the costDist function from *terra* package [275], global friction maps [276], the locations and operational years of potash [55] and phosphate mines, the locations of ammonia plants [274, 277] and the centroid of the cropland area on the country based on the Monfreda, Ramankutty and Foley (2008) [145] crop maps [145]. Assessing the output prices for crops faces a similar problem: there is no standardized dataset with national-level data for the entire period. To resolve this, we used two proxies for crop prices: a) global real prices for specific commodities like wheat, maize, rice, palm oil, soybeans, sugar, and cotton, compiled by the World Bank [273], and b) standardized data from two FAOSTAT datasets [278, 279] that provide prices paid to producers at the country-level. The first dataset [278] contains information from 1990 onwards in United States dollars (USD), and local currency units (LCU), while the second dataset [279] covers 1966 to 1990, only in LCU. To standardize both datasets, we converted the older dataset into USD using annual currency exchange rates [280]. We then removed outliers independently for each crop by considering only values within 1.5 times the interquartile range. Before applying this method to the 1966-1990 dataset, we tested it on the LCU data for maize, wheat, and rice from the 1990 onwards dataset. We compared the original USD values with those obtained after converting the LCU data using exchange rates. The outlier detection method retained more than 99% of equivalent values (defined by a ratio between the original and calculated USD values of 0.99 to 1.01), while removing over 90% of non-equivalent values. Finally, the data was converted to real prices by applying the Consumer Price Index [281].

Other socioeconomic factors, that are not directly related to the profitability of fertilizer use, have also been linked to country-level fertilizer use. These factors include the income level, reflected in the gross domestic product (GDP) per capita [282]; the population pressure, defined as the country's population divided by its agricultural land area [283]; and the farmers' knowledge about fertilizer use, as well as general education levels [270], which we measured by the percentage of total GDP spent on education. We used the sources listed in Table 2.2 to obtain data for these variables.

Table 2.2. Environmental, agrological and socioeconomic features used in the prediction of the fertilizer application rates, accompanied by their description, unit and data source. The *Model* column indicates whether the feature was an input for either the N, P_2O_5 or K_2O prediction, or for all three predictions.

Feature	Description	Unit	Model	Source
Year	Year of the data		All	
Crop	Crop class		All	
Country	Code of the country or region in FAOSTAT		All	
Country surface	Surface of the country	km^2	All	[284]
Region	World region		All	[285]
Environmental				
PET	Annual potential evapotranspiration	mm yr^{-1}	All	[262]
MAP	Annual precipitation	mm yr^{-1}	All	[262]
TMN	Average annual temperature	°C	All	[262]
Aridity index	Aridity index		All	[262]
Soil N	Average soil nitrogen content at 0–30 cm depth	cg kg^{-1}	All	[263]
Soil OCS	Average soil organic carbon stock at 0–30 cm depth	t ha^{-1}	All	[263]
Soil sand	Average soil sand content at 0–30 cm depth	g kg^{-1}	All	[263]
Soil silt	Average soil silt content at 0–30 cm depth	g kg^{-1}	All	[263]
Soil clay	Average soil clay content at 0–30 cm depth	g kg^{-1}	All	[263]
Soil pH	Average soil pH at 0–30 cm depth		All	[263]
Soil CEC	Average soil cation exchange capacity at pH 7 at 0–30 cm depth	mmol(c) kg^{-1}	All	[263]
Agronomical				
Crop area	Harvested area of the crop	ha	All	[163]
Crop area perc	Area of the crop over total cropland area	%	All	[163]
Country N per ha	Amount of N used per cropland area	t ha^{-1}	N	[68]
Country P_2O_5 per ha	Amount of P_2O_5 used per cropland area	t ha^{-1}	P_2O_5	[68]
Country K_2O per ha	Amount of K_2O used per cropland area	t ha^{-1}	K_2O	[68]
Country N use	Amount of N used in the country	t	N	[68]
Country P_2O_5 use	Amount of P_2O_5 used in the country	t	P_2O_5	[68]
Country K_2O use	Amount of K_2O used in the country	t	K_2O	[68]
% of N used on crop	Percentage of N used for this crop	%	N	[132, 152, 153, 164]
% of P_2O_5 used on crop	Percentage of P_2O_5 used for this crop	%	P_2O_5	[132, 152, 153, 164]
% of K_2O used on crop	Percentage of K_2O used for this crop	%	K_2O	[132, 152, 153, 164]
Crop N content	N content of the crop	kg t^{-1}	N	[89]
Crop P content	P content of the crop	kg t^{-1}	P_2O_5	[89]
Crop K content	K content of the crop	kg t^{-1}	K_2O	[89]

Continued on next page

Feature	Description	Unit	Model	Source
Crop N removal per ha	Average N removal per ha (crop, country, year)	kg ha^{-1}	N	[89, 163]
Crop P removal per ha	Average P removal per ha (crop, country, year)	kg ha^{-1}	P_2O_5	[89, 163]
Crop K removal per ha	Average K removal per ha (crop, country, year)	kg ha^{-1}	K_2O	[89, 163]
Holding size stand	Standardized average farm size (country, year)	ha	All	[142]
Irrigation implementation	Share of agricultural land irrigated	%	All	[286]
Machinery use	Number of agriculture machinery per ha of arable land (country, year)	ha^{-1}	All	[287, 288]
Socioeconomic				
Global urea price	Current urea price per metric tonne	$ current	N	[273]
Global P-rock price	Current P price per metric tonne	$ current	P_2O_5	[273]
Global K_2O price	Current K_2O price per metric tonne	$ current	K_2O	[273]
Global crop price	Real global crop price	$ current	All	[273]
Education	Fraction of GDP used for education	%	All	[289]
GDP per capita	Current GDP per capita	$ current	All	[290]
N cost from production	N fertilizer cost from production		N	[274]
P cost from production	P_2O_5 fertilizer cost from production		P_2O_5	[274]
K cost from production	K_2O fertilizer cost from production		K_2O	[274]
Population pressure	Population per ha of agricultural land	persons ha^{-1}	All	[288, 291]
National crop price	Real price paid to farmer (country-level)	$ current	All	[278, 279]

Data preprocessing

Several preprocessing steps were performed to prepare the raw data for the ML models. First, drawing from both expert domain knowledge and exploratory data analysis, the features relevant to N, P_2O_5 and K_2O fertilizer application rate were selected (Table 2.2). Since not every feature was relevant for each of the three targets, we narrowed down the dataset to data points where the average fertilizer application rate is known for all three fertilizers. This restriction ensured that the dataset comprised only labeled data points, which is crucial for supervised ML techniques. Subsequently, anomalies in the data where the fertilizer application rate was unrealistically large, i.e., greater than 5000 kg ha^{-1}, were removed. Finally, categorical features were one-hot encoded (OHE).

Machine learning

Previous studies within this domain typically propose linear equations to estimate the fertilizer application rate, and only consider a limited set of agricultural factors [126, 127]. However, it is well-established that natural phenomena frequently exhibit nonlinear relationships [292], rendering them unsuitable for modeling with linear methodologies.

Similar studies have also employed Bayesian methods [131], with certain modeling assumptions that are not present in our study. ML has the potential to overcome these limitations. The field of ML has seen major increases in research [293] and industry [294], and, more specifically, ML has shown promising results in the field of ecology [295, 296], including agricultural research [297, 298], fertilizer consumption [299, 300] and fertilizer management [301]. For this reason, ML was used in this study to estimate the annual fertilizer application rate at the crop- and country-level. The benefit of using ML is threefold. First, ML allows us to include a larger range of variables, for example also including socioeconomic factors. Second, nonlinear ML techniques enable us to model nonlinear relationships between the variables in our dataset. Lastly, the model output can provide insights into the drivers associated with crop fertilization on a global scale, through the use of SHAP values [141] outlining the feature importance. The employed ML methods to estimate fertilizer application rate for crops differ from previous research, which typically relied solely on changes in crop area, overall fertilizer consumption, and limited data regarding fertilizer application rate at the individual crop-level [126, 127]. An advantage of our method is that it enables us to estimate values for countries where specific data is lacking by relying on other related variables. For example, the projected data for the USSR aligns closely with national totals, even in the absence of country-specific data and without adjustments based on total consumption, as conventionally done [126, 127].

Models

In this study, two ML models based on gradient boosted regression trees were selected to predict the average annual fertilizer application at the crop- and country-level. In gradient boosting [302], an ensemble of weak learners (in our case regression trees) is trained sequentially. First, a weak learner is fitted to the original data. In the next iteration, another weak learner is fitted to the residuals, i.e., the differences between the ground truth target values and the current predictions made by the ensemble. When fitting a new weak learner to the residuals, gradient boosting adjusts its parameters in the negative gradient direction, aiming to reduce the residual error of the ensemble. This sequential learning process enables gradient boosting models to create a strong learner by combining multiple weak learners. The specific gradient boosting models employed in this study are XGB [139] and HGB [140, 303]. XGB has been shown to be a powerful tool for predictive modeling in a wide range of applications in both industry and research, including agricultural research [298] and fertilizer research [299]. It offers an optimized and scalable implementation of gradient boosting, and includes regularization techniques to prevent overfitting [139]. The HGB model is primarily based on LightGBM [303], which addresses one of the major bottlenecks in gradient boosting model training, namely the requirement to sort all samples at each node [140]. Indeed, in a traditional gradient boosting model, samples must be sorted at each node to determine the best split. This sorting process can become computationally expensive, especially when dealing with large datasets or deep trees. In HGB, the samples are first collected into a histogram, which removes the need for sorting as samples in a histogram are implicitly ordered. This optimization results in a model that is much faster to train than traditional gradient boosting models, while still achieving similar or better performance [140]. The choice for these two methods over other conventional ML approaches, such as neural networks, was primarily driven by the fact that both methods natively handle missing values. This constitutes a significant advantage, given that global fertilizer application rate data, along with the socioeconomic and agricultural variables used to predict the annual

fertilizer application, are often incomplete. This also demonstrates another advantage of applying ML to this problem over the conventional approach using linear equations. Indeed, the absence of just one variable in the equation renders it impossible to compute.

Model training and evaluation

The selection of the optimal set of model hyperparameters is usually done using cross validation (CV), after which the CV error is reported as the performance of a model [304]. However, based on Stone (1974) [305], model assessment and model performance require different CV approaches. For this reason, we used nested CV, as it allowed us to find the optimal set of hyperparameters for a model and provide an unbiased estimate of the model's performance [306]. In nested CV, two levels of CV loops are used: an outer loop and an inner loop. In the outer loop, the dataset is split into training and testing sets, typically using k-fold CV. Each fold of the outer loop trains the model on the training set and evaluates the model on the testing set. Within each fold of the outer loop, the training data is provided to an inner CV loop, in which the training data is further split into training and validation sets, also typically using k-fold CV. The inner loop is responsible for selecting the set of hyperparameters that performs best on the validation set. Finally, the performance of the selected set of hyperparameters is evaluated on the corresponding test set in the outer loop. In our study, we used a 2×5 nested CV, i.e., we had two outer loops and five inner loops. We employed a grid search that iteratively went over all possible combinations of hyperparameters, based on the explored hyperparameters as shown in Table B.2 for both the HGB and XGB models. The performance of the models was evaluated by averaging the performances of the two models in the outer CV loop. The considered performance metrics included the determination coefficient (R^2), MAE, mean squared error (MSE), and root mean squared error (RMSE), all computed between the predicted and reported data points.

Model interpretability through SHAP value analysis

Unfortunately, gradient boosting methods are so-called black-box models, i.e., it is not immediately clear how certain predictions are made. However, assessing the impact of the features on the predicted fertilizer application rate in the learned models could provide us with valuable insights into the drivers of fertilizer application rate. Therefore, we resorted to eXplainable artificial intelligence (xAI) methods to understand the predictions made by our models. More specifically, we used SHAP values [141] as they are model-agnostic, can account for interactions between features and have an intuitive interpretation. Indeed, summing the SHAP values for all features in one sample results in the prediction of the model. Additionally, like XGB and HGB, SHAP values are robust with respect to missing data by design [141]. Special attention was given to categorical values, as retrieving one SHAP value for a categorical feature that is divided into OHE features is non-trivial. However, as the SHAP values are calculated using the preprocessed input data (i.e., containing the OHE categorical features), the SHAP values for one categorical variable were obtained by adding together all SHAP values for its respective OHE features.

Adjustment to country totals

Previous research has always started with the same premise of allocating total fertilizer consumption at the country-level for estimating crop-level use [126, 127]. However, here we adopt a different strategy, initiating the estimation of the fertilizer consumption at the

crop-level directly. Despite this shift in strategy, we still consider country-level data to be more reliable than datasets compiled from various FUBC sources. To reconcile our approach with the more dependable country-level data, we adjusted the ML predictions to align with FAOSTAT's total fertilizer consumption at the country-level [68]. As shown in Eq. (2.5), we distributed the differences between the predicted total fertilizer consumption and the FAOSTAT totals equally among crops, after excluding the fraction used for grasslands and fodder crops from FAOSTAT totals.

$$Fert_Pred_{icj} = FertML_Pred_{icj} \cdot \frac{FAOSTAT_FERTng_{ij}}{\sum_{d \in C}(FertML_Pred_{idj} \times HArea_FAO_{idj})} \tag{2.5}$$

Where, $Fert_Pred_{icj}$ represents the fertilizer application rate predictions after the adjustment for year i, crop c, and country j. $FertML_Pred_{icj}$ denotes the ML model predictions, C is the set of all crops classes included in the models, $HArea_FAO_{idj}$ the FAOSTAT harvested area [163] of each crop class d, and $FAOSTAT_FERTng_{ij}$ is the total FAOSTAT fertilizer consumption for the country, after removing the fraction used for grasslands and fodder crops.

Validation

To validate the model predictions, we compared the model predictions with national databases containing information about the average use per hectare for different fertilizers and crops. This validation is quantified using the MAE and mean absolute percentage error (MAPE) as well as with comparative plots if enough data was obtainable from the various national databases. The MAE gives an idea about the actual deviation, whilst the MAPE makes the comparison between prediction errors easier. The evaluated national databases include data obtained from for the USA [154], UK [166], India [155–161], Sweden [170–173], Philippines [168], and New Zealand [174]. For Pakistan [167], only data for the sum of fertilizer application rate is available, hence the sum of N, P_2O_5, and K_2O was used, expressed as NPK. This approach is restricted by available data in national databases for average fertilizer application rate across various crops and nutrients.

Gridded crop-specific application rate per fertilizer

Following the generated comprehensive dataset of global fertilizer application rate, we constructed detailed 5-arcmin resolution gridded maps for each fertilizer (N, P_2O_5, and K_2O), crop class and year from 1961 to 2019. The final gridded map dataset was compiled in a three-step process, as highlighted in Fig. 2.1. First, data of the gridded harvested area spanning from 1961 to 2019 for the 13 distinct crop classes (see Table B.1) were acquired by combining data from the EARTHSTAT project of the year 2000 ($HArea_M2000$) [145], supplemented with historical arable land and permanent crop areas per year ($CArea_Hyde$) from the History Database of the Global Environment (HYDE version 3.3) [146]. The EARTHSTAT maps were created by combining national-, state-, and country-level census statistics with an up-to-date global dataset of croplands, organized on a 5-arcminute by 5-arcminute latitude-longitude grid. These datasets, reflecting land use around the year 2000, detail both the area harvested and the yield of 175 diverse crops worldwide [145]. Innovative maps outlining major crop groups were generated by consolidating these individual crop maps. The HYDE 3.3 project provides long time series estimates and maps for land use, including the cropland

areas, based on an allocation algorithm with time-dependent weighting [146]. The elaborate information from the crop specific EARTHSTAT maps for the year 2000, in combination with the yearly changes in gridded cropland from HYDE 3.3, allowed us to make detailed gridded 5-arcmin resolution crop specific harvested areas for each of the evaluated years and crops using Eqs. (2.6) to (2.9):

For $CArea_Hyde_{gi} > 0$ and crop is rice:

$$HArea_M_{gic} = CArea_Hyde_R_{gi} \tag{2.6}$$

For $CArea_Hyde_{gi} > 0$ and crop is not rice:

$$HArea_M_{gic} = CArea_Hyde_NR_{gi} \times \frac{HArea_M2000_{gc}}{CArea_Hyde_NR_{g2000}} \tag{2.7}$$

For $CArea_Hyde_{gi} > 0 \cup \sum_{c \in C} HArea_M2000_c = 0$ and crop is rice:

$$HArea_M_{gic} = CArea_Hyde_R_{gi} \tag{2.8}$$

For $CArea_Hyde_{gi} > 0 \cup \sum_{c \in C} HArea_M2000_c = 0$ and crop is not rice:

$$HArea_M_{gic} = CArea_Hyde_NR_{gi} \times \frac{\sum_{k \in K} HArea_M2000_{gc}/K}{CArea_Hyde_NR_{g2000}} \tag{2.9}$$

Here, the indices denote the grid cell (g), the year (i), the crop (c). The harvested area ($HArea_M_{gic}$) was generated through a series of conditional operations. These conditions stipulate that if the value of the HYDE3.3 cropland area map ($CArea_Hyde_{gi}$) for that year i and grid cell g is larger than 0, and the crop is not rice, then the value of that grid cell for that specific crop and year is given by the HYDE3.3 cropland area ($CArea_Hyde_NR_{gi}$) for that grid cell/year combination. The value of the grid cell is then further adjusted by the ratio of the HYDE3.3 map of the year 2000 to the EARTHSTAT map of the year 2000 for the corresponding grid cell and crop ($\frac{HArea_M2000_{gc}}{CArea_Hyde_NR_{g2000}}$). In the case of rice, the specific HYDE3.3 map for cropland area of rice was selected and not altered as this is readily available. Additionally, in instances where $CArea_Hyde_{gi}$ was larger than 0 and the sum of all crops across the EARTHSTAT maps of the year 2000 is equal to 0 (e.g., when new lands are cultivated), a progressively expanding area K was evaluated to find an appropriate ratio based on the average of the k neighboring cells. The evaluated values for k were 5, 10, 25, 50, 100, 150, 200 and 250, up until a value different from zero for the ratio is found. If no value different from zero was found, the ratio value was set equal to 1. This last step made the assumption that the crop distribution in neighboring cells adequately represents the distribution in the newly cultivated area, allowing for the calculation of adjusted harvested areas. Furthermore, as the $HArea_M2000_{gc}$ is consistently used, we assumed that the changes in crop distribution over time remain constant. To ensure the accuracy of the generated maps, we capped the harvested area at the maximum feasible value in each cell.

To ensure consistency with FAOSTAT data used in the model predictions, the gridded harvested area ($HArea_M1961_2019$) was aligned with the country-specific harvested area reported by FAOSTAT ($HArea_FAO2000$). Additionally, due to this alignment, some cells may initially have harvested area values that exceed the maximum possible for that cell. To correct this, we cap the harvested area at the maximum feasible value per cell and then redistribute any excess proportionally across other cells with harvested area values, ensuring overall consistency with FAOSTAT data. These adjustments, applied through Eq. (2.10),

provided a corrected gridded harvested area for the 13 crop classes over the 60-year period ($HArea_1961_2019$):

$$HArea_{gic} = HArea_M_{gic} \times \frac{\sum_{j \in J} HArea_FAO_{icj}}{\sum_{j \in J} HArea_M_{icj}} \tag{2.10}$$

In this equation, $HArea_FAO_{icj}$ represents the harvested area for year i, crop c, and country j as reported by FAOSTAT, summed over all countries (J) in grid cell g (to accommodate grid cells with multiple countries). Similarly, $HArea_M_{icj}$ represents the estimated harvested area for the same combinations, also summed over all countries in grid cell g. The ratio of these sums adjusts the model gridded harvested area ($HArea_M_{gic}$) to match FAOSTAT data, ensuring the resulting gridded harvested area on a country level is consistent with official statistics across the 60-year period.

Finally, the gridded harvested area ($HArea_{1961_2019}$) was augmented with the average application rate of each predicted fertilizer (N, P_2O_5, K_2O) as per Eq. (2.11):

$$FertCrop_{gic} = HArea_{gic} \times \sum_{j \in J} (Fert_Pred_{icj} \times PercCountry_g) \tag{2.11}$$

where $Fert_Pred_{icj}$ is the country-level prediction resulting from the HGB model after applying the adjustment, and $PercCountry_g$ refers to the percentage of grid cell g that is occupied by the country j. This process was then applied to each fertilizer separately to obtain gridded maps for each fertilizer, year, and crop combination.

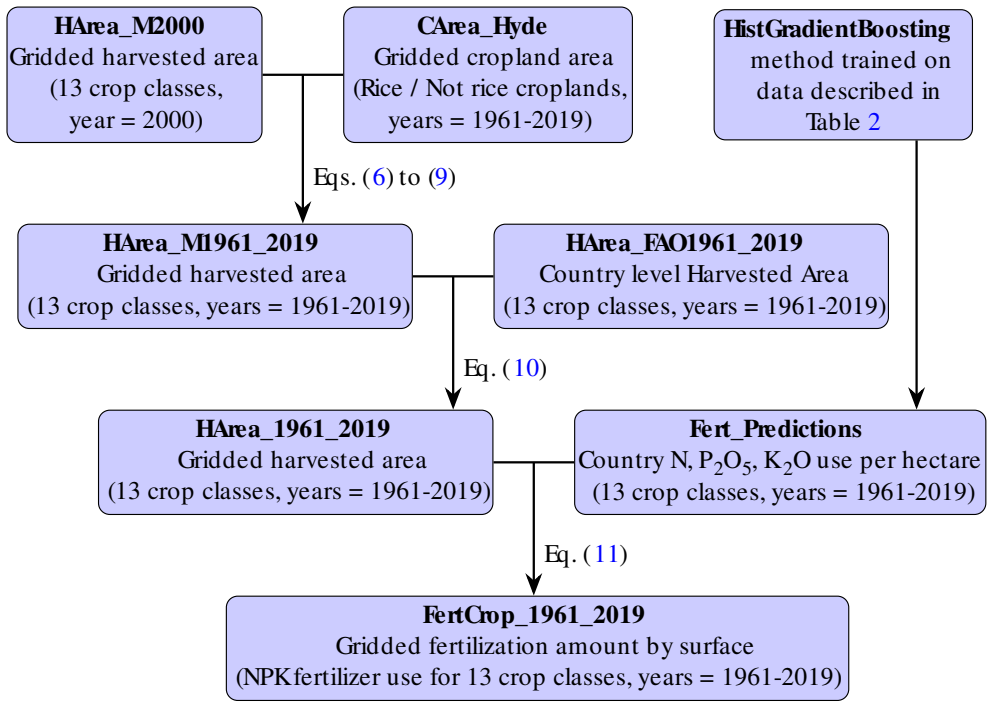


Figure 2.1. Outline of the process for generating the gridded crop-specific fertilizer dataset.

Data Records

The gridded fertilizer application data for N, P_2O_5, and K_2O by crops from 1961 to 2019 are available in a Figshare repository [307]. The dataset spans from 180ºE to 180ºW and 90ºS to 90ºN at a resolution of 5 arc-min in WGS84 (EPSG: 4326). It is provided in *.tiff* format, which can be read by many tools, such as R and Python. The gridded application data by crops and fertilizers are stored in several files named "$Crop_NameFertilizerYear.tiff$". Here, "$Crop_Name$" represents each crop class listed in Table B.1, "$Fertilizer$" refers to N, P_2O_5, or K_2O, and '$Year$' indicates any year from 1961 to 2019.

Crop-specific N application

On a global scale, the N application has grown for all crops (Fig. 2.2). For example, the average N use of the three main cereals has risen from 17.1 ± 6.1 kg ha^{-1}, 26.6 ± 7.2 kg ha^{-1}, 12.1 ± 3.9 kg ha^{-1} for wheat, maize and rice, respectively, in the 1960s, to 97.8 ± 4.2 kg ha^{-1}, 118.8 ± 4.2 kg ha^{-1}, 113.8 ± 1.9 kg ha^{-1} in the 2010s decade. Moreover, the largest increases in N application occurred in vegetable crops, with a global growth of more than 120 kg ha^{-1} between these two decades (Fig. 2.2). Conversely, the lowest increases occurred in soybean, where N application rates grew by less than 20 kg ha^{-1}. At the regional scale, the intensification of N fertilizer use has shifted from higher use at the beginning of the period in the USA and Europe to being currently dominated by Asian countries such as China and India (Fig. 2.2). This trend is particularly evident for some crops like vegetables and fruits, where China now has the areas with the highest N use worldwide, whereas in the 1960s, these areas were primarily in Southern Europe and California.

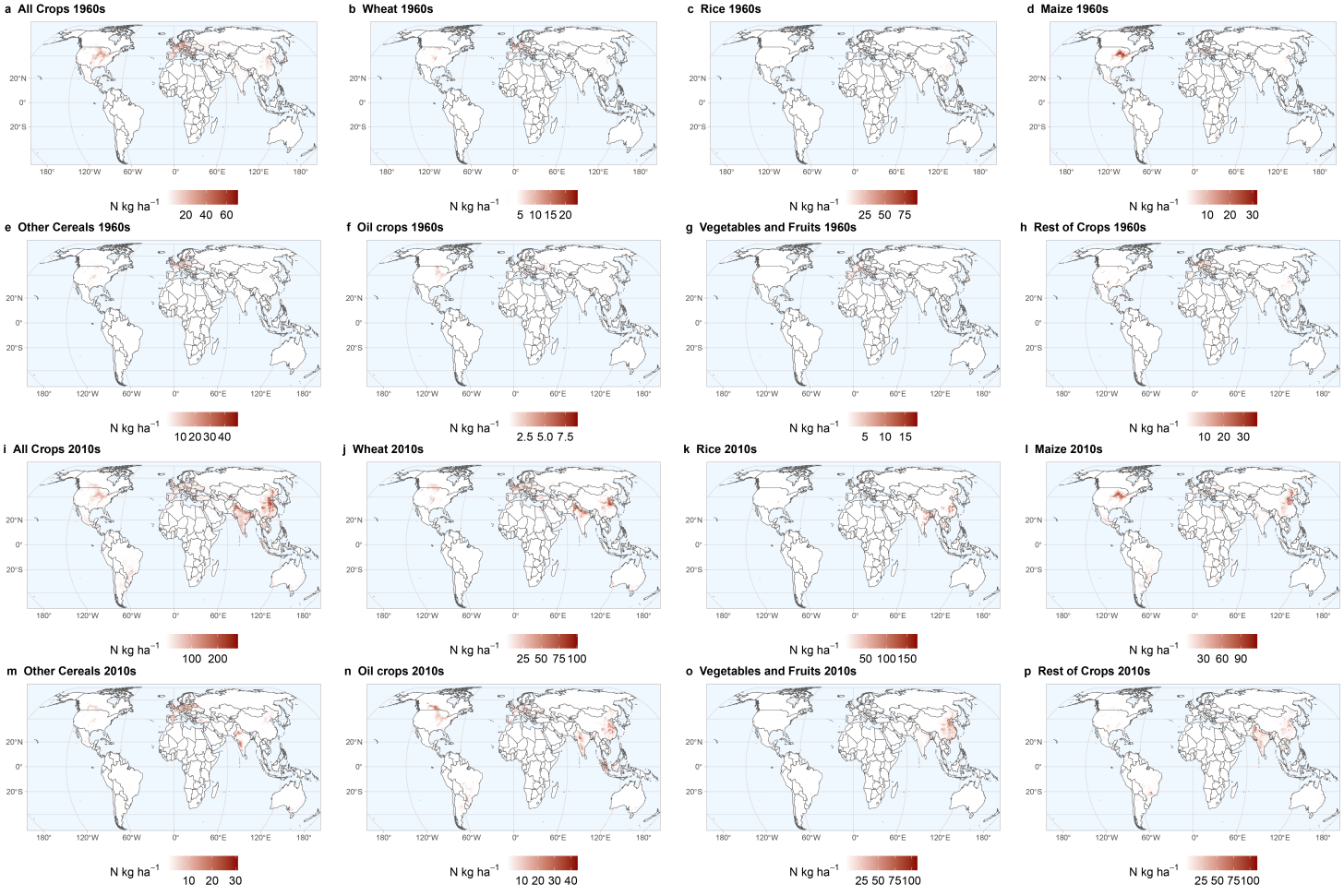


Figure 2.2. Spatial pattern of crop-specific fertilizer (N) kg ha^{-1} consumed by each 0.05° grid cell for the following: **1960s:** (a) all crops, (b) wheat, (c) rice, (d) maize, (e) other cereals, (f) oil crops, (g) vegetables and fruits, (h) roots and tubers, sugar crops, fiber crops and other crops. **2010s:** (i) all crops, (j) wheat, (k) rice, (l) maize, (m) other cereals, (n) oil crops, (o) vegetables and fruits, (p) roots and tubers, sugar crops, fiber crops and other crops. The 1960s include 1961–1969; the 2010s include 2010–2019.

Crop-specific P_2O_5 application

The application of P_2O_5 also experienced global increases across all crops (Fig. 2.3), but to a lesser extent than N. The average P_2O_5 used for the three main cereals and soybean rose from 13.8 ± 3.3 kg ha^{-1}, 13.1 ± 2.4 kg ha^{-1}, 6.3 ± 1.9 kg ha^{-1}, and 12.6 ± 2.4 kg ha^{-1} for wheat, maize, rice and soybean, respectively, in the 1960s to 35.5 ± 4.9 kg ha^{-1}, 43.0 ± 5.7 kg ha^{-1}, 39.9 ± 5.0 kg ha^{-1}, and 39.1 ± 6.6 kg ha^{-1} in the 2010s. Similar to N, the largest increases occurred in vegetable crops, where P_2O_5 application rates increased by more than 50 kg ha^{-1}. Conversely, the smallest increases were observed in the other cereal crop class, where the average P_2O_5 application rate increased by only about 2.5 kg ha^{-1} between the two decades. Regionally, a similar pattern occurred with P_2O_5 use, following the trend previously seen with N, where the hotspot shifted from Europe to Asia. This shift is particularly notable for wheat, where the hotspot of P_2O_5 intensification moved from Western Europe to northern India and northeastern China (Fig. 2.3).

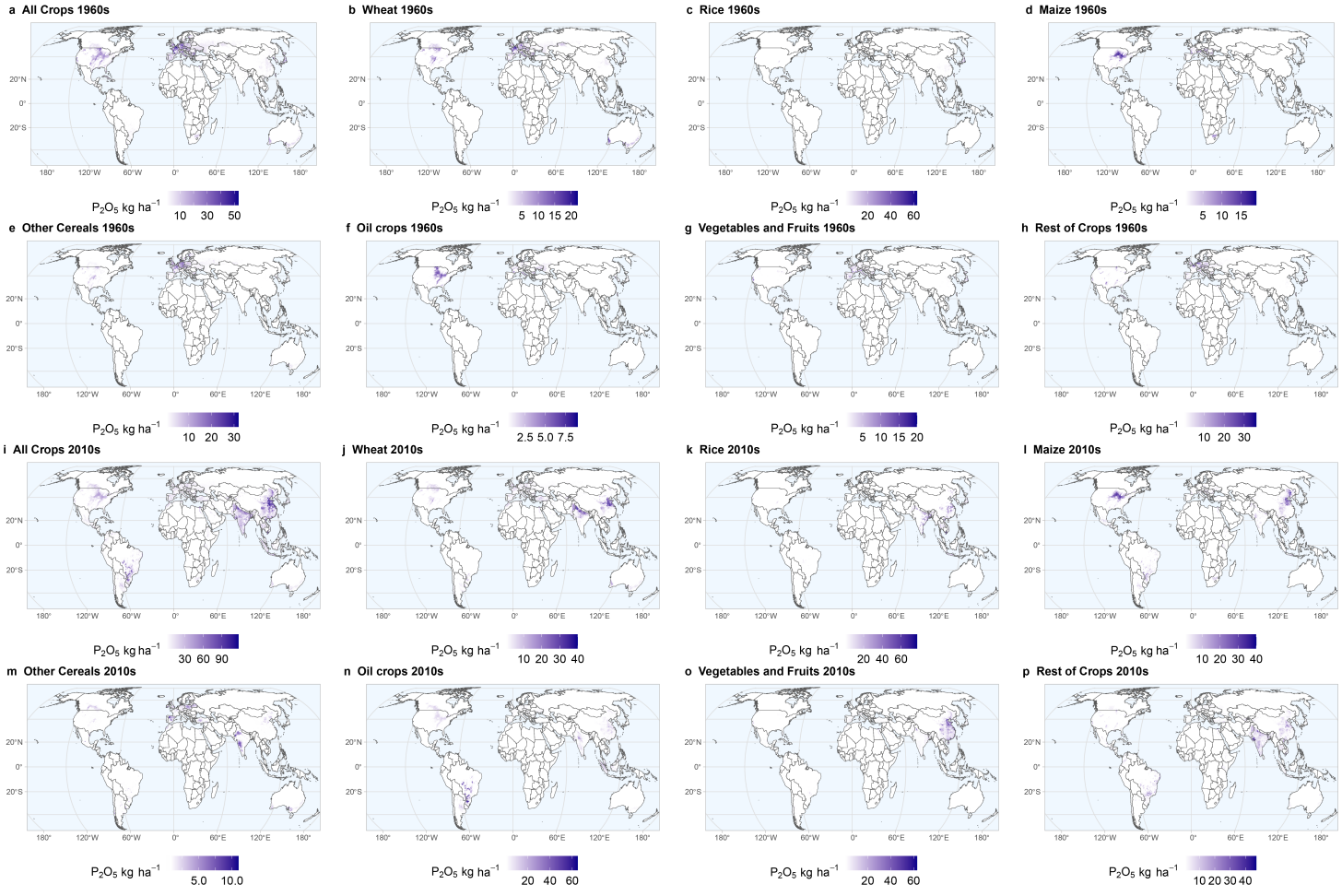


Figure 2.3. Spatial pattern of crop-specific fertilizer (P_2O_5) kg ha^{-1} consumed by each 0.05° grid cell for the following: **1960s:** (a) all crops, (b) wheat, (c) rice, (d) maize, (e) other cereals, (f) oil crops, (g) vegetables and fruits, (h) roots and tubers, sugar crops, fiber crops and other crops. **2010s:** (i) all crops, (j) wheat, (k) rice, (l) maize, (m) other cereals, (n) oil crops, (o) vegetables and fruits, (p) roots and tubers, sugar crops, fiber crops and other crops. The 1960s include 1961–1969; the 2010s include 2010–2019.

Crop-specific K_2O application

Globally, the use of K_2O has also increased across almost all crop classes (Fig. 2.4). For wheat, maize, rice, and soybean, the average K_2O application rates have risen from 7.2 ± 1.6, 9.8 ± 2.0, 3.4 ± 0.5, and 11.6 ± 2.6 kg ha^{-1}, respectively, to 15.4 ± 4.1, 33.1 ± 4.8, 27.3 ± 3.9, and 9.8 ± 3.2 kg ha^{-1}. Unlike N and P_2O_5, the largest difference in average K_2O application occurred for the oil palm crop, which increased from 3.7 ± 1.4 kg ha^{-1} during the 1960s to 87.6 ± 8.3 during the 2010s. Similar to P_2O_5, the other cereal class experienced the smallest change in K_2O use. In this case, the average K_2O application rate decreased from 11.7 ± 1.9 kg ha^{-1} during the 1960s to 9.8 ± 3.2 kg ha^{-1} during the 2010s. Regionally, a similar pattern emerged with K_2O, following the trend observed with N and P_2O_5, with the hotspot of K_2O fertilization shifting from Europe and the USA to Asia. However, this change was more pronounced in different crops, such as oil crops, where the use of K_2O has increased significantly in countries like Malaysia and Indonesia (Fig. 2.4).

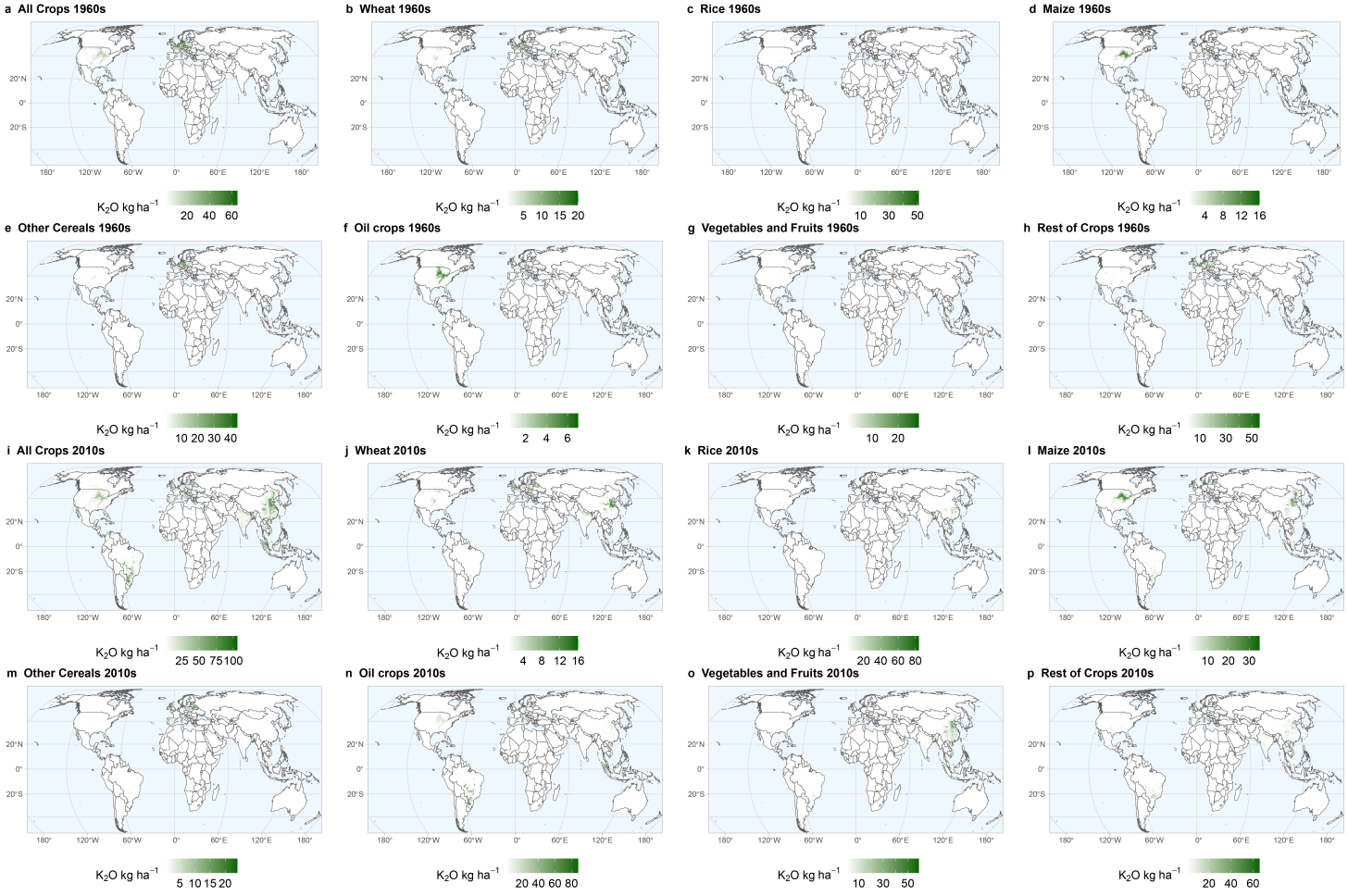


Figure 2.4. Spatial pattern of crop-specific fertilizer (K_2O) kg ha^{-1} consumed by each 0.05° grid cell for the following: **1960s:** (a) all crops, (b) wheat, (c) rice, (d) maize, (e) other cereals, (f) oil crops, (g) vegetables and fruits, (h) roots and tubers, sugar crops, fiber crops and other crops. **2010s:** (i) all crops, (j) wheat, (k) rice, (l) maize, (m) other cereals, (n) oil crops, (o) vegetables and fruits, (p) roots and tubers, sugar crops, fiber crops and other crops. The 1960s include 1961–1969; the 2010s include 2010–2019.

Technical Validation

This section provides a detailed discussion of the validation efforts made to confirm the validity, consistency, and plausibility of our compiled dataset and predictions. First, the performance of the ML models is evaluated. Subsequently, we use SHAP values to confirm that our models used sensible features to make their predictions, based on literature. Finally, the predictions are validated by comparing them with reported data in both national and global databases.

ML Model performance

The performance of the ML models predicting the fertilizer application rates for the three fertilizers is shown in Table 2.3. Both XGB and HGB significantly outperformed the naive prediction, which uses the mean fertilizer application as its prediction. HGB consistently outperformed (or matched) XGB for all three fertilizers and performance metrics. For this reason, we will use the HGB model in the remainder of this technical validation, as well as any subsequent analyses.

Table 2.3. Performances of the eXtreme Gradient Boosting (XGB) and HistGradientBoosting (HGB) models on the test sets in a 2x5-fold nested cross validation grid search. The performance is quantified using the mean absolute error (MAE), root mean squared error (RMSE), mean squared error (MSE) and determination coefficient (R^2). The naive performance of a model is defined as the performance of a model that uses the mean of all training samples as its prediction. It serves as a baseline value to compare the test performances of the models with. The best performances are indicated in boldface.

Fertilizer	Model	MAE	RMSE	MSE	R^2
N	HGB	**26.01 ± 0.94**	43.50 ± 5.13	**1905 ± 446**	**0.62 ± 0.04**
	XGB	26.67 ± 1.48	**43.35 ± 7.12**	**1905 ± 617**	**0.62 ± 0.08**
	naive	53.09 ± 0.75	70.13 ± 4.19	4927 ± 588	0.00 ± 0.00
P_2O_5	HGB	**15.19 ± 0.67**	**25.68 ± 1.18**	**660 ± 61**	**0.63 ± 0.05**
	XGB	16.83 ± 0.23	26.40 ± 0.74	697 ± 39	0.61 ± 0.04
	naive	29.97 ± 0.23	42.12 ± 1.02	1774 ± 86	0.00 ± 0.00
K_2O	HGB	**19.18 ± 0.27**	**35.74 ± 4.56**	**1287 ± 326**	**0.65 ± 0.08**
	XGB	19.99 ± 0.20	36.24 ± 4.66	1324 ± 338	0.64 ± 0.09
	naive	43.08 ± 0.76	60.25 ± 0.52	3631 ± 63	0.00 ± 0.00

SHAP value analysis

To examine the impact of the features on the prediction of the N, P_2O_5 and K_2O application rates, the SHAP values of the ten most important features for the three corresponding HGB models are illustrated in Fig. 2.5. Agrological drivers dominated the predictions, comprising six, seven, and eight of the ten highest ranked features, respectively. The impact of the features remained consistent across all fertilizers, albeit with varying magnitudes (Fig. 2.5 d,e,f). In particular, the predicted fertilizer application rates were consistently positively impacted by the country fertilizer per ha and the crop nutrient removal per ha (as red dots,

i.e. high values of country fertilizer per ha and high nutrient removal per ha, corresponded with positive SHAP values), while it was negatively impacted by the crop nutrient content (red dots corresponding with negative SHAP values; Fig. 2.5 d,e,f). These relationships align with the expected influence of these features on fertilization at the crop-level [308]. Across the different fertilizers, the most important socioeconomic features varied. For instance, the GDP per capita was the most important socioeconomic feature in the prediction of the P_2O_5 and K_2O application rates, while in the N prediction, the global crop price was more important. Fertilization at the country-level is usually associated with the economic development of the country, measured by GDP [282, 309]. However, at the crop-level, this relationship only held true for the most expensive fertilizers, P_2O_5 and K_2O. For N, the most affordable nutrient [273], factors such as global crop price and N cost from production appeared to be more significant (Fig. 2.5). Few environmental features seemed to be relevant for the predictions (Fig. 2.5); only the soil pH, soil organic carbon stock (OCS), and aridity index appeared in the top ten for some nutrients. Although the influence of these variables appeared to be low, the direction of these relationships confirmed the findings of other authors at the farm- or regional-level for soil organic carbon content and soil pH. [259–261].

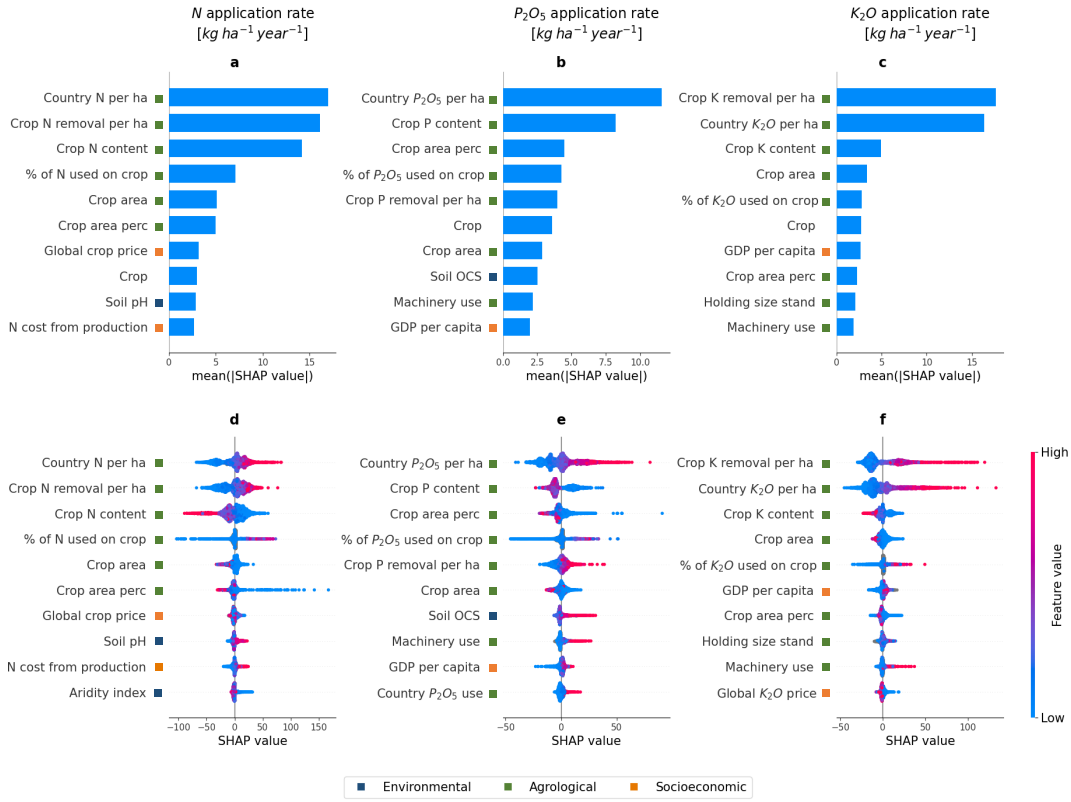


Figure 2.5. SHapley Additive eXplanation (SHAP) values of the top 10 most important features in the prediction of, respectively, the crop N (a,d), P_2O_5 (b,e) and K_2O (c,f) application rates using Histogram-based Gradient Boosted regression. (a,b,c) The top plots present the average feature importance, determined by the mean absolute SHAP value of each feature. (d,e,f) The bottom plots depict a SHAP value for each prediction and show the local feature importance and the feature effect. The color of a dot represents the value of the feature in that instance - red indicating relatively high, blue indicating relatively low values. A dot with a high SHAP value for a feature suggests a positive contribution to the prediction, whereas a negative SHAP value leads to a lower prediction. The features are ranked in order of descending average importance and the blue, green and orange squares indicate whether the feature is an environmental, agrological or socioeconomic characteristic.

Validation

To evaluate the validity of our results, we compare the compiled dataset based on the predictions against several national databases [154–161, 166–168, 170–174] based on the MAE and MAPE errors between both, averaged over the available years as illustrated in Table 2.4. For most country/crop combinations, the differences are within reasonable ranges, with MAE values between 5-40 kg ha^{-1} and MAPE values between 10%-50%. However, for some countries, the deviations are larger, suggesting that our models may not capture all the underlying intricacies in the data for each country or crop. This can be seen for Sweden where most results deviate between 20%-100%, or New Zealand where similar results can be found. However, it should be noted that these larger differences between our compiled dataset and the national databases cover only limited years as data was not always available for certain countries, as was the case for Sweden and New Zealand. Still, these discrepancies are slightly better than in earlier research [126]. Additionally, more detailed plots to evaluate the results per year for the USA and UK, based on the United States Department of Agriculture (USDA) and Department for Environment, Food & Rural Affairs (DEFRA) respectively, are included in Figs. 2.6 and 2.7. For the USDA and DEFRA crop nutrient data, the MAPE values are less than 50% and usually less than 25%, except for USDA soybean N (Fig. 2.6). Figures 2.6 and 2.7 show that our predictions follow the real observed trend for the samples and thus form a reliable end source with only minimal differences. These discrepancies between the national databases and our compiled dataset can be attributed to occasional disparities between the application rates in the training data (data provided by the global dataset compilation) and the data in the national databases, e.g., the USA data for soybean N in 1998 differed by 400% between the two samples. These differences should be taken into account when comparing our results to the national databases, as our predictions are based on the global compiled dataset. As can be seen in Table 2.5, where the global databases data and the national databases are compared based on MAE and MAPE, most country/crop combination indicate an MAPE values between 10%-50%, which is similar to our resulting error in Table 2.4. Also, the lack of training samples for some country/crop combinations resulted in larger errors for these occurrences.

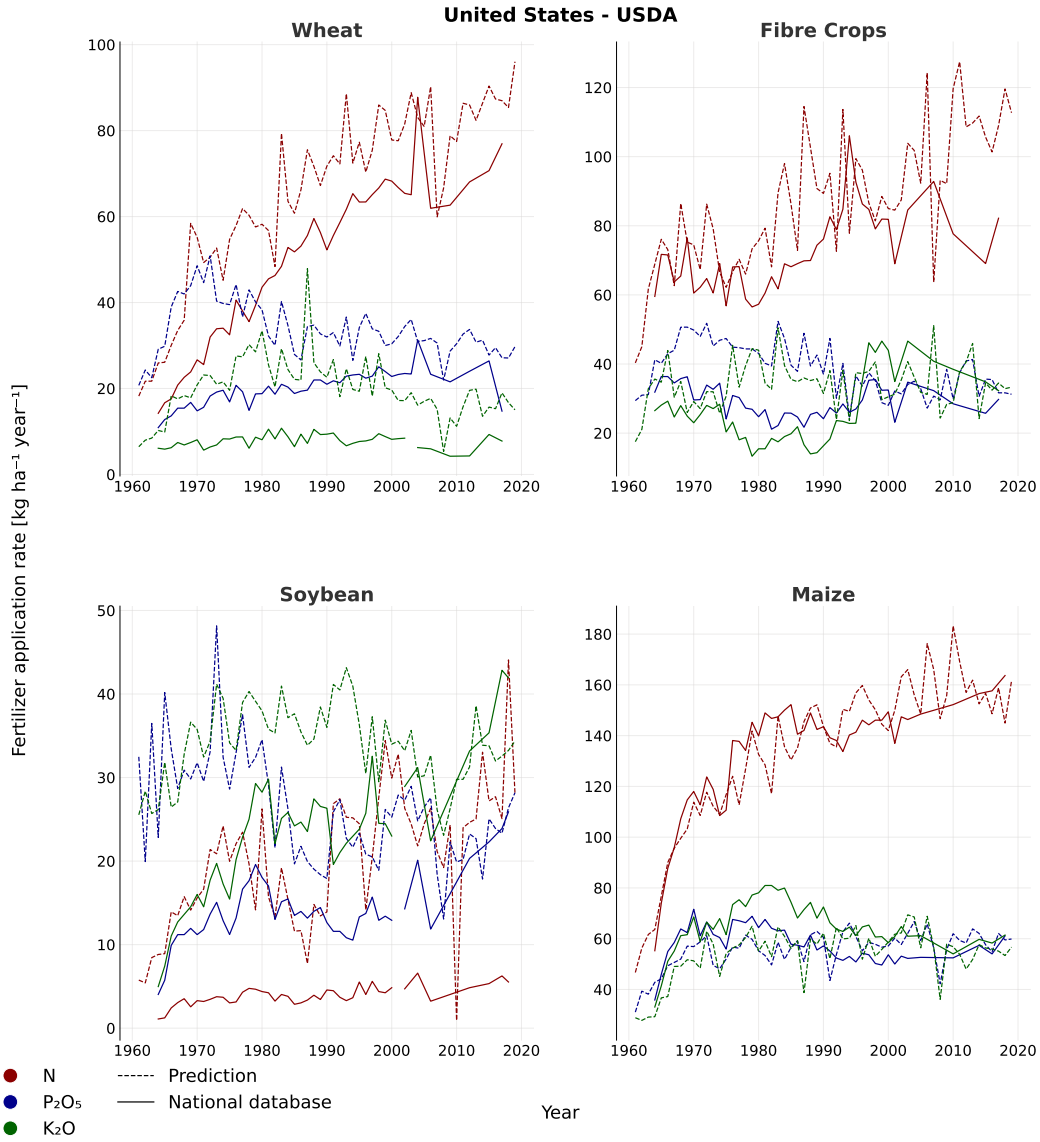


Figure 2.6. Comparison of the application rates per ha per year for various crops between our predicted model output and the data reported by the United States Department of Agriculture (USDA) for the USA.

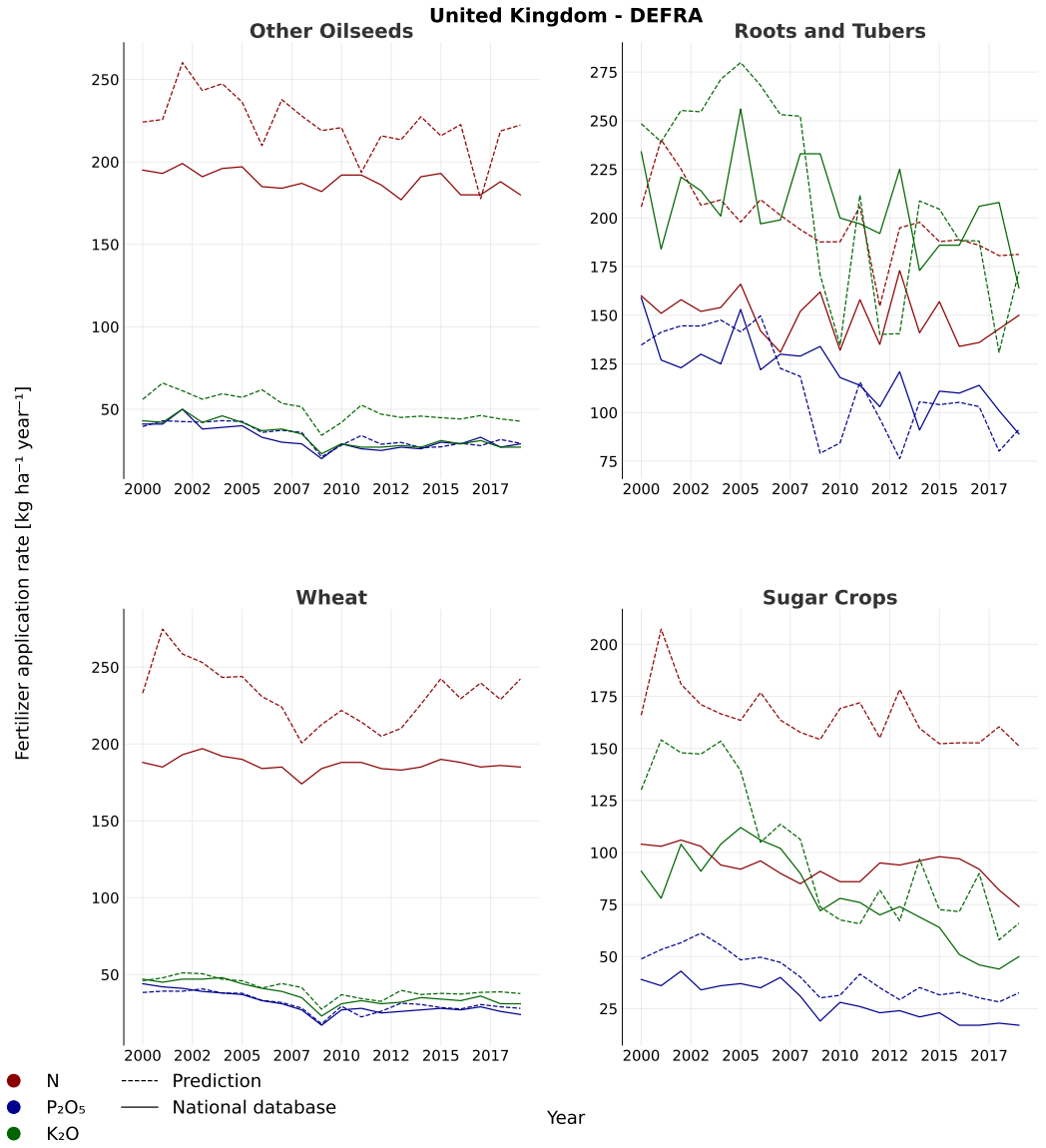


Figure 2.7. Comparison of the application rates per ha per year for various crops between our predicted model output and the data reported by the Department for Environment, Food & Rural Affairs (DEFRA) for the UK.

Table 2.4. Validation of our model predictions of the average application rate per ha against national database information for certain countries and crops per fertilizer. The validation is quantified using the mean absolute error (MAE) and mean percentage error (MAPE) per fertilizer between the two data sources, expressed in the table as MAE and MAPE respectively (fertilizer). The NPK stands for the sum of all fertilizers used in the country for certain crops, this is only discussed for Pakistan as more granular data is not available. Unavailable data points are expressed as – in the table. The sample size of the comparison per country is indicated in parentheses.

Country	**Crop**	N		P_2O_5		K_2O		NPK	
		MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE
USA	Soybean (45)	16.25	79.27	13.00	45.30	13.08	37.11	–	–
	Maize (45)	9.31	7.03	7.08	12.84	10.38	19.72	–	–
	Wheat (46)	16.20	26.38	15.23	41.01	14.21	62.69	–	–
	Fiber crops (43)	14.76	16.55	11.90	27.51	11.87	32.06	–	–
UK	Other Oilseeds (22)	37.20	16.00	3.66	10.36	16.29	32.08	–	–
	Wheat (22)	47.87	19.98	2.21	7.09	4.07	9.78	–	–
	Sugar crops (22)	72.83	43.49	11.99	29.32	24.85	22.04	–	–
	Roots and tubers (22)	46.62	23.20	17.95	17.03	40.51	21.44	–	–
India	Other Cereals (6)	11.24	30.43	6.08	34.93	1.59	38.14	–	–
	Rice (8)	11.43	12.70	3.54	15.40	2.86	36.29	–	–
	Maize (8)	5.58	12.95	5.16	35.56	3.08	59.67	–	–
	Wheat (8)	7.56	15.47	4.43	21.64	1.40	36.68	–	–
	Fiber crops (6)	15.91	15.97	12.63	49.14	4.06	91.06	–	–
	Sugar crops (8)	13.59	10.57	13.36	25.17	12.34	30.65	–	–
Sweden	Maize (4)	176.04	67.81	50.75	68.76	52.41	55.16	–	–
	Wheat (4)	54.80	29.05	11.15	48.54	24.17	108.43	–	–
	Sugar crops (4)	66.60	39.80	22.16	50.53	51.88	49.24	–	–
Philippines	Rice (13)	8.34	18.91	5.01	75.49	–	–	–	–
	Maize (12)	33.96	89.01	5.66	64.65	–	–	–	–
New Zealand	Fruits (5)	71.92	61.17	80.43	81.74	–	–	–	–
	Vegetables (5)	105.43	55.06	141.94	87.28	–	–	–	–
Pakistan	Rice (23)	–	–	–	–	–	–	66.06	41.12
	Wheat (23)	–	–	–	–	–	–	31.18	18.34
	Fiber crops (23)	–	–	–	–	–	–	71.25	29.69

Table 2.5. Comparison of the data reported by global datasets [132–138, 148–153] of the average application rate per fertilizer per ha against national database information for certain countries and crops per fertilizer. The validation is quantified using the mean absolute error (MAE) and mean percentage error (MAPE) per fertilizer between the two data sources, expressed in the table as MAE and MAPE respectively (fertilizer). The NPK stands for the sum of all fertilizers used in the country for certain crops, this is only discussed for Pakistan as more granular data is not available. Unavailable data points are expressed as – in the table.

Country	**Crop**	N		P_2O_5		K_2O		NPK	
		MAE	MAPE	MAE	MAPE	MAE	MAPE	MAE	MAPE
USA	Soybean	3.04	25.37	4.94	17.33	7.78	18.98	–	–
	Maize	10.45	6.38	8.41	12.36	13.69	45.07	–	–
	Wheat	6.04	8.96	5.34	18.20	9.65	66.89	–	–
	Fiber crops	21.51	20.80	8.74	24.49	11.76	32.04	–	–
UK	Other Oilseeds	12.42	7.31	3.41	10.55	3.01	7.85	–	–
	Wheat	5.80	3.04	2.00	6.67	1.20	3.32	–	–
	Sugar crops	3.80	3.93	3.20	9.45	9.20	10.03	–	–
	Roots and tubers	11.20	7.97	6.60	5.77	12.40	5.74	–	–
India	Other Cereals	0.30	1.03	2.49	18.89	1.01	36.54	–	–
	Rice	12.30	13.05	1.81	5.73	0.78	4.31	–	–
	Maize	19.12	43.84	13.13	124.63	0.57	19.34	–	–
	Wheat	3.71	3.40	1.05	2.51	0.29	4.16	–	–
	Fiber crops	26.52	29.83	5.70	12.94	4.28	33.55	–	–
	Sugar crops	14.93	9.11	2.97	5.01	26.03	46.83	–	–
Philippines	Rice	8.30	16.67	6.23	76.49	–	–	–	–
	Maize	31.32	69.56	6.60	78.31	–	–	–	–
Pakistan	Rice	–	–	–	–	–	–	44.64	27.54
	Wheat	–	–	–	–	–	–	29.97	18.68
	Fiber crops	–	–	–	–	–	–	54.30	23.83

To conclude, the model performances and logical feature importances, derived from the SHAP values, in conjunction with the relatively minor differences between this study and regional statistics, as well as earlier literature [126], indicate that our crop-specific fertilizer application rate dataset is comparatively reasonable across regions and years.

Usage Notes

In this study, we provide detailed estimates on global N, P_2O_5, and K_2O fertilizer application rate based on the HGB model output and compile a comprehensive dataset of these estimates by major crop groups between 1961 - 2019. Tabular data of the country- and crop-level predictions are made available as well as the 5-arcmin resolution gridded maps from our application, rendering an easy to use complete dataset. Subsequent analysis can be done both on the tabular data and the outputted maps, such as a trend analysis of fertilizer application rate or causal discovery to identify drivers of fertilizer application rate. Furthermore, our dataset can be leveraged as a source in other models where for example yield, ecological impact or fertilizer pricing can be seen as the output rather than use.

Our results represent an improvement and advance in efforts to evaluate historical fertilizer consumption for different crop groups and fertilizers. However, as demonstrated during the validation process, this approach still has limitations that data source users should be made aware of. The limited amount of available data for some crops, nutrients, and regions can lead to biases, particularly in regions such as Africa, during certain years, especially in the 60s, and for certain nutrients, mainly K_2O. Hence, the ML approach can be sensitive to outlying data points or noise and the limited data can make it prone to overfitting, which was mitigated as much as possible in the CV setup. In addition, our model is trained on data provided by global datasets [132–138, 147–153], which means that while our predictions may align closely with them, it is essential to acknowledge that they might diverge from national data mainly due to the difference between the two data sources as highlighted by the validation. This discrepancy between global and national databases such as the USDA [154] or DEFRA [166] databases highlights the complexity of accurately capturing historical fertilizer consumption trends across different regions and crop types. Moreover, the gridded cropland data provided by the HYDE 3.3 project [146], is inconsistent with the one from satellite-derived land use (e.g., China and India [310, 311]) or data derived from a national census at regional scale (e.g., USA [312]), as stated by Adalibieke et al. (2023) [126]. Furthermore, utilizing neighboring cells to allocate harvested areas across different crops, as well as leveraging the EARTHSTAT map [145], implies some assumptions (see Eqs. (2.6) to (2.9)). The main assumption is the suggestion that the distribution pattern of a specific cell mirrors that of its neighboring cells, which constrains potential changes in cropland over cells. The consistent use of the EARTHSTAT map [145] of the year 2000 also assumed that the crop group distribution of harvested area remains constant over time between 1961-2019. Finally, it is important to recognize that there are additional uncertainties stemming from the utilization of various data sources and methodological decisions within each data source, but these lie beyond the scope of our study.

Nevertheless, our study extends the current literature by providing a more detailed historical geospatial distribution of fertilizer application rate by crop and using ML to obtain detailed predictions with high precision. The detailed description and open-source code, in combination with the limited data sources used and ability to forecast, also make the method reproducible and easy to extend to forecast fertilizer application rate. In addition,

our approach does not entail any assumptions, making it more flexible and robust than precious studies. Future research can build upon our study by expanding on more detailed specific fertilizer application rate. Considering the frequency of fertilizer application as well as the timing can be valuable for future research on the evaluation of fertilizer effectiveness and use. In addition, our study focuses on broad fertilizer applications, however, more detailed maps can be made for different types of specific fertilizers considered in our study (e.g., N fertilizer types). Furthermore, the time granularity of our maps can be improved. In addition, satellite data can be used to obtain even more fine-grained predictions, both in regions and more detailed time periods. Finally, a deeper investigation into the drivers of fertilizer application rate could enrich our understanding. While our focus has primarily been on the explainability of our model, exploring methodologies such as causal discovery or causal ML within a temporal setting could unveil the drivers of fertilizer application rate over time, potentially providing valuable insights and facilitating more detailed predictions.

Code availability

Our Python (3.10.3) code, encompassing the model training, prediction generation, SHAP value computation, model validation and plot creation, as well as the R (4.2.2) scripts made for map generation are made available alongside the provided data map resources [313]. Open source packages used in the code are tabulated with their respective version in Table B.3. Access to these resources is available at the designated location [307, 313].

Chapter 3

From intensification to decline:

Crop-specific patterns of fertilizer use intensity

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Author contributions. All authors contributed to the study design. F.C. compiled the data. I.J. and F.C. developed the models and wrote the code. I.J. produced the visualization, I.J. and F.C. drafted the paper. All co-authors discussed the methods and results and reviewed and commented the chapter.

Abstract

With growing global concerns about the environmental impacts of fertilizer use, understanding historical trends is critical for achieving sustainable agricultural practices. However, existing analyses often lack the granularity to capture the complex, crop-specific dynamics driving these trends. We overcome this limitation by developing a novel framework that integrates a modified technology adoption model with Bayesian inference to quantify Nitrogen (N), phosphorus pentoxide (P_2O_5), and potassium oxide (K_2O) fertilizer use across global, regional, and national scales for thirteen key crop classes. Our framework accurately captures >90% of observed fertilizer use trajectories, revealing distinct patterns of intensification and, critically, diverse post-peak behaviors previously masked by aggregated analyses. This marked diversity in peak timing and intensity underscores the pivotal role of context-specific socioeconomic and environmental factors in shaping fertilizer use, highlighting the need for regionally tailored strategies to promote sustainable nutrient management and mitigate environmental risks.

Introduction

The use of natural substances such as guano, manure and midden as fertilizers to enhance plant nutrition and increase crop yields began as early as 6000 Before Common Era (BCE) and developed independently in various human cultures between 6000 and 2000 BCE [30–32]. The production of artificial (inorganic) fertilizers, however, did not begin until the 19th century CE, following discoveries by, among others, Karl Sprengel and Justus von Liebig, about the role of chemical elements (nutrients) in plant growth [1, 2]. These breakthroughs laid the foundation for the inorganic fertilizers industry, from the first commercial production of superphosphate of lime in 1843 [2] to the present-day use of more than 200 Tg of inorganic fertilizers annually [314]. Over the last 170 years, the global use of inorganic fertilizers has become indispensable for food production and, by extension, human nutrition [63, 315]. Today, inorganic fertilizers are the primary means of replenishing the N, Phosphorus (P) and Potassium (K) removed from soils during crop harvesting [89], with at least 30-50% of global crop production relying on their use [63, 315].

N, P and K are used in fertilizers because they play key roles in plants. They are fundamental components of biomolecules such as nucleotides, proteins, and membrane lipids [5, 121, 316, 317] and they are crucial for plant processes such as energy metabolism, water transportation, growth and reproduction [5, 121, 316, 317]. While the widespread application of N, P and K inorganic fertilizers ('fertilizers' hereafter) has increased crop yields and sustained the growth of the human population, it has also strongly altered the pre-industrial biochemical cycles of these elements [3–5]. The changes induced in the N and P chemical cycles are among the main concerns of global change [6] due to their impacts on

the water pollution and eutrophication [96, 318], emissions of greenhouse gases [319], loss of biodiversity [320, 321] and soil degradation [322, 323]. The social and economic impacts and implications of fertilization have also sparked extensive research into topics such as the risks of food security from vulnerabilities in the fertilizer market [54], the potential depletion of P and K mining resources [50, 55], or the impact of fertilizer prices on crop production and food security in Africa [324].

The (Food and Agriculture Organization (FAO)) estimates that approximately 120 Tg of N, 45 Tg of P_2O_5, and K_2O are applied each year to agricultural soils globally [314]. The historical pathways that have led to this point, however, differ across nutrients, regions and crops. Numerous examples illustrate the differences across nutrients and regions. A prime example of the different evolution of the use of the three nutrients is the invention of the Haber-Bosch process in 1908 [2], which increased the supply of N and altered the ratios of nutrients applied to agricultural soils. In 1913, before the implementation of the process on an industrial scale, the world consumed 0.73 Tg of N [2]; 0.86 Tg of K_2O [325], and around 1.5 Tg of P_2O_5 [325]. Global N consumption surpassed that of P_2O_5 and K_2O 50 years after the global expansion of industrial ammonia production [326] and the use of N is now more than double the use of P_2O_5 and K_2O [314]. A good example of regional differences in the evolution in fertilization is the comparison between African and Latin American (here defined as South America, Central America and Mexico) countries. The intensification of fertilizer use in both regions was similar in 1950, at approximately 1.2 kg of N and P_2O_5 ha^{-1} of cropland, and < 1 kg ha^{-1} for K_2O (estimated based on [88, 326]). The consumption per hectare of N, P_2O_5, and K_2O by 1980, however, remained below < 10 kg ha^{-1} in Africa, but their use in Latin America exceeded 15 kg ha^{-1} [314]. The intensity of fertilizer use in 2019 remained < 15 kg ha^{-1} for all nutrients in Africa but surpassed 40 kg ha^{-1} in Latin America [314].

Fewer available sources illustrate the differences in fertilization across crops, but a well-documented illustration is the evolution in the United States of America (U.S.A.). The development of the fertilizer industry in the U.S.A. was closely tied to cotton production, and over half of the nation's use of commercial fertilizers by 1880 was concentrated in states specializing in cotton cultivation [190]. Fertilization was therefore adopted for cotton before other crops [190]. The proportion of total fertilizers used for cotton production has steadily decreased from 28% in 1929 [190], to 9.7% in 1950 [190] and to 4.2% today [132]. The proportion used for wheat, however, has increased from 9.7% in 1950 [190] to 12.7% today [132]. The N application rates since 1960 have remained between 60 and 80 kg/ha for cotton [327], while for wheat the rates have increased from 20 kg ha^{-1} to 80 kg ha^{-1} nowadays [327]. This pathway is completely different in other countries, where fertilizer intensification started in other decades and is linked to other crops. Fertilization in Argentina, where some data are available, was first linked to intensive and semi-intensive crops, such as sugar cane, fruits and vineyards [328], but is currently driven by cereals and soybean [132]. In Argentina, the production of sugar cane consumed around 50 kg N ha^{-1} in 1962, which accounted for at least a third of the N-fertilizers used in the country [328]. N consumption per hectare has since increased by 77% for sugar cane [132, 328] and by 6541% for all croplands together [314], reducing the impact of sugar cane on total N consumption in the country to < 3% [132].

The intensity of fertilizer use, defined as the annual amount (in kg) applied per hectare, has likely reached its maximum in some countries, such as China, and might even have declined, like in the former Soviet states and other European countries [314]. The adoption of fertilization in other regions, such as most of the countries in Sub-Saharian Africa, however,

has not even started [329]. While prior studies examined regional fertilizer trends [127, 330], none addressed crop-specific intensification globally. Our study bridges this gap by leveraging newly available crop-level data [331] to discuss how economic, agronomic, and policy drivers may shape fertilizer-use pathways. Characterizing these historical patterns of the intensity of fertilizer use across crops, nutrients and countries can help to elucidate how policy and patterns of intensification have co-occurred and inform objectives for sustainable policy changes.

We used the technology adoption framework [332] as a baseline to assess and compare the adoption and intensification of fertilizer use for different regions and crops. Theoretical models of technological diffusion typically associate the cumulative adoption of a technology with an S-curve, characterized by slow initial growth, a subsequent rapid increase, and a plateauing behavior [333]. We hypothesized that patterns of the intensity of fertilizer use would be linked to this theoretical framework, where adoption is driven by the goal of maximizing profitability subject to constraints [334]. For example, a seminal study has linked the diffusion of hybrid corn in the U.S.A. to a logistic increase as early as 1957 [335]. Extensive research on agronomy and fertilizer adoption has since used S-curve models to describe its adoption at the local level [336]. Fertilizer adoption refers to the proportion of producers (farmers) using fertilizers, which typically follows a temporal S-curve trajectory due to social learning and market penetration [332, 333]. Our study, however, focuses on the average amount of fertilizer (in kg) used per hectare annually in a country or region, which we refer to as fertilizer use intensity. Although it is closely related to fertilizer adoption, fertilizer use intensity is a continuous variable influenced by farmer adoption, but also by economic, environmental, and policy-related factors [334]. The trajectory of fertilizer use intensity may thus not strictly adhere to the traditional S-curve.

A different curve could therefore better describe the evolution of fertilizer use intensity. We modified the standard S-curve model by introducing a lognormal adjustment term to account for post-peak deviations in fertilizer use intensity. This modification provides a simple approach to describe the potential decreases in intensity due to short-term supply problems and policy interventions of technological improvements, which can alter trends of intensification. The use of a lognormal decay captures an asymmetric trend in which the decay slows in later periods. We hypothesized that these changes would alter the temporal patterns by modifying the asymptotic behavior of the S-curves with a non constant decrease over time. This simple approach allowed us to model post-peak decays without the need to explicitly incorporate these complex country-specific socioeconomic factors, given the high variability of national policies and economic conditions that may temporally vary S-curve maxima. Previous research has applied similar lognormal functions in both socioeconomic [337] and environmental contexts [338].

The historic trajectories of global and regional N, P_2O_5, and K_2O fertilizer use intensification were assessed at three levels:

1. nutrient × region/global (from 1927 to 2019, globally and for six regions)
2. nutrient × crop × region/global (from 1961 to 2019, globally and for six regions and for thirteen major crop classes)
3. nutrient × crop × country (from 1961 to 2019, for the countries with high harvested crop areas and for thirteen major crop classes)

The fertilizer use intensity framework was fitted for each of these 922 trajectories using Bayesian inference. The Bayesian approach was chosen because of its flexibility in model specification, its capacity to incorporate prior knowledge and the ability to produce robust

estimates, even with relatively short time series [339]. By estimating the critical points of the fertilizer use intensity framework for all temporal trajectories, we were able to compare the historic evolution of fertilizer use across nutrients, crops, regions and countries. These comparisons provide insights into the spatial and temporal heterogeneity of fertilizer application and help to identify patterns relevant to food security, sustainability and strategies of nutrient management.

Methods

To analyze long-term trends in rates of fertilization, we first assembled data across different spatial resolutions; global, regional, and national; focusing on both overall fertilizer use and crop-specific patterns. Motivated by empirical patterns and literature-based expectations of how fertilizer use has evolved historically, we formulated a piecewise mathematical function designed to capture both increase and potential decline phases in rates of fertilization. We employed a Bayesian inference framework to estimate the parameters of the piecewise function and quantify uncertainty. This allowed us to incorporate prior knowledge while flexibly fitting the complex trends of crop-specific and overall rates of fertilization at the different spatial resolutions. Lastly, the reliability of our results was evaluated in terms of convergence, robustness, and sensitivity to prior assumptions.

Data sets on global, national and regional levels

We began by constructing a comprehensive data set of N, P_2O_5, and K_2O use intensity in croplands, leveraging both historical records and modern databases. This data forms the basis of our long-term analysis of fertilizer adoption at regional and global scales. To understand fertilizer application at the level of individual crops, we next focused on national-scale data from 1961 to 2019. This data includes countries and other territorial units as defined by FAOSTAT (Table C.1). Using the national crop level data, we aggregated values to regional and global scales, allowing us to investigate broader patterns in crop-specific fertilization trends (Regional and global crop-level fertilizer use intensity). We grouped the countries using the region classification detailed in Fig. C.1 and Table C.1.

Regional and global fertilizer use intensity

We first compiled a comprehensive data set of the intensity of N, P_2O_5, and K_2O in croplands since data first became available in 1927 [340]. FAO provided a comprehensive data set on the intensities of N, P_2O_5, and K_2O in cropland at the national and regional levels beginning in 1961 [314]. For the earlier period of fertilizer adoption (pre-1961), we compiled existing global data sets at the country level from FAO and other sources for 1927, 1938 and 1950 to 1960 [326, 340–343]. The data sets from 1927 to 1960 presented two main issues: (a) they lacked information on fertilizer consumption in the Union of Soviet Socialist Republics (USSR) and mainland China, and (b) they included fertilizer consumption on all agricultural land, but consumption in permanent grassland, not only cropland, was high in a few countries before 1960. To address the first issue (a), we used the limited information available for these two countries [344, 345]. We assumed that fertilizer consumption equaled production in the USSR because only production data were available and fertilizer exports from the USSR appeared to be minimal before 1961 [345]. For mainland China, we assumed the same nutrient proportions as in 1961 [314] and applied them to earlier years because only data

on total NPK consumption existed [344]. To address the second issue (b), we excluded the fraction of fertilizer used on grassland in the U.S.A. and Australia, the only two countries with reliable information for 1938–1960. For the U.S.A., we performed linear interpolation for the years with available data [190] and for Australia, we considered previous research estimates [331]. Despite these adjustments, our assumptions likely resulted in small overestimations for some regions, particularly Europe, because some countries may have used a fraction of the fertilizers used in agriculture prior to 1960 for grassland. Finally, to calculate the fertilizer use per hectare of cropland, we calculated the total cropland area for each region using cropland maps from the HYDE v3.3 project [88], country boundaries from the CShape data set [346] and the regional country classification as defined in Fig. C.1 and Table C.1. We used the cropland areas for 1930 and 1940 to estimate fertilizer consumption per hectare for the years 1927 and 1938 respectively.

National crop level fertilizer use intensity

The analysis of the trends of crop-specific rates of fertilization was focused on 1961–2019, because data for other periods were scarce. We used an intermediate result of the data set that was previously developed on crop level fertilizer use per hectare [331]. In Coello and Decorte et al. (2025) [331], reports and scientific data about crop level fertilization in different countries over the period 1961-2019 were compiled and, to assess the large ratio of missing data, the rates of fertilization were predicted using Histogram-based Gradient Boosting [331]. The resulting data set contains complete information on N, P_2O_5, and K_2O use per hectare for thirteen crop classes (wheat, maize, rice, other cereals, soybean, oil-palm fruit, other oilseeds, roots and tubers, sugar crops, fiber crops and other crops) for 173 countries from 1961 to 2019.

Regional and global crop-level fertilizer use intensity

Lastly, the regional and global annual values of fertilization at the crop level were calculated using the average country data in each region (Table C.1), weighted by the annual harvested area of the crop in each country [347].

Piecewise function to represent the trends

A combination of literature review and a visual inspection of the time series data identified a characteristic pattern across fertilizers, crops, and countries: fertilizer use intensity generally started with an S-curve growth over time (intensification phase), peaking ($\sim A$) at a specific year (X_{max}) and sometimes followed by a sharp or smooth decrease, leading to either stabilization or a secondary growth. Based on this observation, we hypothesized that the data could be adequately modeled using a piecewise function consisting of a logistic increase that transitions at the observed peak (X_{max}) to a negative lognormal function. We fixed the transition point (X_{max}) at 99% of the logistic asymptotic maximum (A) to ensure that the lognormal function started at the end of the logistic increase.

In the final piecewise function (Fig. 3.1, see Appendix C.2 for a complete derivation), ΔX_1 is the time interval between the inflection point (X_0) and the peak (X_{max}), ΔX_2 is the time lag between the peak and the minimum of the lognormal decay (X_D), B scales the decrease in fertilizer use intensity and σ is the scale parameter of the lognormal term. We also calculated other parameters for further comparisons: X_{start} marks the beginning of the

growth phase and is fixed at 1% of the logistic asymptotic maximum (A), and D quantifies the intensity of the decay (Fig. 3.1).

Using this formulation, a potential increase in intensity after the lognormal decrease cannot exceed the intensity at X_{max}, because the lognormal part approaches A asymptotically. Fits of specific cases that contain a local maximum and a larger secondary increase will therefore ignore the local maximum, ensuring that the estimated X_{max} will be at the global maximum.

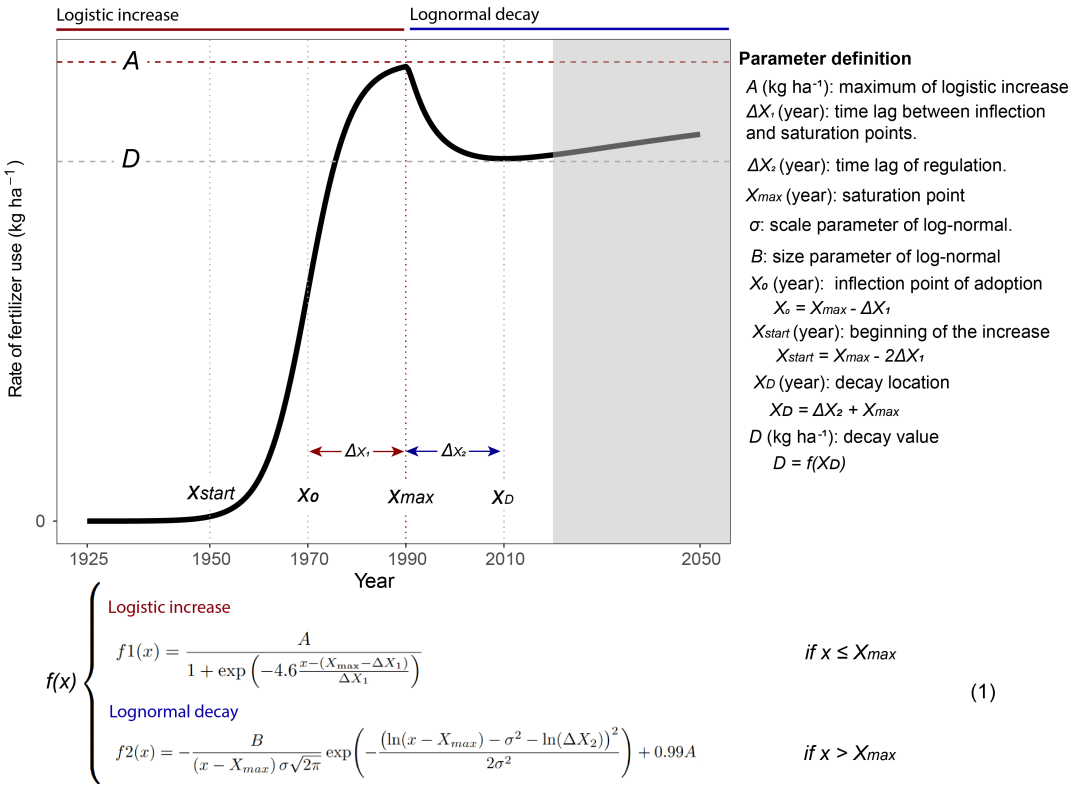


Figure 3.1. Piecewise function consisting of a phase of logistic increase and an phase of inverse lognormal decay.

Bayesian inference

The piecewise function was fitted using Bayesian inference, which was implemented in *Stan* [348] using the *rstan* interface (version 2.26.6) in *R* (version 4.3.1) [349]. The function was first fitted for the intensity of use of total N, P_2O_5 and K_2O fertilizers at a global scale and for each region (from 1927 to 2019). The function was subsequently fitted to crop-specific N, P_2O_5 and K_2O fertilizers at the global level and by region (from 1961 to 2019) to further investigate variations in intensity across crops. To extend the analysis to country resolution, the analysis was repeated for the intensity of use of crop-specific N, P_2O_5 and K_2O fertilizers for the countries with more than 1% of global harvested crop area since 1990 according to FAOSTAT [347].

The function parameters for each time series were estimated by maximizing the posterior probability given the observed data. The likelihood was modeled assuming Gaussian errors,

and a combination of informative and weakly informative priors was used. The following sections specify the prior distributions and the posterior sampling methodology.

Prior specification

The logistic parameters were sampled from the following weakly informative priors for global and regional non-crop-specific fits:

$$A \sim \mathcal{N}(50, 50) \tag{3.1}$$

$$X_{max} \sim \mathcal{N}(60, 100) \tag{3.2}$$

$$\Delta X_1 \sim \mathcal{N}(20, 50) \tag{3.3}$$

with the constraint that A and ΔX_1 must be > 0. To encompass all plausible values for A, X_{max}, and ΔX_1 we used weajly informative priors that allow flexibility while avoiding implausible extremes. The constraints ensured that impossible values, such as negative A and ΔX_1 could not occur. The prior distribution for A, $\mathcal{N}(50, 50)$, assigned 15.9% probability to values > 100, and 21.2% to values < 10. This reflects the belief that high national fertilizer use intensity peaks (>100) are possible (A), but uncommon. For instance, according to the most recent global report from 2018 on fertilizer use by crop in the top fertilizer-consuming countries, only 13.84% of crop-country nutrient combinations exceed 100 kg ha^{-1} [132]. Similarly, the priors for X_{max}, and ΔX_1 on average defined the year in which the logistic growth finished (99% of A) in 1988, and the subsequent potential decay ΔX_1 20 years later. The large standard deviation of the priors, however, assigned probabilities of > 25% to X_{max} occurring before 1930 or after 2050. Although there is no strong prior information to justify the specific location of the centers of the distributions, the large standard deviation provides enough flexibility to place the parameter estimates across a wide and plausible range of years. Furthermore, sensitivity analyses (Sensitivity analysis) confirmed that these priors had only a weak influence on the likelihood.

For crop-level fits, we informed the logistic priors based on the non-crop-specific fertilizer use per hectare of cropland in a country or region ($Av_Fertilizer_Cropland$). Using the 90% quantile of $Av_Fertilizer_Cropland$ as a robust estimate of the maximum intensity ($\hat{A}$), the first year when $Av_Fertilizer_Cropland$ reached $\hat{A}$ ($\hat{X}_{max}$) and the first year (before $\hat{X}_{max}$) when $Av_Fertilizer_Cropland$ reached $\hat{A}/2$ ($\hat{X}_0$), we defined the following nutrient and country/region-specific priors:

$$A \sim \mathcal{N}(\hat{A}, 20) \tag{3.4}$$

$$X_{max} \sim \mathcal{N}(\hat{X}_{max}, 10) \tag{3.5}$$

$$\Delta X_1 \sim \mathcal{N}(\hat{X}_{max} - \hat{X}_0, 10) \tag{3.6}$$

We aimed to link crop-level fits with country- or region-level information while maintaining sufficient flexibility for crop-specific variations using informative priors. For example, the standard deviation assigned to A ensured that 32% of the probability mass was outside the interval $\hat{A} \pm 20$ kg ha^{-1}. Similarly, the standard deviation assigned to the X_{max} and ΔX_1 priors ensured that 32% of the probability mass of the two priors was after $\hat{X}_{max} \pm 10$ or $\hat{X}_0 \pm 10$ years.

For all fits, the lognormal parameters were assigned the following weakly informative priors:

$$B \sim \mathcal{N}(1500, 500) \tag{3.7}$$

$$\sigma \sim \mathcal{N}(1, 3) \tag{3.8}$$

$$\Delta X_2 \sim \mathcal{N}(25, 20) \tag{3.9}$$

with the constraint that B, σ and ΔX_2 must be > 0. These priors ensured flexibility in modeling the potential decay. The prior specification for ΔX_2 centered the decay 25 years after reaching X_{max}, while allowing wide variation. Specifically, 32% of the probability mass of the prior was before $X_{max} + 5$ and after $X_{max} + 45$, ensuring sufficient prior uncertainty in whether the decay occurred immediately after X_{max}, or extended beyond the study period. This prior specification could influence the models beyond the study period, potentially generating artificial decays, but we did not consider this influence as a limitation, because the goal of our study was to describe past trends in rates of fertilization and not to forecast future patterns. Parameters B and σ are not easily interpretable. Therefore, we conducted a prior predictive check (see Appendix C.3) to show the flexibility of the selected values, together with the other priors used.

The final parameter of the model, τ, represented the standard deviation of the residuals. We specified a weakly informative prior for this parameter, allowing large values (up to 100), but constraining to positive values by setting a lower bound of 0.

$$\tau \sim \mathcal{N}(0, 50) \tag{3.10}$$

3.0.0.1 Sampling

We used the No-U-Turn Sampler (NUTS) [350] for posterior sampling, running four parallel Markov chains with 8000 iterations each (4000 warm-up, 4000 sampling). To improve chain convergence while maintaining an automated process without the need for manually tuning the parameters, each time series was fitted using three combinations of the average probability of accepting a posterior draw ($adapt_delta$) and the maximum size (in exponents of two) of the binary tree size in the NUTS algorithm ($max_treedepth$):

1. $adapt_delta = 0.8$ and $max_treedepth = 10$
2. $adapt_delta = 0.9$ and $max_treedepth = 10$
3. $adapt_delta = 0.99$ and $max_treedepth = 15$

Validation

The Bayesian models were validated in multiple ways. Convergence, model robustness and accuracy were evaluated, and constraints were introduced to retain only reliable fits (see Validity constraints). Moreover, a sensitivity analysis was conducted to evaluate the extent to which prior assumptions influenced the posterior results, helping to validate the robustness of our findings (see Sensitivity analysis).

Assessing convergence, robustness and accuracy (Validity constraints)

We assessed the number of divergences, potential scale reduction factor ($\hat{R}$) and effective sample size (ESS) to ensure good convergence and robutness for each fit. The accuracy was measured using the Bayesian Coefficient of Determination (R^2), which accounts for uncertainty in the model parameters and predictions [351]. Fits with divergences $> 1\%$, average $\hat{R} > 1.1$ or average ESS < 400 were discarded from the three models obtained by varying $adapt_delta$ and $max_treedepth$. We then selected the fit with the highest R^2.

Sensitivity analysis

We performed a sensitivity analysis using the R package *Priorsense* [352] to assess the impact of the priors on the posterior distribution. After fitting each model, the priors were powerscaled with varying power α. This scaling led to perturbed posterior distributions, which were compared with the base posterior distribution visually and using the cumulative Jensen–Shannon distance (CJS_{dist}) [353]. This measure of distance is symmetric and bounded by 0 and 1, with 0 indicating equal distributions. Many measures of distance are based on probability density functions, but the CJS_{dist} compares cumulative distribution functions, which can be efficiently estimated from the Monte Carlo draws without the need for estimates of kernel density or assumptions about smoothness [352].

Visualizations were conducted using *Python* (version 3.10.15) [354].

Results

Of all fitted trends, 92.7% had a convergence and robustness within accepted constraints (see Validity constraints) and an $R^2 > 0.5$. Detailed results and discussion of prior predictive checks and of prior sensitivity analysis of all fits are included in Appendix C.3. To summarize, most CJS_{dist} values were < 0.25, with the most extreme cases as high as 0.84. The perturbed posterior distributions of the cases with the highest CJS_{dist} values had medians within the Credible Interval (CI), so we deemed the observed prior sensitivities acceptable.

The following sections present the fitted trends of the global and regional non-crop-specific time series, the global and regional crop level time series and the country and crop level fits for crop classes wheat, maize, rice and soybean. The results for the other crop classes (other cereals, oil-palm fruit, other oilseeds, vegetables, fruits, roots and tubers, sugar crops, fiber crops and other crops), as well as other defining points of the trajectories, are presented in Appendix C.4.

Global and regional trends

The trends in the global and regional uses of N, P_2O_5 and K_2O fertilizers from 1927 to 2019 (Fig. 3.2) were obtained by fitting the piecewise function to the crop generic timeseries (Fig. 3.1). The shaded areas are the 95% CI, which are defined as the highest posterior density intervals, i.e. for each year, the smallest (disconnected) interval that contained 95% of the posterior samples. The application of P_2O_5 for Northern America did not meet the criteria for validity (i.e. $R^2 > 0.5$, average $\hat{R} < 1.1$ and average ESS > 400; Validity constraints) and was therefore omitted from the plots.

Most of the fits followed a logistic increase with no or a flat lognormal phase. The global use of all three fertilizers plateaued at the beginning of the 21st century following a logistic increase (Fig. 3.2 - upper plots). This was also the case on a regional level for Africa, Northern America, Latin America (for N) and Oceania (for N and K_2O), while the rate was still increasing for Asia and Latin America (for P_2O_5 and K_2O) (Fig. 3.2 - lower plots). In contrast, fertilizer use intensity in Europe peaked around 1990, then sharply decreased and has since been gradually increasing again. P_2O_5 use in Oceania peaked even earlier (between 1940 and 1950) and has since been decreasing.

The rates of N application in Latin America and Oceania were special cases. Their fits were only defined by a logistic increase (Fig. 3.2 d), but the original data for Latin America and Oceania clearly indicated local maximum around the years 1987 and 2000 respectively

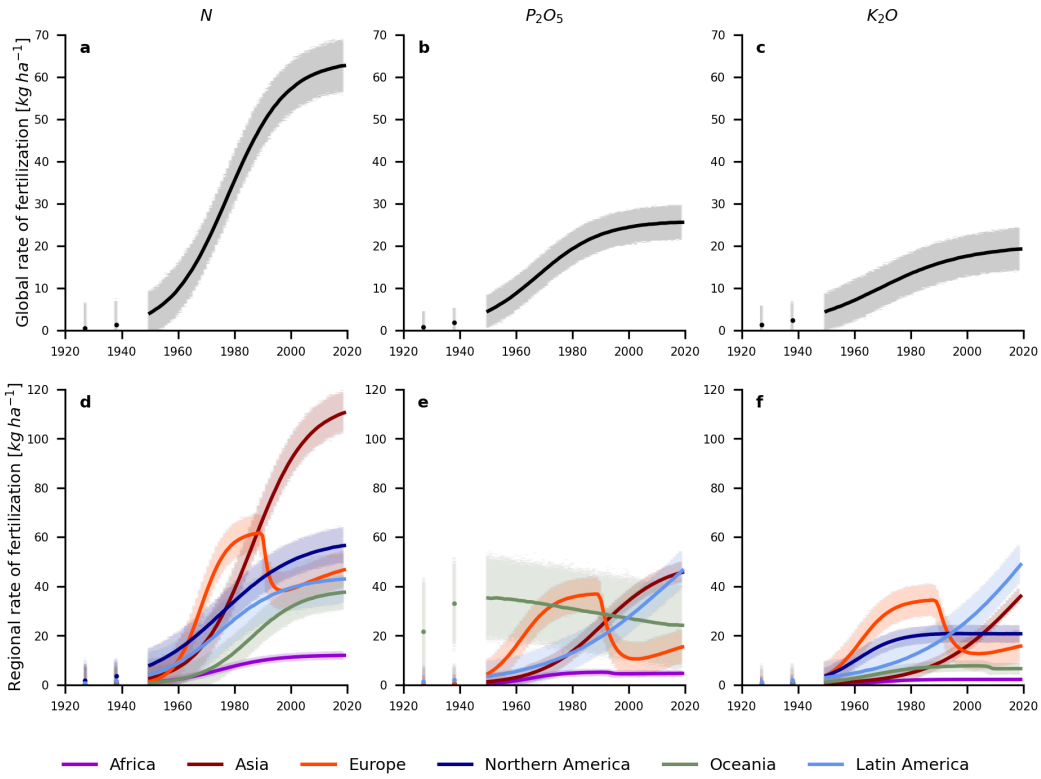


Figure 3.2. Global (upper plots) and regional (lower plots) intensities of N, P_2O_5 and K_2O use from 1927 to 2019. Medians and 95% credible intervals (highest posterior density intervals) are indicated with lines and shaded areas, respectively.

(Fig. C.4). The intensity of N in later years, however, increased beyond these local maxima, which produced a fitted logistic curve with an estimated maximum at the global maximum of the data.

Global and regional crop level trends

The global and regional trends differed among the crops. Fig. 3.3 depicts the peaks in global and regional fertilizer use intensity for wheat, maize, rice and soybean. These peaks, defined as the estimated saturation year (X_{max}) and 99% of the estimated logistic maximum ($0.99A$), are summarized by the geometric median and the 95% credible region. This 95% credible region was defined as the 95% highest posterior density region, i.e. the smallest (disconnected) two-dimensional interval that contained 95% of the posterior samples. Fits with $R^2 < 0.5$, average $\hat{R} > 1.1$ or average ESS < 400 were omitted from the plots.

As was the case for the non-crop-specific N applications in Latin America and Oceania (Fig. C.4), local maxima were typically disregarded when fitting the piecewise function. The estimated peaks therefore represented global maxima in fertilizer use intensity. Peaks occurring before 2019 suggest that the fertilizer rate has since plateaued or decreased, while peaks after 2019 reflect projections based on assumed continued logistic increase. As this assumption may not hold in many cases, these projections are only included to illustrate

potential trends, and should not be interpreted as forecasts. The projected peaks also often had wide horizontal credible regions, indicating greater uncertainty.

Several patterns emerged: Europe reached all its fertilizer use peaks before 2000, and Africa has also already reached its maxima, which were the lowest of all regions. Exceptions for Africa were the N application for wheat cropland, which was projected to peak around 2040, and the application of K_2O for rice and wheat cropland, which were excluded from the figure because they did not meet the criteria for validity (Validity constraints). In contrast, Latin America was expected to reach all its fertilizer use peaks in the future, many after 2060, considering the current trajectories. The estimated peaks for Asia were either recent or projected for the future, and the intensity in Northern America also had maxima both in the past and in projections. Oceania had a distinct pattern: peaks for P_2O_5 and the application of K_2O for soybean occurred very early, mostly before the beginning of the data set in 1961 (Fig. 3.3), similar to the non crop-specific intensity (Fig. 3.2). The peak rate of N in Oceania, however, was predicted to occur in the future. Finally, global years for peak rates varied from 1990 (for the applications of P_2O_5 and K_2O on wheat cropland) to after 2060 (for the application of P_2O_5 on soybean cropland and the application of K_2O on rice and soybean cropland).

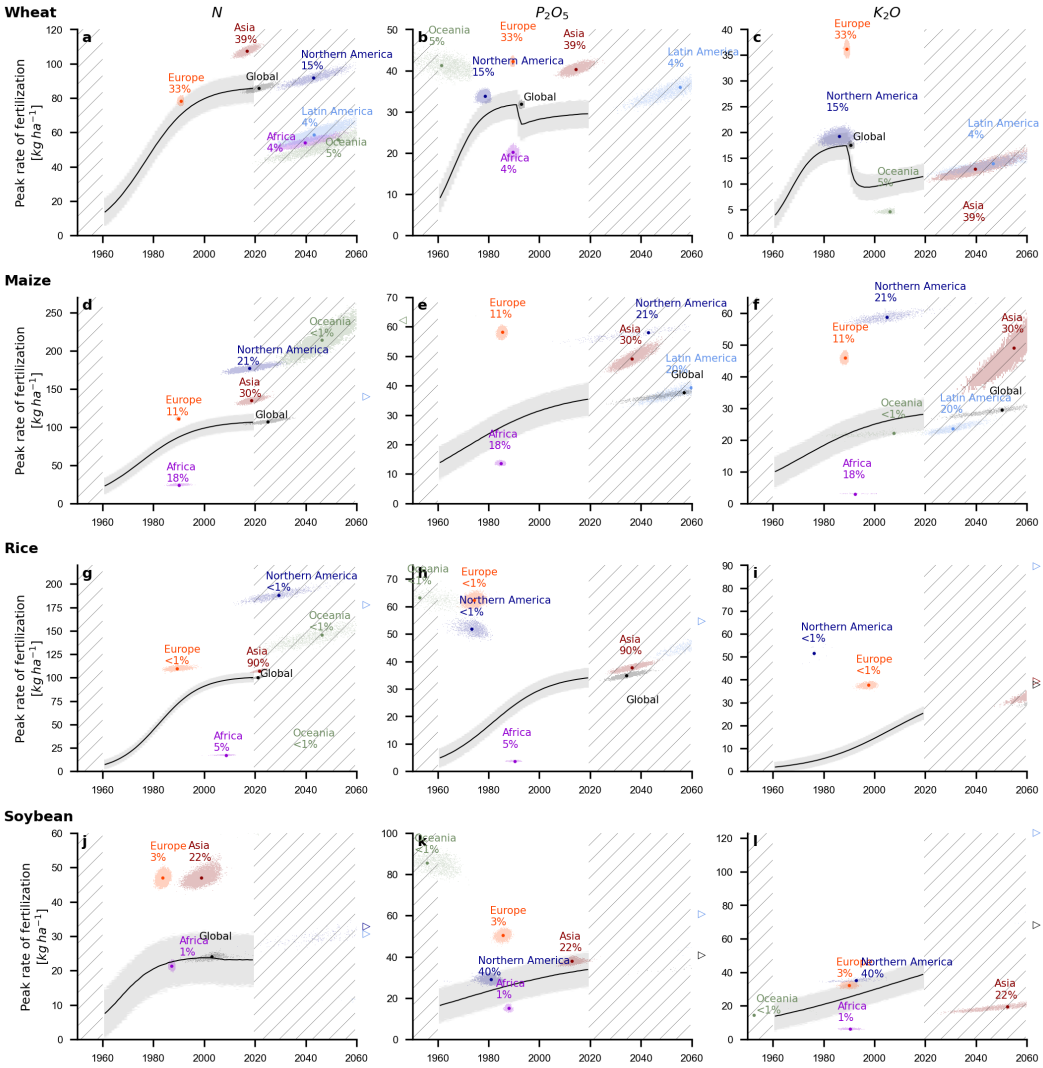


Figure 3.3. Peaks in global and regional intensities of N, P_2O_5 and K_2O for wheat (a-c), maize (d-f), rice (g-i) and soybean (j-l). Geometric medians and 95% credible regions (highest posterior density regions) are indicated by dots and shaded areas, respectively, and the global trendlines (with 95% highest posterior density intervals) until 2020 are in black. The percentages are the average areas of harvested crops of the regions since 1990 relative to the global average. Estimated peaks after 2060 are indicated with arrows.

National crop level trends

Fig. 3.4 depicts the peaks in the intensity of N, P_2O_5 and K_2O use intensity, defined by (X_{max}, $0.99A$), for the countries with > 1% of the global harvested area of wheat, maize, rice and soybean, respectively. Fits with $R^2 < 0.5$, average $\hat{R} > 1.1$ or average ESS < 400 were omitted from the plots.

The CI were often horizontally wide, similar to the regional peaks in fertilizer use intensity (Fig. 3.3). China was consistently among the countries with the highest estimated

peak rates for all fertilizers and all four crops. Logically, the peaks were similar for Australia and Oceania.

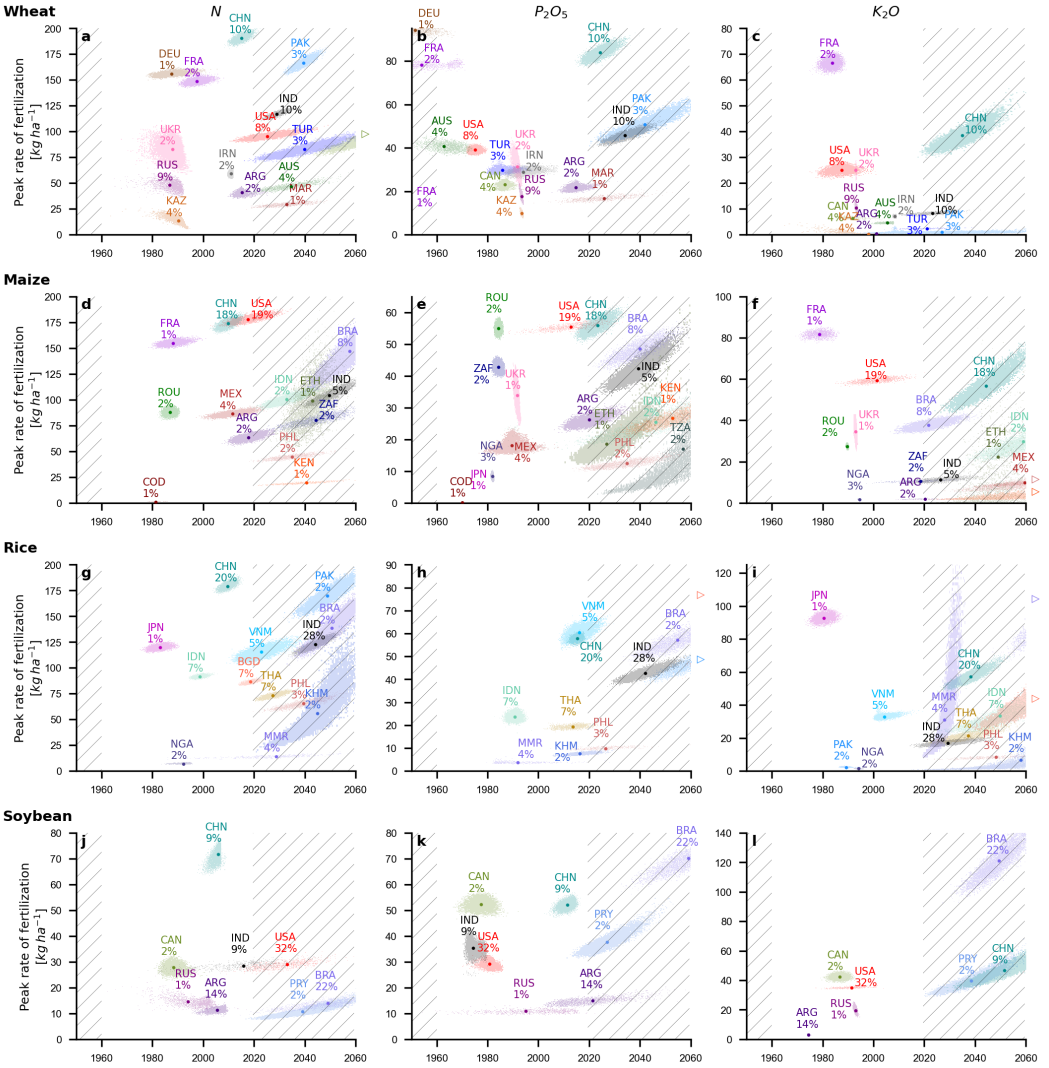


Figure 3.4. Peaks in intensities of N, P_2O_5 and K_2O use for wheat (a-c), maize (d-f), rice (g-i) and soybean (j-l) in countries with > 1% of the global harvested area of each crop. Geometric medians and 95% credible regions (highest posterior density regions) are indicated by dots and shaded areas, respectively. Countries are abbreviated using their three-letter ISO codes [355]. The percentages are the average areas of harvested crops in the countries since 1990 relative to the global average areas. Estimated peaks after 2060 are indicated with arrows.

Discussion

Our results indicate that the trends of fertilizer use intensity in croplands align with the proposed theoretical framework, as 93% of the fitted models converged, were robust and

achieved an R^2 greater than 0.5.

Comparison across regions and nutrients indicated that: 1) The increase over the last few decades (Fig. 3.2) has stagnated globally and also for most regions. Notable exceptions are the dip in the rates of all three fertilizers in Europe following the peaks, and the continued increase in fertilizer use intensity for P_2O_5 and K_2O in Latin America and for K_2O in Asia; 2) the adoption of N and K_2O in Europe, and of P_2O_5 in Oceania happened earliest; 3) the highest N fertilizer use intensity is reached in Asia, and current trends suggest that the P_2O_5 and K_2O intensities are currently and will in the near future remain highest in Latin America (Fig. 3.2 d,e,f). In some regions, especially in Africa, the rate of fertilization remained well below the global peaks (Fig. 3.2). The model effectively identified historical trends during the last decades, but further fertilizer adoption and intensification may occur in regions in which fertilizer use has plateaued or is low, such as Africa, as suggested by several scientists and promoted by various organizations such as the African Green Revolution Forum [356].

A comparison of global and regional patterns of fertilizer use intensification patterns across crops indicated similar trends for the three main cereals (wheat, maize and rice) and soybean for N, with stagnation occurring around the year 2000 at 100 kg ha^{-1} for the cereals and at 20 kg ha^{-1} for soybean (Fig. 3.3 a,d,g). In contrast, the period and intensity for the other nutrients varied (Fig. 3.3). The fertilizer use for wheat have declined after the peak whereas for the other three major crops have remained at the same levels of the peaks (Fig. 3.3). The country-level fits for all crops, while representing differences between countries within the same region, generally followed the broader regional trends.

Drivers of fertilizer use intensification

The potential reasons for the different trends across nutrients, crops, countries and regions are diverse and may vary or interact depending on the context. The following subsections describe how various factors can account for our results.

Relevance of a secure supply

While the onset and end of the global fertilizer use intensification occurred in different decades for each nutrient, the period of steepest increase (x_0) was between 1969 and 1979 for all nutrients (Fig. C.5). Differences in the historical pathways of nutrient production, supply, pricing, and global policies can explain why.

Fertilizer production before the invention of the Haber-Bosch process relied almost entirely on mineral sources [2]. While the phosphate rock deposits found in Florida (exploited since 1888) and carnallite deposits in Saxony (exploited since 1861) sustained the global demands for P and K during the end 19th century, the availability of inorganic nitrogen, which were mainly Chilean nitrates, did not cover the global demands at the beginning of the 20th century [2]. The historical lag between the exploitation of the Florida and Saxony deposits and the invention of the Haber-Bosch process is reflected in our results, which indicated a temporal lag in the onset of the global intensification of fertilizer use for the three nutrients. Our models indicated that the intensification of K_2O fertilizer began around 1898, 37 years after mining began in Saxony, the intensification of P_2O_5 started around 1916, 28 years after phosphate exploitation began in Florida, and the intensification of N began around 1931, 23 years after the invention of the Haber-Bosch process (Fig. C.5). These start dates for the intensification of P_2O_5, and K_2O use were estimated before the period covered by available data and therefore are highly uncertain, but these results suggest that the onset of

global fertilizer use intensification was mostly driven by the availability of supply. The dates also indicated that the time lag between resource discovery and the onset of intensification decreased with each new secure source of supply.

The notion that the intensification of fertilizer use requires a secure supply helps to account for the patterns in developed countries. For example, Germany, France and the U.S.A. were among the world's top 15 producers of wheat in the last century [347]. Their patterns of K_2O intensification (Figs. C.19 and C.20), however, differed due to their histories of national supply. The estimated start (X_{start}) and fastest increase (X_0) in K_2O intensification in wheat occurred earlier in Germany than in France, and earlier in France than in the U.S.A. (Figs. C.19 and C.20). This sequence is consistent with historical trends of production: K_2O was first produced in Germany, which remained the sole producer until 1924, when France took control of the Alsatian mines following World War I [34, 55]. The U.S.A. did not achieve self-sufficiency until the 1940s, relying on imports from France, and especially from Germany, often disrupted before the end of World War II [34, 55].

The comparison of the K_2O and P_2O_5 intensification between Australia and Canada is another example that illustrates this point. Both countries are high-income countries and are among the top global producers of wheat and other cereals [347]. The intensification of K_2O use was earlier in Canada, but Australia led the intensification of P_2O_5 (Figs. C.19 and C.20). Australia secured its national P_2O_5 supply in 1905 by gaining control over phosphate production in Nauru, a Pacific island once home to some of the purest and most accessible deposits of phosphate rock [83]. The exploitation of these deposits, which eventually led to their exhaustion, not only allowed an early intensification of fertilizer use in Australia, but also transformed Nauru into one of the most environmentally degraded nations [83]. In addition to the secure P_2O_5 supply, the ancient and weathered soils of Australia, which are poor in P [83], are also an important explanation of the wide use of superphosphates in Australia. This factor, however, will be discussed in further sections (Farmer profitability). In contrast to P_2O_5, the production of K_2O in Australia has been almost negligible, and the country relies strongly on imports [314]. The currently successful fertilizer industry in Canada was developed in connection with potash mining in the 1960s in the province of Saskatchewan, home of the largest known potash deposits in the world [55]. Canada is now a major producer of P_2O_5 due to the presence of large fertilizer companies such as *Nutrien* [314, 357] but imports all its phosphate rock because no deposits are currently being exploited domestically [358].

The global fertilizer supply for all three nutrients is now secured, because the production capacities of P_2O_5, K_2O, and N mostly exceeds global consumption [55, 359]. Only major events in the last 50 years such as the 1973 oil crisis, the 2008 financial crisis and the COVID-19 pandemic have affected production costs and disrupted international fertilizer trade, leading to temporary reductions in global and regional supplies [359]. Future long-term supplies, however, are not entirely guaranteed because several factors threaten global, and regional availabilities: (i) the limited lifetime of phosphate and potash reserves has raised concerns among researchers and policymakers over the last two decades [50, 59, 359], although estimates have varied widely, from decades to nearly a thousand years [50, 55, 59]; (ii) the depletion of phosphate reserves may not occur within the next century, but the projected increase in the global demand for P_2O_5 could exceed world production capacities during that time [359]; (iii) the concentration of phosphate and potash reserves in a few regions (Morocco and western Sahara for phosphates [50], and Belarus, Canada and the Russian Federation for potash [55]) makes national supplies in most other regions highly sensitive to geopolitical tensions, as demonstrated by disruptions in the potash market during World

War I [34] and the Russian invasion of Ukraine recently [360].

Farmer profitability drives intensification

The expected profitability also accounts for some of the differences in the timing (X_{start}, X_0, X_{max}), and the amplitude (A) of the intensification between countries and between crops within a country. The profitability of fertilizer use is optimal when the marginality earnings match the factor costs, i.e. when the costs of the inputs, application and management of the extra production match the economic return generated from the increases in production [7]. Some of the patterns can be attributed to changes due to subsidies. Subsidies in countries where farmers have limited purchasing power can play a key role in enabling fertilizer use, although the effectiveness of such programs has been widely debated [361]. Some results can be explained by temporal and regional differences in the implementation of subsidies, i.e. between targeted or universal subsidies.

For example, the results for Nigeria were closely linked to the historical programs for subsidizing fertilizer use and other agricultural policies. Due to its large cropland, Nigeria ranks among the countries analyzed for ten of the studied crops (Fig. 3.4 and Figs. C.19 to C.26), and most of the fits had a pattern characterized by local maxima in fertilizer use intensity, which were reached in the 1990s ($median(X_{max}^{NGA}) = 1993$) and have not been observed again in the 21st century. Untargeted fertilizer subsidies and federally financed fertilizer imports and distribution began in 1976 [362] and continued with varying intensity until the period of liberalization between 1992 and 1999 [363] when the government halted state-led imports, privatized distribution and abolished the subsidies [363]. Fertilizer consumption thus decreased sharply in the late 1990s, prompting the government to reinstate some of the subsidies [363]. Our results represent this decrease ($median(X_D^{NGA}) = 2002$), because current intensities have not returned to the peak in the 1990s. Previous research has also criticized the limited success of the policies implemented in the country [364], indicated by the low peaks reached during the 1990s ($< 15\ kg\ ha^{-1}$ for all crops; Figs. C.19 to C.26).

Another way to illustrate the importance of economic profitability is by highlighting how the difference across crops. In the introduction, we described how the development of fertilizer in countries like the U.S.A. [190] and Argentina [328] was linked to cash crops such as cotton and sugarcane, suggesting that the intensification of fertilizer use was earlier for crops with greater economic return. Indonesia and Thailand are another clear example of how fertilizer policies and crop species have determined the fertilizer use. Both southeastern Asian countries rank among the largest producers of rice and oil-palm fruit. Thailand has historically engaged in limited intervention in the fertilizer market [365], excluding import controls before 1985 to protect domestic producers [365], but Indonesia has subsidized the cost of fertilizers since 1971 [366]. Despite these contrasting policies, fertilizer use in both countries peaked earlier for oil-palm fruit, a cash crop primarily grown for export, than for rice, which is mainly used for domestic consumption [367] (Figs. C.19 and C.21). Their peak amplitudes (A), however, differed (Figs. C.20 and C.22), potentially due to the policies applied in each country. The efforts of the Indonesian government for self-sufficiency have driven fertilizer subsidies particularly for urea, and was mostly directed at rice production [366]. These subsidies can account for: i) the higher N peaks for rice in Indonesia than Thailand, but similar peak amplitudes for P_2O_5 and K_2O use (Fig. C.20) and ii) the larger differences in peak amplitudes for oil-palm fruit compared to rice in Thailand than Indonesia, particularly for N (Figs. C.20 and C.22).

In the previous paragraph, we discussed how the marginal economic returns per unit

increase in crop yield could help explain why fertilizer adoption has typically occurred first for cash crops. The response of yield to fertilizer use, however, also depends on other factors such as soil characteristics, management practices, and crop type. For example, Brazil and Argentina illustrate how contrasting soil characteristics influenced the patterns of the intensification of fertilizer use. For all crops in which both countries rank among the largest global producers (maize, soybean, sugar crops and fiber crops), Brazil consistently had higher estimated peak amplitudes (A), particularly for K_2O (Figs. C.20 and C.26). The weathered soils of important agricultural regions in Brazil, such as the Brazilian Cerrado, are naturally low in nutrients [368], which explains why intensification there has led to higher peaks compared to Argentina. In contrast, Argentinian agriculture is primarily based on Mollisols, nutrient rich soils with high natural concentrations of K, which explains why these differences are more pronounced for K than for N and P. The differences between crops within a country can also be explained by the crop-specific yield response to fertilization. An example is the lower peak in the intensification of N fertilizers for wheat compared to maize in Argentina (Fig. 3.4). This finding is substantiated by several experimental studies conducted in Argentina, which found that the response of yield to N fertilization stagnated at lower doses for wheat ($\sim 60\ kg\ ha^{-1}$ of N soil + N fertilizer) compared to maize ($\sim 180\ kg\ ha^{-1}$ of N soil + N fertilizer) [369].

Other barriers to fertilizer adoption

The optimization of profitability within the technology adoption framework is considered subject to constraints such as access to credit or the availability of land [334, 336]. Credit constraints have been analyzed as a factor influencing the adoption and intensity of fertilizer use because the lack of liquidity has constrained the adoption of fertilizers, especially for poor farmers [336, 370]. For example, recent studies on the effect of access to credit on fertilizer adoption among small farmers in Ethiopia and Tanzania concluded that credit constraints were less common in Ethiopia than in Tanzania, and that fertilizer adoption and intensity were more affected by farmers with credit constraints in Tanzania than Ethiopia [370], as is also indicated by our results. Both countries had a high ratio of poor model fits, especially Tanzania, where fertilizer use intensity across crops remained very low throughout the study period (Table C.4). The estimates of the good fits for crops such as maize or roots and tubers, however, indicated a lower intensification in Tanzania, consistent with the limited access to credit (Fig. 3.4 and Fig. C.20).

When and why do fertilization rates decrease

In several cases, fertilizer use intensity has decreased during the study period, indicated by the lognormal term in the piecewise function. Rapid decreases are mostly associated with socioeconomic crises, but slower decreases were more often linked to gradual political or socioeconomic transitions. For example, the sharp reductions in fertilizer use intensity in former Soviet countries, and in other countries from the former Socialist Bloc such as Romania and Poland, were closely linked to the collapse of the socialist system in the early 1990s. For most combinations of nutrients and crops, peak amplitudes (A) were reached in these countries in the late 80s, and dips (D) occurred during the 1990s for all nutrients and crops (Figs. C.19, C.21, C.23 and C.25). The liberalization of the fertilizer sector, together with the reduction of subsidies, dramatically increased fertilizer prices and decreased fertilizer consumption [371]. Other fast decreases occurred, for example, in Nigeria, as explained

in Farmer profitability, and for the use of P_2O_5 during the 1980s in South Africa, which occurred for similar reasons [366, 372] (Figs. C.19 and C.20). The removal of state support for fertilizers can disrupt fertilizer use intensity and may in some cases never recover for several reasons: (i) the economic profitability of fertilizer use may not return to levels seen under state intervention as prices increased; (ii) a lack of liquidity in poorer countries may limit the farmer's ability to purchase fertilizers at previous levels and (iii) the replacement of public distribution systems with private companies may not always be straightforward, particularly affecting smallholder farms in rural areas, where distribution costs are high.

In other cases, such as in western European countries, Australia and Japan, fertilizer use intensity has decreased more steadily (Figs. C.19 and C.20) due to a combination of reduced state support, the implementation of environmental regulations [373, 374], and improvements in nutrient use efficiency [89]. Environmental regulations such as the European Union (EU) Nitrate Directive have restricted the use of N fertilizer with wet conditions, on sloped areas and near bodies of water [373]. Similarly, Japan's "Law for Promoting the Introduction of Agricultural Practices" of 1999 aimed to improve nutrient use efficiency by controlling fertilizer release and promoting techniques like localized placement or side dressing [374]. These reductions, e.g. for wheat or rice, have not led to decreased average national yields [347].

Limitations and future research

Some limitations due to data constraints and methodological approach, however, must be acknowledged, because they may affect the robustness of the conclusions. First, the crop-level data were derived from predictions of machine learning models [331]. The validation of the model predictions in our study indicated that the predictions were generally reliable [331], however, the use of modeled data introduces a degree of uncertainty that may influence the results, especially in regions with sparse input data. Second, parameter estimates outside the period of available data should be interpreted with caution.

Future research should focus on developing more comprehensive models that statistically link the onset, peak, or decrease in the intensification of fertilizer use to socioeconomic and political events. Exploring alternatives to the piecewise function used in this study, such as generalized additive models (GAMs) or spline-based approaches, could improve modeling of fluctuating trajectories that involve multiple phases of intensification. Extending the analysis beyond the temporal scope of this study could also improve the assessment of countries where intensification began earlier, as was the case for P_2O_5 in Australia. The evaluation of large countries, such as the U.S.A., could be improved by incorporating subnational statistics and historical estimates available since the early commercialization of fertilizers [129, 375]. Integrating this framework with national patterns of yield to explore national mismatches between intensification and gains in productivity could contribute to a deeper understanding of the efficiency of fertilizer use, supporting efforts to enhance global food security while reducing fertilizer consumption. Assessing the environmental and socioeconomic consequences of different pathways of intensification would provide a more holistic perspective for targeting policy interventions that promote the sustainable management of fertilizers.

Conclusion

This study analyzed and compared the temporal trajectories of the intensification of fertilizer use across countries and crops. These trajectories have shed light on how global agriculture has utilized these inputs in the last century. For example, the widespread earlier use of fertilizers on cash crops at the country level suggests that economic profitability, rather than food security, has been the primary driver of intensification. Specific historical policies and socioeconomic factors, however, can modify these general patterns, as we discussed in Farmer profitability. These results can therefore help us to understand how the application of these country-specific policies have entailed different patterns of intensification, and to design future policies depending on the objective (e.g. promoting fertilizer use where adoption remained low and yield gaps are driven by nutrient deficiencies such us in Africa [356], or reducing use in areas where overuse has caused environmental concerns they have created environmental problems, as seen in Europe and Japan[373, 374]).

Code availability

The code used in this study is available on GitHub at `https://github.com/STAN-UAntwerp/fertilizers_trends_by_crop`

Chapter 4

A multidecadal analysis of fertilizer use and allocation

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Author contributions: All authors contributed to the study design. F.C. compiled the data, developed the models and wrote the code, produced the visualization and drafted the chapter. All authors discussed the methods and results and reviewed and commented the chapter.

Abstract

Inorganic nitrogen, phosphorus, and potassium (NPK) fertilizers have driven major yield gains since the mid-20th century, supporting population growth, shifts toward protein-rich diets, and industrial applications such as biofuel production. Extensive fertilizer use, however, has disrupted natural biogeochemical cycles, raising environmental, social, and economic concerns. The allocation of fertilizers among *food*, *feed*, and *other uses* for major crops remains poorly understood. We hypothesized that the demand directed to non-food uses has increased in recent decades. We found that between 1961 and 2019: 1) the global consumption of NPK fertilizers for maize, rice, wheat, and soybean crops increased across all three categories of use, 2) the ratio of fertilizer use for *feed* compared to *food* increased significantly in two-thirds of countries, 3) changes in total fertilizer consumption have been driven primarily by intensification (rate) rather than changes in crop area, 4) global changes in the category of *other uses* were driven mainly by maize cultivation in the United States of America (USA) for producing bioethanol, and 5) international trade increased the demand for fertilizer, primarily due to *feed* production. These findings highlight the growing competition for fertilizers among *food*, *feed*, and *other uses*, underscoring the urgent need for international policies that efficiently allocate fertilizer, thereby maximizing food security while minimizing the impacts of fertilizer use.

Introduction

Since the second half of the 20th century, inorganic fertilizers (henceforth referred to as fertilizers) have become the primary source of replenishing nutrients extracted from soils during crop production [89]. More than 30% of current crop production, and consequently the human population, relies on their use [63, 315]. The adoption of fertilizers, combined with high-yield seed varieties, mechanization, and improvements in irrigation, supported the generalized increases in agricultural productivity during the Green Revolution (GR) [376]. The increase in crop yields, coupled with the expansion of agricultural land, has not only maintained a 225% growth in the human population since 1950 [377], but has also facilitated dietary shifts toward protein-rich foods [376, 378] and the diversification of crop uses, such as biofuel production, in recent decades [376]. The supply of meat protein per capita has thus more than doubled since 1961, now contributing approximately 20% of the global protein supply [379] compared to approximately 13% in 1960 [380]. The production of bioethanol and biodiesel has increased ten-fold over the last three decades: from 19.7 million metric tonnes of oil equivalent (MMTOE) in 1990 (approximately 0.5% of the consumption of crude oil in that year) to 196.9 MMTOE in 2020 (approximately 4% of the consumption of crude oil) [69].

More than 200 Tg of Nitrogen (N), phosphorus pentoxide (P_2O_5), and potassium oxide (K_2O) are currently used in agricultural land to sustain global crop production for direct human consumption (*food*), animal feeding (*feed*), and uses other than feeding humans and livestock (*other uses*) [89]. The three main nutrients supplied by fertilizers, N, Phosphorus (P), and Potassium (K), are essential for plants [121, 316, 317]. N and P are fundamental components of nucleotides, proteins, and membrane lipids and play key roles in energy metabolism [121, 317]. K is essential for the transport of water, metabolites, and nutrients across plant tissues and organs and for defense against oxidative stress and the maintenance of osmotic homeostasis [316]. The use of inorganic fertilizers has not only allowed crop yields to increase, but has also disrupted the natural NPK biogeochemical cycles [3–5], leading to environmental impacts such as water eutrophication [96], emissions of greenhouse gases [319], soil degradation [322, 323], and the loss of biodiversity [321]. The social and economic impacts and implications of the use of inorganic fertilizer have led to extensive research into topics such as the potential depletion of P and K mining resources [50, 59], the risks to food security in countries due to vulnerabilities of the fertilizer market [54], or the impact of fertilizer prices on crop production and food security in Africa [324].

Together with the implementation of new technologies for crop production, the second half of the 20th century witnessed a homogenization of the crop species used between countries [381]. The introduction of new crops at the country level increased global national crop richness, especially during the 1980s [381], but four crops (maize, rice, soybean, and wheat) currently dominate agricultural production. These crops occupy over 50% of global cropland [163], and the NPK fertilizers used for their production account for 60% of global agricultural fertilizer use (estimation based on [163, 331]), whereas these percentages in 1961 were 35% [163] and 41% [163, 331], respectively. These crops also provide nearly two-thirds of the protein consumed by humans [378, 382]. These four crops currently lead agriculture, but not all of their production is directed toward food [383–385]. Wheat and rice are primarily used directly for human consumption, and maize and soybean are primarily used for livestock feed, although in some countries they remain as important staple crops [383, 384]. Most livestock are fed by resources not edible by humans, however, >30% of global cereal production (primarily maize) and >80% of soybean production are allocated to livestock feed [385]. Other uses unrelated to protein production, such as bioethanol from corn, have increased sharply in the last 30 years [383, 386].

The cropped areas used for maize and soybean have tripled relative to wheat and rice since 1990 to meet the demands of new industrial applications and dietary shifts [35]. The intensity of fertilizer use, defined here as amount per hectare, has concurrently increased approximately ten-fold for N, four-fold for P, and five-fold for K since 1961 [68]. These changes in crop areas and the intensity of fertilizer use, combined with shifts in crop usage, may have driven the overall changes in total fertilizer consumption over the years for each use. The specific changes in fertilizer consumption due to each use (*food*, *feed*, and *other uses*) and the drivers behind these changes, however, remain poorly understood [387]. The debate about food *vs* feed (*vs* biofuels) has generated substantial research interest [35, 387–389], focusing primarily on the allocation of land use [35] or on the yielded proteins and calories [388] rather than the inputs of resources required, such as fertilizers [387]. Some research has estimated the consumption of individual fertilizers for specific uses on both the global scale [116, 315, 390] and the country scale [389, 391]. These estimates are nevertheless temporally static [116, 315, 391] and thus do not identify the drivers behind the changes. Addressing this knowledge gap by understanding the impact of different crops, uses, and drivers behind global and regional changes in NPK fertilizer use since 1961 is therefore crucial

for optimizing fertilizer consumption, ensuring food security, and reducing environmental and socioeconomic impacts [392], particularly with shifting dietary patterns [376, 378], the emergence of non-food crop applications, and increasing global crop trade [393].

In this study, we addressed temporal changes in total fertilizer consumption for the three main nutrients (N, P,K) and the four main crops (maize, rice, soybean, and wheat), distinguishing between their final uses (*food*, *feed*, and *other uses*). We combined a recent dataset on national fertilizer use by crop from 1961 to 2019, including its associated uncertainty [331], with information on crop consumption from the Food Balances (FB) [379, 380] and Detailed Trade Matrix (DTM) [394] from Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) to estimate fertilizer use by nutrient–crop–year–country combination and end use. We then examined national and global changes in total fertilizer consumption by nutrient and use category; quantified the relative contributions of intensity of fertilizer use, harvested area, and crop allocation to these changes; explored the relationship between bioethanol production and fertilizer use in the *other uses* category; and assessed the role of international trade through virtual fertilizer flows for each use category and nutrient. Together, we provide a comprehensive picture about the evolution of fertilizer use for major crops over the past six decades.

Results

Trends in global fertilizer consumption for all three uses

Global fertilizer consumption for the four crops increased between 1961 and 2019 by 1372.9 ± 44.9% for N, 596.4 ± 18.0% for P, and 791.6 ± 29.1% for K in absolute amounts. This growth was observed across the three categories of use: *food*, *feed*, and *other uses* (Fig. 4.1 a-c). The trends, however, differed greatly among the nutrients and use categories. The fertilizer used for *feed* relative to *food* (FFR) for N and P fertilizers fluctuated within a range of 0.4-0.8 with peaks in 2018 for P and in 1971 for N (Fig. 4.1 d) , and between 0.8-1.4 K with the peak in 1972. The FFR for N and P fluctuated during two main periods: a) between 1970 and 1990, when FFR decreased by 59.0 ± 19.7% for N and 48.4 ± 23.7% for P, and b) since 1990, when FFR increased by 33.2 ± 26.0% for N and 68.2 ± 14.6% for P. The amount of fertilizer used for the *other uses* category increased throughout this period, accounting for approximately 15% of the overall growth in fertilizer consumption across all three nutrients.

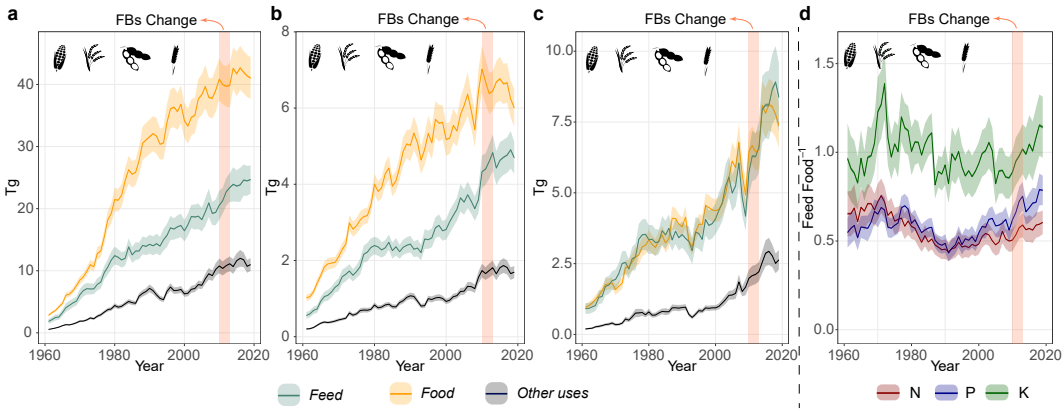


Figure 4.1. Fertilizer used for producing maize, rice, wheat, and soybean for *food*, *feed*, and *other uses*. The solid line represents the average, and the shaded areas the sd of 500 Monte Carlo (MC) simulations. a) Nitrogen, b) Phosphorus, c) Potassium, and d) ratios between the fertilizer used for *food* and *feed* for the three nutrients. The orange band indicates the period when the Food Balances Sheets of FAOSTAT changed their methodology.

Fertilizer consumption for *feed* compared to *food*

The fluctuations and trends globally for FFR were more pronounced at the country scale (Fig. 4.2). Among the 150 countries with available data for two decades, the average FFR between the first and last decade with available data increased substantially ($|$Cliff's delta (δ)$|$ > 0.474) for all three nutrients in 60.1% of these countries and by 73.3% for at least one of the three nutrients (Figs. 4.2, D.1, D.2, D.3 and D.4). The regions with the largest changes were South America and southern and northern Europe, where average FFR between these decades increased by > 0.5 for all nutrients. Important fertilizer consumers such as Brazil (currently the 5th largest global fertilizer consumer) and Spain (23rd) increased their FFR by >1 since the 1960s (Fig. 4.2). FFR decreased considerably ($|\delta|$ > 0.474) in only a few countries (12.0% for N, 12.0% for P, and 15.3% for K) between the first and last decades with available data for each country (Figs. D.1, D.2, D.3 and D.4). Of the ten largest current consumers of N fertilizer, FFR decreased only in the USA for one nutrient (K) over the decades with available data. In contrast, FFR increased substantially ($|\delta|$ > 0.474) in 70% of the ten largest fertilizer-consuming countries for all three nutrients since the 1960s. FFR , however, they remained low (< 0.25) for some large Asian countries, such as India, Indonesia, and Pakistan (Figs. 4.2 and D.2).

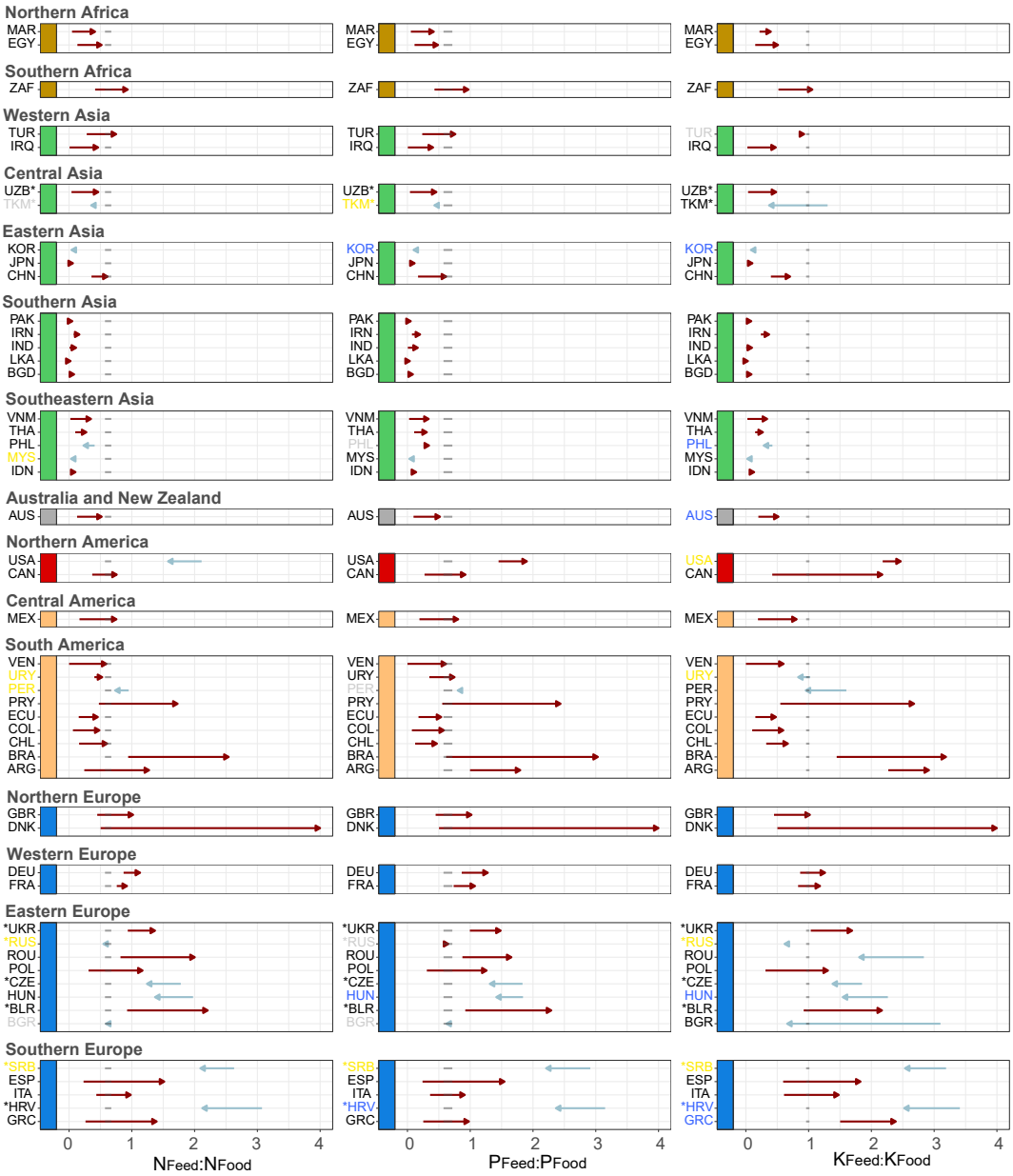


Figure 4.2. Ratios between the amount of fertilizer used for *feed* and *food* (FFR) in the 50 largest fertilizer-consuming countries for the four crops since 2000. Each arrow represents the change in FFR between the 1960s (arrow start) and the 2010s (arrow end) for each country. Red and blue arrows indicate an increase and decrease, respectively. Gray lines represent global changes in the ratios over time, with the right end marking the 2010s for all three nutrients. The left, middle, and right panels display data for N, P, and K, respectively. Colors indicate broader Food and Agriculture Organization (FAO) regions, as used throughout the plots. Country labels indicate the ISO3 code of the country, and all ISO3 codes are defined in Table C.1. Labels indicate the absolute value of Cliff's delta (black > 0.474; blue > 0.33; yellow > 0.147; light grey < 0.147). Asterisks mark countries where the first decade shown is not the 1960s.

At the crop level, global FFR increased greatly only for soybean for all three nutrients during the study period (Fig. 4.3). FFR for soybean increased from 1.4 ± 0.07 to 3.6 ± 0.09 for N, from 1.6 ± 0.02 to 3.8 ± 0.04 for P, and from 1.6 ± 0.01 to 3.8 ± 0.06 for K. For the other three crops, FFR remained within a similar range throughout the period, albeit with fluctuations. FFR remained < 1 for rice and wheat, indicating that a larger fraction of fertilizers was used for *food* products compared to *feed*. FFR for wheat, however, exceeded 0.3 for P and N and exceeded 0.6 for K during the 1970s, but for rice, FFR remained <0.1 for all nutrients over the 60 years. These values, surpassing 0.3 and 0.6, imply that > 23 and 46% of the fertilizers used for wheat, respectively, were allocated to *feed* production. For maize, unlike wheat and rice, FFR values for all nutrients were >1 throughout the period. Although they fluctuated, especially for K, they remained around 4 for most years, indicating that approximately 80% of fertilizers inputs were used for *feed*.

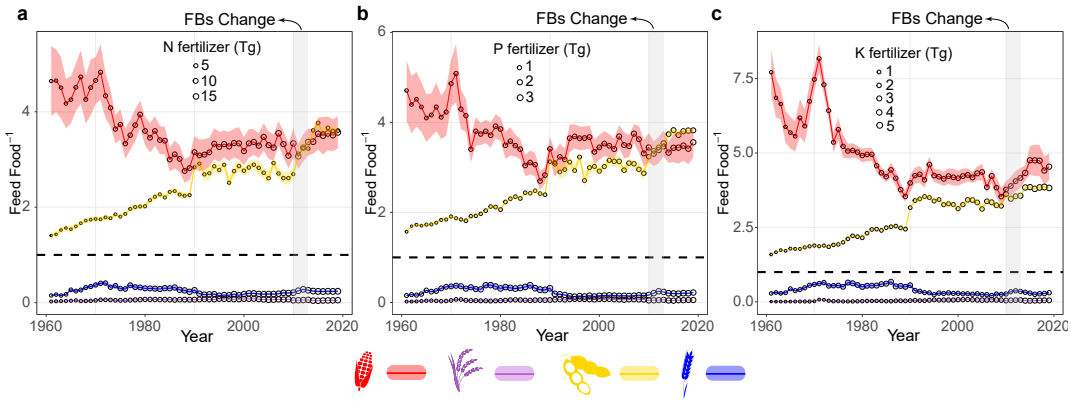


Figure 4.3. Ratios of total fertilizer inputs allocated to *feed* compared to *food* (FFR), for maize (red), rice (purple), soybean (yellow), and wheat (blue). Results for a) N, b) P, and c) K. Each line represents the average estimate, with the shaded areas indicating the sd from the 500 MC simulations. Point size corresponds to the global annual fertilizer use (Tg) for crop production.

Drivers behind the changes in global fertilizer use

The changes for each nutrient and use throughout the study period (Fig. 4.1) were mainly driven by shifts in the intensity of fertilizer use (fertilizer rate) rather than changes in harvested area or the fraction of production allocated to each use (Fig. 4.4). Fertilizer rate was the primary driver behind the increases across most nutrient-use-period combinations, although the magnitude of each driver varied greatly across the combinations. All the results of this subsection refer to the factors of the additive factor decomposition (see Materials and Methods for further details). The decomposition isolates the contribution of each driver (fertilizer rate (F), harvested area (A), or percentage of the crop production allocated to the use (U)) to the total change (ΔQ), for each nutrient, and use category (Fig. 4.4).

Over the long-term (1965-2015) N fertilizer use increased predominantly due to changes in fertilizer rate ($\Delta Q^{F}_{1965-2015} \gg \Delta Q^{A}_{1965-2015}$, $\Delta Q^{U}_{1965-2015}$) (Fig. 4.4 a,d,g). In contrast, for P and K, the differences between $\Delta Q^{F}_{1965-2015}$ and the contributions of the other drivers were lower (Fig. 4.4 b,c,e,f,h,i). In some cases, particularly for the *feed* use, $\Delta Q^{F}_{1965-2015}$ and $\Delta Q^{A}_{1965-2015}$ were nearly equivalent, the difference between them was only 0.14 ± 0.18 Tg for P (Fig. 4.4 e) and 1.01 ± 0.50 Tg for K (Fig. 4.4 f). For N, for *feed* use, on the contrary,

$\Delta Q^{F}_{1965-2015}$ was clearly higher than $\Delta Q^{A}_{1965-2015}$ largely due to the low N-fertilization rates of soybean because, resulting from its ability to fix atmospheric N_2. Changes in the allocation of crop production to each use ($\Delta Q^{U}_{1965-2015}$) were only generally minor, except for the *other uses* category, where they accounted for approximately 15-20% of the total change (Fig. 4.4 g-i).

Over the short term (1961-1975, 1975-1989, 1990-2005, 2006-2019, 2010-2019) fertilizer rate (ΔQ^{F}) was the dominant contributor to total changes in the *food* category, although their absolute values declined over time, and approached 0 for P in most recent periods (Fig. 4.4 a-c). Changes in harvested area (ΔQ^{A}) contributed positively during the earliest and latest periods but contributed negatively to total changes (ΔQ^{Q}) between 1990 and 2005 (Fig. 4.4 a-c). For the *feed* category, ΔQ^{F} was also the main contributor in the early decades; however, in the most recent period, changes in area (ΔQ^{A}) have become the dominant important driver (Fig. 4.4 d-f). For the *other uses* category, the most notable difference relative to *food* and *feed* categories is the importance of ΔQ^{U}, which became the largest contributor for the period 2005-2019 (Fig. 4.4 g-i).

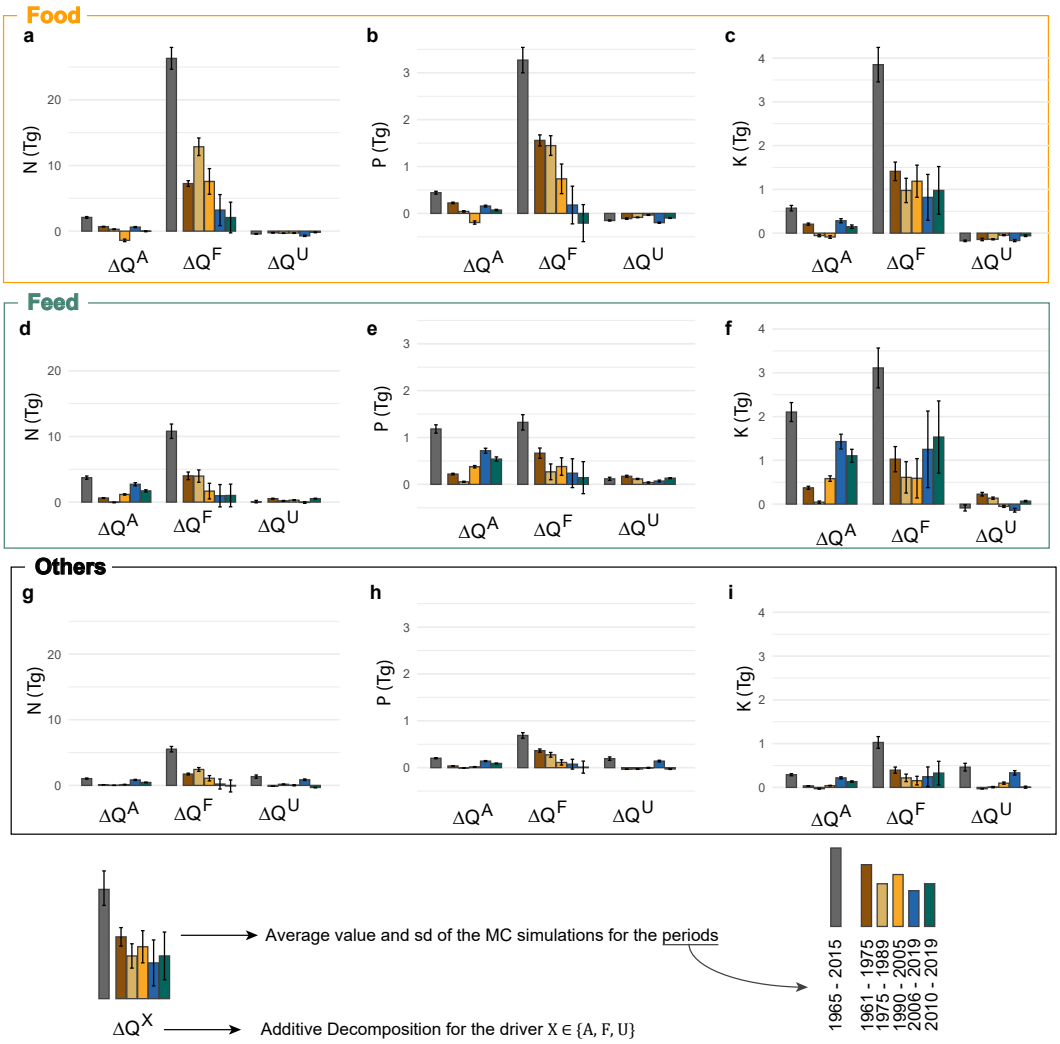


Figure 4.4. Additive factor decomposition of changes in total N, P, and K inputs between: 1965-2015 (grey), 1961-1975 (dark brown), 1975-1989 (light brown), 1990-2005 (yellow), 2006 – 2019 (blue), 2010 – 2019 (green). Bars represent the contributions of the three drivers of fertilizer use, harvested area (A), fertilizer rate (F), and the share of crop production allocated to each use (U).Top row show the results for the fertilizer allocated to *food*: (a) Nitrogen, (b), Phosphorus, (c) Potassium. Middle row, fertilizer allocated to *feed*: (d) Nitrogen, (e), Phosphorus, (f) Potassium. Bottom plots, fertilizer allocated to *other uses*, (g) Nitrogen, (h), Phosphorus, (i) Potassium. The bars indicate the average of the Monte Carlo simulations, and the error bars the standard deviation (sd). The results for 1965-2015 are based on the 500 simulations; 200 were used for the other periods.

Virtual trade of NPK fertilizers

Virtual fertilizer trade flows are defined as the amount of fertilizer required to produce the crop products that are traded internationally [395, 396]. The total virtual fertilizer consumption across the four crops has increased over the study period by 1444.5 ± 98.7% for N, 450.3 ± 45.2% for P, and 829.7 ± 138.1% for K (Figs. D.5 to D.11). The percentages of virtual fertilizer for the three nutrients consumed relative to their total fertilizer consumption changed: the percentages remained in the same levels from 13.0 ± 2.2 to 13.6 ± 1.4% and 19.6 ± 4.9 to 20.5 ± 3.9% respectively, for N and K but decreased from 23.7 ± 3.9 to 18.8 ± 2.2% for P. The changes of the fractions for the specific categories of use, however, were larger than the overall changes. For example, ≤ 6% of all the fertilizer used for the four crops in 1961 was applied for traded crops destined for *feed* (< 3% for N). These fractions had increased in 2019 to 6.0 ± 0.7% for N, 10.7 ± 1.4% for P, and 13.5 ± 2.8% for K. Two regions, South America (>35%) and northern America (>30%), accounted for > 65% of the use of major crops for *feed* since 2000 (Figs. 4.5, D.7, D.9 and D.11). In contrast, the consumption of fertilizers destined for *food* decreased or remained steady. The percentages of total virtual fertilizer consumption destined for *food* varied during the study period from 8.7 ± 1.6 to 6.5 ± 0.7% for N, from 15.6 ± 2.6 to 7.0 ± 0.8% for P, and from 10.8 ± 2.5 to 6.1 ± 1.0% for K. The use of fertilizer for traded products destined for *feed* was now mostly concentrated in the regions mentioned, but virtually traded fertilizer for the *food* category was more widely distributed (Fig. 4.5). The consumption for the six highest regions needed to be grouped in 2015 to account for 70% of the global virtually traded fertilizer destined for *food* (Figs. D.7, D.9 and D.11).

The flows of virtual fertilizer due to traded products varied across both exporting and importing regions (Figs. D.5 to D.11). As discussed in detail in Materials and Methods, uncertainties in the import data were large for the period prior to 1990. We therefore focused on accounting for the results for imports from 1990 onward. The overall patterns remained similar for all three nutrients, but the specific results varied depending on the nutrient (Figs. 4.5 and D.5 to D.11). Countries in eastern Europe, north America, and some developing countries such as Brazil, India and Argentina were virtual net exporters of NPK fertilizers for both *food* and *feed* after 2000 (Fig. 4.5). In contrast, most of the poorest countries, including those in Africa or Central America, were net importers for both uses, with virtual import higher for *food* than *feed*. Only a few countries were virtual net importers for one category and exporters for another category: South Africa and Nigeria were net importers for *food* but net exporters for *feed*, and Germany and Vietnam were net importers for *feed* and net exporters for *food*. Virtual trade balances, however, sometimes changed over the study period (Figs. D.7, D.9 and D.11). The main importing regions for *food* in 1990 included eastern Asia, especially China, and northern Africa. In contrast, other African regions, particularly western Africa, became key importers recently, while the importance of eastern Asian countries decreased (Figs. D.5 to D.11). Nearly all African regions are not major importers for *feed*, except for northern African countries in recent years. Some long-term *feed* importers, such as southern Europe and eastern Asia, remained consistent throughout the study period. New actors, such as southern Asia, however, have emerged in recent years, but others such as eastern Europe, stopped being major importers of *feed*.

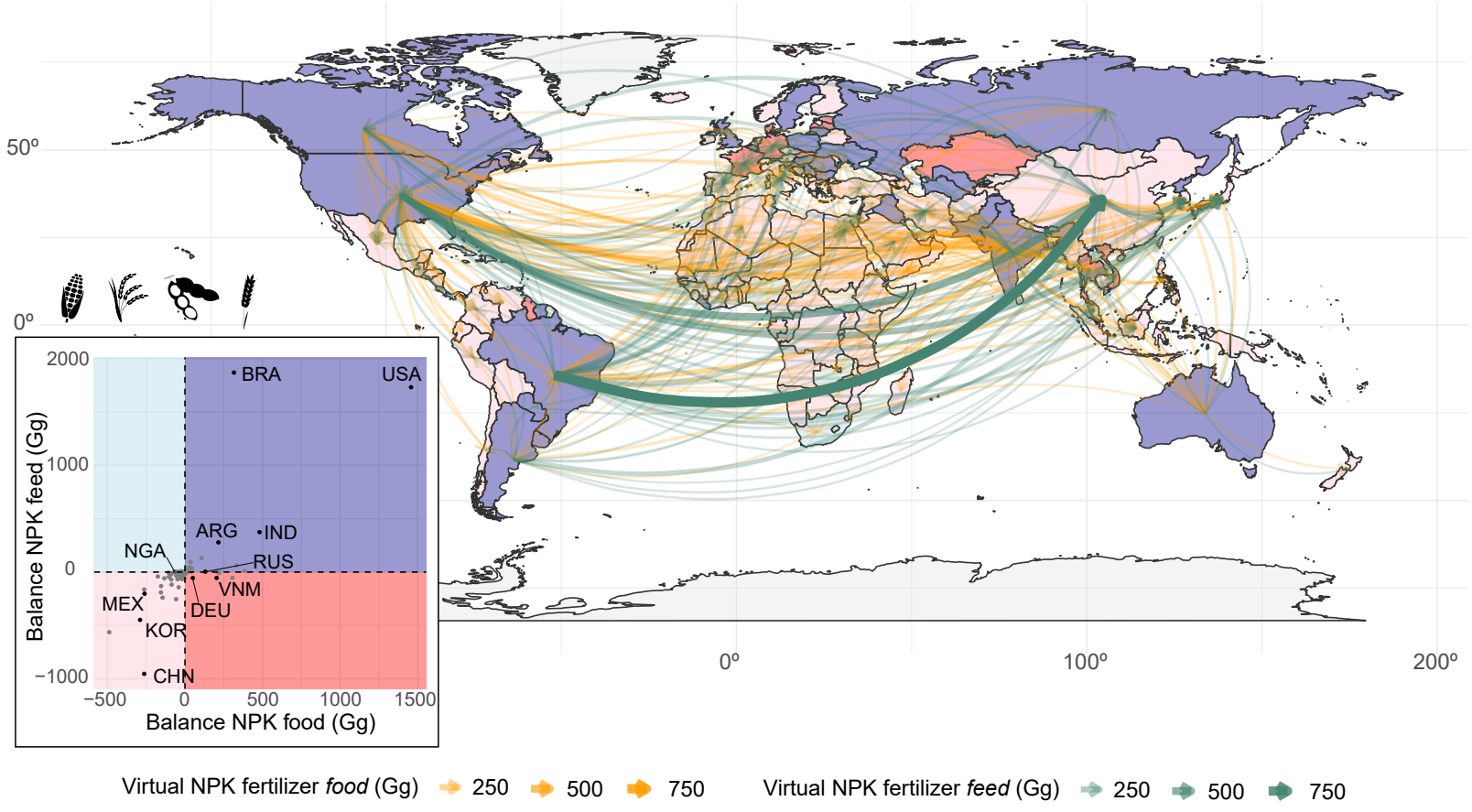


Figure 4.5. Average annual virtual NPK fertilizer trade associated with corn, rice, soybean and wheat production between 2000 and 2019. Green arrows represent virtual NPK fertilizer trade linked to products consumed for *feed*, and orange arrows represent trade linked to products consumed for *food*. The colors of the countries indicate their net trade status for virtual NPK fertilizer: dark blue, net exporters of both *food* and K-related NPK fertilizer; pink, net importers of both *food* and K-related NPK fertilizer; light blue, net importers due to *food* consumption but exporters due to *feed* production; red, net importers due to *feed* consumption but exporters due to *food* production. The inset shows the position of the trade balance for all countries, highlighting specific countries.

Discussion

Fertilizer use among the four main crops for the three nutrients (N, P, and K) and across the three use categories (*food*, *feed*, and *other uses*) has increased significantly over the last six decades. The increases in fertilizer use for the two main uses (*food* and *feed*) were relatively balanced at the global level, but at the country level, most countries have shifted toward a higher proportion of fertilizer use for *feed* compared to *food*. At the crop level, only fertilizer used for soybean shifted between *feed* and *food* uses, coinciding with a two-fold increase in FFR. Changes in total fertilizer consumption across all nutrient-use combinations were mainly driven by increases in the fertilizer rate rather than changes in area or crop usage. Changes in total P and K consumption for *feed* use, however, were similarly influenced by increases in harvested area. The changes in fertilizer use for the *other uses* category were primarily driven by maize, especially since 1990, and may be closely linked to bioethanol production in the USA, the leading producer. Our findings also suggest that international trade has slightly increased as a driver of fertilizer use for N and K but has decreased for P. The importance of traded crops for *feed* nevertheless clearly increased global NPK-fertilizer consumption during the study period.

Food *vs* feed debate

Global demand for animal-based proteins more than doubled during the study period, particularly in developing economies [397, 398]. This growing demand has been mostly supported by systems of monogastric livestock that rely heavily on cereals and oilseed cakes for feed [385]. Our global analysis of the main crops, however, did not identify a clear transition toward higher fertilizer consumption for *feed* compared to *food* over the entire study period (Fig. 4.1). Despite these global trends, the national-level results (Figs. 4.2, D.1, D.2, D.3 and D.4) were the opposite: fertilizer allocation for *feed* compared to *food* increased in most countries. The apparent contradiction of these two results may be due to the interaction between regional changes in total fertilizer consumption and to trends in FFR. Countries with the largest increases in fertilizer consumption during the study period often had a low or stable FFR that moderated the global ratios.

Asian Green Revolution: 1961-1990

The most substantial increases in fertilizer consumption for the four crops during the first three decades of our study period were in Asian countries, which accounted for 58% of the global increase. The widespread adoption of fertilizers and other GR technologies improved crop yields during this period [399]. The initial yield gains, however, were not primarily directed toward increasing the per capita supply of livestock products in the region, despite a modest increase in demand for animal-based proteins. For example, in India as a political response to the poor performance of national crop production between 1947 and 1960 the Indian government, in collaboration with United States Agency for International Development (USAID) targeted economic efforts toward the promotion of high-yield varieties of wheat and rice, which were highly responsive to fertilizers [400, 401]. Fertilizer use and wheat and rice yields and production increased, but the production of traditional coarse grains barely augmented [400]. The increasing availability of wheat and rice also led to shifts in the diet of the Indian population, contributing to an increase in per capita energy supply [400, 402]. In contrast, the availability and consumption of animal-based products remained very low throughout the period, except for milk, which began to increase after 198050. Therefore, the increased fertilize consumption in India, >30-fold

during these decades, was primarily directed toward food crops rather than maize and soybean, keeping FFR for NPK fertilizers >100-fold lower than the global average (Fig. D.2).

The development and allocation of fertilizer in India cannot be generalized to all Asian countries, as dietary transition patterns and the promotion of fertilizer use during the GR varied across the region. FFR in most of these countries, however, remained well below the global average prior to 1990 (Fig. D.2), which combined with the large increases in fertilizer consumption in the region, partially accounted for why overall FFR decreased moderately during the period. FFR either did not change or even decreased between 1961 and 1990 in developed countries that greatly increased fertilizer consumption across the four crops before 1990, e.g. USA (second) and France (seventh). The factors driving these trends in FFR are likely complex and country-specific. For example, several potential factors may account for this pattern in the USA: i) on the production side, the intensification of fertilizer use was higher for wheat than feed crops, particularly for N during the 1980s [129], ii) on the demand side, energy intake increased more from flour and cereal products than from meat and eggs, also during the 1980s, especially due to an increase in the consumption of wheat products [403], and iii) the general improvements in Feed Conversion Ratios (FCR) all livestock systems likely enhanced the efficiency of feed use [404], thereby mitigating the increases in production of additional feed crops.

Emergence of Latin America as a key actor in global agriculture (1990–2019)

The global patterns of fertilizer consumption for *feed* compared to *food* changed after 1990, especially for P. Asia continued to lead the increases in global fertilizer use, accounting for 54.4% of NPK global increases for the four crops, but 25.5% of the global increases have since been in countries in the Western Hemisphere (excluding the USA and Canada), whereas this percentage was only 5.4% during the first 30 years. One cause has been the expansion of soybean croplands linked to the deforestation and over-fertilization of natural South American ecosystems, such as the Amazonia or the Brazilian Cerrado [368, 405, 406], which are typically characterized by nutrient-poor soils [407]. This new actor is quite different from Asian countries: 1) populated Latin American countries such as Brazil (second largest fertilizer increases since 1990) or Argentina (seventh largest) were already obtaining about half of their proteins from animal products in the early 1990s [408], and these percentages are even larger today [379], 2) they have become some of the main exporters of cereals and oilseeds used for feed in recent decades [409, 410], and consumers of virtually traded fertilizers (Figs. 4.5 and D.5 to D.11). These factors have simultaneously caused FFR for Brazil and Argentina to more than double since 1990 for almost all nutrients, nearly tripling the global averages (Figs. 4.2 and D.3), influencing global increases in FFR since 1990 (Fig. 4.1).

Nevertheless, Asian countries, especially those in the east and south, continued to lead the total increases in fertilizer consumption for the four crops since 1990. The onset of dietary transitions toward a higher consumption of animal protein occurred before 1990 in some populous Asian countries, such as China, and has accelerated in recent decades 50. For example, the consumption of meat (poultry, pork, and red meat) products in China increased by 28.8 g person^{-1} d^{-1} between 1952 and 1992 [411] but by 38.8 g person^{-1} d^{-1} between 1992 and 2012 [412]. This acceleration was reflected in our estimates of FFR for the country: for N, it fluctuated between 0.3 and 0.4 before 1990 but was >0.6 for seven years in the 2010s. For P, the values were even larger, with no years before 1990 exceeding 0.3 and some years in the 2010s surpassing 0.7. China was not the only example in the region (Figs. 4.2 and D.2), although FFR is currently closer to that of western countries compared with most Asian countries.

Crop-level changes in the study period

At the crop level only a clear increase in FFR occurred for soybeans (Fig. 4.3). The worldwide expansion of areas of soybean crops has been linked to livestock feeding, with the expansion in South America likely driven partially by imports from the European livestock sector [413]. The development of the livestock sector has promoted the use of soybean cakes for animal feeding, even in countries where soybean was a traditional crop before World War (WW) II, such as China, [414]. In contrast, the stable FFR values for the three cereals suggest that overall changes were influenced more by the expansion of cropland area and the intensification of fertilizer use between crops than by shifts in the patterns of consumption of each crop.

Crops and drivers behind changes to fertilizer use

The importance of each crop in accounting for the total changes in fertilizer consumption can be easily understood by considering the use and physiology of each crop. 1) Maize drove the changes in consumption for *other uses* (Fig. D.13), supporting the idea that the first generation of biofuels was behind these changes (Appendices D.1.4 and D.2.1). 2) Changes in the *feed* category were driven by feed crops (Fig. D.12). Maize contributed substantially to all three nutrients, whereas soybean contributed mainly to P and K. Soybean did not drive changes in the intensity of N fertilization for *feed* because its ability to fix atmospheric N has kept N fertilizer use intensity in soybean croplands low [384]. 3) Changes in the *food* category were driven by rice and wheat, although their effects varied by nutrient. Both food crops drove global increases in N and P for *food*, but their impacts on K differed (Fig. D.12): wheat contributed to declines in K fertilizer consumption, linked to the decline in its consumption after 1990 in western Europe [331] (Fig. D.12), whereas rice drove increases due to rising K fertilizer use intensity in Asia [89, 163, 390].

The relative relevance of each driver (fertilizer rate, area, and fraction allocated to each use) varied by use and nutrient, but changes in fertilizer rate were the dominant driver of global fertilizer consumption changes (Fig. 4.4). Increases associated with food production were clearly driven by higher fertilizer rates rather than cropland expansion or to a larger fraction of the crops for food, consistent with cropland increases occurring mainly in the Southern Hemisphere and linked to soybean and maize [405, 415, 416]. In contrast, *feed* related increases in P and K combined effects of cropland expansion and intensification, particularly due to the soybean expansion [368, 405].

Virtual trade of NPK fertilizers

Our results for total fertilizers across the major crops indicated similar growing trends to those in previous studies of virtual N and P [395]. Earlier work analyzing virtual flows of P through traded crop products reported an increase in the share of virtually traded P fertilizer relative to total P fertilizer consumption, reaching about 20% in 2011 [396], whereas our results indicate similar values but relatively stable proportions over time, with a slight decrease. This discrepancy reflects that our analysis focused on fertilizer inputs rather crop nutrient content and on major crops only [396]. This distinction is important because major exporters at the beginning of the study period, such as the USA, had a greater share of global fertilizer consumption than of total crop production [68, 163] which may explain the differing trends.

Virtual K-fertilizer trade has not been assessed in previous studies, unlike N and P, despite K having the largest share of fertilizer use associated with traded crops for *feed*. For

example, Brazil alone uses > 1.2 Tg of K fertilizers for traded *feed* crops (Fig. D.11), exceeding total use of the sixth largest consumer 2019 [68]. The main areas for fertilizer used for traded crops for *feed* (the USA, Brazil, and eastern Europe; Figs. D.6 to D.11) align with patterns reported for N and P [395], but differ from other resources such as groundwater and surface irrigation water [393, 417].

Our results show that global trade has become an increasingly important driver of fertilizer use, largely due to rising exports of feed crops. Major current exporters such as Brazil, Argentina, and eastern European countries have substantially increased fertilizer use to produce feed crops, while import-dependent regions such as China, southern Europe or northern Africa have driven fertilizer demand in exporting countries (Figs. 4.5, D.7, D.9 and D.11). For example, southern European countries such as Spain have increased feed cereal imports from eastern Europe to support expanding pork production and exports [418], while northern Africa has relied on imports from multiple exporting regions to sustain growth in egg and broiler production and meet rising demand for animal protein [419].

Implications

Competition for biomass to produce enough for *food*, *feed*, and *other uses* has determined how we use our resources for crop production. Fertilizers play a central role in this system, and our findings show that nearly half of the global consumption of NPK fertilizers for major crops is now directed to *feed* and *other uses* (Fig. 4.1). Given the environmental and socioeconomic impacts of fertilizer production and use, our results underscore the urgent need for policies that promote sustainable diets, improve nutrient-use efficiency, optimize global fertilizer allocation, and reduce fertilizer waste.

Current trends are particularly concerning, as fertilizer use has grown faster for *feed* and *other uses* than for direct *food* production over the past three decades (Figs. 4.1, 4.2 and 4.4). This shift has been driven by the accelerating dietary transition toward animal based products in Asian countries [402, 411], the expanding export oriented feed production in Latin America (Figs. D.6 to D.11), and the first-generation production of bioethanol in the USA [386, 391]. Future scenarios also suggest that this trend will continue as the global population increases [420], the demand for meat and dairy products increases, shifts toward the consumption of monogastric animals accelerate [398], and total NP-fertilizer use generally increases [421, 422]. Addressing these trends will require coordinated efforts from policymakers, technological innovation to improve nutrient-use efficiency, and demand-side changes, particularly in regions with high fertilizer use or strong dependence on imported agricultural products.

Policy interventions and technological advances over the last few decades have contributed to reducing fertilizer consumption, although their implementation has not been global. Environmental regulations, such as the European Union (EU) Nitrate Directive in the European Union and the "Zero Increase Action Plan" for fertilizer-use policy since 2015 in China, have reduced N losses and stabilize fertilizer use [373, 423], without compromising the yields of major crops in these regions [163]. Limitations on first-generation biofuels, such as the Renewable Energy Directive (RED II) in the European Union (maintained in the RED III 2023 update [424]), have stagnated first-generation biofuel production in European countries [425], likely influencing fertilizer consumption for bioethanol crops. Technological advances in various fields of agronomy and soil science, including advances in fertilization products and techniques, precision farming, practices of crop management, plant physiological attributes, conventional breeding, and molecular approaches, have demonstrated various pathways to enhance nutrient crop efficiency [426]. Complementing these approaches,

reducing demand for feed-intensive products offers a major opportunity to lower fertilizer use and its environmental impacts.

Previous studies have shown that dietary shifts can substantially reduce greenhouse gas emissions [427], water use [428], croplands expansion [35], and the loss of N [410]. Our results extend this evidence by showing that transitions toward more sustainable diets, particularly in Europe and the Western Hemisphere, together with a slowdown in the ongoing dietary transition in Asian countries, could reduce total fertilizer consumption for the four main crops by up to 50%. This reduction is potentially larger for P and K (Fig. 4.1), which are derived from finite mining resources [50, 59]. Reducing demand for traded feed products would further decrease fertilizer use, particularly in South America, where fertilizer consumption has increased to satisfy the supply of livestock monogastric system from Asia and Europe [413]. For example, eliminating K fertilizer associated with traded *feed* production in Brazil alone could reduce global K consumption by up to ≈ 4%. Although this reduction may have economic implications given the central role of agriculture in Brazil, it may also help mitigate deforestation, reduce nutrient pollution, and improve national fertilizer security following recent global supply disruptions [429].

Limitations

This study provides a global overview of the trends of fertilizer use since 1960, but it is limited by data constraints that led to two major assumptions. First, we assumed similar fertilization rates regardless of crop end use. This assumption is supported by the dominance of a single use accounting for > 75% of total crop consumption in > 70% of crop-country-year combinations. Although agronomic and management factors may influence fertilization decisions (e.g. N fertilization management in wheat affects biomass, grain yield and protein content [430]; and application rates may therefore differ depending on whether wheat is intended for milling or other uses (Fig. D.17)), the dominance of a single use limits variation in fertilization use between uses to at most ≈ 5%, even under worst-case scenarios (Appendix D.2.2).

Second, we assume that trade patterns before 1990 were similar to the average patterns observed since 1990. This assumption only affects the allocation among importing countries of each exported fraction and influences < 24% of total fertilizer use. In addition, the stable proportions of fertilizer allocated to different uses in major cereals over time (Fig. 4.3) suggests that any resulting bias in fertilizer allocation across uses is unlikely to be large. Additional limitations include the focus on four major crops, changes in the methodology of the FB (Appendix D.3), the inclusion of only items reported in the FB which exclude coproducts from the cereals used for biofuel as dry distiller's grains, and uncertainties in the underlying databases (e.g., robustness of the fertilizer use by crop (FUBC) database is lower for earlier decades and some regions, particularly Africa).

Future directions

Future research should develop integrated frameworks linking fertilizer use at crop scale with crop production, consumption, trade, and environmental impacts to improve estimates of fertilizer allocation and its consequences. Expanding analyses to include all crops and grasslands, refining estimates of fertilizer use associated with biofuel production as was previously done for P in 2008 [391], and incorporating high-resolution, country- and sub-national data would provide a more complete representation of global patterns, particularly in large countries with diverse conditions. A detailed analysis of *feed* demand and conversion efficiencies would also help clarify links between fertilizer use and the final outputs of protein or energy for human consumption. Such expansion together with the

inclusion of other crops would help quantify the evolving relationships between fertilizer intensification, farm structure, crop diversity, trade and the supply of nutrient for human consumption, which have previously been examined independently [265, 431].

Materials and Methods

We combined annual crop-specific fertilizer data [331] with the annual harvested area of each crop [163] to estimate the global consumption of different fertilizers for various crops since 1961. We also incorporated information for crop consumption and use [379, 380] and trade between countries to determine where and how the crops have been consumed [394]. All information used was global information at a country-level scale. All calculations, statistical analyses, and visualizations were performed using R version 4.3.1 [349]. The following subsections will describe the methods applied in each step (Fig. D.26).

Country crop production: Allocation of consumption

For each year (i) and country (j), we first estimated the fraction of the production of each crop (k) that had been consumed domestically or exported (P_{ijk}^{exp}) and where has been consumed the exported fraction (P_{ijk}^{imp}). We used the FB from FAOSTAT as the source of data [379, 380] to estimate P_{ijk}^{exp}. The FB databases provide annual data on the production, export, import, domestic supply, and stock of each crop at the country level [379, 380]. Determining whether the exported quantity comes from stock, imports, or production, however, is impossible using the FB data, with the exported amount sometimes exceeding production. We consequently applied Eq. (4.1), assuming that production, imports, and stocks were exported in the same proportion.

$$P_{ijk}^{\text{exp}} = \frac{Q_{ijk}^{\text{exp}}}{Q_{ijk}^{\text{exp}} + Q_{ijk}^{\text{dom}}} \tag{4.1}$$

where P_{ijk}^{exp} is the exported percentage in year i for country j and crop k,Q_{ijk}^{exp} is the quantity exported, andQ_{ijk}^{dom} is the quantity used for domestic supply.

The FB databases changed their methodology in 2013, producing two data sets: one covering data from 1960 to 2013, and the other covering data from 2010 onward. For the overlapping years (2010–2013), we used the means of the two data sets to smooth out the differences between them (see Appendix D.3 for further details of the FB differences and the Table D.2 for all the information of items used).

We estimated the percentage of annual production exported (P_{ijk}^{exp}) and then used annual data for bilateral commodity trade to calculate where the production from each country was consumed (P_{ijkf}^{imp}). We used the DTM from FAOSTAT [394] as the source, which provides bilateral trade information for crop commodities beginning in 1986 [394]. Import-reported data were used because they are generally more reliable than export-reported data, because customs reports are made at the port of entry [432]. These import data tend to be more accurate because they are collected for tax purposes [432]. We calculated a three-year moving average for each bilateral trade relationship to minimize missing data in the DTM and to smooth annual fluctuations. The inability to account for re-exported products is one limitation of using the DTM directly. A country with no crop production can have

substantial exports, leading to large import volumes. We addressed this issue by applying the approach proposed by Kastner, Kastner and Nonhebel (2011) [433], which uses the proportional composition of supply from trading partners and the production for each country to trace the origin of the consumption by a country.

We first individually summarized the products and by-products listed in the DTM for each of the four crops, converting them to dry matter using their Dry matter content (DMC) (Table D.3). We excluded the products derived from soybean crushed from this step because the export figures of the FB for the item soybean did not account the exported soybean cakes and oil. After summarizing the data, we obtained an annual bilateral trade matrix for each crop that combined all products and by-products excluding soybean cakes and oil. The Kastner, Kastner and Nonhebel (2011) [433] method was then applied using production data from the FB and the three-year moving average of the DTM. This procedure allowed us to determine the share of production from each country used domestically and abroad. We only used the information for the fraction exported to other countries, because the fraction used domestically was calculated using Eq. (4.1). This decision was made because the FB covered the entire study period, whereas the DTM only had data beginning in 1986, and the FB data set was more complete.

A large fraction of the soybean production is processed into soybean cake and soybean oil. In the FB, the soybean commodity accounts only for exports of raw soybean, but not for the exports of processed soybean products. Information on exports and domestic consumption of soybean cake and oil for each country and year is available as separate commodities. For soybean oil, this information is provided in the FB [379, 380], and for soybean cake in the Commodity Balances (CB) of FAOSTAT [434, 435]. To account the exported fraction (P_{ijk}^{exp}) of the produced soybean cake and oil in each country, as well as the share attributed to each importing countries (P_{ijkf}^{imp}), we applied the same procedure used for crop commodities. First, we used **??** together with FB data for soybean oil and CB data for soybean cake to estimate the exported fraction of each commodity (P_{ijk}^{exp}). We then employed the information regarding these two commodities in the DTM and the Kastner, Kastner and Nonhebel (2011) [433] methodology to estimate the corresponding shares for each importer country (P_{ijkf}^{imp}).

As mentioned above, the DTM only contained data beginning from 1986 and was less complete than the FB databases. Some countries therefore did not have information for bilateral trade during the study period. We made three assumptions to handle these missing data in the DTM. 1) For 1961–1989, we used the country averages from the period with available data (1990–2019, because we used three-year moving averages), assuming that the patterns of bilateral trade remained similar throughout the period. 2) For individual years with missing information for a country in the DTM but where P_{ijk}^{exp} was > 0 based on the FB, we applied the same assumption as in the first point. 3) For countries with no data in the DTM (7% of the 184 countries with an exported fraction for some year; $P_{ijk}^{\text{exp}} > 0$), we used regional averages of use allocation (further details are provided in the following subsections on use allocation). We used the FAO regional classification 90 for estimating the regional averages (see Table C.1 for details of the regional country classification used).

Country crop consumption: Allocation of uses

We also used the FB databases from FAOSTAT as the source of data to assess how each product was consumed [379, 380]. The FB databases provide data on the use of various items

(crops and products) for different purposes, including food, feed, seed, losses, processing, and other industrial uses (excluding food processing) [379, 380]. For cereals (maize, rice, and wheat), FB items include grains and crop parts (e.g. bran or starch) commonly used for feed and industrial purposes [379, 380]. We grouped the FB categories into three broader categories: *food* (including food and processing), *feed* (including feed), and *other uses* (including seed, losses, and non-food industrial uses). For oilseed products such as soybeans, the processing category included meal feeds. We thus used the same criteria as previous research, dividing processing for soybean into oil (used for *food*) and meal (used for *feed*), because 19% of processed soybean is oil [35]. This assumption allowed us to allocate the use of the fertilizer applied to soybean to different production uses.

We estimated how each crop was consumed in each country using Eq. (4.2). For years when data were available in both FB data sets, we averaged the fractions to smooth discrepancies between them. The FB databases have methodological differences, but the linear model comparing all shared data points (P^{use}_{ijku}) yielded R^2 >0.8 and slopes around 0.92 for the three uses (Fig. D.25), indicating a strong correlation and small differences between the two FB data sets.

$$P^{use}_{ijku} = \frac{Q^{\text{use}}_{ijku}}{\sum_{s \in S} Q^{\text{use}}_{ijks}} \tag{4.2}$$

where P^{use}_{ijku} is the percentage of crop k consumed for the use u in a year in country j, Q^{use}_{ijku} is the amount of crop used for each use, and S is the set of uses (*food*, *feed* and *other uses*) for each combination of country, crop, and year. To fill the missing data in the data set: 1) we considered the period median P^{use}_{jku} of a country for empty years for the country, and 2) we considered the annual regional median P^{use}_{ku} for countries with no information for any year for a crop. We estimated the regional medians using the FAO regional classification (Table C.1).

Country fertilizer consumption: Allocation of uses

We used the data set from Coello and Decorte et al. (2025) [331] as the source of data for fertilizer consumption at the crop level. Coello and Decorte et al. (2025) [331] provided the fertilizer rate, the average annual fertilizer use consumption per hectare (F) of N, P_2O_5, and K_2O in kg ha $^{-1}$ for 13 classes of crops and all countries from 1961 to 2019. We converted the oxidative forms P_2O_5 and K_2O to their elemental forms, P and K, by multiplying by their molecular-weight conversion factors: 0.436 and 0.830, respectively. We multiplied the fertilizer rate (F_{ijk}) by the country-crop annual harvested area (A_{ijk}) from the FAOSTAT database [163] to estimate total fertilizer consumed by each crop (Q^{fer}_{ijku}) Eq. (4.3). We then integrated this information with data for crop use, trade, and fertilizer use, as outlined in Eqs. (4.4) to (4.6), to estimate the annual amounts of fertilizer applied for different uses. We first estimated the amount of fertilizer used for domestic consumption using Eq. (4.3) and then estimated the amount of fertilizer used for the exported portion using Eq. (4.5) Finally, we summed the results using Eq. (4.6) to obtain the total fertilizer use for each crop.

$$Q^{\text{fer}}_{ijk} = F_{ijk} \cdot A_{ijk} \tag{4.3}$$

$$Q^{\text{fer}}_{\text{dom},ijku} = Q^{\text{fer}}_{ijk} \cdot \left(1 - P^{\text{exp}}_{ijk}\right) \cdot P^{\text{use}}_{ijku} \tag{4.4}$$

$$Q^{\text{fer}}_{\text{exp},ijku} = Q^{\text{fer}}_{ijk} \cdot P^{\text{exp}}_{ijk} \sum_{f \in F} \left(P^{\text{imp}}_{ijkf} \cdot \ P^{use}_{ifku} \right) \tag{4.5}$$

$$Q^{\text{fer}}_{ijku} = Q^{\text{fer}}_{\text{dom},ijku} + Q^{\text{fer}}_{\text{exp},ijku} \tag{4.6}$$

where $Q^{\text{fer}}_{\text{dom},ijku}$ represents the amount of fertilizer used for the specific use u in year i in country j for the domestic supply of crop k, and $Q^{\text{fer}}_{\text{exp},ijku}$ is the amount of fertilizer used for the same year, country, and use but applied to the crop production consumed in other countries. We refer to this latter component as virtually traded fertilizer. Q^{fer}_{ijku} is the total fertilizer used, combining both domestic and exported portions. All other terms are defined in the previous equations.

For soybeans, the calculation of virtually traded fertilizer includes an additional step to account for fertilizer associated with exported soybean cake and oil. In this case the $Q^{\text{fer}}_{\text{exp},ijku}$ is calculated for *food* and *feed* using the Eqs. (4.7) and (4.8), respectively. These equations include, on the right-hand side, the fertilizer embodied in soybean oil and soybean cake that are exported after processing.

$$Q^{\text{fer}}_{\text{exp},ij,soy,food} = Q^{\text{fer}}_{ij} \cdot P^{\text{exp}}_{ij} \cdot \sum_{f \in F} \left(P^{\text{imp}}_{ijkf} \cdot \ P^{food}_{f} \right) + Q^{\text{fer}}_{ij} \cdot \left(1 - P^{\text{exp}}_{ij,soy} \right) \cdot P^{processed}_{ij} \cdot 0.19 \cdot P^{\text{exp}}_{ij,oil} \tag{4.7}$$

$$Q^{\text{fer}}_{\text{exp},ij,soy,feed} = Q^{\text{fer}}_{ij} \cdot P^{\text{exp}}_{ij} \cdot \sum_{f \in F} \left(P^{\text{imp}}_{ijkf} \ \cdot P^{feed}_{f} \right) + Q^{\text{fer}}_{ij} \cdot \left(1 - P^{\text{exp}}_{ij.soy} \right) \cdot P^{processed}_{ij} \cdot 0.81 \cdot P^{\text{exp}}_{ij,cake} \tag{4.8}$$

where $Q^{\text{fer}}_{\text{exp},ij,soy,food}$ and $Q^{\text{fer}}_{\text{exp},ij,soy,feed}$ represent the virtually traded fertilizer embodied in soybean exports allocated to *food* and *feed*, respectively; $P^{processed}_{ij}$ is the fraction of the domestic consumption that is processed; and $P^{\text{exp}}_{ij,oil}$ and $P^{\text{exp}}_{ij,cake}$ are the fractions of soybean oil and cake that are exported. The constants 0.19 and 0.81 represent the averages proportions of processed soybean allocated to oil and cake, respectively.

Uncertainty analysis

We used a two-step methodology to assess the uncertainties for fertilizer use across various purposes. We first estimated the uncertainty for the annual rate of fertilizer application by crop (intensity of fertilizer use) based on the process of validation outlined by Coello and Decorte et al. (2025) [331]. This validation indicated that the deviation of predictions compared to national databases varied between 3% and > 100%, depending on the crop and country. We used all available validation data points to calculate the mean absolute percentage error (MAPE) for all data points for each nutrient. We used all data points for each nutrient rather than crop-nutrient combinations due to the limited validation data for some combinations or available for a single country [331]. Based on these MAPE values, we simulated 500 intensities of fertilizer use for each combination of country, nutrient, and crop using a truncated normal distribution with the mean equal to the combination predicted using the intensity of fertilizer use [331], the lower bound set to 0, and sd calculated as $((MAPE \times mean) \div 0.8)$. This formulation assumes that errors represent the variability in the underlying data and that they follow a normal distribution. We used a truncated normal

distribution to ensure that all simulated intensities of fertilizer use remained positive and because the relationship between sd and mean absolute error (MAE) is well defined under a normal distribution. We performed this simulation using the *truncnorm* package (v-1.0-9) [436] in *R*. To aggregate the results, e.g. at the global level, we conducted 500 MC simulations. In each simulation, we randomly selected one value for each country and applied the methods described above to allocate fertilizer consumption across *food*, *feed*, and *other uses*. This method accounted only for the uncertainties in the database for the rate of fertilizer application and did not incorporate any uncertainties in the FAOSTAT input data, such us figures for production, consumption, or trade. Comparisons between distributions were performed using the effect size metric Cliff's delta (δ) [437], considering it as large when $|\delta| > 0.474$, intermedium when $|\delta| > 0.33$, small when $|\delta| > 0.147$ and negligible when $|\delta| < 0.147$ [438].

Factor decomposition

To understand the factors influencing the changes in total fertilizer consumption over the study period, we developed a additive factor decomposition using the Logarithmic Mean Divisa Index (LMDI) approach [439]. This method provides a perfect decomposition (with no residual term) and allows the grouping of decomposed factors into aggregation levels such as crops or regions [439]. We applied this method to analyze the variation in the consumption of N, P, and K across several periods and across the three uses (*food*, *feed* and *other uses*). To capture long-term changes, we performed the decomposition between the three-year averages centered on 1965 and 2015. To capture shorter-term dynamics, we decomposed changes over the periods 1961–1975, 1975–1989, 1990–2005, 2006–2019, and 2010–2019. These windows were selected to provide approximately 15-year intervals while avoiding years affected by changes in data sources, such as the start of the DTM series in 1990. We selected the LMDI method because i) it enabled us to isolate the contribution of each crop (maize, rice, wheat, and soybean) or driver (intensity of fertilizer use, harvested area, and fraction of crop production allocated to the use) with no residual term, and ii) it allowed the aggregation of the impact of each driver or crop from the country-level decomposition to a regional or global level.

Specifically, we decomposed the change in total fertilizer consumption, denoted as ΔQ_{un}^{fer}, into variations in harvested area (ΔQ_{un}^{A}), intensity of fertilizer use (ΔQ_{un}^{F}), and the fraction allocated to each use (ΔQ_{un}^{U}) (Eqs. (4.9) to (4.14)). We also used decomposition to understand the importance of each crop in the change between every two years, grouping the decomposed factors by crop (Eqs. (4.13) and (4.14)). Finally, we accounted for uncertainty in the decomposition analysis by repeating the factor decomposition (LMDI) across the 500 MC simulations for the long-term decomposition and 200 MC for the short term decomposition to estimate fertilizer allocation by crop, country, and use, as described in the previous subsection, reporting the $mean$ and sd of all results.

$$Q_{ijun}^{\text{fer}} = Q_{ijku}^{\text{fer}} = F_{ijk} \cdot A_{ijk} \cdot U_{ijku} \tag{4.9}$$

$$L(a,b) = \frac{a-b}{ln\ a - ln\ b} \tag{4.10}$$

$$\Delta Q_{un}^{\text{fer}} \equiv Q_{iun}^{\text{fer}} - Q_{i'un}^{\text{fer}} = \Delta Q_{u}^{U} + \Delta Q_{u}^{F} + \Delta Q_{u}^{A} \tag{4.11}$$

$$\Delta Q_{un}^{X} = \sum_{j} \sum_{k} \left[L\left(Q_{i\prime jkun}^{\text{fer}}, Q_{ijkun}^{\text{fer}}\right) \cdot ln\left(\frac{X_{i\prime jkun}}{X_{ijkun}}\right) \right] \quad , \quad X \in \{U, F, A\} \tag{4.12}$$

$$\Delta Q_{unjk}^{X} = L\left(Q_{i\prime jkun}^{\text{fer}}, Q_{ijkun}^{\text{fer}}\right) \cdot ln\left(\frac{X_{i\prime jkun}}{X_{ijkun}}\right), \quad X \in \{U, F, A\} \tag{4.13}$$

$$\Delta Q_{unk} = \sum_{j} \sum_{X \in \{U,F,A\}} \left[\Delta Q_{unjk}^{X} \right] \tag{4.14}$$

For each use (u), we applied the factor decomposition for each fertilizer (n) between years i and i', as described in Eq. (4.9). We first applied Eq. (4.1), for each country (j), crop (k), use (u), and the driver (X) underlying the total use (Q): harvested area (A), intensity of fertilizer use (F), and fraction of the production allocated to the use (U). We also performed the decomposition at the crop level (ΔQ_{unk}) using Eqs. (4.13) and (4.14), where (x) represents each factor in the set of factors X that includes (A, F, U).

Chapter 5

Crop demand limits gains in global fertilizer use efficiency:

A global analysis at crop level since 1961

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Abstract

Global fertilizer use has more than tripled since the 1960s, yet efficiency gains in crop nutrient use have not fully translated into improved fertilizer productivity for human food supply. We analyze six decades (1961–2019) of crop-level fertilizer Partial Factor Productivity (PFP) for nitrogen (N), phosphorus (P), and potassium (K) across four major crops (maize, wheat, rice and soybean), disaggregating between the production allocated to food and feed. We find that after initial declines, PFP for feed and food has consistently improved, but PFP for all uses (PFP_{all}) have not followed this increase, reflecting the growing share of fertilizer-intensive feed crops such as maize and soybean. A counterfactual reallocation of feed crops to food suggests maximum potential savings of ≈ 13% of current global fertilizer use (≈ 12 Tg Nitrogen (N), ≈ 3 Tg Phosphorus (P), and ≈ 5 Tg K), with the largest opportunities in the United States of America (USA), China, and Brazil. These results highlight that demand-side changes, particularly reducing feed crop demand, can complement field-level efficiency measures to mitigate nutrient pollution and enhance food system sustainability.

Introduction

The discoveries by Karl Sprenger and Justus von Liebig on the role of chemical elements (nutrients) for plant growth were crucial in overcoming Malthus predictions of population driven food shortages [440]. Since these discoveries, and particularly after World War II, inorganic fertilizers (here in after 'fertilizers') have become a key tool to enhance plant nutrition and to boost crop yields globally [63, 315]. Today, they are the main source of N, P, and Potassium (K) in agriculture [89], and it is estimated that at least 30% to 50% of crop production depends on their use [63, 315]. Their widespread use, however, has severely disrupted the N, P, K natural biochemical cycles [3–5] becoming one of the major concerns of global change [6]. A substantial portion of anthropogenic N, P, and K anthropogenic inputs end up in watersheds via leaching [89] contributing to: i) eutrophication causing harmful algal blooms, hypoxia and loss of biodiversity [96–98], ii) salinization and other groundwater pollution [100, 101]. In the case of N, another significant fraction, is emitted to the atmosphere [89] contributing to greenhouse gas emissions as Nitrous oxide (N_2O) [102], promoting acidification and eutrophication with Amonnia (NH_3) deposition [103] and affecting the tropospheric ozone dynamics as nitrogen oxides (NOx) [104]. These environmental consequences reinforce the urgent need for more efficient and sustainable fertilizer management strategies.

The last century, also, have witnessed a homogenization of crop species across countries [381]. Today, just four crops (maize, rice, wheat and soybean) dominate global agriculture occupying > 50% [163] of world agricultural lands, producing nearly two thirds of global protein supply and consuming > 60% of global fertilizers [163, 331] making them critical

to understanding fertilizer use trends. However, the production of these crops, and thus fertilizer used, has not been exclusively directed toward human consumption. The growing demand for animal protein has augmented the use of grain and oilseed cakes for livestock feed, thereby driving fertilizers use (Chapter 4). While livestock production play a role in food security by supplying essential macro and micro nutrients, by contributing to agricultural productivity through manure and draught power, and by generating income [385], it also contributes to food insecurity, land degradation, and greenhouse gas emissions. One key factor is the use of human-edible resources as livestock feed: in 2010, 32% of global grain production (primarily maize), and over 80% of soybean production were used for feed [385]. These shares are even larger when looking at fertilizer consumption among major crops (Chapter 4). Another contribution to food insecurity is by lowering the efficiency in converting feed into human-edible products compared with direct human consumption, despite the generalized improvements occurred in intensive systems. Beyond food systems, the emergence in industrial uses of human-edible crops such as maize-based bioethanol production has further affected food security and global fertilizer consumption.

Therefore, changes in the efficiency of the fertilizer use to finish as protein or energy consumed by human is affected by several factors: (i) overall trends in fertilizer consumption, (ii) changes in crop-level fertilizer use efficiency, (iii) the allocation of crop products across uses (*food*, *feed*, *other uses*), (iv) how feed crops have been distributed between the different livestock production systems, (v) changes in Feed Conversion Ratios (FCR) within livestock systems. While nutrient and fertilizer use efficiency for croplands and food systems has received significant attention over the last three decades [410, 441], at crop level, most analysis have been limited at national scale [441] and have not captured the full life cycle of crops from field to human consumption. The main limitation has been the lack of data at crop level with temporal and national level resolution. Recently, new data sources have begun to fill this gap for certain nutrient inputs, such as inorganic fertilizers [331] or nitrogen deposition [442], although, other inputs lack crop level disaggregation such as manure. Crop level assessments can allow a more nuanced understanding of nutrient flows within food systems providing information about the role of individual crops in driving inefficiencies in the system.

We here assess these inefficiencies by using these new data sources to provide a first global crop level estimate of fertilizer use efficiency across all the food system. We focused on fertilizer because it is currently the dominant nutrient input in agriculture [89], and because crop-level fertilizer application data are available from 1961 onwards [331]. This study, therefore, has two main goals: 1) To analyze how the efficiency of fertilizer use for major crops has evolved over time, distinguishing between fertilizer use efficiency for the crop fraction allocate d to direct human food and for the food fraction allocated to animal feed 2) To estimate how much fertilizer could be saved under a different crop use scenario. To address the first objective, we estimated the PFP [443] defined here as the ratio between the total energy (kcal) or protein (kg) produced per unit of fertilizer (kg) applied to four major crops: maize, rice, soybean and wheat. We applied a bottom-up methodology that integrates crop production, trade, utilization and fertilizer consumption data to allocate both crop production and fertilizer use between *food*, *feed*, *other uses* (including industrial use, seeds and losses). To quantify the energy and protein supply from the four crops we combined nutritional composition data with information on livestock production, livestock systems and feed use efficiency. To address the second goal, we calculated the Fertilizer Potential Savings (FPS) defined here as the maximum potential amount of fertilizer that could be saved if the fertilizer used for feed production were instead allocated to food

production.

Results

Global Partial Factor Productivity PFP at crop level

The global PFP for energy and protein has followed different trajectories across nutrients and crop allocation. We assessed global PFP trends for (i) all crop uses (PFP_{all}), (ii) the crop fraction used for direct human food (PFP_{food}), and for the crop fraction used for animal feed (PFP_{feed}). Across all nutrients, PFP_{feed} is consistently lower than PFP_{food} or PFP_{all}, likely due to the inefficiencies inherent in converting plant-based nutrients into animal products. However, PFP_{feed} is the only category to show a continuous upward trend since 1961 (Fig. 5.1). Between 1961 and 2019, $PFP_{protein,feed}$ increased by 120.1% ± 53.9 % for N, 245.5 % ± 63.2 % for P and 213.7 % ± 97.5 % for K. $PFP_{energy,feed}$ changes were slightly higher, with increases of 133.6% ± 56.6 % for N, 269.1 % ± 66.5 % for P and 233.9 % ± 102.6 % for K. In contrast, PFP_{food} and PFP_{all} changed the trends during the period. They initially declined for all nutrients but began to recover around 1990. Overall, during the study period, $PFP_{energy,food}$ and $PFP_{energy,all}$ showed either larger declines, or smaller gains than $PFP_{protein}$. PFP_{all} were lower than PFP_{food} and tended to show larger decreases or modest increases over time. For example, $PFP_{protein,all}$ for K remained over the period (-16.9 % ± 117.5 %), and $PFP_{protein,food}$ for K remained (-10.6 % ± 126.5 %) between 1961 and 2019 (Fig. 5.1-c).

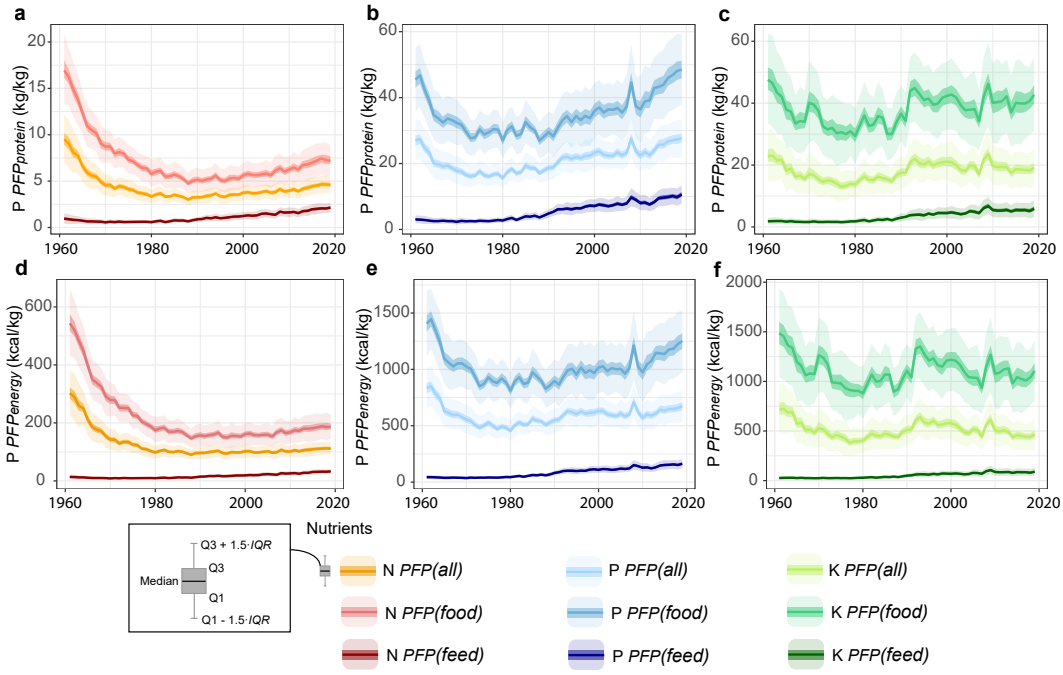


Figure 5.1. Historical global trends in partial factor productivity (PFP) for proteins and energy relative to fertilizer use. Subplots show PFP for protein relative to nitrogen (a), phosphorus (b), and potassium (c), and PFP for energy relative to nitrogen (d), phosphorus (e), and potassium (f). Each panel includes PFP estimates for: the entire food system (lighter color), crop production allocated to direct human food (medium color) and crops used for livestock feed (dark color). Lines represent the median across all Monte Carlo simulations; dark shaded areas indicate the interquartile range (IQR), and light shaded areas represent 1.5 times the IQR. Red, blue, and green correspond to nitrogen (N), phosphorus (P), and potassium (K), respectively.

Global Partial Factor Productivity PFP across major crops

Global results of PFP at crop level (Figs. 5.2 and E.3) can be summarized in four main points: 1) For all crop-nutrient combinations the median $PFP_{food} > PFP_{all} > PFP_{feed}$, 2) The gap between median PFP_{all} and PFP_{feed} is lower for maize and soybean than for rice and wheat, whereas the gap between median PFP_{all} and PFP_{food} is lower for rice and wheat, 3) The gap between PFP_{all} and PFP_{feed} has narrowed for most of the nutrient and crop combinations, particularly for maize, 4) The gap between PFP_{food} and PFP_{all} has clearly widened in the case of soybean.

Global trends in PFP_{all} since 1961 vary by crop and nutrient. For N, the three cereals have exhibited exponential declines reaching average minimums in different years: maize 1983 ($PFP_{protein}$ = 1.04 ± 0.16 kg/kg, PFP_{energy}= 37.1 ± 5.8 kcal kg^{-1}), wheat in 1988 ($PFP_{protein}$ = 2.5 ± 0.3 kg/kg, PFP_{energy}= 76.5 ± 9.5 kcal kg^{-1}) and rice in 2006 ($PFP_{protein}$ = 2.7 ± 0.4 kg/kg, PFP_{energy}= 119.2 ± 19.5 kcal kg^{-1}). Since those lows, PFP has increased modestly: for maize of 71.7 ± 30.3 % for $PFP_{protein}$ and 34.1 ± 25.6% for PFP_{energy}, for wheat of 26.2 ± 18.3 % for $PFP_{protein}$ and 22.7 ± 18.0 % for PFP_{energy}, and for rice of 21.9 ± 25.1 % for $PFP_{protein}$ and 21.8 ± 25.1 % for PFP_{energy}. However, they have not recovered the PFP values of the 1960s decade (Fig. 5.2 a-c). In contrast the P and K trajectories for the three cereals also show initial declines but follow distinct, crop-specific patterns after reaching their respective minimums. For maize, PFP for P and K reached their 1980 and 1977 respectively. Since then, PFP values have increased, $PFP_{protein}$ has even surpassed the levels of the 1960s (Fig. 5.2 b,c). For wheat, the minimum occurred in 1977 for both PFP and fertilizers, but the subsequent increases were more pronounced than for maize recovering the 1960s values not only for $PFP_{protein}$, but also for PFP_{energy} (Fig. 5.2 b,c). Rice followed a different pattern: PFP values for both P and K have not recovered to 1960s levels, with the respective minimums occurring more recently, in 2009 and 2014. Soybean followed different trajectories for all nutrients compared with major cereals, presenting fluctuating trajectories and larger uncertainties than major cereals (Figs. 5.2 and E.3).

PFP_{feed} for all crops and nutrients has steadily improved since 1961 narrowing the gap between PFP_{all} and PFP_{feed}, primarily due to the initial decreases of PFP_{all} (Figs. 5.2 and E.3). More recently, however, the gap has continued to shrink due to increases in PFP_{feed}. This pattern is particularly evident in the case of maize where current PFP_{all} values have returned to levels similar to those in 1961, yet the difference PFP_{feed} and PFP_{all} has narrowed substantially. For N the gap has decreased by 91.5% ± 22.4 % for $PFP_{protein}$ and by 68.9 ± 24.3 % for PFP_{energy}; for P, by 84.9% ± 20.0 % for $PFP_{protein}$ and by 44.2 ± 21.2 % for PFP_{energy} and for K, by 83.2% ± 38.5 % for $PFP_{protein}$ and 49.1 ± 40.8 % for PFP_{energy}. In contrast, improvements in the efficiency of fertilizer use for croplands (PFP_{food}) over the past three decades, combined with the stagnation of PFP_{all}, have widened the gap between PFP_{all} and PFP_{food} for some crop–nutrient combinations, particularly for soybean (Figs. 5.2 and E.3).

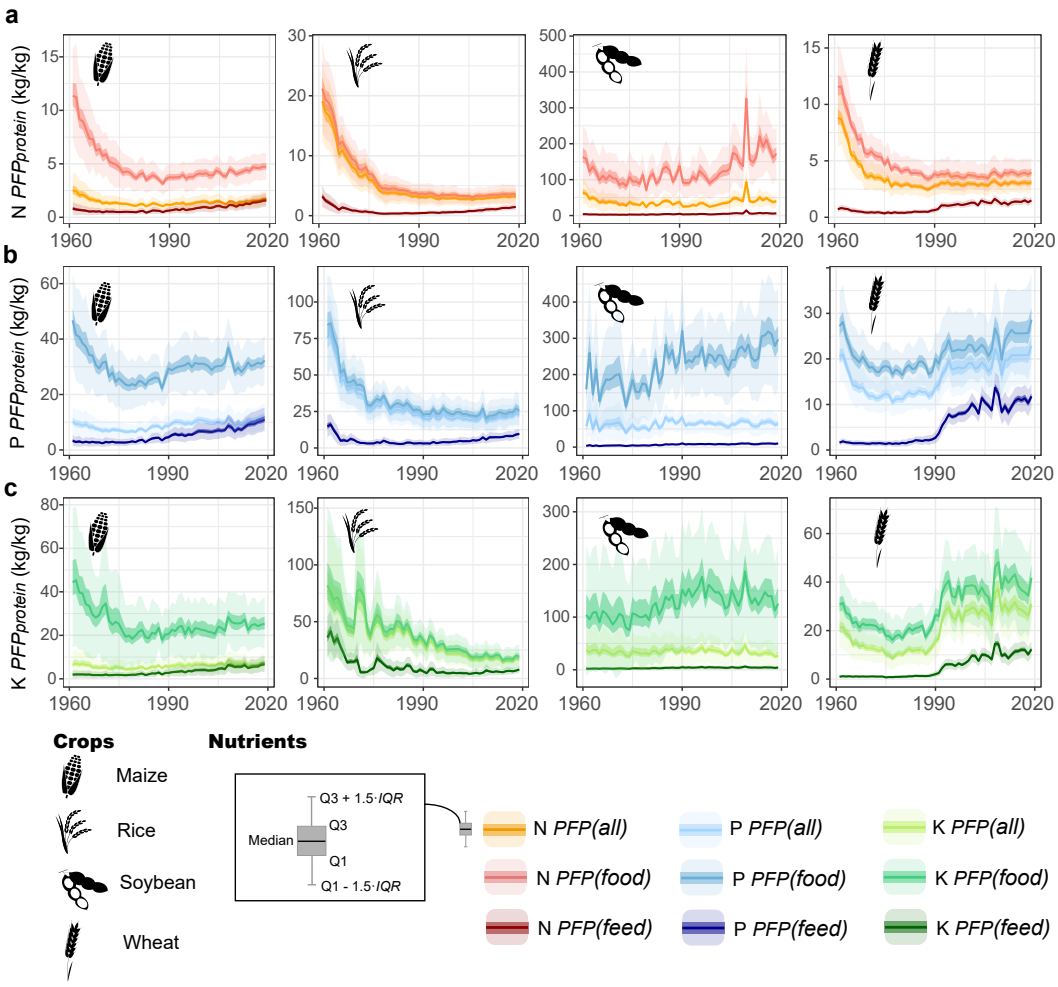


Figure 5.2. Historical global trends in partial factor productivity (PFP) for proteins relative to fertilizer use across major crops. Subplots show PFP for protein relative to nitrogen (a), phosphorus (b), and potassium (c). Each subplot includes four panels to isolate crop-level results. Each panel includes PFP estimates for: the entire food system (lighter color), crop production allocated to direct human food (medium color) and crops used for livestock feed (dark color). Lines represent the median across all Monte Carlo simulations; dark shaded areas indicate the interquartile range (IQR), and light shaded areas represent 1.5 times the IQR. Red, blue, and green correspond to nitrogen (N), phosphorus (P), and potassium (K), respectively.

Partial Factor Productivity (PFP) at national level

Fig. 5.3 shows national-level results for three decades combining PFP_{all}, fertilizer application rates, and land productivity (expressed as the number of people nourished by hectare, assuming an average protein requirement of 56g per person per day [444]). This integration allows comparison of PFP across countries and decades with differing fertilization intensity. The following paragraphs summarize the regional patterns observed. All the results of this section will be referred to proteins, although, results for energy are included in Appendix E.2.

For N (considering only the cereals), Latin America exhibited some of the most pronounced changes. Initially, in the 1960s (Fig. 5.3 a) most countries in the region showed high PFP_{all} values above the third quartile (Q3) of all national PFP_{all} results), largely driven by low N fertilization rates and low productivity. Over time, however, PFP_{all} declined, particularly in Brazil and Caribbean nations, whereas southern countries increased their productivity without substantial reductions in PFP_{all}. P (considering all four crops) and K shared similar patterns, with a general shift toward higher productivity per hectare without major reductions in PFP_{all}. In the other section of the continent, United States and Canada, the productivity has steadily increased over the past six decades while PFP_{all} values for all nutrients have improved or remained stable (Fig. 5.3).

For Africa distinct dynamics emerge between Northern, sub-Saharan and Southern Africa. With some exceptions, such as Egypt or South Africa, fertilizer applications rates and the productivity per hectare in the 1960s-decade were among the lowest globally (Fig. 5.3 a, d, f). Since then, their trajectories have diverged, with notable differences even within each subregion. In Northern Africa N fertilization rates increased sharply during the first three decades, leading to higher productivity but lower efficiency (PFP_{all}). In contrast, increases in P and K fertilization were more modest, resulting in smaller declines in PFP_{all} for these nutrients. In sub-Saharan Africa, with some exceptions, both fertilization and productivity have remained low throughout the study period, with only minor changes in PFP_{all} (Fig. 5.3). In Southern Africa, fertilizer use has become more intensive, primarily in recent decades and across all three nutrients, accompanied by rising productivity but decreasing PFP_{all} (Fig. 5.3).

In Europe, overall trends show continuous progress toward higher productivity and improved efficiency PFP_{all}. However, the pace and magnitude of these changes differ substantially between countries and nutrients. Across all nutrients there is latitudinal and longitudinal gradients: western and northern European countries initially exhibit larger fertilization values, and they have progressively reduced fertilizer use over time while maintaining productivity values. Easter countries presented lower productivity values, and larger changes in fertilization: marked by increases during the first decades followed by declines in recent years resulting in corresponding fluctuations PFP_{all}.

Asian countries have experienced the most pronounced increases in fertilization application rates over the study period. These changes have substantially reduced PFP_{all}, despite generalized gains in productivity. Several densely populated countries, such as China, India, and Pakistan, have transitioned from low to high productivity systems, accompanied by sharp rises in fertilization (Fig. 5.3). However, these increases have come at the cost of declining efficiency, particularly in China, where current PFP_{all} values are lower than those observed in other very productive systems like the USA or Europe, reversing the pattern seen in the 1960s.

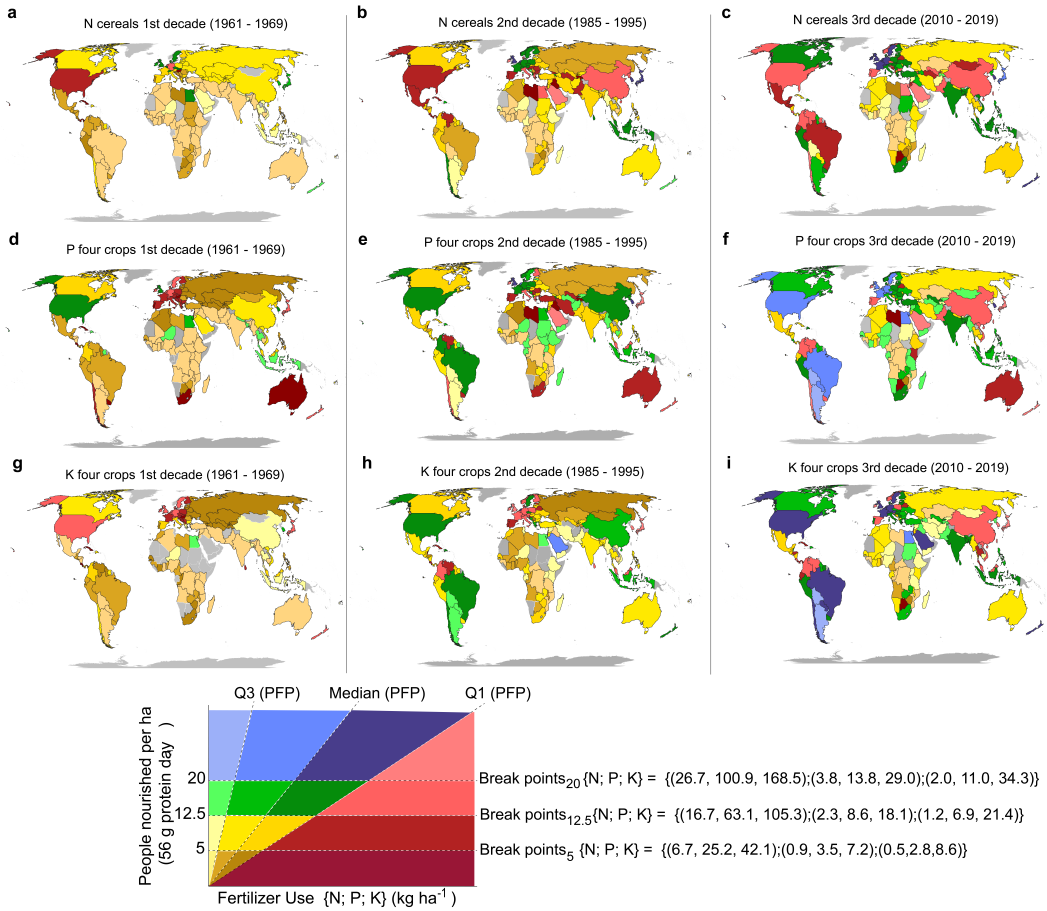


Figure 5.3. Historical national values of the relationship between fertilizer use per hectare (x-axis), people potentially nourished per hectare, and PFP (oblique lines). Breakpoints indicate the fertilizer use per hectare at which the three selected values of people potentially nourished per hectare intersect the first quartile, median, and third quartile of all PFP values. Subplots show PFP for protein relative to nitrogen (N) (a–c), phosphorus (P) (d–f), and potassium (K) (g–i). Each panel corresponds to the classification of the entire food system for the decades 1961–1969 (a, d, g), 1985–1995 (b, e, h), and 2010–2019 (c, f, i). Colors represent the median location across all Monte Carlo simulations within the intervals defined in the legend.

Fertilizer Potential Savings (FPS)

We define the FPS as the maximum amount of N, P or K fertilizer that could have been saved from feed use if the same amount of protein or energy had been produced using crop allocations for food. Based on this definition, a small number of countries have accounted for most of the global FPS over the past 60 years. In the first decade of the study period (1961-1969), the USA, alone represented 58.1 ± 25.8 %, 50.8 ± 20.8 % and 59.4 ± 29.2 % for N, P and K respectively of the FPS for N, P, and K, respectively, when equalized by protein (Fig. 5.4). In the subsequent decades, although the USA remained among the countries with the largest FPS, China and Brazil emerged with substantial FPS values. In the last decade analyzed, China led the ranking for N, while Brazil ranked first for P and K (Figs. 5.4 and E.4). For example, in China, the annual FPS for N equalized by energy reached 4.8 ± 1.4 Tg y^{-1}, equivalent to 4.5 ± 1.3% of global agricultural N-fertilizer consumption in 2019 [68]. For P and K, Brazil could potentially save 0.8 ± 0.3 Tg y^{-1} of P and 2.0 ± 0.8 Tg y^{-1} of K, corresponding to 4.4 ± 1.3% of global agricultural P-fertilizer and 6.7 ± 2.8% of global agricultural K-fertilizer consumption in 2019 25. At the crop level, maize and soybean accounted for most of the FPS. While maize has been the main contributor to N FPS throughout the study period (Figs. 5.4 and E.4), soybean has emerged in recent decades as the primary crop for P and K, particularly in South American countries (Figs. 5.4 and E.4). With a few exceptions, such as the Union of Soviet Socialist Republics (USSR) during the 1985–1995 decade, neither wheat nor rice has played a major role compared with maize and soybean in contributing to FPS for any of the nutrients.

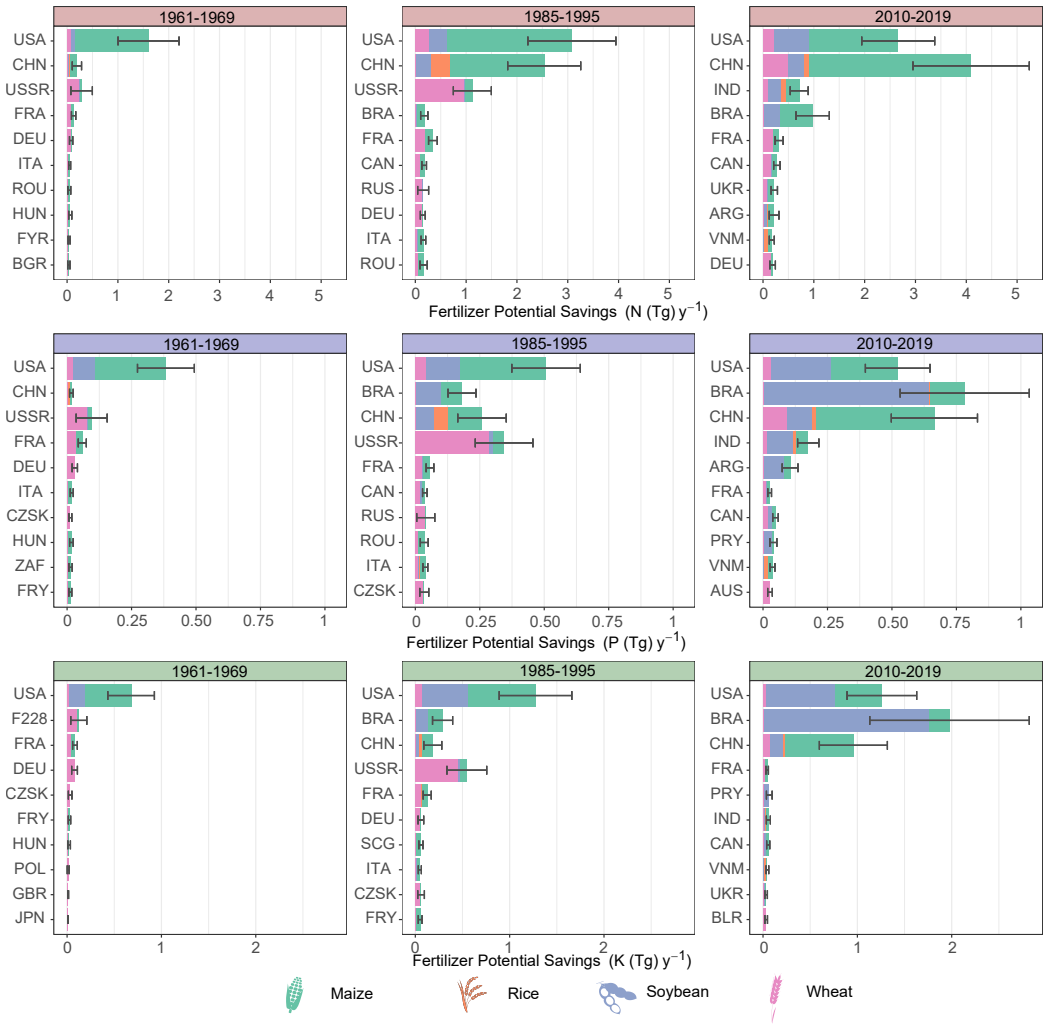


Figure 5.4. Mean Fertilizer Potential Savings (FPS) by decade for the top 10 countries per nutrient and decade equalized by energy production. Bars show the mean FPS from all *Monte Carlo* simulations, disaggregated by crop (maize in green, rice in orange, soybean in blue, wheat in pink). Error bars indicate the sum of the standard deviations of the *Monte Carlo* simulations for each crop within the decade. Top panels show the results for Nitrogen (N); middle panels show the results for Phosphorous (P) and bottom panels show the results for Potassium (K).

Discussion

Summary of Findings

During the study period, global PFP_{all} for major crops combined showed initial decreases, but later recoveries for $PFP_{protein}$ in the case of P and K. At the crop level, this recovery pattern of PFP_{all} occurred for wheat and maize for P and K, but not for rice. Soybean followed a different trajectory, with marked fluctuations throughout the entire study period (Fig. 5.2). High-income countries, such as European countries or the USA followed similar trajectories to the global ones, whereas other major current fertilizer consumers, such as China and Brazil recorder their lowest PFP_{all} values in the most recent decades. However, PFP_{all} in South American countries remained higher than in Europe or in North America (Fig. 5.3). PFP_{food} displayed diverse trajectories at global level, although for most nutrient-crop combinations it began with declines and recovered only in a few cases such as P and K for wheat. In contrast, PFP_{feed} has presented general increases during the study period for all crops, although, values were consistently lower than those of PFP_{food} and PFP_{all}. These trends combined with total fertilizer use and allocation have increased the FPS from the crop allocated to feed. At present, these savings are driven largely by maize and soybean production in a few countries: the USA, China and Brazil.

Interpretation and Comparison

Our results show patterns broadly consistent with those reported for all croplands. For example, global nutrient budget assessments indicate that nitrogen use efficiency increased from roughly 50% to 60% during the 2010–2019 decade [89]. Although our estimates are not directly comparable, since they account only for fertilizer inputs and not for all nutrient sources, we observed a similar upward trend for PFP_{food} (Fig. 5.1), which is analogous to cropland nutrient use efficiency. Using a nitrogen concentration in protein of 6.25% and the 2020 proportion of fertilizers in total N inputs (57.5%) [89], our values for major crops combined during 2010–2019 shifted from 36.3% in 2010 to 42.0% in 2019. Comparison at the crop level can be illustrated for the USA, where previous research has used national statistics to estimate PFP_{food} for maize and wheat [445]. Their results, expressed as kilograms of grain per kilogram of N fertilizer, showed parabolic trends, with minimum values occurring in 1987–2004 for wheat and 1975–1985 for maize. Similarly, our estimates of PFP_{food} display comparable patterns, with minimum values reached in 1993 for wheat and 1983 for maize.

Globally (Fig. 5.1) and for most countries (Fig. 5.3) and crops (Fig. 5.4), fertilizer use efficiency within individual uses (food and feed) has improved over the last three decades. However, shifts in crop allocation toward feed and industrial uses are dampening overall gains in fertilizer use efficiency for human-edible resources, even when efficiency within individual uses is improving. In particular, the diversion of production from direct human consumption toward livestock feed have reduced the benefits of improvements in crop-level PFP_{food} and PFP_{feed}. This pattern is especially evident for maize and soybean, the two crops mostly used for feed currently, where the distance between PFP_{food} and PFP_{all} is increasing and the distance between PFP_{food} and PFP_{feed} is consistently decreasing. These changes indicated that allocation effects, rather than agronomic efficiency alone, are driving overall trends within and across crops. These trends are also reflected in the potential savings of fertilizer from feed use, where although the increases in PFP_{feed} the larger allocation of fertilizer use for feed is increasing the FPS particularly from soybean and maize.

Implications

The changes in crop demand have therefore limited the global gains in nutrient crop efficiency and in feed conversion ratios by livestock. For example, in countries such as Brazil, meeting both domestic and international demand for feed crops has generated environmental impacts and socioeconomic concerns such as deforestation [368], over-fertilization [368], and risk to national fertilizer supply [429]. Although agriculture plays a key role in the Brazilian economy, shifts in both domestic and international demand could reduce national K-fertilizer consumption by 78.2 ± 23.1% (based on 2010–2019 FPS estimates and compared with 2019 national fertilizer consumption [272]). China offers another example of the potential impact of demand-side changes: national policies such as the "Zero Increase Action Plan" for fertilizer use, implemented in 2015, have successfully stabilized N-fertilizer consumption [423]. However, further policies targeting demand could reduce the national requirement for N fertilizer by an addition-al 16.5 ± 4.1%, only considering major crops (based on 2010–2019 FPS estimates; Fig. 5.4, and 2019 national fertilizer consumption [272]).

Demand-side measures can help reduce fertilizer consumption, aligning with the Sustainable Development Goals (SDG) 12 "Responsible consumption and production", without compromising other goals such us the SDG 2 "Zero Hunger". One important pathway is through dietary change. Recent studies in China have shown how that adopting healthy and sustainable diets like the EAT-Lancet diet [444], can reduce water consumption and enhance biodiversity, while at the same time improving dietary health indicators and lowering household food expenditures [446]. The adoption of the EAT-Lancet diet would lower the consumption of animal products compared with the current Chinese diet, thereby reducing the demand for feed crops and, consequently, for fertilizers. Further specific assessments are needed to estimate the actual reduction in fertilizer consumption from this specific measure, although the maximum potential among major crops is estimated at 16.5 ± 4.1% total N-fertilizer consumption reduction under current agronomic nutrient use efficiency.

Limitations and Future Direction

While these results shed light on the global evolution of fertilizer use efficiency at the crop level, the absence of crop-scale data for other nutrient sources, such as manure, crop residues and biological fixation, limits a comprehensive assessment of nutrient use efficiency. The results, therefore, should be interpreted with caution, as these other inputs account for approximately one-third of current nutrient inputs to agricultural land [89]. Additionally, limitations include potential biases from using national or regional level statistics rather than subnational data, the assumptions of crop and fertilizer allocation for different uses (Chapter 4), constant crop energy and protein concentrations or constant feed rations within each regional livestock system. Future research could strengthen this framework by integrating other nutrient inputs, expanding coverage to additional crops and grasslands, downscaling analyses to subnational resolution, and coupling nutrient efficiency metrics with socioeconomic drivers such as economic development or the relative importance of agriculture in each country and with environmental indicators such as nutrient losses to water or N_2O emissions. Future research also can explore how PFP or other nutrient use efficiency metrics can change at crop level under different socioeconomic and environmental scenarios providing a more complete picture of nutrient use efficiency at crop level across

global food systems. Moreover the assessment of specific measures linked to the demand can help to develop targeted policies for improving PFP_{all}.

Materials and Methods

In this section we describe the sources, methods and assumptions used to estimate: 1) Annual fertilizer use for major crops (maize, rice, wheat and soybean) by country, disaggregated by use type (*food*, *feed* and *other uses*); 2) Annual protein and energy production from each crop, separately attributed to food and feed uses; 3) The potential energy and protein output if all crop production were allocated exclusively to food; 4) The maximum potential savings of achievable by shifting crop use from feed and other uses to food. To perform all these methods we compiled global datasets on: fertilization use by crops [331], crop harvested area and production [163], bilateral trade of crop commodities [394], national crop utilization [379, 380, 434, 435], livestock production [163], livestock systems shares [447–449], livestock feed rations [450], livestock feed conversion ratios. The following subsections and the Appendix E.1 provide detailed explanations of the sources and every step of the methods. Conceptual diagrams of the methodology are shown in Figs. D.26 and E.1. All calculations, statistical analyses, and visualizations were conducted using R version 4.3.9.39.

Fertilizer use and allocation

To estimate fertilizer use for the four studied crops during the study period and the intended purpose (*food*, *feed* and *other uses*) we relied on the work developed previously in this thesis (Chapters 2 and 4). In the first, we estimated crop-level fertilizer use from 1961 to 2019 across all countries by using global datasets and machine learning (ML) models. We compiled the most comprehensive global dataset regarding national level fertilizer use by crops, and we filled the gaps using environmental, socioeconomic, and agronomic variables, and applying HistGradientBoosting (HGB). In the second publication, we allocated the fertilizer use across the end-use categories (*food*, *feed* and *other uses*) by combining production and bilateral trade data to estimate the country where each product has ultimately consumed. We then used the Food Balances (FB) [379, 380] data set from Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) to determine the breakdown of crop consumption by use category. Further methodological details and definitions are provided in both chapters. These two chapters together estimated the total N, P and K used for major crops (maize, rice, wheat and soybean) from 1961 to 2019 for three use categories (*food*, *feed* and *other uses*).

Protein and energy historic production

To estimate the annual amount of energy and proteins produced from *feed* and *food* uses by major crop annually and by country: (a) we estimated where the annual production of each crop has been consumed (Country crop production: Allocation of crop production), (b) we assessed how each crop has been consumed between food, feed and other uses (Country crop production: Allocation of uses), (c) we calculated the plant proteins and energy produced because of the fraction of the crop used for direct human crop consumption (Protein and energy production from food use), (d) we calculated the animal proteins and energy produced because of the fraction of each crop production used for livestock feeding (Protein and energy production from feed use).

Country crop production: Allocation of crop production

To estimate where each country's annual production of a crop has been consumed, we determined the end-consumer countries by integrating crop production and international trade data from FAOSTAT [379, 380, 394, 434, 435]. First, we calculated the percentage of exported fraction of each country-crop annual production by using the information of the FB sheets from FAOSTAT [379, 380]. We then applied the proportional composition methods proposed by Kastner, Kastner and Nonhebel, Kastner, Erb and Haberl (2011, 2014) [433, 451] to trace the origin of the consumption of a country using the bilateral trade information of Detailed Trade Matrix (DTM) from FAOSTAT [394]. A full description of the preprocessing steps, equations, and assumptions is provided in Chapter 4.

Country crop production: Allocation of uses

We also used the methodology of Chapter 4 for allocating the crop production into the three considered use categories (food, feed and other uses). This methodology starts using the information contained in the FB databases from FAOSTAT as the source of data [379, 380]. The FB databases provide data on the use of various items (crops and products) for different purposes, including food, feed, seed, losses, processing, and other industrial uses (excluding food processing) [379, 380]. For cereals (maize, rice, and wheat), FB items include grains and crop parts (e.g. bran or starch) commonly used for feed and industrial purposes [379, 380]. We grouped the FB categories into three broader categories: *food* (including food and processing), *feed* (including feed), and *other uses* (including seed, losses, and non-food industrial uses). For oilseed products such as soybeans, the processing category included meal feeds. We thus used the same criteria as previous research, dividing processing for soybean into oil (used for *food*) and meal (used for *feed*), because 19% of processed soybean is oil [35]. This assumption allowed us to allocate the use of the fertilizer applied to soybeans to different production uses, although it did not allow for the specific location (country) of the consumption of the processed soybean. As we described in Chapter 4 we process the proportional composition method for accounting the location where soybean cakes and oil were consumed.

Protein and energy production from food use

For estimating the energy and proteins ($NUT_{Food\{i,j,c,l\}}, NUT\ \epsilon\ Energy,\ Protein$) produced from the crop production directly used for human consumption, we multiply the amount of crop allocated to food ($P_{Food,i,j,c}$) for each crop (c), country (i) and year (j) by the energy, or protein concentration of the crop (Table E.1). Due to the lack of country specific data with temporal resolution on protein and energy concentration, we used the average values compiled from multiple sources (Table E.1 and Appendix E.1). Although this approach does not account for processing reductions that affect final nutrient supply it serves as a consistent baseline for comparing protein and energy outputs across crops, countries and years.

Protein and energy production from feed use

To estimate the annual energy and proteins produced from each crop production used for animal feed ($P_{Feed\{i,j,c\}}$), we used country-annual data on crop production, crop trade, livestock production, Feed Rations (FR), FCR and the share of production under different Livestock Systems (LS). Detailed information on the sources and preprocessing steps used to

obtain annual country-level estimates for each of these factors is provided in Appendix E.1.2. The estimation process was divided into three main steps: (1) We estimated the fraction of feed consumption ($XC_{Feed\{i,j,c\}}$) allocated to different animal products ($C_{Feed,i,j,c,pl}$), (2) We calculated the nutrients (NUT) (energy and proteins) produced by kg of crop used for feed in each country and year ($NUT_{PerKgFeed\{i,j,c,l\}}$), (3) We estimate the annual proteins and energy produced for the crop production of a country by tracing where the crop production of a country has been consumed

Fraction of feed allocated to different animal products

To estimate the fraction of the crop consumption for feed allocated to different animal products we based our calculations on the total feed requirements for each livestock product (l). Due to limited data on feed conversion ratios ($FCR_{\{i,j,s,l\}}$) and livestock systems ($LS_{\{i,j,s,l\}}$), we simplified the analysis by focusing on the five main animal products by protein output: hen eggs, chicken meat, pork, dairy milk, and beef. These five livestock products consumed in 2010 >99% of the grain and >99% oilseed cakes used for livestock production [385]. First, we estimated the feed demand ($F_{Req\{i,j,c,l\}}$) for each crop (c) used to produce each livestock product (l) in each country (i) and year (j) using Eq. (5.1).

$$F_{Req\{i,j,c,l\}} = \sum_{s} \left(FCR_{\{i,j,s,l\}} \cdot LS_{\{i,j,s,l\}} \cdot FR_{\{i,s,l\}} \cdot \frac{1}{DM_c} \cdot P_{\{i,j,l\}} \right) \tag{5.1}$$

where $F_{Req\{i,j,c,l\}}$ is the feed requirements (total amount of crop (c) in fresh mass needed to produce the livestock product (l)); $FCR_{\{i,j,s,l\}}$ is the feed conversion ratio in each livestock system (s), LS is the share of the livestock production (l) under system (s); $FR_{\{i,s,l\}}$ is the fraction of the feed ration made by crop (c) in system (s); DM is the dry matter content of the crop (c) and P is the production of the livestock product (l). We assumed that the FCR is crop-independent within each livestock system, applying the same value across all four crops. While this simplification overlooks differences in the energy and protein content of individual feed crops, it reflects the reality that FCR are typically measured at the level of the entire ration, not individual ingredients [452].

After estimating the feed requirements for each product, we calculated the fraction of the crop allocated to feed destined to each livestock product (Eq. (5.2)):

$$XC_{Feed\{i,j,c,l\}} = \frac{F_{Req\{i,j,c,l\}}}{\sum_{l' \in L} F_{Req\{i,j,c,l'\}}} \tag{5.2}$$

We estimated the fraction of the consumption used for each of the considered livestock products ($XC_{Feed\{i,j,c,l\}}$) dividing the feed requirements of each livestock product by the sum of all the set of considered livestock systems (L).

Energy and proteins by kg of feed for each crop, country and year

We calculated the kg of nutrient (energy or proteins) produced for kg of a crop used for feed in each country and year ($NUT_{PerKgFeed\{i,j,c,l\}}$, $NUT \in Energy, Protein$) by the Eq. (5.3). considering the $FCR_{\{i,j,s,l\}}$,$LS_{\{i,j,s,l\}}$,$FR_{\{i,s,l\}}$ (Eq. (5.3)).

$$NUT_{PerKgFeed\{i,j,c,l\}} = \sum_{s \in S} (XC_{Feed\{i,j,c,l\}} \cdot LS_{\{i,j,l,s\}} \cdot \frac{XNUT_l}{FCR_{\{i,j,l,s\}}}) \tag{5.3}$$

Where $XC_{Feed\{i,j,c,l\}}$ the fraction of the consumption of a crop (c) used for each of the considered livestock products (l) by country (i) and year (j), $LS_{\{i,j,l,s\}}$ is the share of the livestock production under system (s), $FCR_{\{i,j,l,s\}}$ the feed conversion ratio, $XNUT_l$ the protein or energy concentration, and S the set of livestock system under each livestock product is produced (S = Extensive, Mixed, Intensive.

Energy and proteins by kg of feed for each crop, country and year

Finally, we estimate the amount of proteins and energy (NUT) (Eq. (5.4)) by tracing where the consumption of each country has been consumed, and the annual kg of proteins and energy produced by kg of the crop used for feed in each country calculated in the previous step.

$$\begin{aligned} NUT_{Feed\{i,j,c,l\}} = P_{\{i,j,c\}} \cdot DM_c \cdot \Big[& \\ & (1 - XP_{Exp\{i,j,c\}}) \cdot DM_c \cdot NUT_{PerKgFeed\{i,j,c,l\}} \cdot XP_{Feed\{i,j,c\}} \\ & + XP_{Exp\{i,j,c\}} \cdot \sum_{i' \in I} \Big(NUT_{PerKgFeed\{i,j,c,l\}} \\ & \cdot XP_{Exp \rightarrow Imp\{j,i \rightarrow i',c\}} \cdot XP_{Feed\{i,i',c\}} \Big) \Big] \end{aligned} \tag{5.4}$$

Where $P_{\{i,j,c\}}$ is the production of the crop for each country (i) and year (j), $XP_{Exp\{i,j,c\}}$ the percentage of the crop exported, $XP_{Feed\{i,j,c\}}$ the percentage of the crop allocated for feed, i' denotes the importer countries from the set of importer countries (I) each year, and $XP_{Exp \rightarrow Imp\{j,i \rightarrow i',c\}}$the percentage from all the exported crop from the country (i) to the country (i'). Further details on the calculation of the trade information (exports $XP_{Exp\{i,j,c\}}$ and imports $XP_{Exp \rightarrow Imp\{j,i \rightarrow i',c\}}$) are given in Chapter 4.

Country Partial Factor Productivity (PFP) for energy and protein

PFP is commonly defined as the ratio of harvested output per unit of nutrient applied [443]. We apply this concept to assess the PFP by country (i), year (j), crop (c) and nutrient ($F \in N, P, K$), defining it as the ratio between the amount of energy or protein produced and the amount of fertilizer applied. To compute this, we first calculate the total output of energy or protein produced for each country, year and crop by summing the food and feed contributions across all livestock products (L) (Eq. (5.5)). Then, we compute the $PFP_{NUT\{i,j,c,F\}}$ where $NUT \in Energy, Protein$ by Eq. (5.6).

$$NUT_{PerKgFeed\{i,j,c,l\}} = \sum_{s \in S} \left(XC_{Feed\{i,j,c,l\}} \cdot LS_{\{i,j,l,s\}} \cdot \frac{XNUT_l}{FCR_{\{i,j,l,s\}}} \right) \tag{5.5}$$

$$PFP_{NUT\{i,j,c,F\}} = \frac{NUT_{\{i,j,c\}}}{F_{\{i,j,c\}}} \tag{5.6}$$

Fertilizer Potential Savings (FPS)

We have defined the maximum potential fertilizer savings as the amount of N, P or K fertilizer that could have been saved from feed if the same amount of protein or energy had been produced using crop allocations for food. To calculate these savings, we apply Eq. (5.7)

which uses the annual PFP of crop fraction allocated to food, calculated previously by year, country, fertilizer and crop.

$$FPS_{\{i,j\}} = \sum_{c} \frac{P_{Feed\{i,j,c\}}}{PFP_{Food,NUT\{i,j,c,F\}}} \tag{5.7}$$

Together with fertilizer savings from feed, fertilizer savings from other uses can be considered mostly as fertilizer potential savings, excluding the fraction for seed.

Uncertainty analysis

To assess the uncertainty, we followed the methodology applied of Chapter 5 where we only accounted for the uncertainty on the fertilizer use to produce the major crops. We applied a two-step process: (1) we used the predictions and the validation results from Coello and Decorte et al. (2025) [331] to perform 500 simulations of fertilizer per hectare for each nutrient, crop, country and year. For each case, we randomly sampled a truncated normal distribution using the predicted value from Coello and Decorte et al. (2025) [331] as mean and the mean absolute percentage error (MAPE) from their validation process to define the SD of the distribution. Secondly, to aggregate results across crops or countries we ran 500 Monte Carlo (MC) simulations. In each iteration, we selected one simulated value per crop or country to propagate the uncertainty through the system. Further details can be found in Chapter 5. To compare the distributions of simulation results between decades or countries, we used Cliff's delta (δ), a non-parametric effect size measure that quantifies the degree of overlap between two distributions [437]. This method was selected because it is robust to non-normal data, does not assume equal variances, and is unaffected by differences in measurement scale, making it well suited for comparing simulation outputs derived from MC approaches.

Results Visualization

To represent global PFP trends for both the four main crops combined and each crop individually, we show the Interquartile Range (IQR) and 1.5 times the IQR. To represent the national evolution of protein and energy supply from the four crops while simultaneously accounting for fertilizer use (rates) and PFP_{all}, we estimated the number of people potentially nourished per hectare, assuming an average requirement of 56 g of proteins per person per day [444]. This indicator was plotted against fertilizer use per hectare, with PFP_{all} represented by oblique isolines. For each nutrient, breakpoints were calculated as the fertilizer application rates at which selected values of people potentially nourished per hectare intersected the first quartile, median, and third quartile of the PFP_{all} distribution. National observations were then classified according to their position relative to these breakpoints for each decade.

Chapter 6

General discussion

In this thesis, we examine the historical evolution of fertilizer use, from its early development to its rapid expansion during and after the Green Revolution (GR). This historical perspective provides a basis for identifying both past and persistent inefficiencies along the food chain by addressing remaining knowledge gaps in the field. In particular, we extend previous analyses by explicitly including Potassium (K) alongside Nitrogen (N) and Phosphorus (P), despite its central role in crop nutrition and the fact that environmental and socioeconomic implications associated with its use having received comparatively little attention [5]. In addition, the analysis is conducted at the crop level, allowing fertilizer use and efficiency patterns to be examined with greater resolution. These gaps largely arose from the absence of long-term, crop- and nutrient-specific datasets, which constrained the integrated analysis of historical trends, underlying drivers, and efficiency outcomes on a global scale.

To address these gaps, this thesis advances the literature through four main contributions. First, by using machine learning (ML) models, we developed a new database of fertilizer use by crops, providing a longer temporal resolution than previous assessments and harmonized information for the three major nutrients (N, P, and K). Building on this dataset, we analyzed how fertilizer intensification processes have varied across crops, countries, and nutrients over the past century. We then identified the drivers that have shaped changes in total fertilizer consumption for major crops (maize, rice, wheat, and soybean) by disentangling the contributions of expanding crop areas, fertilizer application rates, and changes in crop consumption patterns. Finally, we quantified how efficiently fertilizer-derived nutrients are converted into human nutritional proteins and calories for these four crops, identifying where major losses occur along the farm-to-fork system (food system). Here, we quantified fertilizer use efficiency by measuring the Partial Factor Productivity (PFP), the ratio between energy/proteins produced and the fertilizer application rate per hectare, at the plant (crop), livestock, and food system levels.

Taken together, the results of all chapters demonstrate how crop type, nutrient type, and region-specific intensification (fertilizer use per hectare) patterns have jointly shaped both total fertilizer consumption and the efficiency of its use. On a global scale, fertilizer intensification has progressively shifted from Western countries to Asia and, more recently, to South America, while remaining comparatively low in Africa. Along this transition, fertilizer use has moved from being predominantly directed toward food production to being increasingly allocated toward livestock feed and other non-food uses over the last three decades, particularly in the case of P. This shift has had important implications for fertilizer efficiency. PFP initially declined as fertilizer applications expanded from very low baseline

rates, before stabilizing as intensification matured. In more recent decades, crop-level PFP has shown signs of recovery; however, these gains have not been fully transmitted to the food system. The incomplete translation of crop-level efficiency improvements into higher food-system PFP reflects the growing diversion of crop production, and associated fertilizer use, toward feed and other uses, especially regarding K and P. The following sections examine these patterns in greater depth through a chronological perspective, followed by a discussion of the main limitations of the thesis and its overall conclusions.

Before 1960: The pre-global industrial fertilizer period

During the first one hundred years (1850–1950) of the history of inorganic fertilizers, their use was limited to a few countries with large mining resources and high economic wealth. Although data for this period are scarce, the global and regional results of the second chapter support this observation. The intensity of fertilizer utilization grew early in wealthy countries where secure supplies for each nutrient were found. For example, consumption of K fertilizers increased early in Germany [453], where the first major potash deposits were discovered and exploited [55]. Similarly, early P fertilizer intensification in Australia was driven by the combination of secure phosphate supplies from Pacific islands and declining wheat yields resulting from the depletion of inherently P-poor soils, which promoted early adoption of superphosphates [37, 454].

The lack of global data prior to 1960 prevents a global quantification of how fertilizers were utilized for different crops and end-uses during this period. Nevertheless, valuable insights can be gleaned at the country level for nations where fertilizer consumption was significant, such as the United States of America (USA)., Australia, Japan, and select European countries. Crop-specific information suggests that fertilizer intensification began with cash and staple crops, rather than crops used for livestock feeding. For example, early intensification occurred in USA. cotton production [190, 375], sugar beet in Germany and the United Kingdom and Northern Ireland (UK) [453, 455], and sugar cane production (for N and K) in Australia [37, 454]. Additionally, in some countries, fertilizer intensification was directly associated with staple crops, such as wheat in Australia [454], rice in Japan, and potatoes in the UK or Germany [453, 455].

1961–1980: Asian Green Revolution (GR)

Since 1960, the availability of global statistics has allowed us to quantify the patterns and drivers behind global fertilization. In the period from 1960 to 1980 (extending to 1990), global fertilizer intensification is intrinsically related to the Asian GR. While Asian countries accounted for 12.3% of global fertilizer consumption in 1960, this share increased to 25.2% in 1979 and 37.2% in 1989 [456]. The emerging primacy of Asian countries as global consumers was associated with a decrease in the global food chain efficiency (PFP) of fertilizer use. This decline was driven by diminishing returns; as nutrient inputs increased rapidly from near-zero baselines, they outpaced yield gains.

These increases in fertilizer rates in the region not only drove global changes in total consumption but were also associated with substantial increases in yields, and total crop production [163]. The additional crop output, and the corresponding increase in fertilizer consumption, was largely directed towards direct human consumption, at least for the four major crops analyzed in Chapter 4. This shift contributed to a substantial reduction in

undernourishment rates in the region [457]. Because of this allocation of production gains, food system PFP followed a trajectory closely aligned with plant-level PFP, declining in parallel during this period.

This relationship is particularly evident when comparing rice and wheat. Rice production is heavily concentrated in Asia, whereas wheat production is more geographically dispersed [163]. Food chain efficiency declined for both crops over this period; however, while food system PFP and plant-level PFP for rice exhibit almost identical values (the ratio between food system and plant PFP is on average 87%) wheat shows consistently lower food system PFP (the same ratio is 68%). Moreover, the divergence between plant and food system PFP for wheat increased approximately 10% throughout the 1960s and 1970s, reflecting both a greater allocation of fertilizer-associated wheat production to livestock feeding compared to rice, and an expansion of this gap during this period. These PFP patterns were observed for all three nutrients. However, the trends are more pronounced for N than for P and K, reflecting the intensification patterns identified in Chapter 3, where both the pace of intensification and the magnitude of fertilizer application rates were greater for N than for P and K in Asia.

1981–2000: A Tipping Point in Global Fertilizer Use and Food-Chain PFP

The following two decades were globally marked by several events that affected both total fertilizer consumption and the efficiency of its use. Importantly, these events influenced consumption and food-chain PFP in opposite directions. On one hand, the collapse of the socialist bloc led to a global decline in fertilizer application rates, particularly for crops with a large production share in these countries (such as wheat) and for nutrients whose supply was more concentrated there (notably P and K). On the other hand, fertilizer rates continued to increase in Asia, albeit at a slower pace, while beginning to rise in Latin America.

The effects of the declining relative importance of socialist bloc countries are particularly evident in the P and K results for wheat. The global decrease in the share of fertilizer use allocated to feed relative to food can be partly attributed to this shift, as a substantial fraction of domestic wheat production in these countries (e.g., the former Union of Soviet Socialist Republics (USSR)) was directed toward livestock feeding [458]. One consequence of this reallocation was an improvement in food chain PFP. Nevertheless, food chain PFP increased not only due to this reallocation but also as a result of concurrent improvements in global plant-level and livestock feeding PFP, following the reduced contribution of socialist countries characterized by comparatively low nutrient use efficiency [89].

The deceleration in the growth of fertilizer application rates in Asia halted the decline in plant-level PFP in the region. In addition, crop utilization patterns changed little during this period compared with the following decades, as dietary transitions in the region remained limited [402]. Although Latin America started to gain importance in global fertilizer consumption during this period, fertilizer application rates and production volumes were still insufficient to substantially influence global food-chain PFP trends.

At the livestock level, PFP began to rise during this period for most major crop-nutrient combinations, driven by several factors. On the one hand PFP of livestock products increased because global improvements in PFP at plant level reduced the amount of fertilizer required per unit of feed production. On the other hand, Llivestock feeding PFP also improved due to global increases in feed conversion ratios [404, 447, 448], as well as a growing share of

livestock protein production coming from monogastric animals raised in industrial systems, which have higher FCRs than ruminants [385, 397]. Although their superior feed efficiency resulted in higher livestock-level PFP, intensive monogastric systems require larger inputs of grains and oilseed cakes than ruminant systems [385], resulting in an increasing demand for these crops.

Taken together, the 1981–2000 period represents a tipping point in which structural and regional shifts in crop utilization outweighed pure fertilizer intensification as the dominant drivers of global food-chain PFP, stagnating the previous decreases.

2000–2020: South American soy production

The last two decades have been marked by a global stagnation of fertilizer application rates, alongside generalized increases in plant and livestock-level PFP for major crops. However, these gains have not been fully translated into food-chain PFP, as a growing share of fertilizer use has been allocated to livestock feeding and non-food uses. In this process, the increasing relative importance of South America in global fertilizer consumption has been particularly influential. This growth occurred across all three nutrients; however, while increases in N applications have begun to level off in recent years, P and K application rates have continued to rise in the region.

In contrast to the Asian GR of previous decades, fertilizer intensification in South America was linked not only to staple crops but also to crops predominantly used for livestock feeding. Consequently, gains in crop production that occurred during this period were translated into increased livestock production [459, 460] and higher grain and oilseed exports [461], rather than increases in per capita energy intake within the region [462]. Our results for fertilizers reflect these patterns, as we observe how countries like Brazil have become some of the world's largest fertilizer consumers, particularly for K, largely driven by exports of feed grains and soybean cakes.

Implications

Given the environmental and socioeconomic implications of fertilizer production and use highlighted in the introduction, our results underscore the urgent need for policy interventions. Although fertilizer-use efficiency gains at the plant and livestock levels were achieved over recent decades, these gains partially disappear when assessed across the entire food chain. A major driver of this decline is the increasing share of fertilizer use allocated to crop production for livestock feeding and other non-food uses, at least for major crops. This growing separation between fertilizer inputs, crop production, and final food availability highlights the importance of considering end-use pathways when evaluating fertilizer efficiency and sustainability. Without accounting for shifts toward livestock feeding and biofuel production, assessments based solely on crop-level productivity risk overestimating the contribution of fertilizer intensification to global food security.

Moreover, future scenarios suggest that this trend will continue as the global population grows [420], the demand for meat and dairy products increases, shifts toward the consumption of monogastric animals accelerate [398], and total NP-fertilizer use generally increases [421, 422]. Potential solutions to reduce fertilizer consumption can nevertheless arise from policymakers, new technologies, or consumers, especially when targeted at

countries with overuse of fertilizers and at countries importing agricultural products for non-food uses.

Limitations

Here, we provide an initial overview of the long-term trends in fertilizer use and fertilizer use efficiency at the crop level for N, P, and K. However, the analysis, results, and interpretation are subject to several limitations arising from data availability and quality, as well as assumptions required by the methodological approaches. These factors introduce uncertainty into the estimates and constrain the ability to fully disentangle the processes driving changes in fertilizer consumption and their relationship with food production.

Methodological and data-related limitations have been discussed in detail within the individual chapters. Nevertheless, some cross-cutting limitations emerge when integrating all results. The most relevant ones relate to the general analytical framing of the thesis, particularly in the last chapter. The exclusive focus on inorganic fertilizer ignores the effect of other nutrient sources, such as manure applications or atmospheric deposition. A fraction of these inputs is itself a consequence of fertilizer use, as nutrients applied to crops used for livestock feed are partially recycled through manure, and N deposition is partially influenced by ammonia emissions from agricultural soils [463]. This recycling process was not accounted for due to the lack of crop-level data. As a result, some conclusions, particularly those related to nutrient use efficiency, should be interpreted with caution.

The other major limitation arising from the analytical framing concerns the focus on the four major crops. Conclusions regarding the end use of fertilization and the PFP of fertilizer are therefore restricted to the four crops included in the third and fourth chapters (maize, rice, wheat, and soybean). These findings may not be universally applicable to total fertilizer consumption, given that approximately 40-50% of global fertilizer use during the study period was applied to other crops or grasslands [331].

Future Research

These limitations related to the scope of the thesis could be partially addressed with new available datasets providing crop-level and temporal resolution of N deposition [442], as well as nutrient inputs and outputs associated with crop-residue management [464] and irrigation [465]. These resources can enable a more comprehensive representation of nutrient cycles at the crop level beyond fertilizer use and crop production. Furthermore, Food and Agriculture Organization (FAO) statistics on agricultural trade, crop production, and crop utilization used in Chapters 4 and 5 could be further employed to provide a complete overview of most agricultural lands, not only major crops.

A more comprehensive analysis could improve the understanding of inefficiencies in global food production; future research should not only refine crop-level analyses but also address how different measures can reduce fertilizer consumption without compromising per-capita energy and protein intake. The results across chapters suggest that demand-side measures, particularly those affecting how crop production is allocated among different uses, can strongly influence total fertilizer consumption, as inefficiencies may intensify during downstream utilization. Nevertheless, closing nutrient cycle evaluations at the crop level by explicitly accounting for manure application and other recycling fluxes is essential to quantify the mitigation potential of these measures.

Final Thoughts

Although a more detailed assessment of demand-side measures and a complete evaluation of nutrient cycles (accounting for all inputs and outputs) would help resolve remaining uncertainties, the results of this thesis indicate that a substantial share of the gains in nutrient use efficiency achieved through technological advances is being partially offset by current crop utilization patterns. In particular, the increasing allocation of crops to non-food uses and livestock feeding weakens the translation of agronomic efficiency improvements into food-system efficiency. Policy interventions that limit non-food uses of crops—such as the Renewable Energy Directive [424] have proven effective in reducing fertilizer demand and may provide a starting point for more ambitious policies addressing livestock feed use. Such measures could help realign nutrient efficiency gains with food security and sustainability objectives.

Chapter 7

Conclusions

This thesis combined data reconstruction, statistical modelling, and food-system analysis to examine the historical evolution, drivers, and efficiency of fertilizer use across the major global crops. The main conclusions of the thesis, following the order of the chapters, are summarized below.

Conclusion I:

Machine learning techniques are a powerful and effective tool for imputing global datasets, such as fertilizer use by crop, which have significant data gaps.

Conclusion II:

The modified technology adoption model combined with Bayesian inference successfully captured the historical fertilizer-use trajectories, while also revealed the strong context dependence of intensification patterns.

Conclusion III:

Across the major crops (maize, rice, wheat, and soybean), increases in fertilizer use since 1960 for the two main end uses (*food* and *feed*) have been relatively balanced at the global level. However, at the country level, most countries have shifted toward a higher share of fertilizer use allocated to *feed* relative to *food*.

Conclusion IV:

Across the major crops, changes in total fertilizer consumption among nutrient-use combinations were driven primarily by increases in fertilizer application rates rather than by changes in harvested area or crop use. In contrast, changes in total Phosphorus (P) and Potassium (K) consumption for *feed* use were influenced to a similar extent by increases in harvested area.

Conclusion V:

Across the major crops, global changes in the *other uses* category were driven mainly by maize cultivation associated with bioethanol production, with the United States playing a particularly important role.

Conclusion VI:
Across the major crops, international trade has transitioned from a mechanism of regional resource optimization to a global driver of nutrient translocation, where export-driven demand in hubs like Brazil decouples local fertilizer application from domestic nutritional needs.

Conclusion VII:
During the study period, global crop-to-fork fertilizer use efficiency for the major crops combined, measured by Partial Factor Productivity (PFP_{all}), showed an initial decline followed by a recovery, particularly for $PFP_{protein}$ in the case of P and K.

Conclusion VIII:
The systemic shift toward feed-heavy allocation has created a 'trophic drag' on global fertilizer efficiency. Consequently, technological improvements in agronomy may be insufficient to keep nutrient use within planetary boundaries without a concomitant shift in consumption patterns through demand-side policies.

Conclusion IX:
Taken together, these findings show that understanding fertilizer use requires not only crop- and country-specific analyses, but also attention to the final destination of crop production, since food-system allocation strongly shapes both fertilizer demand and fertilizer use efficiency.

Appendix A

Supplementary information:

General introduction

This appendix provides a detailed description of the data sources, assumptions, and methodological approach used to generate Fig. 1.4 in the Chapter 1.

Reactive Nitrogen (Nr) Produced

The natural global reactive Nitrogen (Nr) production since 1850 was calculated by integrating Nitrogen (N) fixed by lightning [85], terrestrial N released from weathering [86] and the natural Biological Nitrogen Fixation (BNF) [84]. For BNF, because land-use changes have reduced fixation rates since the industrial revolution, we applied a linear interpolation between the pre-industrial (1850) value and the present-day estimate reported by Reis Ely et al. (2025) [84]. All uncertainties are expressed as $1sd$, based on the uncertainty ranges provided in the respective sources.

The artificial Nr production since 1850 was calculated by integrating the Nr fixed from fossil fuels and industrial activities [90, 91], the inorganic N fertilizer use [2, 68], and the BNF in agricultural lands [84, 89, 146].

Artificial global emissions from fossil fuels and industrial activities as nitrogen oxides (NOx) were constructed by combining the CEDS inventory [91], and the EDGAR dataset for the most recent decade [90]. Both datasets were aggregated across fossil fuel related sectors and converted to N using the NO_2 stoichiometric factor (14/46). We primarily relied on the CEDS inventory which covers most of the historical period represented (1850-2014), whereas EDGAR is available only from 1970. Because there are discrepancies between datasets, although they are minimal (R2 = 93.22%, y = 1.39x + 24.3, $p < 0.01$), EDGAR emissions from 2015 onward were scaled to match CEDS over their overlapping years in the 2010s, yielding a continuous global time series.

For inorganic N fertilizer use we used the FAOSTAT data from 1950 onwards [68], and the compilation by [2] for the previous period. We linearly interpolated the data from Smil (2004) [2], as it does not cover all years. Smil (2004) [2] includes not only N fixed through the Haber–Bosch process, but also N derived from guano, Chilean saltpeter, coke ovens, and the cyanamide process.

For BNF on agricultural lands, we used two different sources for croplands and grasslands. For croplands we relied on Food and Agriculture Organization Corporate

Statistical Database (FAOSTAT) estimates from 1960 onward [89]. For the period prior to 1960, we used historical cropland area data from the HYDE project [146] and the ratio of BNF-derived nitrogen during the 1960–1970 decade to cropland area for the same period in the HYDE dataset. We then extrapolated this ratio to the 1850–1960 period. For grasslands we used the ratio between the BNF estimates for agricultural grasslands from [84] and the corresponding grassland area in the HYDE dataset, and extrapolated this ratio across the entire period.

Phosphorus (P) Produced

For natural Phosphorus (P) inputs we accounted for the natural weathering with $1sd$ uncertainty [92]. For the anthropogenic inputs, we used data from the United States Geological Survey (USGS) as the source for mined P since 1900 [44]. To convert phosphate rock (PR) data to phosphorus pentoxide (P_2O_5), we applied the PR-to P_2O_5 (0.31) conversion ratio observed during the 1980–2024 period [44] to the 1900–1980 data. This likely results in a slight underestimation of P_2O_5 production in the early decades, as ore grades have generally declined over time. However, no systematic decrease is observed in the available data for the past 45 years, and earlier grade-specific information is not available. For years prior to 1900, we used single superphosphate (SSP) production as a proxy for mined P [93]. We also included P used as fertilizer from 1960 onward [68].

Potassium (K) Produced

For natural Potassium (K) inputs we assumed that annual global natural weathering is equal to the dissolved fraction of riverine transport [94, 95]. For the anthropogenic inputs, we used data from the USGS as the source for mined K since 1920 [57]. For earlier years, we used the Germany production as they were the only producer [56]. We also included K used as fertilizer from 1960 onward [68].

Appendix B

Supplementary information:

Global crop-specific fertilization dataset (1961–2019)

Table B.1. Crop classification with Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) item codes.

Crop class	Code	Description	Crops FAOSTAT (item code)
Wheat	1_1	Wheat	Wheat (15)
Maize	1_2	Maize, only for grain	Maize, corn (56)
Rice	1_3	Rice	Rice (27)
Other Cereals	1_4	Other cereals not mentioned above	Barley (44), Buckwheat (89), Canary seed (101), Fonio (94), Millet (79), Oats (75), Rye (71), Sorghum (83), Triticale (97), Quinoa (92), Cereal n.e.c (108)
Soybean	2_1	Soybean	Soya beans (236)
Palm Oil fruit	2_2	Palm oil fruit	Oil Palm fruit (254)
Other Oilseeds	2_3	Other oilseed crops not soybean and palm oil fruit	Castor oil seeds (265), Coconut, in shell (249), Jojoba seeds (277), Linseed (333), Mustard seed (292), Olives (260), Poppy seeds (296), Rape and colza seed (270), Safflower (280), Sesame seed (289), Sunflower seed (267), Tallowtree seed (305), Tung nuts (275), Other oil seeds, n.e.c (339)

Continued on next page

Crop class	Code	Description	Crops FAOSTAT (item code)
Vegetables	3_1	Vegetables	Artichokes (366), Asparagus (367), Cabbages (358), Cauliflowers and broccoli (393), Chillies and peppers, green (401), Cucumber and gherkins (397), Eggplants (399), Green garlic (406), Leeks and alliaceous (407), Cantaloupes and other melons (568), Melonseed (299), Mushrooms and truffles (449), Okra (430), Onion and shallots, green (402), Onion and shallot, dry (403), Pumpkins, squash and gourds (394), Spinach (373), Tomatoes (388), Watermelons (567), Carrots and turnips (426), Lettuce and chickory (372), Cassava leaves (378), Green corn (446), Other vegetables fresh n.e.c (463)
Fruits	3_2	Fruits	Apples (515), Apricots (526), Avocados (572), Bananas (486), Blueberries (552), Cherries (531), Sour cherries (530), Cranberries (554), Currants (550), Dates (577), Figs (569), Gooseberries (549), Pomelos and grapefruits (507), Grapes (560), Kiwi fruits (592), Lemos and limes (497), Oranges (490), Papayas (600), Peaches and nectarines (534), Pears (521), Perssimons (587), Pineapples (574), Plantains (489), Plums and sloes (536), Quinces (523), Raspberries (547), Strawberries (544), Tangerines, mandarins, clementines (495), other berries n.e.c (558), other citrus n.e.c. (512), other fruits n.e.c. (619), Other pome fruits n.e.c (542), Other stone fruits n.e.c (541), Other tropical fruits n.e.c (603)
Roots and tubers	4	Roots and tubers	Cassava (125), Potatoes (116), Sweet potatoes (122), Taro (136), Yams (137), Yautia (135), Edible roots and tubers n.e.c. (149)
Sugar crops	5	Sugar cane, sugar beet and only sugar crops	String beans (423), Sugar beet (157), Sugar cane (156), Locust beans (461), Other sugar Crops n.e.c. (161)
Fiber crops	6	Cotton and other fiber crops	Coir (813), True hemp (777), Hempseed (336), Jute (780), Kapok fruit (310), Kapok seed (311), Karite nuts (263), Abaca, manila, hemp (809), Ramie (788), Seed cotton (328), Sisal (789), Agave fibres (800), Flax (773), Kenak (782), Other fibre crops (821)

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Crop class	Code	Description	Crops FAOSTAT (item code)
Other crops	7	Nuts, pulses, stimulants and aromatics, natural rubber, tobacco	Almonds (221), Areca nuts (226), Cashew nuts (217), Chestnuts (220), Hazelnuts (225), Pistachios (223), Walnut (222), Brazil nuts (216), Kola nuts (224), Other nuts (234), Broad beans and horse beans, dry (181), Broad beans and horse beans, greens (420), Chick peas (191), Cow peas, dry (195), Lentils, dry (201), Lupins (210), Peas, dry (187), Peas, green (417), Pidgeon peas, dry (197), Bambara beans (203), Vetches (205), Other beans, green (414), Other pulses n.e.c (211), Coffee, green (656), Green tea (675), Tea leaves (667), Cocoa beans (661), Chickory roots (459), Mate leaves (671), Other stimulant, spice and aromatic n.e.c (723), Anise, badian, coriander, cumin, caraway, fennel and juniper (711), Cinnamon (693), Cloves (698), Ginger (720), Hop cones (677), Pepper (Piper spp.) (687), Nutmeg, mace, cardamoms (702), Vanilla (692), Chillies and peppers (689), Peppermint (748), Pyrethrum (754), Tobacco (826), Natural rubber (836), Balata, gutta-, percha-, chicle, and similar natural gums (839)

Table B.2. Overview of the explored hyperparameters for the Histogram-based Gradient Boosting (HGB) and eXtreme Gradient Boosting (XGB) regression models.

Method	Hyperparameter	Possible values
HGB	max_depth	2, 5, 10, 20
	max_iter	25, 50, 100, 200, 500
	learning_rate	0.01, 0.1, 0.5, 1
	min_samples_leaf	5, 10, 20, 50
XGB	max_depth	2, 3, 4, 5
	n_estimators	25, 50, 100, 200, 300, 400
	colsample_by_tree	0.6, 0.7, 0.8, 0.9, 1.0
	subsample	0.6, 0.7, 0.8, 0.9, 1.0
	min_child_weight	3, 4, 5, 6, 8, 10

Table B.3. Overview of the open-source packages and respective programming languages used for model training, SHAP value computation, validation and map building.

Language	Package	Version
Python	`Python` [354]	3.10.3
	`numpy` [466]	1.23.2
	`pandas` [467]	1.4.1
	`rasterio` [468]	1.3.9
	`scikit-learn` [140]	1.3.2
	`shap` [141]	0.44.0
	`xgboost` [139]	2.0.3
R	`R` [469]	4.2.2
	`sf` [470, 471]	1.0-15
	`ncdf4` [472]	1.22
	`exactextractr` [473]	0.10.0
	`readxl` [474]	1.4.3
	`stringr` [475]	1.5.0
	`dplyr` [476]	1.1.2
	`readr` [477]	2.1.4
	`ggplot2` [478]	3.4.2
	`tidyverse` [479]	2.0.0
	`cshapes` [346]	2.0
	`terra` [275]	1.7-65

Appendix C

Supplementary information:

From intensification to decline: Crop-specific patterns of fertilizer use intensity

C.1 Country classification

This section includes all countries and other territorial units considered in the study (Table C.1). As a starting point, we used the countries listed in the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) database, together with the FAOSTAT regional classification [480]. We aligned with Food and Agriculture Organization (FAO) statistics considering separately for China, Taiwan and mainland China. Belgium and Luxembourg were combined into a single entry before 2000. A map is provided to summarize the regional classification and allow easier identification of the regions used for fitting the models (Fig. C.1).

Table C.1. Country and region classification used throughout the paper: three-letter ISO (ISO3) codes [355], country/area name, M49 code [481], FAO regional classification (Region FAO) [480], and the regional classification used in this study (Region).

ISO3 Code	Country/area	M49 Code	Region FAO	Region
BDI	Burundi	108	Eastern Africa	Africa
IOT	Chagos Archipelago	86	Eastern Africa	Africa
COM	Comoros	174	Eastern Africa	Africa
DJI	Djibouti	262	Eastern Africa	Africa
ERI	Eritrea	232	Eastern Africa	Africa
ETH	Ethiopia	231	Eastern Africa	Africa
F62	Ethiopia PDR	230	Eastern Africa	Africa
ATF	French Southern Territories	260	Eastern Africa	Africa
KEN	Kenya	404	Eastern Africa	Africa
MDG	Madagascar	450	Eastern Africa	Africa

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
MWI	Malawi	454	Eastern Africa	Africa
MUS	Mauritius	480	Eastern Africa	Africa
MYT	Mayotte	175	Eastern Africa	Africa
MOZ	Mozambique	508	Eastern Africa	Africa
REU	Réunion	638	Eastern Africa	Africa
RWA	Rwanda	646	Eastern Africa	Africa
SYC	Seychelles	690	Eastern Africa	Africa
SOM	Somalia	706	Eastern Africa	Africa
SSD	South Sudan	728	Eastern Africa	Africa
UGA	Uganda	800	Eastern Africa	Africa
TZA	United Republic of Tanzania	834	Eastern Africa	Africa
ZMB	Zambia	894	Eastern Africa	Africa
ZWE	Zimbabwe	716	Eastern Africa	Africa
AGO	Angola	24	Middle Africa	Africa
CMR	Cameroon	120	Middle Africa	Africa
CAF	Central African Republic	140	Middle Africa	Africa
TCD	Chad	148	Middle Africa	Africa
COG	Congo	178	Middle Africa	Africa
COD	Democratic Republic of the Congo	180	Middle Africa	Africa
GNQ	Equatorial Guinea	226	Middle Africa	Africa
GAB	Gabon	266	Middle Africa	Africa
STP	Sao Tome and Principe	678	Middle Africa	Africa
DZA	Algeria	12	Northern Africa	Africa
EGY	Egypt	818	Northern Africa	Africa
LBY	Libya	434	Northern Africa	Africa
MAR	Morocco	504	Northern Africa	Africa
SDN	Sudan	729	Northern Africa	Africa
F206	Sudan (former)	736	Northern Africa	Africa
TUN	Tunisia	788	Northern Africa	Africa
ESH	Western Sahara	732	Northern Africa	Africa
BWA	Botswana	72	Southern Africa	Africa
SWZ	Eswatini	748	Southern Africa	Africa
LSO	Lesotho	426	Southern Africa	Africa
NAM	Namibia	516	Southern Africa	Africa
ZAF	South Africa	710	Southern Africa	Africa
BEN	Benin	204	Western Africa	Africa
BFA	Burkina Faso	854	Western Africa	Africa
CPV	Cabo Verde	132	Western Africa	Africa
CIV	Côte d'Ivoire	384	Western Africa	Africa
GMB	Gambia	270	Western Africa	Africa
GHA	Ghana	288	Western Africa	Africa
GIN	Guinea	324	Western Africa	Africa
GNB	Guinea-Bissau	624	Western Africa	Africa
LBR	Liberia	430	Western Africa	Africa
MLI	Mali	466	Western Africa	Africa

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
MRT	Mauritania	478	Western Africa	Africa
NER	Niger	562	Western Africa	Africa
NGA	Nigeria	566	Western Africa	Africa
SHN	Saint Helena, Ascension and Tristan da Cunha	654	Western Africa	Africa
SEN	Senegal	686	Western Africa	Africa
SLE	Sierra Leone	694	Western Africa	Africa
TGO	Togo	768	Western Africa	Africa
KAZ	Kazakhstan	398	Central Asia	Asia
KGZ	Kyrgyzstan	417	Central Asia	Asia
TJK	Tajikistan	762	Central Asia	Asia
TKM	Turkmenistan	795	Central Asia	Asia
UZB	Uzbekistan	860	Central Asia	Asia
CHN	China	159	Eastern Asia	Asia
HKG	China, Hong Kong SAR	344	Eastern Asia	Asia
MAC	China, Macao SAR	446	Eastern Asia	Asia
CHN	China, mainland	156	Eastern Asia	Asia
TWN	China, Taiwan Province of	158	Eastern Asia	Asia
PRK	Democratic People's Republic of Korea	408	Eastern Asia	Asia
JPN	Japan	392	Eastern Asia	Asia
MNG	Mongolia	496	Eastern Asia	Asia
KOR	Republic of Korea	410	Eastern Asia	Asia
BRN	Brunei Darussalam	96	South-eastern Asia	Asia
KHM	Cambodia	116	South-eastern Asia	Asia
IDN	Indonesia	360	South-eastern Asia	Asia
LAO	Lao People's Democratic Republic	418	South-eastern Asia	Asia
MYS	Malaysia	458	South-eastern Asia	Asia
MMR	Myanmar	104	South-eastern Asia	Asia
PHL	Philippines	608	South-eastern Asia	Asia
SGP	Singapore	702	South-eastern Asia	Asia
THA	Thailand	764	South-eastern Asia	Asia
TLS	Timor-Leste	626	South-eastern Asia	Asia
VNM	Viet Nam	704	South-eastern Asia	Asia
AFG	Afghanistan	4	Southern Asia	Asia
BGD	Bangladesh	50	Southern Asia	Asia
BTN	Bhutan	64	Southern Asia	Asia
IND	India	356	Southern Asia	Asia
IRN	Iran (Islamic Republic of)	364	Southern Asia	Asia
MDV	Maldives	462	Southern Asia	Asia
NPL	Nepal	524	Southern Asia	Asia
PAK	Pakistan	586	Southern Asia	Asia
LKA	Sri Lanka	144	Southern Asia	Asia
ARM	Armenia	51	Western Asia	Asia
AZE	Azerbaijan	31	Western Asia	Asia
BHR	Bahrain	48	Western Asia	Asia

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
CYP	Cyprus	196	Western Asia	Asia
GEO	Georgia	268	Western Asia	Asia
IRQ	Iraq	368	Western Asia	Asia
ISR	Israel	376	Western Asia	Asia
JOR	Jordan	400	Western Asia	Asia
KWT	Kuwait	414	Western Asia	Asia
LBN	Lebanon	422	Western Asia	Asia
OMN	Oman	512	Western Asia	Asia
PSE	Palestine	275	Western Asia	Asia
QAT	Qatar	634	Western Asia	Asia
SAU	Saudi Arabia	682	Western Asia	Asia
SYR	Syrian Arab Republic	760	Western Asia	Asia
TUR	Türkiye	792	Western Asia	Asia
ARE	United Arab Emirates	784	Western Asia	Asia
YEM	Yemen	887	Western Asia	Asia
F246	Yemen Ar Rp	886	Western Asia	Asia
F247	Yemen Dem	720	Western Asia	Asia
BLR	Belarus	112	Eastern Europe	Europe
BGR	Bulgaria	100	Eastern Europe	Europe
CZE	Czechia	203	Eastern Europe	Europe
F51	Czechoslovakia	200	Eastern Europe	Europe
F77	Germany Nl	278	Eastern Europe	Europe
HUN	Hungary	348	Eastern Europe	Europe
POL	Poland	616	Eastern Europe	Europe
MDA	Republic of Moldova	498	Eastern Europe	Europe
ROU	Romania	642	Eastern Europe	Europe
RUS	Russian Federation	643	Eastern Europe	Europe
SVK	Slovakia	703	Eastern Europe	Europe
UKR	Ukraine	804	Eastern Europe	Europe
F228	USSR	810	Eastern Europe	Europe
ALA	Åland Islands	248	Northern Europe	Europe
CHA	Channel Islands	830	Northern Europe	Europe
DNK	Denmark	208	Northern Europe	Europe
EST	Estonia	233	Northern Europe	Europe
FRO	Faroe Islands	234	Northern Europe	Europe
FIN	Finland	246	Northern Europe	Europe
GGY	Guernsey	831	Northern Europe	Europe
ISL	Iceland	352	Northern Europe	Europe
IRL	Ireland	372	Northern Europe	Europe
IMN	Isle of Man	833	Northern Europe	Europe
JEY	Jersey	832	Northern Europe	Europe
LVA	Latvia	428	Northern Europe	Europe
LTU	Lithuania	440	Northern Europe	Europe
NOR	Norway	578	Northern Europe	Europe
SJM	Svalbard and Jan Mayen Islands	744	Northern Europe	Europe
SWE	Sweden	752	Northern Europe	Europe

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
GBR	United Kingdom of Great Britain and Northern Ireland	826	Northern Europe	Europe
ALB	Albania	8	Southern Europe	Europe
AND	Andorra	20	Southern Europe	Europe
BIH	Bosnia and Herzegovina	70	Southern Europe	Europe
HRV	Croatia	191	Southern Europe	Europe
GIB	Gibraltar	292	Southern Europe	Europe
GRC	Greece	300	Southern Europe	Europe
VAT	Holy See	336	Southern Europe	Europe
ITA	Italy	380	Southern Europe	Europe
F275	Kosovo	412	Southern Europe	Europe
MLT	Malta	470	Southern Europe	Europe
MNE	Montenegro	499	Southern Europe	Europe
MKD	North Macedonia	807	Southern Europe	Europe
PRT	Portugal	620	Southern Europe	Europe
SMR	San Marino	674	Southern Europe	Europe
SRB	Serbia	688	Southern Europe	Europe
SCG	Serbia and Montenegro	891	Southern Europe	Europe
SVN	Slovenia	705	Southern Europe	Europe
ESP	Spain	724	Southern Europe	Europe
F248	Yugoslav SFR	890	Southern Europe	Europe
AUT	Austria	40	Western Europe	Europe
BEL	Belgium	56	Western Europe	Europe
F15	Belgium-Luxembourg	58	Western Europe	Europe
FRA	France	250	Western Europe	Europe
DEU	Germany	276	Western Europe	Europe
F78	Germany Fr	280	Western Europe	Europe
LIE	Liechtenstein	438	Western Europe	Europe
LUX	Luxembourg	442	Western Europe	Europe
MCO	Monaco	492	Western Europe	Europe
NLD	Netherlands (Kingdom of the)	528	Western Europe	Europe
CHE	Switzerland	756	Western Europe	Europe
AIA	Anguilla	660	Caribbean	Latin America
ATG	Antigua and Barbuda	28	Caribbean	Latin America
ABW	Aruba	533	Caribbean	Latin America
BHS	Bahamas	44	Caribbean	Latin America
BRB	Barbados	52	Caribbean	Latin America
BES	Bonaire, Sint Eustatius and Saba	535	Caribbean	Latin America
VGB	British Virgin Islands	92	Caribbean	Latin America
CYM	Cayman Islands	136	Caribbean	Latin America
CUB	Cuba	192	Caribbean	Latin America
CUW	Curaçao	531	Caribbean	Latin America
DMA	Dominica	212	Caribbean	Latin America
DOM	Dominican Republic	214	Caribbean	Latin America
GRD	Grenada	308	Caribbean	Latin America
GLP	Guadeloupe	312	Caribbean	Latin America

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
HTI	Haiti	332	Caribbean	Latin America
JAM	Jamaica	388	Caribbean	Latin America
MTQ	Martinique	474	Caribbean	Latin America
MSR	Montserrat	500	Caribbean	Latin America
ANT	Netherlands Antilles (former)	530	Caribbean	Latin America
PRI	Puerto Rico	630	Caribbean	Latin America
BLM	Saint Barthélemy	652	Caribbean	Latin America
KNA	Saint Kitts and Nevis	659	Caribbean	Latin America
LCA	Saint Lucia	662	Caribbean	Latin America
MAF	Saint Martin (French part)	663	Caribbean	Latin America
VCT	Saint Vincent and the Grenadines	670	Caribbean	Latin America
SXM	Sint Maarten (Dutch part)	534	Caribbean	Latin America
TTO	Trinidad and Tobago	780	Caribbean	Latin America
TCA	Turks and Caicos Islands	796	Caribbean	Latin America
VIR	United States Virgin Islands	850	Caribbean	Latin America
BLZ	Belize	84	CentraL. Am	Latin America
CRI	Costa Rica	188	CentraL. Am	Latin America
SLV	El Salvador	222	CentraL. Am	Latin America
GTM	Guatemala	320	CentraL. Am	Latin America
HND	Honduras	340	CentraL. Am	Latin America
MEX	Mexico	484	CentraL. Am	Latin America
NIC	Nicaragua	558	CentraL. Am	Latin America
PAN	Panama	591	CentraL. Am	Latin America
ARG	Argentina	32	South America	Latin America
BOL	Bolivia (Plurinational State of)	68	South America	Latin America
BVT	Bouvet Island	74	South America	Latin America
BRA	Brazil	76	South America	Latin America
CHL	Chile	152	South America	Latin America
COL	Colombia	170	South America	Latin America
ECU	Ecuador	218	South America	Latin America
FLK	Falkland Islands (Malvinas)	238	South America	Latin America
GUF	French Guiana	254	South America	Latin America
GUY	Guyana	328	South America	Latin America
PRY	Paraguay	600	South America	Latin America
PER	Peru	604	South America	Latin America
SGS	South Georgia and the South Sandwich Islands	239	South America	Latin America
SUR	Suriname	740	South America	Latin America
URY	Uruguay	858	South America	Latin America
VEN	Venezuela (Bolivarian Republic of)	862	South America	Latin America
BMU	Bermuda	60	Northern America	Northern America
CAN	Canada	124	Northern America	Northern America

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
GRL	Greenland	304	Northern America	Northern America
JTN	Johnston Island	396	Northern America	Northern America
MID	Midway Island	488	Northern America	Northern America
SPM	Saint Pierre and Miquelon	666	Northern America	Northern America
USA	United States of America	840	Northern America	Northern America
AUS	Australia	36	Australia and New Zealand	Oceania
CXR	Christmas Island	162	Australia and New Zealand	Oceania
CCK	Cocos (Keeling) Islands	166	Australia and New Zealand	Oceania
HMD	Heard and McDonald Islands	334	Australia and New Zealand	Oceania
NZL	New Zealand	554	Australia and New Zealand	Oceania
NFK	Norfolk Island	574	Australia and New Zealand	Oceania
FJI	Fiji	242	Melanesia	Oceania
NCL	New Caledonia	540	Melanesia	Oceania
PNG	Papua New Guinea	598	Melanesia	Oceania
SLB	Solomon Islands	90	Melanesia	Oceania
VUT	Vanuatu	548	Melanesia	Oceania
GUM	Guam	316	Micronesia	Oceania
KIR	Kiribati	296	Micronesia	Oceania
MHL	Marshall Islands	584	Micronesia	Oceania
FSM	Micronesia (Federated States of)	583	Micronesia	Oceania
NRU	Nauru	520	Micronesia	Oceania
MNP	Northern Mariana Islands	580	Micronesia	Oceania
F164	Pacific Islands Trust Territory	582	Micronesia	Oceania
PLW	Palau	585	Micronesia	Oceania
UMI	United States Minor Outlying Islands	581	Micronesia	Oceania
ASM	American Samoa	16	Polynesia	Oceania
COK	Cook Islands	184	Polynesia	Oceania
PYF	French Polynesia	258	Polynesia	Oceania
NIU	Niue	570	Polynesia	Oceania
PCN	Pitcairn	612	Polynesia	Oceania
WSM	Samoa	882	Polynesia	Oceania
TKL	Tokelau	772	Polynesia	Oceania
TON	Tonga	776	Polynesia	Oceania
TUV	Tuvalu	798	Polynesia	Oceania
WAK	Wake Island	872	Polynesia	Oceania

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ISO3 Code	Country/area	M49 Code	Region FAO	Region
WLF	Wallis and Futuna Islands	876	Polynesia	Oceania

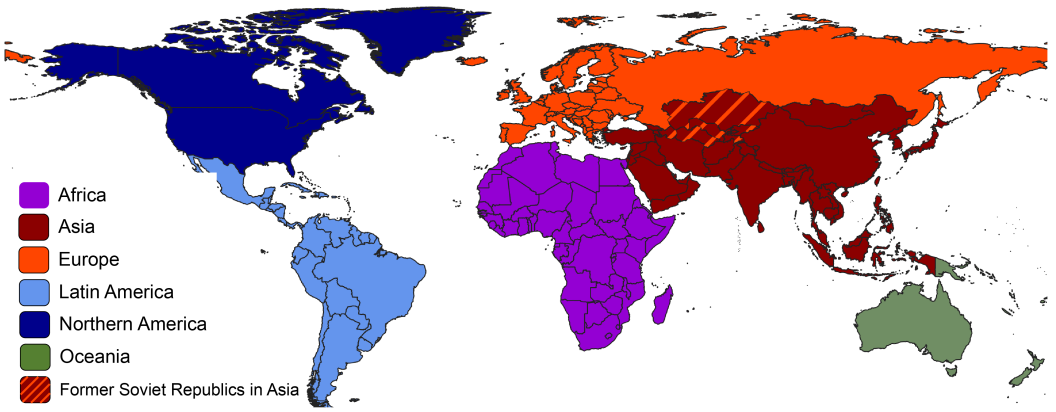


Figure C.1. Regional classification used for grouped model fits. The regional classification used for grouping countries considered the former Soviet republics in Asia as part of Europe before 1991 and as part of Asia after 1991, because the entire Union of Soviet Socialist Republics (USSR) was categorized under Europe prior to its dissolution.

C.2 Derivation of piecewise function

This section derives the piecewise logistic and lognormal function used for Bayesian inference of the fertilization time series.

We started from standard logistic and (negative) lognormal functions that transitioned into each other at transition point x_T:

$$\begin{cases} f_1(x) = \frac{A}{1+\exp(-k(x-X_0))} & x <= x_T \\ f_2(x) = \frac{-B}{x\sigma\sqrt{2\pi}} exp(\frac{-(ln\, x-\mu)^2}{2\sigma^2}) & x > x_T \end{cases} \tag{C.1}$$

where A is the asymptotic maximum, k is a scale parameter, X_0 is the inflection point of the logistic function f_1, μ is a location parameter, and B and σ are scale parameters of the lognormal function f_2.

We next reparametrized the piecewise function so that the function parameters were interpretable for subsequent analyses. Quantities of interest were

1. the maximal fertilizer use, which we set at $0.99A$
2. the year of maximal fertilizer use (X_{max}),
$$f_1(X_{max}) = 0.99A \tag{C.2}$$
3. the duration of the logistic increase ($2\Delta X_1$), for which
$$\Delta X_1 = X_{max} - X_0 \tag{C.3}$$
4. the time interval between the peak and the dip of the lognormal decline (ΔX_2), for which
$$\Delta X_2 = X_{min} - X_{max} \tag{C.4}$$
with X_{min} the year of the dip in the lognormal function,
$$f_2'(X_{min}) = 0 \tag{C.5}$$

The transition point between the logistic and lognormal functions was anchored at the peak (X_{max}, $0.99A$), the point when the lognormal function started, ensuring that the lognormal modification did not interfere with the phase of increase, allowing decays to be modeled only after the S-curve was fully developed. The lognormal function was, therefore, shifted vertically ($f_2 \rightarrow f_2 + 0.99A$) and horizontally ($x \rightarrow x - X_{max}$).

After substituting the original parameters $\{k, X_0, \mu\ and\ X_T\}$ with the new parameters $\{X_{max}, \Delta X_1, \Delta X_2\}$ using equations C.2-C.5, the final piecewise function becomes

$$\begin{cases} f_1(x) = \frac{A}{1+\exp\left(-4.6\frac{x-(X_{max}-\Delta X_1)}{\Delta X_1}\right)} & x <= X_{max} \\ f_2(x) = -\frac{B}{(x-X_{max})\,\sigma\sqrt{2\pi}} \exp\left(-\frac{\left(\ln(x-X_{max})-\sigma^2-\ln(\Delta X_2)\right)^2}{2\sigma^2}\right) + 0.99A & x > X_{max} \end{cases} \tag{C.6}$$

This final formulation guaranteed that the logistic term nearly reached the saturation point, allowing us to confidently introduce the lognormal term after the system had stabilized.

C.3 Prior analysis

C.3.1 Prior predictive checks

This section presents a prior predictive check of the distributions chosen for the global and regional model fits. As shown in Fig. C.2, the selected priors for the logistic increase (Fig. C.2 A) and the lognormal decay (Fig. C.2 B) demonstrate substantial flexibility, allowing for a wide range of plausible trajectories consistent with the likelihood.

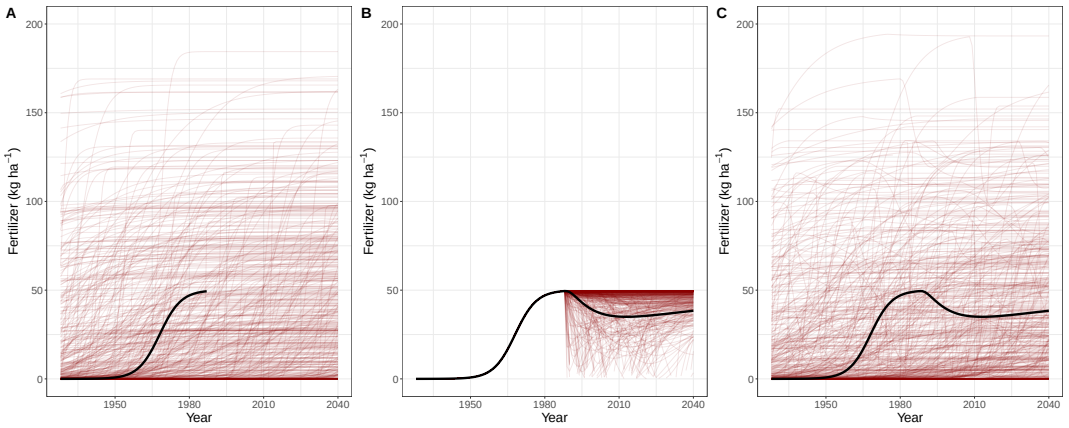


Figure C.2. Prior predictive checks of the broad priors used. A) Logistic increase: The black line represents the logistic increase using the mean of the normal distributions specified for the broad priors. The red lines represent 500 simulations (random samples draws from the prior distributions) incorporating the broad prior specification for the logistic increase; B) Lognormal decay: the black line represents the lognormal decay based on the mean of the normal distributions. The red lines show 500 simulations incorporating the broad prior specification for the lognormal decay, starting from the onset of the decay and using the mean values for the logistic increase; C) Complete piecewise function. The black line represents the full piecewise function using the mean of all prior distributions. The red lines represent 500 simulations incorporating the broad prior specification.

C.3.2 Sensitivity analysis

This section discusses in detail the cumulative Jensen–Shannon distance (CJS_{dist}) values, which were calculated from the perturbed posterior distributions of the fitted parameters after powerscaling the priors, for the global/regional non-crop-specific fits (Table C.2), the global/regional crop level fits (Table C.3) and the country and crop level fits (Table C.4). The CJS_{dist} values in the tables corresponding to a fit with Bayesian Coefficient of Determination (R^2) < 0.5, average potential scale reduction factor ($\hat{R}$) > 1.1 and average effective sample size (ESS) < 400 are grayed out, because these fits were not used again in this study. The values of the lognormal parameters (B, ΔX_2 and σ) of instances with an insufficiently defined lognormal part are grayed out and were not used in the analyses. These instances are defined as cases for which either fewer than ten data points determined the lognormal curve (i.e. median X_{max} was estimated after > 10 years before the end of the data), or fertilizer use had plateaued after the logistic increase. We defined such a plateau to occur when the mean

absolute error, calculated between the median fertilizer use at the peak and the median fertilizer use in the subsequent years (until the last year of the data, 2019), was < 1:

$$\frac{1}{2019 - X_{max}} \sum_{year=X_{max}}^{2019} |median(fertilizer\ use_{year}) - 0.99 \cdot median(A)| < 1 \qquad \text{(C.7)}$$

Note that this plateau phase could still be defined by the lognormal curve. Analogously, values of the logistic parameters (A, ΔX_1 and X_{max}) were grayed out for cases with an insufficiently defined logistic part (i.e. < 10 data points were available to determine the logistic curve, or the median X_{max} was estimated before 10 years after the start of the data). The missing rows for oil-palm fruit in Europe and Northern America are because the crop is not produced in these regions according to FAOSTAT data [347] .

Table C.2. Cumulative Jensen-Shannon distances of global and regional fits.

	N							P_2O_5							K_2O						
	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
Africa	0.01	0.02	0.02	0.09	0.17	0.21	0.0	0.02	0.03	0.03	0.13	0.15	0.1	0.01	0.01	0.0	0.01	0.09	0.16	0.2	0.0
Asia	0.01	0.01	0.01	0.09	0.17	0.21	0.01	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.08	0.04	0.06	0.09	0.18	0.21	0.01
Europe	0.02	0.02	0.03	0.16	0.03	0.09	0.01	0.04	0.03	0.08	0.27	0.03	0.17	0.05	0.03	0.02	0.05	0.23	0.01	0.14	0.04
N. Am	0.01	0.02	0.02	0.09	0.17	0.21	0.0	0.03	0.01	0.01	0.12	0.16	0.16	0.03	0.03	0.01	0.01	0.09	0.17	0.18	0.0
Oceania	0.01	0.01	0.01	0.09	0.19	0.21	0.0	0.03	0.13	0.06	0.13	0.13	0.05	0.02	0.01	0.02	0.02	0.1	0.12	0.09	0.01
L. Am	0.02	0.02	0.02	0.09	0.17	0.21	0.0	0.19	0.11	0.13	0.09	0.17	0.21	0.0	0.27	0.14	0.19	0.09	0.18	0.2	0.03
World	0.01	0.01	0.01	0.09	0.16	0.21	0.0	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.09	0.08	0.09	0.09	0.16	0.22	0.0

Latin and Northern America are abbreviated as L. Am and N. Am, respectively. Values of all parameters corresponding to fits with Bayesian coefficients of determination < 0.5, potential scale reduction factors > 1.1, average effective sample sizes > 400 and values of lognormal parameters (B, ΔX_2 and σ) of fits with an insufficiently defined lognormal part (median X_{max} after 2005) are grayed out.

Table C.3. Cumulative Jensen-Shannon distances of global and regional crop-specific fits.

		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
Wheat	Europe	0.03	0.03	0.05	0.1	0.06	0.08	0.01	0.07	0.09	0.15	0.34	0.04	0.24	0.11	0.05	0.04	0.09	0.27	0.02	0.18	0.07
	Asia	0.01	0.01	0.01	0.09	0.16	0.2	0.0	0.01	0.01	0.02	0.1	0.16	0.2	0.0	0.03	0.02	0.02	0.1	0.17	0.2	0.01
	Africa	0.02	0.02	0.02	0.09	0.18	0.21	0.0	0.03	0.03	0.07	0.18	0.11	0.19	0.04	0.05	0.02	0.03	0.09	0.14	0.15	0.01
	N. Am	0.04	0.04	0.04	0.09	0.18	0.22	0.01	0.01	0.01	0.01	0.09	0.0	0.04	0.0	0.02	0.02	0.02	0.11	0.05	0.03	0.0
	L. Am	0.01	0.01	0.01	0.09	0.17	0.22	0.01	0.09	0.08	0.09	0.09	0.17	0.21	0.0	0.15	0.09	0.1	0.09	0.18	0.21	0.01
	Oceania	0.19	0.12	0.14	0.08	0.17	0.2	0.0	0.07	0.2	0.15	0.16	0.14	0.04	0.01	0.0	0.0	0.01	0.01	0.01	0.0	0.0
	World	0.0	0.0	0.01	0.09	0.17	0.23	0.0	0.01	0.0	0.01	0.09	0.03	0.09	0.01	0.0	0.0	0.01	0.09	0.01	0.04	0.0
Maize	Europe	0.03	0.03	0.05	0.17	0.05	0.1	0.01	0.09	0.08	0.1	0.3	0.02	0.22	0.08	0.07	0.08	0.12	0.31	0.03	0.19	0.09
	Asia	0.01	0.01	0.01	0.09	0.17	0.2	0.0	0.01	0.01	0.01	0.09	0.18	0.21	0.0	0.08	0.04	0.05	0.09	0.18	0.22	0.0
	Africa	0.05	0.01	0.01	0.09	0.18	0.18	0.01	0.0	0.01	0.01	0.11	0.01	0.05	0.0	0.03	0.04	0.04	0.09	0.15	0.08	0.01
	N. Am	0.03	0.03	0.03	0.09	0.17	0.21	0.0	0.17	0.17	0.19	0.1	0.17	0.2	0.0	0.03	0.04	0.04	0.09	0.16	0.18	0.01
	L. Am	0.18	0.12	0.14	0.09	0.18	0.2	0.01	0.1	0.08	0.09	0.08	0.17	0.21	0.01	0.02	0.02	0.02	0.09	0.17	0.21	0.0
	Oceania	0.22	0.17	0.19	0.1	0.18	0.22	0.03	0.07	0.19	0.16	0.09	0.16	0.21	0.01	0.1	0.16	0.13	0.09	0.16	0.18	0.01
	World	0.01	0.01	0.01	0.09	0.18	0.21	0.0	0.13	0.11	0.12	0.08	0.17	0.2	0.01	0.09	0.09	0.09	0.09	0.17	0.21	0.01
Rice	Europe	0.02	0.01	0.0	0.09	0.17	0.17	0.0	0.05	0.01	0.01	0.21	0.08	0.11	0.03	0.0	0.01	0.01	0.12	0.02	0.04	0.0
	Asia	0.0	0.0	0.0	0.09	0.17	0.21	0.0	0.01	0.01	0.01	0.09	0.18	0.22	0.01	0.06	0.04	0.05	0.09	0.16	0.21	0.01
	Africa	0.0	0.01	0.01	0.1	0.04	0.01	0.0	0.02	0.05	0.03	0.09	0.11	0.06	0.01	0.34	0.25	0.27	0.09	0.17	0.19	0.01

		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
	N. Am	0.09	0.09	0.09	0.09	0.17	0.21	0.0	0.01	0.17	0.06	0.11	0.06	0.04	0.01	0.09	0.25	0.2	0.09	0.14	0.25	0.05
	L. Am	0.22	0.16	0.19	0.09	0.18	0.2	0.03	0.25	0.17	0.19	0.09	0.17	0.21	0.0	0.27	0.14	0.17	0.09	0.17	0.21	0.02
	Oceania	0.22	0.19	0.2	0.1	0.17	0.21	0.01	0.09	0.2	0.14	0.16	0.15	0.04	0.02	0.1	0.21	0.12	0.08	0.16	0.2	0.01
	World	0.0	0.0	0.0	0.1	0.17	0.22	0.0	0.01	0.01	0.01	0.1	0.17	0.21	0.0	0.04	0.03	0.04	0.08	0.17	0.22	0.0
Other cereals	Europe	0.03	0.01	0.04	0.08	0.03	0.06	0.01	0.05	0.09	0.17	0.35	0.1	0.27	0.13	0.03	0.08	0.13	0.27	0.08	0.18	0.06
	Asia	0.0	0.0	0.0	0.09	0.17	0.21	0.0	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.11	0.05	0.07	0.1	0.18	0.2	0.01
	Africa	0.04	0.01	0.01	0.16	0.15	0.15	0.05	0.01	0.02	0.02	0.11	0.08	0.04	0.01	0.04	0.05	0.06	0.09	0.18	0.18	0.01
	N. Am	0.08	0.08	0.08	0.09	0.17	0.21	0.0	0.08	0.1	0.12	0.3	0.12	0.22	0.06	0.01	0.01	0.01	0.12	0.06	0.03	0.0
	L. Am	0.01	0.01	0.01	0.09	0.16	0.18	0.0	0.01	0.02	0.02	0.09	0.17	0.22	0.01	0.13	0.08	0.09	0.09	0.17	0.22	0.01
	Oceania	0.18	0.11	0.13	0.09	0.17	0.2	0.01	0.05	0.21	0.13	0.17	0.13	0.04	0.01	0.01	0.13	0.05	0.15	0.18	0.15	0.03
	World	0.02	0.02	0.03	0.08	0.05	0.09	0.0	0.01	0.06	0.09	0.23	0.06	0.15	0.03	0.02	0.04	0.06	0.21	0.02	0.14	0.02
Soybean	Europe	0.05	0.03	0.04	0.22	0.05	0.13	0.03	0.07	0.05	0.07	0.28	0.02	0.16	0.05	0.01	0.0	0.01	0.13	0.03	0.06	0.0
	Asia	0.05	0.02	0.03	0.09	0.16	0.2	0.01	0.02	0.02	0.02	0.1	0.16	0.18	0.02	0.12	0.08	0.08	0.09	0.17	0.22	0.0
	Africa	0.02	0.02	0.02	0.14	0.01	0.07	0.01	0.01	0.02	0.04	0.09	0.03	0.11	0.01	0.01	0.01	0.01	0.1	0.06	0.03	0.0
	N. Am	0.27	0.21	0.15	0.09	0.17	0.21	0.0	0.02	0.14	0.02	0.08	0.03	0.03	0.01	0.04	0.04	0.04	0.15	0.16	0.17	0.05
	L. Am	0.42	0.22	0.26	0.09	0.18	0.2	0.02	0.4	0.27	0.31	0.09	0.17	0.22	0.04	0.27	0.14	0.18	0.09	0.18	0.21	0.03
	Oceania	0.2	0.14	0.17	0.09	0.17	0.2	0.01	0.18	0.19	0.1	0.28	0.09	0.05	0.09	0.11	0.21	0.17	0.1	0.17	0.21	0.02
	World	0.04	0.02	0.02	0.09	0.18	0.19	0.01	0.32	0.27	0.3	0.09	0.18	0.2	0.03	0.39	0.28	0.31	0.1	0.18	0.2	0.08
Oil-palm fruit	Europe	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
	Asia	0.04	0.04	0.04	0.09	0.16	0.2	0.01	0.01	0.01	0.01	0.09	0.01	0.04	0.0	0.03	0.02	0.02	0.11	0.04	0.11	0.0
	Africa	0.02	0.01	0.01	0.13	0.17	0.11	0.02	1.31	0.58	0.35	0.12	0.23	0.18	0.07	0.0	0.0	0.0	0.1	0.01	0.03	0.0
	N. Am	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/
	L. Am	0.09	0.08	0.08	0.09	0.17	0.21	0.0	0.01	0.02	0.02	0.11	0.03	0.04	0.0	0.03	0.03	0.03	0.09	0.17	0.2	0.0
	Oceania	0.33	0.19	0.22	0.09	0.18	0.21	0.02	0.07	0.21	0.2	0.08	0.15	0.17	0.06	0.34	0.31	0.19	0.09	0.2	0.22	0.03
	World	0.0	0.0	0.0	0.08	0.19	0.22	0.0	0.02	0.02	0.02	0.09	0.18	0.2	0.0	0.0	0.01	0.01	0.09	0.17	0.2	0.0
Other oilseeds	Europe	0.02	0.02	0.03	0.15	0.02	0.08	0.01	0.08	0.11	0.14	0.28	0.02	0.2	0.07	0.06	0.07	0.1	0.26	0.03	0.18	0.06
	Asia	0.01	0.01	0.01	0.09	0.16	0.2	0.0	0.0	0.0	0.0	0.09	0.17	0.21	0.0	0.09	0.05	0.06	0.09	0.17	0.21	0.01
	Africa	0.03	0.02	0.02	0.09	0.19	0.18	0.0	0.0	0.01	0.01	0.1	0.03	0.1	0.01	0.01	0.04	0.05	0.09	0.1	0.07	0.01
	N. Am	0.26	0.18	0.2	0.09	0.18	0.2	0.01	0.05	0.16	0.13	0.1	0.17	0.19	0.02	0.01	0.01	0.01	0.12	0.05	0.03	0.01
	L. Am	0.27	0.15	0.18	0.09	0.18	0.21	0.02	0.31	0.16	0.19	0.1	0.17	0.21	0.02	0.3	0.14	0.17	0.09	0.17	0.21	0.01
	Oceania	0.1	0.07	0.08	0.09	0.18	0.21	0.01	0.04	0.14	0.12	0.09	0.18	0.27	0.01	0.42	0.27	0.31	0.09	0.17	0.21	0.02
	World	0.01	0.0	0.0	0.09	0.17	0.2	0.01	0.01	0.01	0.02	0.1	0.17	0.19	0.0	0.03	0.02	0.01	0.09	0.19	0.16	0.01
Vegetables	Europe	0.03	0.03	0.04	0.14	0.04	0.09	0.0	0.08	0.14	0.19	0.3	0.13	0.21	0.07	0.03	0.03	0.04	0.15	0.02	0.09	0.01
	Asia	0.04	0.04	0.04	0.09	0.18	0.22	0.0	0.07	0.06	0.07	0.09	0.16	0.22	0.0	0.33	0.19	0.23	0.09	0.18	0.19	0.07
	Africa	0.02	0.01	0.01	0.11	0.06	0.02	0.0	0.02	0.01	0.02	0.18	0.04	0.08	0.01	0.04	0.04	0.05	0.1	0.1	0.05	0.0
	N. Am	0.01	0.01	0.01	0.09	0.16	0.19	0.0	0.08	0.03	0.04	0.16	0.06	0.12	0.03	0.01	0.02	0.02	0.09	0.16	0.18	0.0
	L. Am	0.0	0.01	0.01	0.09	0.17	0.19	0.0	0.01	0.0	0.01	0.08	0.17	0.19	0.01	0.27	0.19	0.22	0.1	0.17	0.21	0.02
	Oceania	0.26	0.19	0.21	0.09	0.16	0.21	0.04	0.11	0.19	0.14	0.2	0.16	0.04	0.05	0.03	0.23	0.11	0.09	0.18	0.2	0.0
	World	0.04	0.03	0.03	0.09	0.18	0.22	0.0	0.14	0.13	0.14	0.09	0.18	0.22	0.01	0.37	0.27	0.3	0.09	0.17	0.21	0.07

		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
Fruits	Europe	0.04	0.03	0.04	0.09	0.03	0.07	0.01	0.04	0.08	0.12	0.25	0.04	0.17	0.05	0.02	0.02	0.03	0.15	0.01	0.08	0.0
	Asia	0.01	0.01	0.01	0.1	0.17	0.21	0.0	0.03	0.03	0.03	0.09	0.18	0.21	0.0	0.33	0.17	0.23	0.09	0.17	0.22	0.09
	Africa	0.01	0.02	0.02	0.09	0.15	0.18	0.0	0.01	0.03	0.05	0.1	0.01	0.14	0.01	0.06	0.12	0.1	0.09	0.18	0.18	0.01
	N. Am	0.04	0.02	0.03	0.08	0.16	0.19	0.01	0.02	0.15	0.1	0.13	0.1	0.03	0.0	0.03	0.21	0.14	0.14	0.13	0.04	0.01
	L. Am	0.06	0.05	0.06	0.09	0.18	0.21	0.0	0.07	0.06	0.07	0.09	0.17	0.2	0.01	0.07	0.06	0.07	0.09	0.17	0.2	0.0
	Oceania	0.33	0.23	0.26	0.1	0.17	0.22	0.05	0.09	0.2	0.12	0.18	0.11	0.05	0.01	0.06	0.21	0.15	0.09	0.18	0.2	0.01
	World	0.02	0.02	0.02	0.08	0.17	0.21	0.0	0.31	0.25	0.27	0.09	0.17	0.21	0.03	0.41	0.29	0.32	0.09	0.18	0.21	0.08
Roots and tubers	Europe	0.06	0.05	0.09	0.18	0.07	0.14	0.03	0.08	0.07	0.17	0.31	0.12	0.23	0.1	0.08	0.03	0.04	0.14	0.02	0.12	0.01
	Asia	0.02	0.01	0.01	0.09	0.18	0.2	0.01	0.01	0.01	0.01	0.1	0.16	0.21	0.0	0.19	0.13	0.15	0.09	0.16	0.2	0.01
	Africa	0.05	0.01	0.01	0.7	0.17	0.34	0.14	0.0	0.01	0.02	0.09	0.01	0.07	0.0	0.04	0.02	0.02	0.25	0.14	0.17	0.13
	N. Am	0.01	0.01	0.01	0.09	0.17	0.18	0.0	0.02	0.16	0.17	0.1	0.18	0.19	0.01	0.08	0.26	0.1	0.1	0.18	0.21	0.01
	L. Am	0.25	0.16	0.19	0.09	0.16	0.2	0.03	0.23	0.15	0.18	0.09	0.18	0.2	0.01	0.23	0.14	0.16	0.09	0.17	0.21	0.03
	Oceania	0.18	0.13	0.14	0.09	0.17	0.21	0.01	0.06	0.19	0.14	0.16	0.18	0.05	0.02	0.08	0.21	0.14	0.09	0.18	0.19	0.0
	World	0.01	0.01	0.01	0.12	0.05	0.01	0.0	0.03	0.02	0.03	0.12	0.08	0.04	0.01	0.04	0.03	0.04	0.13	0.01	0.1	0.03
Sugar crops	Europe	0.04	0.04	0.05	0.16	0.05	0.11	0.01	0.05	0.03	0.09	0.23	0.05	0.13	0.05	0.09	0.04	0.06	0.22	0.01	0.16	0.04
	Asia	0.02	0.02	0.02	0.09	0.17	0.21	0.0	0.01	0.01	0.01	0.09	0.18	0.22	0.01	0.17	0.14	0.15	0.09	0.17	0.21	0.0
	Africa	0.01	0.01	0.01	0.09	0.17	0.2	0.0	0.01	0.01	0.01	0.13	0.02	0.05	0.0	0.03	0.2	0.09	0.12	0.12	0.12	0.02
	N. Am	0.03	0.03	0.03	0.09	0.14	0.19	0.01	0.08	0.17	0.17	0.08	0.17	0.2	0.01	0.1	0.19	0.18	0.22	0.2	0.04	0.04
	L. Am	0.01	0.01	0.01	0.09	0.17	0.19	0.01	0.12	0.13	0.13	0.09	0.16	0.21	0.01	0.13	0.11	0.12	0.09	0.16	0.21	0.01
	Oceania	0.35	0.28	0.3	0.09	0.16	0.21	0.07	0.12	0.19	0.15	0.21	0.16	0.04	0.03	0.02	0.2	0.14	0.09	0.17	0.2	0.01
	World	0.01	0.01	0.01	0.09	0.16	0.19	0.01	0.11	0.11	0.09	0.45	0.3	0.29	0.18	0.04	0.01	0.01	0.12	0.02	0.1	0.02
Fiber crops	Europe	0.01	0.0	0.0	0.1	0.17	0.18	0.02	0.01	0.01	0.01	0.13	0.06	0.04	0.01	0.02	0.02	0.02	0.09	0.17	0.17	0.01
	Asia	0.03	0.03	0.03	0.09	0.18	0.21	0.01	0.01	0.01	0.01	0.09	0.18	0.21	0.0	0.12	0.06	0.08	0.09	0.18	0.21	0.01
	Africa	0.0	0.01	0.01	0.11	0.01	0.03	0.0	0.0	0.0	0.0	0.11	0.03	0.02	0.0	0.05	0.09	0.1	0.13	0.13	0.21	0.03
	N. Am	0.28	0.26	0.29	0.1	0.18	0.22	0.03	0.02	0.02	0.02	0.09	0.02	0.07	0.0	0.03	0.23	0.1	0.09	0.17	0.23	0.01
	L. Am	0.37	0.2	0.26	0.08	0.17	0.2	0.1	0.31	0.15	0.21	0.09	0.15	0.2	0.05	0.05	0.04	0.04	0.09	0.17	0.19	0.0
	Oceania	0.11	0.1	0.11	0.08	0.17	0.2	0.01	0.13	0.16	0.06	0.24	0.05	0.11	0.05	0.01	0.2	0.03	0.09	0.03	0.04	0.01
	World	0.05	0.05	0.05	0.09	0.18	0.21	0.0	0.05	0.04	0.04	0.09	0.17	0.21	0.0	0.33	0.19	0.22	0.09	0.18	0.21	0.02
Other crops	Europe	0.01	0.02	0.02	0.15	0.01	0.07	0.01	0.05	0.04	0.07	0.28	0.01	0.15	0.06	0.02	0.01	0.02	0.19	0.05	0.08	0.02
	Asia	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.0	0.01	0.01	0.09	0.16	0.22	0.0	0.06	0.05	0.05	0.09	0.18	0.22	0.01
	Africa	0.02	0.02	0.02	0.09	0.18	0.21	0.01	0.13	0.06	0.07	0.09	0.19	0.18	0.04	0.01	0.01	0.01	0.09	0.06	0.03	0.01
	N. Am	0.06	0.06	0.06	0.09	0.15	0.18	0.0	0.01	0.16	0.14	0.08	0.12	0.05	0.0	0.01	0.2	0.05	0.15	0.04	0.09	0.0
	L. Am	0.03	0.02	0.02	0.09	0.17	0.21	0.0	0.05	0.05	0.05	0.09	0.17	0.2	0.01	0.01	0.01	0.02	0.08	0.16	0.21	0.01
	Oceania	0.18	0.13	0.14	0.09	0.18	0.2	0.01	0.05	0.19	0.14	0.14	0.16	0.07	0.02	0.01	0.21	0.01	0.13	0.02	0.06	0.0
	World	0.01	0.02	0.02	0.09	0.16	0.2	0.0	0.0	0.01	0.01	0.09	0.17	0.2	0.0	0.02	0.02	0.02	0.09	0.17	0.19	0.0

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Latin and Northern America are abbreviated as L. Am and N. Am, respectively. Values of all parameters corresponding to fits with Bayesian coefficients of determination < 0.5, potential scale reduction factors > 1.1, average effective sample sizes > 400 and values of lognormal parameters (B, ΔX_2 and σ) of fits with an insufficiently defined lognormal part (median X_{max} after 2005) are grayed out. Values > 0.45 are in red.

Table C.4. Cumulative Jensen-Shannon distances of country level, crop-specific fits for the countries with an average harvested crop area since 1990 greater than 1% of the global average harvested crop area.

		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
Wheat	IND	0.02	0.02	0.02	0.09	0.17	0.21	0.0	0.05	0.05	0.06	0.09	0.17	0.2	0.01	0.04	0.06	0.07	0.09	0.17	0.21	0.0
	CHN	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.02	0.04	0.04	0.09	0.18	0.23	0.01	0.1	0.09	0.09	0.09	0.17	0.19	0.0
	RUS	0.07	0.19	0.12	0.11	0.1	0.04	0.01	0.02	0.19	0.01	0.11	0.01	0.04	0.0	0.02	0.2	0.01	0.12	0.01	0.04	0.0
	United States of America (USA)	0.05	0.07	0.07	0.09	0.17	0.2	0.0	0.01	0.01	0.01	0.12	0.01	0.05	0.0	0.01	0.01	0.01	0.1	0.05	0.02	0.01
	KAZ	0.04	0.18	0.04	0.1	0.03	0.02	0.0	0.02	0.19	0.04	0.22	0.02	0.11	0.05	0.04	0.18	0.04	0.1	0.09	0.02	0.01
	AUS	0.2	0.18	0.2	0.08	0.17	0.21	0.02	0.05	0.22	0.12	0.19	0.12	0.04	0.01	0.0	0.01	0.02	0.05	0.02	0.02	0.0
	CAN	0.25	0.23	0.24	0.09	0.17	0.21	0.05	0.03	0.02	0.02	0.1	0.13	0.12	0.0	0.02	0.06	0.05	0.09	0.12	0.06	0.01
	TUR	0.14	0.14	0.15	0.09	0.18	0.21	0.01	0.04	0.0	0.01	0.09	0.18	0.18	0.01	0.05	0.06	0.07	0.09	0.16	0.2	0.01
	PAK	0.06	0.06	0.06	0.09	0.17	0.2	0.0	0.14	0.13	0.13	0.09	0.17	0.21	0.01	0.34	0.13	0.14	0.09	0.17	0.2	0.01
	IRN	0.0	0.0	0.01	0.09	0.02	0.03	0.0	0.01	0.01	0.01	0.1	0.06	0.05	0.01	0.0	0.01	0.01	0.09	0.01	0.07	0.0
	UKR	0.1	0.22	0.1	0.12	0.08	0.03	0.0	0.09	0.18	0.01	0.14	0.01	0.03	0.01	0.11	0.18	0.05	0.32	0.06	0.19	0.14
	ARG	0.01	0.05	0.05	0.1	0.18	0.15	0.02	0.02	0.04	0.04	0.1	0.18	0.22	0.01	0.05	0.04	0.03	0.08	0.17	0.12	0.02
	FRA	0.01	0.03	0.03	0.09	0.17	0.18	0.01	0.12	0.2	0.12	0.27	0.12	0.13	0.07	0.08	0.06	0.11	0.25	0.06	0.17	0.05
	DEU	0.01	0.02	0.02	0.09	0.15	0.18	0.0	0.2	0.23	0.09	0.32	0.1	0.11	0.16	0.4	0.23	0.27	0.5	0.29	0.07	0.33
	MAR	0.11	0.14	0.15	0.09	0.16	0.21	0.01	0.15	0.17	0.18	0.08	0.16	0.2	0.02	0.09	0.17	0.14	0.09	0.18	0.2	0.02
Maize	USA	0.05	0.04	0.05	0.09	0.17	0.21	0.01	0.16	0.19	0.2	0.09	0.16	0.16	0.03	0.05	0.09	0.09	0.09	0.17	0.17	0.0
	CHN	0.05	0.03	0.03	0.09	0.18	0.25	0.02	0.01	0.02	0.02	0.1	0.18	0.22	0.0	0.11	0.1	0.1	0.09	0.17	0.22	0.0
	BRA	0.3	0.22	0.25	0.08	0.17	0.21	0.05	0.12	0.13	0.15	0.08	0.17	0.22	0.0	0.02	0.03	0.03	0.09	0.17	0.21	0.0
	IND	0.08	0.08	0.08	0.1	0.17	0.2	0.01	0.12	0.1	0.11	0.09	0.17	0.21	0.0	0.09	0.12	0.12	0.09	0.17	0.21	0.0
	MEX	0.03	0.05	0.05	0.09	0.16	0.18	0.0	0.04	0.04	0.04	0.09	0.19	0.17	0.01	0.34	0.26	0.29	0.09	0.19	0.21	0.05
	NGA	0.04	0.04	0.04	0.32	0.13	0.21	0.08	0.03	0.01	0.02	0.16	0.01	0.08	0.01	0.0	0.0	0.0	0.09	0.02	0.09	0.01
	IDN	0.08	0.09	0.1	0.09	0.17	0.21	0.01	0.39	0.24	0.29	0.09	0.17	0.2	0.06	0.3	0.22	0.27	0.09	0.17	0.21	0.05
	ARG	0.02	0.02	0.02	0.09	0.17	0.2	0.01	0.03	0.04	0.04	0.09	0.16	0.2	0.01	0.1	0.15	0.16	0.1	0.16	0.19	0.01
	ZAF	0.28	0.29	0.3	0.09	0.17	0.21	0.08	0.01	0.01	0.01	0.09	0.01	0.03	0.0	0.12	0.18	0.19	0.09	0.16	0.16	0.02
	ROU	0.04	0.03	0.04	0.1	0.04	0.08	0.0	0.09	0.04	0.06	0.2	0.04	0.15	0.04	0.05	0.06	0.12	0.29	0.09	0.19	0.06
	PHL	0.13	0.14	0.14	0.1	0.17	0.2	0.01	0.23	0.2	0.22	0.1	0.17	0.2	0.02	0.46	0.25	0.32	0.09	0.17	0.21	0.11
	TZA	0.15	0.12	0.14	0.16	0.15	0.16	0.09	0.48	0.18	0.25	0.09	0.18	0.22	0.03	0.05	0.22	0.12	0.09	0.17	0.16	0.0
	UKR	0.21	0.14	0.15	0.09	0.15	0.2	0.06	0.07	0.18	0.01	0.13	0.0	0.04	0.0	0.1	0.19	0.05	0.25	0.06	0.12	0.1
	ETH	0.27	0.11	0.16	0.09	0.17	0.22	0.06	0.2	0.11	0.13	0.09	0.18	0.2	0.02	0.26	0.13	0.13	0.09	0.17	0.21	0.03
	COD	0.01	0.1	0.02	0.12	0.08	0.05	0.01	0.07	0.28	0.05	0.09	0.15	0.06	0.03	0.06	0.24	0.09	0.09	0.18	0.2	0.01
	KEN	0.17	0.16	0.18	0.09	0.17	0.22	0.01	0.26	0.21	0.24	0.08	0.17	0.21	0.03	0.5	0.21	0.3	0.08	0.19	0.2	0.08
	FRA	0.01	0.0	0.0	0.09	0.17	0.18	0.0	0.11	0.22	0.13	0.22	0.13	0.07	0.05	0.05	0.09	0.06	0.19	0.03	0.12	0.01
Rice	IND	0.06	0.06	0.06	0.1	0.18	0.21	0.0	0.08	0.09	0.09	0.09	0.18	0.22	0.01	0.07	0.08	0.08	0.1	0.17	0.21	0.0
	CHN	0.04	0.03	0.03	0.1	0.17	0.23	0.01	0.01	0.01	0.01	0.11	0.09	0.08	0.01	0.06	0.06	0.06	0.08	0.17	0.21	0.0
	IDN	0.02	0.01	0.01	0.09	0.15	0.18	0.0	0.04	0.05	0.05	0.31	0.08	0.23	0.07	0.32	0.18	0.23	0.1	0.17	0.21	0.02
	BGD	0.01	0.0	0.0	0.09	0.17	0.22	0.01	0.4	0.28	0.33	0.09	0.17	0.2	0.11	0.32	0.18	0.22	0.09	0.18	0.21	0.02
	THA	0.02	0.03	0.03	0.09	0.17	0.21	0.0	0.01	0.06	0.07	0.09	0.16	0.2	0.01	0.15	0.13	0.15	0.09	0.18	0.22	0.0
	VNM	0.04	0.06	0.06	0.09	0.17	0.2	0.01	0.01	0.03	0.03	0.09	0.18	0.21	0.01	0.02	0.0	0.0	0.09	0.17	0.18	0.0
	MMR	0.19	0.16	0.19	0.09	0.17	0.19	0.01	0.05	0.19	0.15	0.09	0.17	0.18	0.01	0.28	0.08	0.12	0.09	0.16	0.21	0.0
	PHL	0.17	0.15	0.17	0.09	0.17	0.21	0.02	0.09	0.14	0.15	0.1	0.16	0.21	0.01	0.26	0.24	0.28	0.09	0.18	0.21	0.06
	BRA	0.21	0.16	0.19	0.09	0.17	0.21	0.03	0.22	0.22	0.23	0.09	0.16	0.21	0.03	0.35	0.24	0.28	0.08	0.18	0.22	0.08
	PAK	0.15	0.14	0.15	0.09	0.16	0.22	0.01	0.26	0.21	0.22	0.08	0.18	0.2	0.03	0.0	0.03	0.04	0.12	0.03	0.15	0.01
	NGA	0.03	0.06	0.08	0.57	0.08	0.27	0.06	0.07	0.13	0.11	0.2	0.05	0.15	0.06	0.0	0.0	0.01	0.1	0.03	0.1	0.01

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		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
	KHM	0.29	0.14	0.18	0.09	0.16	0.21	0.02	0.01	0.01	0.01	0.09	0.16	0.2	0.0	0.63	0.19	0.28	0.09	0.16	0.2	0.02
	JPN	0.01	0.02	0.02	0.14	0.04	0.06	0.0	0.02	0.01	0.01	0.15	0.05	0.09	0.0	0.02	0.01	0.01	0.17	0.04	0.09	0.01
Other cereals	IND	0.11	0.1	0.11	0.1	0.17	0.21	0.01	0.07	0.06	0.07	0.09	0.17	0.21	0.01	0.07	0.09	0.09	0.09	0.17	0.22	0.01
	RUS	0.09	0.18	0.13	0.1	0.23	0.21	0.06	0.02	0.18	0.03	0.17	0.02	0.07	0.03	0.1	0.19	0.08	0.09	0.24	0.22	0.08
	NGA	0.06	0.04	0.05	0.17	0.04	0.11	0.04	0.05	0.16	0.05	0.09	0.16	0.16	0.03	0.0	0.0	0.0	0.01	0.0	0.0	0.0
	SDN	0.33	0.21	0.12	0.09	0.18	0.22	0.02	0.3	0.19	0.12	0.09	0.17	0.2	0.02	0.25	0.14	0.14	0.08	0.16	0.21	0.01
	NER	0.09	0.13	0.14	0.09	0.17	0.17	0.0	0.02	0.03	0.03	0.09	0.13	0.04	0.01	0.03	0.15	0.08	0.09	0.17	0.16	0.02
	F206	0.04	0.21	0.09	0.09	0.14	0.14	0.03	0.03	0.01	0.01	0.09	0.17	0.22	0.0	0.73	0.56	0.62	0.09	0.12	0.12	0.21
	USA	0.09	0.09	0.1	0.09	0.17	0.21	0.01	0.02	0.01	0.02	0.07	0.0	0.04	0.0	0.03	0.01	0.01	0.11	0.09	0.03	0.01
	AUS	0.25	0.22	0.25	0.09	0.17	0.2	0.04	0.05	0.22	0.11	0.16	0.11	0.05	0.0	0.02	0.15	0.14	0.09	0.18	0.19	0.02
	ETH	0.38	0.21	0.27	0.09	0.18	0.21	0.09	0.12	0.2	0.08	0.09	0.17	0.19	0.01	0.16	0.11	0.08	0.35	0.06	0.18	0.05
	UKR	0.14	0.23	0.09	0.16	0.08	0.03	0.01	0.08	0.18	0.1	0.12	0.08	0.02	0.0	0.11	0.2	0.04	0.29	0.05	0.19	0.13
	CAN	0.22	0.2	0.22	0.09	0.17	0.22	0.03	0.19	0.2	0.21	0.08	0.17	0.2	0.02	0.0	0.01	0.02	0.09	0.03	0.06	0.0
	CHN	0.02	0.01	0.01	0.09	0.16	0.21	0.01	0.01	0.01	0.01	0.09	0.17	0.21	0.0	0.18	0.13	0.15	0.08	0.18	0.21	0.0
	POL	0.07	0.03	0.1	0.21	0.11	0.12	0.02	0.02	0.06	0.06	0.19	0.07	0.14	0.01	0.11	0.03	0.04	0.2	0.03	0.16	0.03
	ESP	0.09	0.11	0.11	0.09	0.16	0.19	0.0	0.06	0.13	0.13	0.09	0.16	0.18	0.01	0.06	0.11	0.11	0.08	0.16	0.19	0.0
	TUR	0.14	0.13	0.14	0.08	0.17	0.2	0.01	0.02	0.01	0.02	0.09	0.17	0.18	0.0	0.05	0.05	0.06	0.09	0.16	0.19	0.0
	DEU	0.06	0.03	0.03	0.08	0.17	0.19	0.01	0.13	0.17	0.1	0.36	0.08	0.21	0.13	0.47	0.21	0.28	0.56	0.29	0.06	0.43
	KAZ	0.13	0.1	0.17	0.08	0.16	0.16	0.06	0.02	0.19	0.02	0.15	0.01	0.06	0.01	0.07	0.19	0.09	0.09	0.16	0.16	0.04
	BFA	0.19	0.18	0.2	0.09	0.18	0.21	0.02	0.56	0.42	0.4	0.09	0.27	0.27	0.15	0.17	0.13	0.16	0.09	0.17	0.21	0.01
	MLI	0.29	0.19	0.23	0.09	0.17	0.22	0.03	0.59	0.39	0.31	0.08	0.29	0.22	0.09	0.04	0.17	0.14	0.09	0.16	0.17	0.0
Soybean	USA	0.12	0.17	0.18	0.09	0.16	0.2	0.01	0.04	0.2	0.02	0.09	0.02	0.05	0.01	0.03	0.05	0.05	0.17	0.14	0.16	0.1
	BRA	0.27	0.23	0.25	0.09	0.16	0.2	0.05	0.28	0.27	0.28	0.09	0.18	0.21	0.07	0.22	0.17	0.19	0.08	0.17	0.21	0.02
	ARG	0.04	0.09	0.09	0.72	0.15	0.46	0.15	0.18	0.26	0.27	0.08	0.17	0.2	0.01	0.01	0.14	0.0	0.11	0.01	0.04	0.0
	CHN	0.04	0.02	0.02	0.09	0.17	0.1	0.01	0.01	0.01	0.01	0.1	0.05	0.07	0.01	0.19	0.14	0.16	0.08	0.18	0.21	0.01
	IND	0.07	0.13	0.14	0.09	0.16	0.2	0.0	0.06	0.05	0.05	0.1	0.07	0.07	0.01	0.04	0.04	0.02	0.18	0.01	0.08	0.02
	PRY	0.21	0.14	0.16	0.09	0.18	0.21	0.0	0.06	0.05	0.06	0.09	0.17	0.21	0.01	0.18	0.11	0.13	0.09	0.18	0.21	0.01
	CAN	0.02	0.02	0.03	0.12	0.07	0.04	0.0	0.03	0.06	0.04	0.16	0.07	0.04	0.02	0.02	0.03	0.02	0.16	0.05	0.05	0.01
	RUS	0.04	0.19	0.09	0.1	0.15	0.17	0.03	0.04	0.19	0.11	0.09	0.14	0.2	0.02	0.03	0.19	0.01	0.16	0.01	0.07	0.02
Oil-palm fruit	IDN	0.01	0.0	0.01	0.13	0.03	0.04	0.0	0.02	0.01	0.04	0.06	0.04	0.04	0.0	0.03	0.02	0.02	0.09	0.18	0.18	0.01
	MYS	0.03	0.11	0.11	0.09	0.2	0.25	0.03	0.12	0.17	0.22	0.22	0.22	0.06	0.07	0.03	0.03	0.03	0.09	0.18	0.21	0.01
	NGA	0.01	0.01	0.01	0.1	0.03	0.05	0.01	0.15	0.2	0.14	0.08	0.15	0.14	0.01	0.01	0.0	0.03	0.18	0.01	0.08	0.01
	THA	0.0	0.02	0.02	0.09	0.18	0.21	0.01	0.06	0.16	0.03	0.13	0.1	0.15	0.01	0.02	0.0	0.01	0.11	0.06	0.07	0.0
	GIN	0.1	0.16	0.13	0.1	0.16	0.18	0.01	0.61	0.35	0.4	0.1	0.16	0.2	0.04	0.09	0.15	0.08	0.1	0.15	0.14	0.02
	GHA	0.52	0.16	0.3	0.11	0.16	0.18	0.07	0.05	0.08	0.06	0.08	0.04	0.04	0.01	0.28	0.21	0.25	0.09	0.17	0.2	0.06
	COD	0.27	0.41	0.3	0.51	0.23	0.35	0.27	0.01	0.0	0.0	0.12	0.0	0.05	0.0	0.02	0.08	0.03	0.09	0.07	0.07	0.01
	CIV	0.03	0.06	0.04	0.1	0.09	0.09	0.02	0.06	0.08	0.04	0.09	0.17	0.18	0.02	0.23	0.05	0.06	0.36	0.03	0.26	0.15
	COL	0.14	0.16	0.16	0.09	0.17	0.22	0.02	0.29	0.18	0.25	0.37	0.23	0.11	0.17	0.31	0.32	0.34	0.08	0.17	0.21	0.09
	ECU	0.28	0.24	0.27	0.09	0.17	0.21	0.06	0.04	0.01	0.03	0.17	0.03	0.07	0.01	0.09	0.1	0.1	0.09	0.17	0.21	0.0
Other oilseeds	IND	0.03	0.04	0.04	0.09	0.17	0.21	0.0	0.1	0.09	0.1	0.09	0.17	0.21	0.01	0.14	0.13	0.15	0.1	0.17	0.2	0.01
	CHN	0.02	0.01	0.01	0.09	0.19	0.21	0.01	0.01	0.04	0.04	0.09	0.19	0.21	0.02	0.15	0.11	0.13	0.09	0.17	0.2	0.0
	CAN	0.35	0.31	0.33	0.09	0.18	0.21	0.1	0.35	0.31	0.36	0.08	0.16	0.22	0.11	0.0	0.01	0.03	0.09	0.01	0.06	0.0
	RUS	0.06	0.18	0.06	0.09	0.14	0.08	0.02	0.03	0.19	0.01	0.16	0.01	0.07	0.01	0.02	0.2	0.06	0.09	0.04	0.02	0.01
	SDN	0.32	0.22	0.11	0.09	0.17	0.19	0.02	0.35	0.19	0.13	0.12	0.18	0.21	0.01	0.32	0.18	0.15	0.1	0.18	0.19	0.04
	UKR	0.14	0.23	0.11	0.16	0.1	0.04	0.01	0.06	0.19	0.04	0.13	0.03	0.02	0.01	0.08	0.19	0.06	0.26	0.04	0.12	0.09
	PHL	0.02	0.12	0.1	0.09	0.17	0.19	0.01	0.04	0.15	0.1	0.09	0.16	0.17	0.01	0.04	0.16	0.17	0.1	0.17	0.18	0.01
	IDN	0.01	0.03	0.03	0.08	0.15	0.19	0.0	0.06	0.12	0.11	0.36	0.14	0.25	0.1	0.43	0.26	0.33	0.09	0.16	0.22	0.07
	ESP	0.12	0.18	0.03	0.23	0.03	0.07	0.05	0.08	0.17	0.05	0.24	0.04	0.09	0.05	0.16	0.19	0.03	0.34	0.02	0.12	0.12
	ARG	0.11	0.1	0.1	0.09	0.17	0.21	0.01	0.07	0.06	0.07	0.08	0.16	0.19	0.0	0.08	0.17	0.1	0.09	0.17	0.16	0.04
	NGA	0.07	0.09	0.09	0.09	0.18	0.2	0.01	0.01	0.01	0.02	0.15	0.01	0.07	0.01	0.0	0.01	0.01	0.1	0.06	0.05	0.01
	F206	0.04	0.2	0.08	0.09	0.14	0.12	0.01	0.37	0.2	0.24	0.09	0.16	0.22	0.02	0.8	0.57	0.43	0.09	0.13	0.16	0.19

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		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
	MMR	0.0	0.03	0.05	0.09	0.06	0.05	0.0	0.01	0.01	0.01	0.09	0.17	0.22	0.0	0.02	0.0	0.0	0.09	0.18	0.21	0.01
	USA	0.04	0.03	0.04	0.09	0.17	0.2	0.0	0.02	0.12	0.02	0.11	0.04	0.04	0.01	0.04	0.14	0.05	0.09	0.16	0.19	0.02
	FRA	0.05	0.02	0.02	0.09	0.19	0.19	0.0	0.15	0.19	0.11	0.31	0.11	0.13	0.11	0.13	0.15	0.1	0.29	0.09	0.15	0.1
	TZA	0.52	0.25	0.32	0.09	0.18	0.2	0.09	0.66	0.35	0.38	0.09	0.37	0.32	0.11	0.01	0.2	0.01	0.1	0.01	0.04	0.01
	TUN	0.26	0.25	0.27	0.09	0.18	0.22	0.05	0.03	0.23	0.08	0.09	0.16	0.18	0.01	0.05	0.21	0.09	0.08	0.16	0.17	0.01
	AUS	0.09	0.13	0.13	0.09	0.17	0.2	0.01	0.04	0.21	0.13	0.14	0.14	0.04	0.02	0.09	0.19	0.14	0.1	0.11	0.09	0.01
	TUR	0.19	0.19	0.19	0.09	0.17	0.2	0.02	0.02	0.01	0.01	0.09	0.17	0.18	0.0	0.04	0.07	0.07	0.09	0.18	0.18	0.01
	ITA	0.03	0.08	0.08	0.09	0.07	0.09	0.01	0.05	0.03	0.05	0.21	0.01	0.13	0.02	0.02	0.02	0.03	0.17	0.05	0.09	0.01
	DEU	0.01	0.07	0.06	0.09	0.17	0.17	0.0	0.27	0.22	0.11	0.42	0.12	0.1	0.21	0.5	0.22	0.28	0.58	0.28	0.06	0.45
Vegetables	CHN	0.09	0.09	0.1	0.09	0.17	0.22	0.0	0.14	0.13	0.14	0.09	0.18	0.22	0.01	0.2	0.16	0.18	0.1	0.19	0.21	0.02
	IND	0.01	0.01	0.0	0.09	0.17	0.2	0.0	0.03	0.04	0.04	0.09	0.16	0.21	0.0	0.09	0.11	0.11	0.09	0.17	0.21	0.01
	NGA	0.11	0.14	0.13	0.2	0.15	0.17	0.12	0.0	0.01	0.01	0.12	0.01	0.05	0.0	0.0	0.0	0.01	0.09	0.01	0.05	0.0
	USA	0.02	0.02	0.02	0.09	0.17	0.19	0.0	0.07	0.02	0.04	0.13	0.04	0.1	0.02	0.02	0.07	0.07	0.09	0.16	0.17	0.01
	IDN	0.18	0.18	0.18	0.09	0.17	0.22	0.03	0.05	0.04	0.06	0.12	0.07	0.11	0.02	0.29	0.24	0.26	0.09	0.17	0.2	0.06
	SDN	0.17	0.25	0.1	0.1	0.17	0.22	0.05	0.22	0.22	0.1	0.08	0.17	0.21	0.01	0.14	0.23	0.08	0.09	0.16	0.22	0.03
	TUR	0.18	0.17	0.19	0.09	0.17	0.21	0.02	0.02	0.07	0.07	0.09	0.16	0.19	0.0	0.25	0.24	0.26	0.08	0.17	0.22	0.04
	RUS	0.09	0.16	0.18	0.1	0.24	0.28	0.04	0.1	0.2	0.1	0.09	0.21	0.18	0.05	0.07	0.18	0.1	0.1	0.08	0.02	0.01
	VNM	0.16	0.16	0.18	0.09	0.18	0.21	0.01	0.18	0.16	0.15	0.11	0.15	0.18	0.04	0.16	0.05	0.03	0.22	0.03	0.12	0.04
	IRN	0.01	0.02	0.02	0.09	0.16	0.21	0.01	0.08	0.02	0.02	0.22	0.02	0.09	0.04	0.01	0.02	0.02	0.1	0.08	0.06	0.01
	PHL	0.02	0.04	0.04	0.09	0.18	0.18	0.01	0.08	0.14	0.15	0.09	0.17	0.21	0.01	0.23	0.22	0.24	0.09	0.17	0.2	0.05
	MEX	0.03	0.02	0.02	0.12	0.02	0.07	0.01	0.01	0.01	0.01	0.12	0.01	0.04	0.0	0.22	0.2	0.22	0.09	0.16	0.2	0.03
	EGY	0.02	0.01	0.01	0.11	0.05	0.04	0.01	0.07	0.15	0.13	0.08	0.24	0.21	0.04	0.01	0.02	0.02	0.1	0.18	0.2	0.0
	UKR	0.13	0.23	0.17	0.14	0.16	0.05	0.02	0.07	0.18	0.05	0.12	0.04	0.02	0.0	0.12	0.18	0.02	0.19	0.02	0.08	0.04
	CMR	0.02	0.03	0.03	0.09	0.17	0.09	0.01	0.01	0.0	0.01	0.14	0.03	0.04	0.0	0.03	0.02	0.03	0.11	0.12	0.06	0.01
	ITA	0.02	0.02	0.02	0.13	0.01	0.06	0.0	0.03	0.03	0.03	0.13	0.01	0.08	0.0	0.01	0.02	0.03	0.14	0.01	0.06	0.01
Fruits	CHN	0.01	0.01	0.01	0.09	0.17	0.2	0.0	0.11	0.1	0.11	0.09	0.17	0.22	0.01	0.28	0.18	0.22	0.09	0.17	0.2	0.06
	IND	0.12	0.11	0.12	0.09	0.17	0.21	0.01	0.01	0.02	0.02	0.1	0.17	0.19	0.0	0.28	0.24	0.26	0.08	0.17	0.2	0.08
	BRA	0.18	0.17	0.19	0.09	0.17	0.22	0.01	0.08	0.11	0.11	0.19	0.12	0.18	0.06	0.15	0.17	0.18	0.09	0.17	0.2	0.02
	ESP	0.08	0.1	0.1	0.09	0.16	0.19	0.0	0.04	0.17	0.07	0.09	0.1	0.04	0.02	0.27	0.25	0.27	0.09	0.16	0.21	0.05
	NGA	0.02	0.08	0.11	0.11	0.07	0.1	0.02	0.01	0.02	0.04	0.15	0.03	0.07	0.01	0.0	0.0	0.01	0.12	0.0	0.05	0.0
	UGA	0.3	0.18	0.19	0.09	0.16	0.2	0.02	0.04	0.27	0.2	0.06	0.18	0.08	0.02	0.07	0.08	0.12	0.69	0.12	0.37	0.17
	ITA	0.01	0.01	0.01	0.12	0.01	0.04	0.0	0.01	0.02	0.02	0.14	0.02	0.07	0.0	0.01	0.01	0.01	0.12	0.02	0.04	0.0
	IRN	0.01	0.02	0.02	0.09	0.09	0.07	0.0	0.04	0.01	0.02	0.17	0.02	0.06	0.02	0.01	0.01	0.02	0.3	0.06	0.14	0.03
	USA	0.06	0.05	0.05	0.09	0.18	0.21	0.01	0.01	0.2	0.07	0.14	0.07	0.04	0.01	0.03	0.2	0.12	0.15	0.12	0.03	0.01
	TUR	0.06	0.06	0.07	0.09	0.17	0.2	0.0	0.05	0.01	0.01	0.09	0.19	0.2	0.02	0.34	0.24	0.27	0.09	0.18	0.23	0.04
	MEX	0.01	0.01	0.01	0.09	0.14	0.07	0.01	0.02	0.03	0.02	0.1	0.18	0.16	0.01	0.1	0.12	0.13	0.09	0.17	0.2	0.01
	FRA	0.01	0.01	0.01	0.09	0.01	0.04	0.0	0.1	0.18	0.08	0.23	0.07	0.13	0.04	0.07	0.04	0.05	0.21	0.02	0.15	0.02
	PHL	0.01	0.02	0.03	0.11	0.03	0.03	0.0	0.06	0.11	0.11	0.09	0.16	0.21	0.01	0.02	0.03	0.03	0.09	0.18	0.21	0.0
	COD	0.04	0.15	0.06	0.08	0.17	0.17	0.01	0.01	0.01	0.0	0.1	0.06	0.05	0.0	0.02	0.06	0.06	0.09	0.18	0.11	0.0
	THA	0.03	0.03	0.04	0.09	0.18	0.21	0.01	0.03	0.04	0.04	0.09	0.15	0.2	0.02	0.01	0.01	0.01	0.09	0.17	0.2	0.0
	TZA	0.45	0.29	0.35	0.1	0.17	0.21	0.1	0.02	0.01	0.01	0.11	0.01	0.07	0.0	0.34	0.24	0.25	0.08	0.17	0.21	0.1
	RUS	0.13	0.2	0.08	0.09	0.17	0.2	0.01	0.14	0.1	0.16	0.09	0.21	0.24	0.01	0.05	0.19	0.02	0.13	0.01	0.02	0.0
	COL	0.12	0.13	0.13	0.09	0.17	0.21	0.01	0.09	0.17	0.13	0.21	0.12	0.2	0.03	0.39	0.32	0.36	0.1	0.18	0.22	0.11
	PAK	0.16	0.14	0.15	0.09	0.17	0.2	0.01	0.03	0.11	0.11	0.12	0.15	0.15	0.05	0.0	0.02	0.02	0.1	0.02	0.05	0.0
Roots/tubers	NGA	0.08	0.19	0.22	0.41	0.15	0.35	0.1	0.01	0.0	0.0	0.09	0.01	0.03	0.0	0.0	0.06	0.08	0.11	0.02	0.14	0.01
	CHN	0.03	0.02	0.02	0.09	0.19	0.21	0.01	0.02	0.05	0.05	0.08	0.19	0.21	0.01	0.19	0.16	0.18	0.09	0.18	0.21	0.02
	COD	0.21	0.13	0.17	0.09	0.17	0.19	0.02	0.02	0.03	0.03	0.1	0.13	0.07	0.0	0.07	0.27	0.14	0.09	0.16	0.16	0.02
	RUS	0.16	0.17	0.12	0.18	0.22	0.09	0.02	0.09	0.18	0.18	0.11	0.16	0.05	0.01	0.12	0.18	0.03	0.21	0.03	0.08	0.07
	IND	0.0	0.01	0.01	0.09	0.17	0.2	0.01	0.01	0.03	0.03	0.09	0.17	0.19	0.0	0.06	0.07	0.07	0.09	0.17	0.23	0.02
	BRA	0.32	0.21	0.25	0.09	0.18	0.22	0.07	0.19	0.16	0.2	0.09	0.19	0.21	0.02	0.26	0.19	0.22	0.09	0.17	0.21	0.05
	IDN	0.01	0.02	0.02	0.09	0.17	0.21	0.01	0.04	0.02	0.03	0.13	0.04	0.11	0.02	0.29	0.18	0.21	0.08	0.16	0.21	0.02
	UKR	0.11	0.22	0.16	0.14	0.16	0.05	0.02	0.05	0.19	0.03	0.12	0.02	0.03	0.0	0.13	0.19	0.02	0.2	0.01	0.05	0.05

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		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
	TZA	0.18	0.16	0.14	0.28	0.14	0.21	0.17	0.31	0.19	0.24	0.09	0.15	0.18	0.02	0.2	0.36	0.15	0.08	0.2	0.19	0.04
	GHA	0.36	0.24	0.31	0.09	0.18	0.21	0.08	0.45	0.27	0.32	0.09	0.16	0.2	0.01	0.38	0.28	0.33	0.09	0.17	0.2	0.05
	THA	0.07	0.07	0.08	0.09	0.17	0.21	0.0	0.02	0.12	0.11	0.09	0.17	0.22	0.01	0.13	0.12	0.13	0.09	0.18	0.21	0.01
	CIV	0.01	0.0	0.0	0.11	0.01	0.03	0.0	0.09	0.11	0.13	0.09	0.17	0.2	0.0	0.04	0.01	0.0	0.22	0.01	0.09	0.02
	UGA	0.31	0.24	0.26	0.09	0.17	0.21	0.01	0.18	0.23	0.17	0.08	0.28	0.22	0.01	0.84	0.17	0.22	0.09	0.17	0.21	0.02
	MOZ	0.19	0.22	0.14	0.11	0.14	0.15	0.06	0.02	0.01	0.02	0.17	0.01	0.08	0.01	0.85	0.24	0.23	0.08	0.18	0.16	0.03
	AGO	0.14	0.15	0.1	0.19	0.13	0.15	0.11	0.11	0.3	0.08	0.08	0.17	0.18	0.04	0.04	0.34	0.22	0.09	0.17	0.21	0.03
	POL	0.03	0.01	0.01	0.08	0.04	0.04	0.0	0.1	0.06	0.07	0.23	0.06	0.17	0.05	0.18	0.04	0.07	0.27	0.06	0.18	0.09
	VNM	0.33	0.28	0.26	0.09	0.18	0.21	0.13	0.06	0.08	0.08	0.09	0.18	0.2	0.01	0.18	0.15	0.17	0.09	0.18	0.22	0.01
Sugar crops	BRA	0.12	0.12	0.13	0.09	0.17	0.21	0.01	0.09	0.05	0.07	0.08	0.3	0.17	0.04	0.06	0.06	0.06	0.09	0.16	0.2	0.01
	IND	0.07	0.07	0.07	0.09	0.18	0.2	0.0	0.03	0.04	0.04	0.09	0.17	0.2	0.01	0.06	0.0	0.01	0.14	0.01	0.05	0.01
	CHN	0.11	0.1	0.1	0.11	0.17	0.21	0.0	0.07	0.08	0.08	0.09	0.17	0.21	0.01	0.18	0.14	0.16	0.09	0.17	0.21	0.02
	THA	0.12	0.12	0.12	0.09	0.18	0.21	0.01	0.02	0.07	0.07	0.09	0.17	0.23	0.02	0.07	0.08	0.09	0.09	0.17	0.22	0.0
	PAK	0.07	0.06	0.07	0.09	0.17	0.2	0.0	0.17	0.15	0.16	0.09	0.17	0.21	0.01	0.14	0.16	0.1	0.18	0.14	0.14	0.08
	USA	0.04	0.07	0.06	0.09	0.15	0.19	0.01	0.11	0.25	0.11	0.1	0.21	0.23	0.03	0.11	0.19	0.2	0.23	0.18	0.03	0.04
	RUS	0.04	0.11	0.13	0.09	0.19	0.21	0.02	0.03	0.16	0.1	0.09	0.17	0.19	0.01	0.06	0.18	0.02	0.1	0.01	0.03	0.01
	CUB	0.21	0.11	0.18	0.37	0.17	0.23	0.13	0.03	0.25	0.13	0.17	0.11	0.19	0.01	0.13	0.06	0.13	0.25	0.13	0.18	0.07
	UKR	0.1	0.22	0.1	0.13	0.09	0.03	0.01	0.05	0.19	0.14	0.1	0.09	0.04	0.01	0.11	0.18	0.02	0.15	0.01	0.05	0.02
	MEX	0.02	0.01	0.01	0.09	0.16	0.14	0.01	0.03	0.04	0.04	0.09	0.18	0.19	0.02	0.11	0.12	0.13	0.09	0.17	0.21	0.01
	FRA	0.02	0.01	0.01	0.06	0.01	0.04	0.0	0.19	0.22	0.18	0.32	0.19	0.04	0.14	0.09	0.22	0.12	0.25	0.12	0.1	0.05
	DEU	0.02	0.03	0.01	0.14	0.04	0.07	0.0	0.31	0.23	0.19	0.43	0.2	0.02	0.25	0.44	0.21	0.26	0.6	0.26	0.03	0.4
	IDN	0.0	0.0	0.0	0.08	0.18	0.18	0.0	0.03	0.06	0.06	0.09	0.18	0.19	0.01	0.16	0.14	0.15	0.09	0.18	0.22	0.01
	COL	0.25	0.24	0.25	0.09	0.18	0.21	0.06	0.33	0.36	0.39	0.08	0.18	0.21	0.11	0.37	0.3	0.35	0.08	0.18	0.21	0.11
	PHL	0.01	0.02	0.02	0.09	0.17	0.19	0.0	0.09	0.13	0.14	0.09	0.17	0.21	0.0	0.04	0.07	0.07	0.08	0.05	0.06	0.01
	AUS	0.34	0.33	0.36	0.09	0.17	0.2	0.1	0.16	0.22	0.15	0.26	0.15	0.03	0.06	0.04	0.19	0.1	0.09	0.18	0.2	0.01
	TUR	0.02	0.01	0.01	0.11	0.05	0.06	0.0	0.05	0.05	0.05	0.1	0.11	0.18	0.02	0.21	0.22	0.24	0.09	0.18	0.19	0.03
	ARG	0.07	0.09	0.09	0.09	0.17	0.22	0.01	0.1	0.12	0.13	0.09	0.17	0.2	0.01	0.04	0.16	0.13	0.09	0.16	0.21	0.01
Fiber crops	IND	0.17	0.15	0.17	0.09	0.17	0.2	0.02	0.07	0.08	0.08	0.09	0.17	0.2	0.0	0.14	0.14	0.17	0.09	0.17	0.21	0.01
	CHN	0.02	0.03	0.03	0.09	0.17	0.21	0.01	0.06	0.06	0.06	0.09	0.17	0.21	0.0	0.26	0.17	0.2	0.09	0.17	0.21	0.03
	USA	0.19	0.23	0.23	0.09	0.17	0.21	0.04	0.03	0.01	0.01	0.09	0.01	0.07	0.01	0.04	0.19	0.1	0.09	0.15	0.16	0.01
	PAK	0.1	0.1	0.1	0.09	0.17	0.2	0.01	0.29	0.22	0.25	0.09	0.17	0.21	0.05	0.02	0.02	0.03	0.1	0.08	0.02	0.0
	UZB	0.16	0.16	0.15	0.09	0.17	0.21	0.01	0.07	0.19	0.01	0.13	0.01	0.04	0.01	0.06	0.2	0.07	0.18	0.13	0.16	0.1
	BRA	0.23	0.17	0.19	0.1	0.18	0.22	0.03	0.37	0.29	0.33	0.09	0.18	0.2	0.09	0.01	0.01	0.02	0.09	0.17	0.21	0.0
	NGA	0.02	0.01	0.02	0.09	0.08	0.05	0.01	0.0	0.0	0.01	0.11	0.0	0.04	0.0	0.0	0.01	0.0	0.1	0.01	0.05	0.0
	TUR	0.21	0.18	0.19	0.09	0.16	0.21	0.03	0.01	0.03	0.03	0.09	0.17	0.18	0.0	0.22	0.18	0.2	0.08	0.17	0.21	0.01
	BGD	0.03	0.07	0.06	0.09	0.17	0.21	0.0	0.29	0.17	0.21	0.1	0.17	0.21	0.04	0.36	0.2	0.27	0.09	0.17	0.21	0.04
	TKM	0.24	0.14	0.18	0.1	0.17	0.22	0.04	0.09	0.19	0.07	0.14	0.13	0.04	0.01	0.36	0.27	0.13	0.09	0.22	0.21	0.11
	MLI	0.13	0.14	0.14	0.09	0.17	0.22	0.01	0.07	0.02	0.02	0.09	0.16	0.18	0.01	0.05	0.24	0.06	0.09	0.17	0.18	0.03
	ARG	0.31	0.23	0.25	0.09	0.17	0.2	0.04	0.15	0.13	0.15	0.09	0.18	0.21	0.0	0.07	0.14	0.16	0.09	0.16	0.16	0.01
	BFA	0.13	0.12	0.12	0.09	0.17	0.2	0.0	0.05	0.04	0.05	0.09	0.12	0.17	0.02	0.02	0.18	0.08	0.09	0.18	0.18	0.0
	TZA	0.55	0.21	0.3	0.1	0.15	0.18	0.06	0.52	0.19	0.27	0.1	0.17	0.19	0.06	0.07	0.21	0.12	0.09	0.17	0.15	0.01

Continued on next page

		N							P_2O_5							K_2O						
		A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ	A	ΔX_1	X_{max}	B	ΔX_2	σ	Σ
Other crops	IND	0.07	0.07	0.07	0.09	0.17	0.2	0.01	0.07	0.07	0.08	0.09	0.17	0.21	0.0	0.15	0.16	0.17	0.1	0.17	0.2	0.01
	CHN	0.04	0.02	0.02	0.09	0.16	0.18	0.0	0.01	0.01	0.01	0.1	0.07	0.11	0.01	0.06	0.06	0.07	0.09	0.17	0.22	0.0
	BRA	0.1	0.09	0.1	0.09	0.17	0.2	0.0	0.14	0.15	0.15	0.08	0.16	0.21	0.01	0.02	0.04	0.04	0.09	0.17	0.2	0.0
	IDN	0.02	0.01	0.02	0.1	0.05	0.03	0.01	0.04	0.03	0.04	0.11	0.04	0.09	0.01	0.4	0.22	0.27	0.09	0.17	0.2	0.04
	NGA	0.35	0.22	0.26	0.09	0.16	0.19	0.04	0.33	0.22	0.25	0.09	0.15	0.14	0.07	0.01	0.0	0.0	0.09	0.01	0.04	0.0
	NER	0.13	0.18	0.2	0.09	0.16	0.16	0.01	0.09	0.37	0.08	0.09	0.18	0.16	0.06	0.1	0.18	0.07	0.09	0.15	0.16	0.02
	CIV	0.02	0.07	0.06	0.11	0.11	0.09	0.02	0.1	0.13	0.14	0.09	0.16	0.19	0.01	0.05	0.15	0.07	0.09	0.13	0.15	0.03
	MMR	0.01	0.08	0.09	0.19	0.11	0.13	0.04	0.27	0.1	0.13	0.09	0.17	0.2	0.01	0.29	0.08	0.12	0.09	0.17	0.22	0.01
	MEX	0.02	0.01	0.01	0.09	0.07	0.06	0.01	0.02	0.06	0.06	0.09	0.17	0.18	0.01	0.15	0.18	0.19	0.08	0.17	0.21	0.02
	THA	0.02	0.02	0.02	0.1	0.18	0.21	0.02	0.01	0.01	0.01	0.09	0.16	0.18	0.0	0.09	0.09	0.1	0.09	0.17	0.22	0.01
	TUR	0.06	0.06	0.07	0.08	0.17	0.2	0.0	0.07	0.01	0.01	0.09	0.18	0.19	0.0	0.22	0.19	0.2	0.09	0.18	0.2	0.01
	CAN	0.02	0.0	0.01	0.17	0.01	0.07	0.01	0.01	0.04	0.05	0.04	0.05	0.04	0.0	0.01	0.14	0.08	0.12	0.08	0.04	0.0
	ETH	0.37	0.21	0.26	0.09	0.19	0.21	0.09	0.04	0.24	0.09	0.09	0.17	0.21	0.01	0.23	0.18	0.16	0.09	0.18	0.21	0.01
	AUS	0.24	0.27	0.28	0.1	0.17	0.21	0.07	0.15	0.22	0.12	0.29	0.11	0.07	0.08	0.02	0.19	0.07	0.21	0.02	0.11	0.03
	TZA	0.41	0.28	0.34	0.09	0.18	0.21	0.11	0.2	0.16	0.2	0.09	0.16	0.19	0.01	0.02	0.23	0.12	0.09	0.16	0.16	0.01
	GHA	0.47	0.25	0.34	0.09	0.17	0.2	0.09	0.72	0.29	0.38	0.09	0.16	0.21	0.03	0.04	0.02	0.03	0.09	0.14	0.14	0.01
	USA	0.13	0.28	0.27	0.09	0.17	0.22	0.05	0.01	0.2	0.15	0.12	0.14	0.04	0.01	0.03	0.2	0.1	0.09	0.15	0.18	0.01
	KEN	0.4	0.31	0.33	0.09	0.17	0.21	0.12	0.14	0.14	0.15	0.09	0.17	0.21	0.01	0.56	0.2	0.27	0.09	0.17	0.2	0.01
	PAK	0.03	0.04	0.04	0.09	0.17	0.2	0.0	0.16	0.13	0.15	0.09	0.17	0.21	0.01	0.02	0.12	0.09	0.08	0.16	0.19	0.0
	VNM	0.12	0.12	0.13	0.09	0.17	0.2	0.01	0.01	0.02	0.02	0.09	0.17	0.19	0.0	0.06	0.04	0.05	0.08	0.18	0.19	0.01
	MYS	0.11	0.15	0.16	0.09	0.18	0.21	0.01	0.1	0.19	0.2	0.09	0.17	0.22	0.01	0.02	0.01	0.01	0.09	0.17	0.19	0.0
	RUS	0.04	0.2	0.09	0.09	0.17	0.18	0.01	0.07	0.2	0.08	0.09	0.17	0.18	0.01	0.02	0.18	0.01	0.16	0.01	0.06	0.01
	IRN	0.05	0.05	0.05	0.09	0.16	0.2	0.01	0.01	0.01	0.01	0.13	0.05	0.03	0.0	0.01	0.05	0.05	0.29	0.02	0.14	0.02

Values of all parameters corresponding to fits with Bayesian coefficients of determination < 0.5, potential scale reduction factors > 1.1 or average effective sample sizes > 400 are grayed out, as well as values of lognormal parameters (B, ΔX_2, σ) of fits with an insufficiently defined lognormal part (median X_{max} after 2005). Values > 0.45 are in red.

Table C.5. Frequencies of cumulative Jensen-Shannon distances for the crop level fits.

	0 - 0.25 [%]	0.25 - 0.35 [%]	0.35 - 0.45 [%]	0.45 - 0.55 [%]	0.55 - 0.65 [%]	0.65 - 0.75 [%]	> 0.75 [%]
A	85.4	9.4	3.4	1.1	0.3	0.1	0.3
ΔX_1	94.4	5.2	0.3	0.0	0.1	0.0	0.0
X_{max}	90.6	8.5	1.0	0.0	0.0	0.0	0.0
B	86.7	8.6	2.8	0.3	1.1	0.6	0.0
ΔX_2	98.3	1.7	0.0	0.0	0.0	0.0	0.0
σ	97.8	1.7	0.3	0.3	0.0	0.0	0.0
Σ	99.5	0.1	0.2	0.1	0.0	0.0	0.0

Most CJS_{dist} values were < 0.25. CJS_{dist} was similar across nutrients and was mostly parameter dependent. The distribution of the CJS_{dist} values in the crop-level fits with R^2 > 0.5, $\hat{R}$ < 1.1, ESS < 400 and a sufficiently defined logistic (for parameters A, ΔX_1 and X_{max}) or lognormal (for parameters B, ΔX_2, σ) part for each parameter is indicated in Table C.3. For the crop-level fits, on global, regional and country levels, the priors of the logistic parameters (A, ΔX_1 and X_{max}) were informed by the amount of fertilizer used per hectare of cropland in the country or region. In contrast, weakly informative priors were used for the lognormal parameters for all fits, for the logistic parameters for the global and regional non-crop-specific fits. Higher CJS_{dist} values were therefore expected for the informative priors of the logistic parameters in the crop level fits. Indeed, the logistic parameters for these fits were more sensitive to the prior assumptions, except for the lognormal parameter B, which had the largest proportion of large CJS_{dist} values (Table C.5).

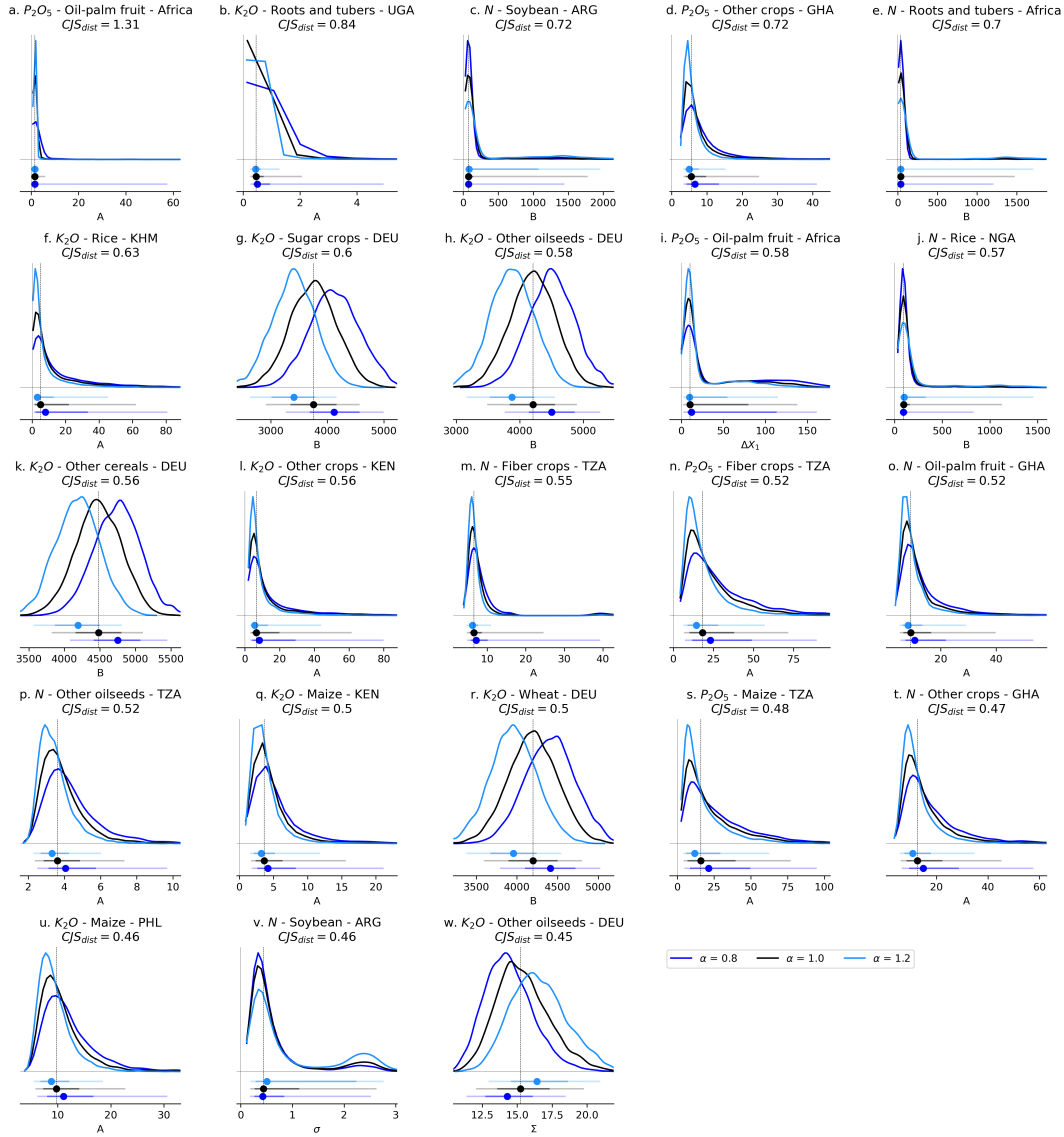


Figure C.3. Posterior distributions after powerscaling the priors (with power α) with cumulative Jensen-Shannon distances (CJS_{dist}) $\geq$ 0.45. The medians of the samples and the 68% (opaque lines) and 95% (transparent lines) credible intervals are plotted below the plots.

Fig. C.3 presents the posterior distributions obtained from the perturbed priors for the 23 cases with CJS_{dist} values > 0.45. The medians of the perturbed posterior distributions remained within the Credible Interval (CI), despite the high CJS_{dist} for these cases, suggesting that the sensitivity was acceptable relative to the width of the CI. The prior sensitivity was generally deemed acceptable for our analysis, because the CI were explicitly taken into account in our interpretation.

C.4 Extended results

C.4.1 Examples of fits with local maxima

Fig. C.4 illustrates two examples of fits, the rate of application of Nitrogen (N) for Latin America and Oceania, for which the data contained a local maximum, followed by a subsequent increase that exceeded the earlier local maximum. The fitted line indicates that the local maxima were ignored for these cases, and the logistic function was fitted until the global maximum. The CI of the estimates were consequently wider, but the model successfully identified the global maximum.

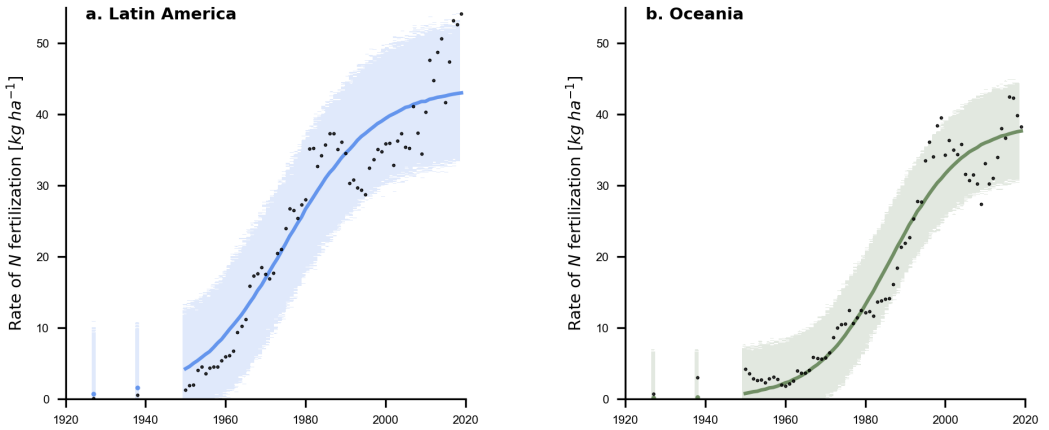


Figure C.4. Rates of N fertilization from 1927 to 2019 for Oceania and Latin America. Medians and 95% credible intervals (highest posterior density intervals) are indicated with colored lines and shaded areas respectively, and the original datapoints are added in black.

C.4.2 Global and regional rates of fertilization

C.4.2.1 Start, peak and dip of the trajectories of rate of fertilization

The following figures compare the global and regional timings (Fig. C.5) and fertilization rates (Fig. C.6) of the start of the logistic increase, the peak and the lognormal dip of fertilizer use for each fertilizer (N, P_2O_5 and potassium oxide (K_2O)) for the non-crop-specific data. As the lognormal decay was insufficiently defined by the data (see Appendix C.3.2), the fertilization rates at the lognormal dips were not plotted.

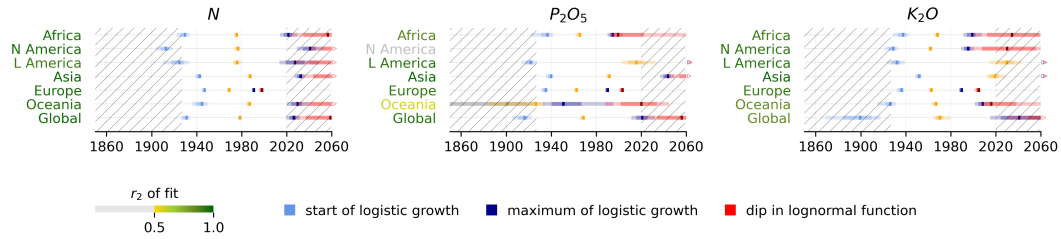


Figure C.5. Start of the logistic increase (X_{start}, light blue), inflection point (x_0, orange), saturation point (X_{max}, blue) and decay location (X_D, red) for global and regional fertilizer use. The median and the 68% and 95% credible interval are shown for all estimates. The striped area denotes temporal range outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

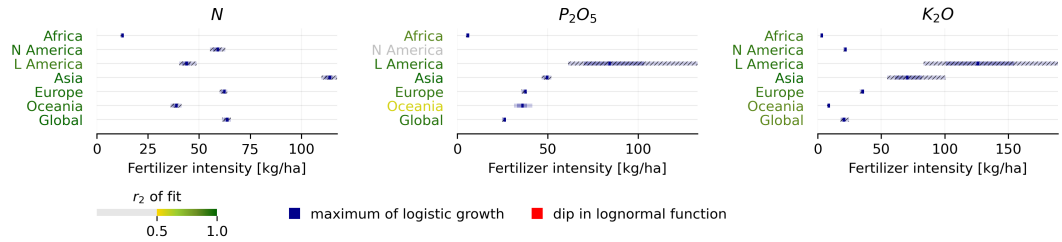


Figure C.6. Maximum of the logistic growth (A, blue) for global and regional intensification of fertilizer use. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the A parameter is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

C.4.3 Global and regional rates of fertilization at crop level

C.4.3.1 Peak rates of fertilization for crop classes *other cereals*, *oil-palm fruit*, *other oilseeds*, *vegetables*, *fruits*, *roots and tubers*, *sugar crops*, *fiber crops* and *other crops*

The timing and fertilization rates of the peaks in the global and regional application rates of N, P_2O_5 and K_2O, for the crop classes *other cereals*, *oil-palm fruit*, *other oilseeds*, *vegetables*, *fruits*, *roots and tubers*, *sugar crops*, *fiber crops* and *other crops*, are summarized in Figs. C.7 and C.8. The shaded areas are the 95% credible ranges, which are defined as the highest posterior density ranges, i.e. the smallest (disconnected) two dimensional interval that contained 95% of the posterior samples. Given that the crop level data span from 1961 to 2019, caution is warranted when interpreting peak values estimated beyond this temporal range.

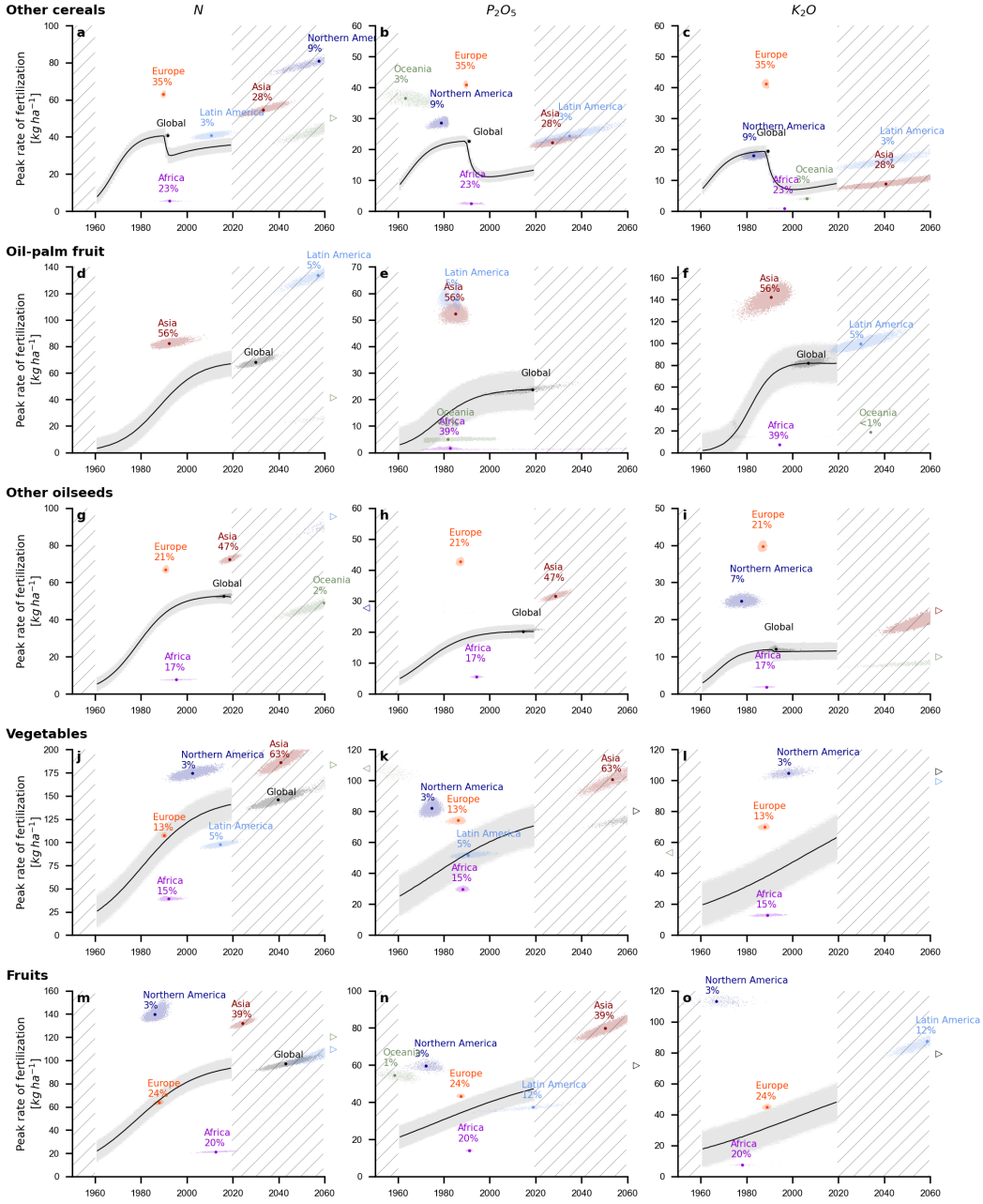


Figure C.7. Peaks in global and regional intensities of N, P_2O_5 and K_2O use for other cereals (a-c), oil-palm fruit (d-f) and other oilseeds (g-i), vegetables (j-l) and fruits (m-o). Geometric medians and 95% highest posterior density regions are indicated by dots and shaded areas respectively, and the global trendlines (with 95% highest posterior density intervals) until 2020 are in black. The percentages are the average areas of harvested crops in the regions since 1990 relative to the global average areas. Estimated peaks after 2060 are indicated with arrows.

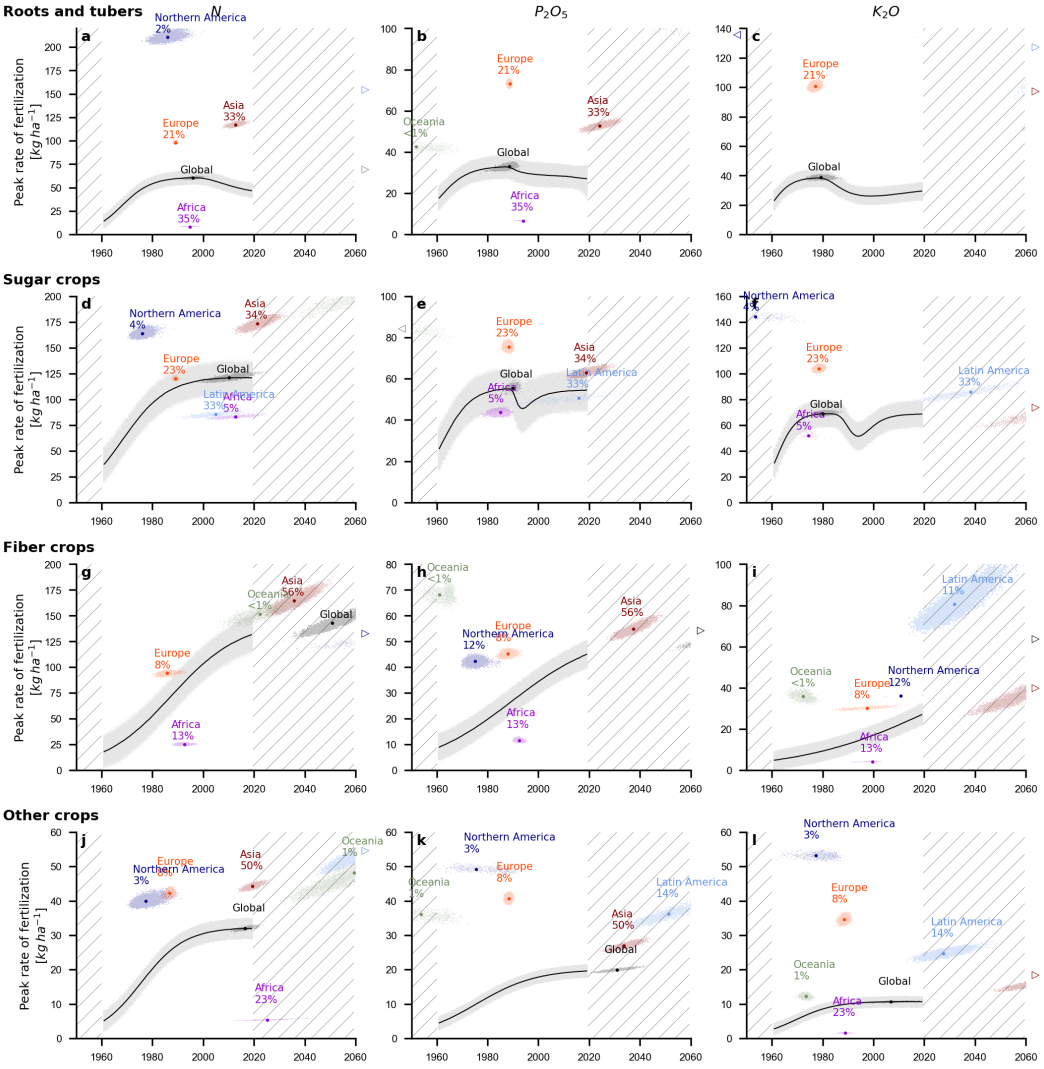


Figure C.8. Peaks in global and regional intensities of N, P_2O_5 and K_2O use for roots and tubers (a-c), sugar crops (d-f), fiber crops (g-i) and other crops (j-l). Geometric medians and 95% highest posterior density regions are indicated by dots and shaded areas respectively, and the global trendlines (with 95% highest posterior density intervals) until 2020 are in black. The percentages are the average areas of harvested crop in the regions since 1990 relative to the global average harvested crop areas. Estimated peaks after 2060 are indicated with arrows.

C.4.3.2 Start, peak and dip of the trajectories of rate of fertilization

The following figures compare the global and regional timings (Figs. C.9, C.11, C.13 and C.15) and fertilization rates (Figs. C.10, C.12, C.14 and C.16) of the start of the logistic increase, the peak and the lognormal dip of fertilizer use for each fertilizer (N, P_2O_5 and K_2O) for the 13 crop classes (wheat, maize, rice, other cereals, soybean, oil-palm fruit, other oilseeds, vegetables, fruits, roots and tubers, sugar crops, fiber crops and other crops). The rates of fertilizer use at the lognormal dips are only shown when the dip was sufficiently defined by the data (see Appendix C.3.2).

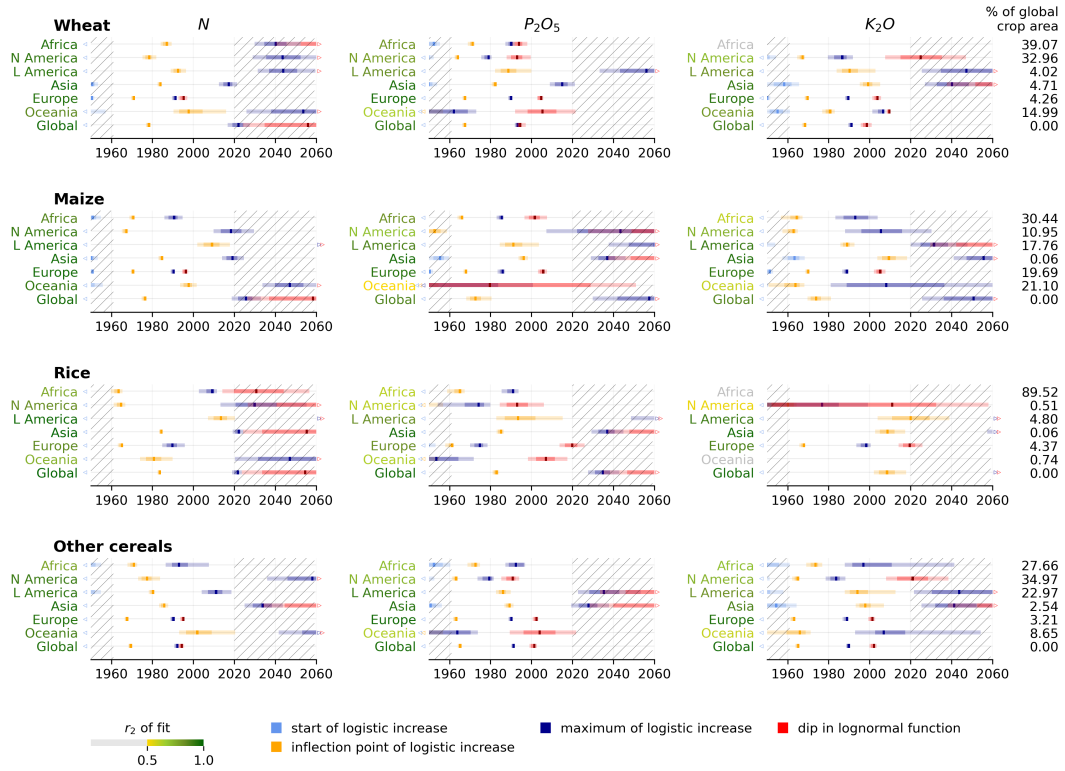


Figure C.9. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the global and regional intensification of fertilizer use for wheat, maize, rice and other cereals. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

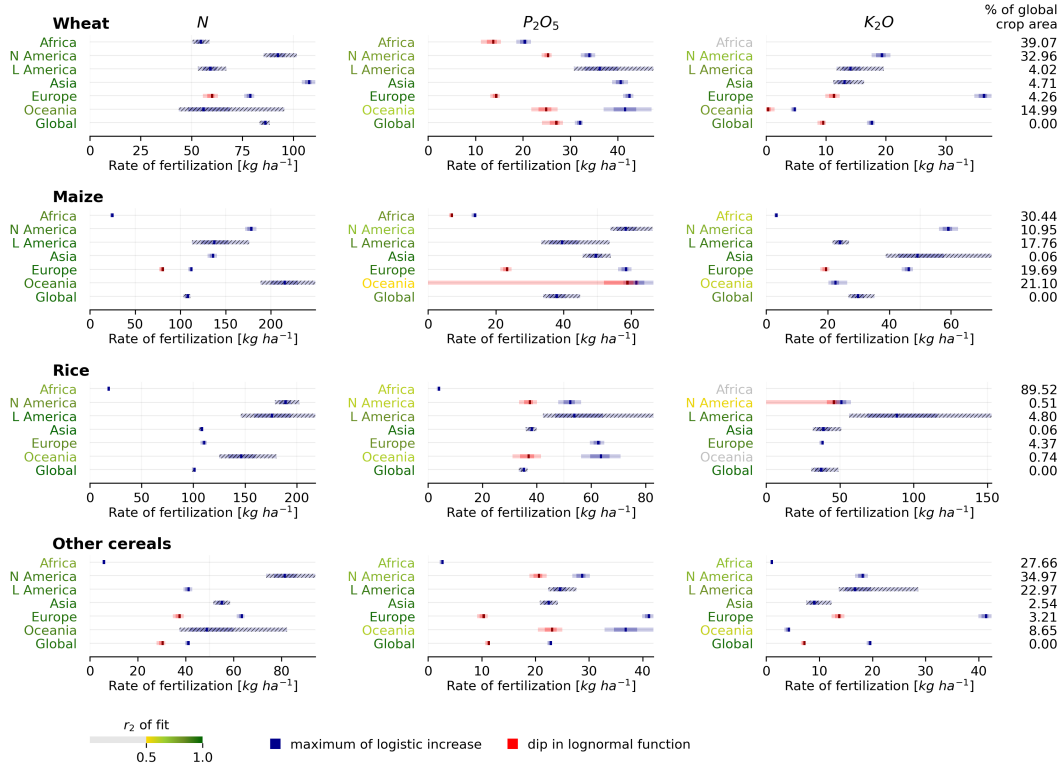


Figure C.10. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the global and regional intensification of fertilizer use for wheat, maize, rice and other cereals. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

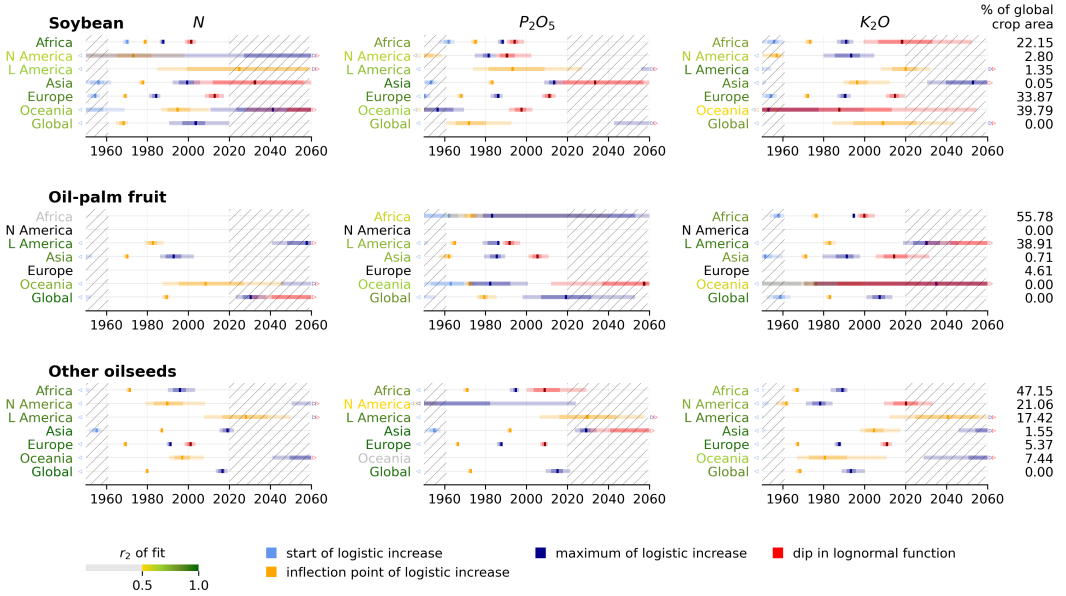


Figure C.11. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the global and regional intensification of fertilizer use for soybean, oil-palm fruit and other oilseeds. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

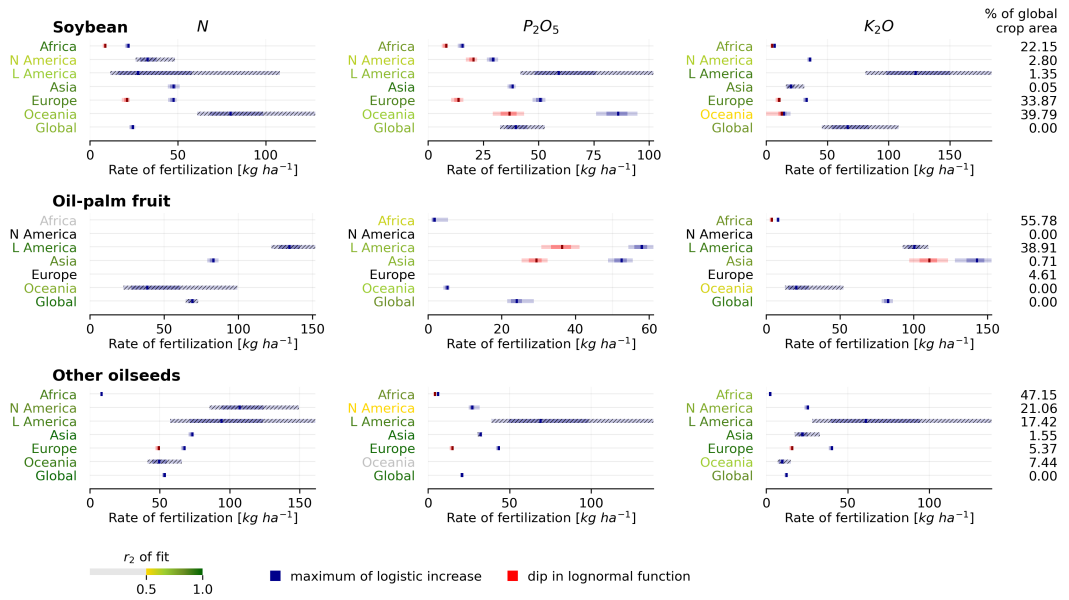


Figure C.12. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the global and regional intensification of fertilizer use for soybean, oil-palm fruit and other oilseeds. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

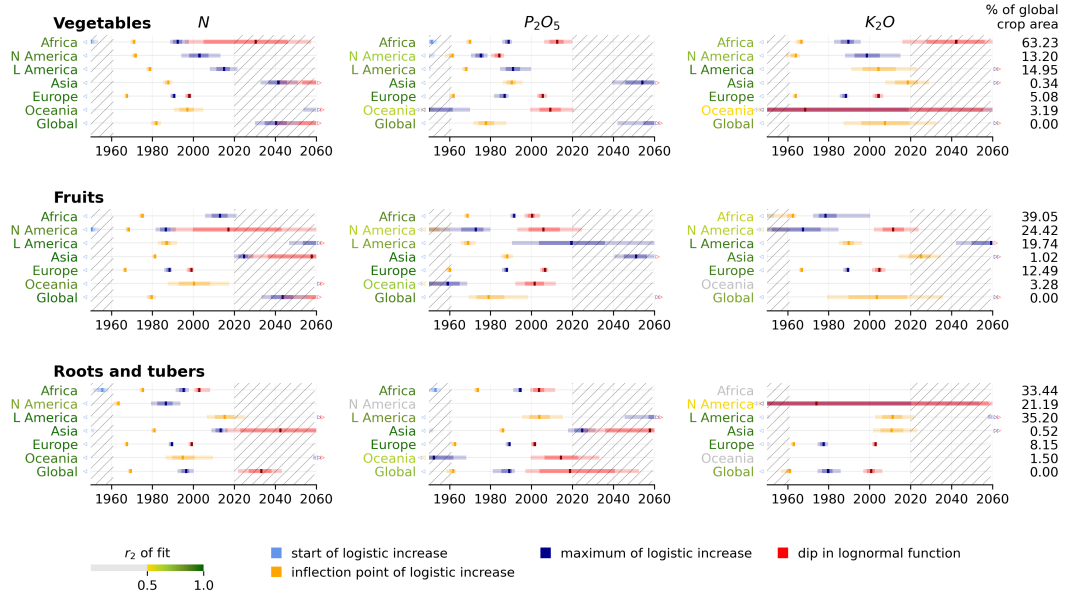


Figure C.13. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the global and regional intensification of fertilizer use for vegetables, fruits and roots and tubers. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

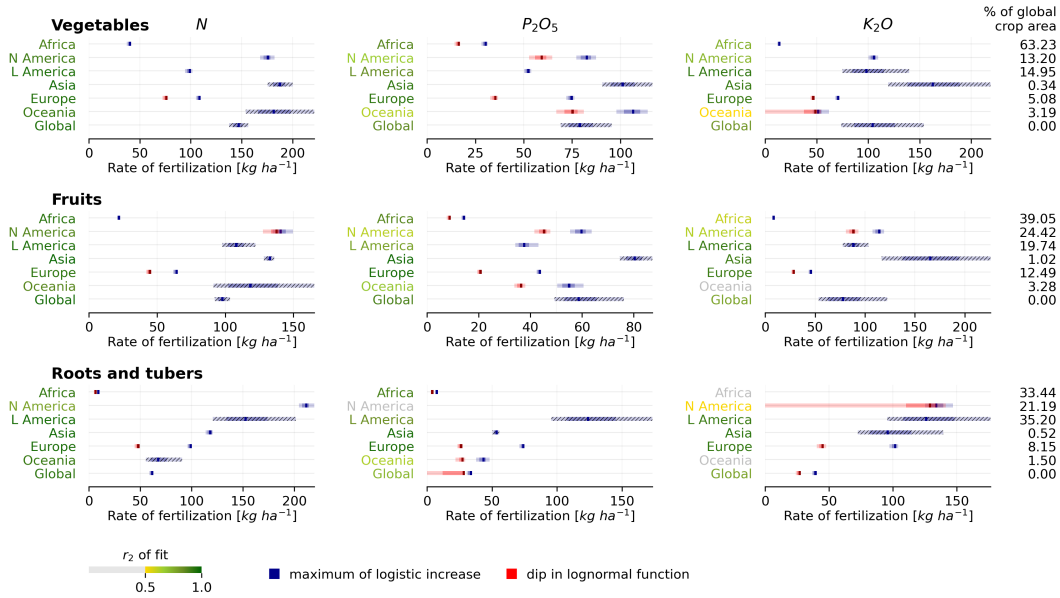


Figure C.14. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the global and regional intensification of fertilizer use for vegetables, fruits and roots and tubers. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

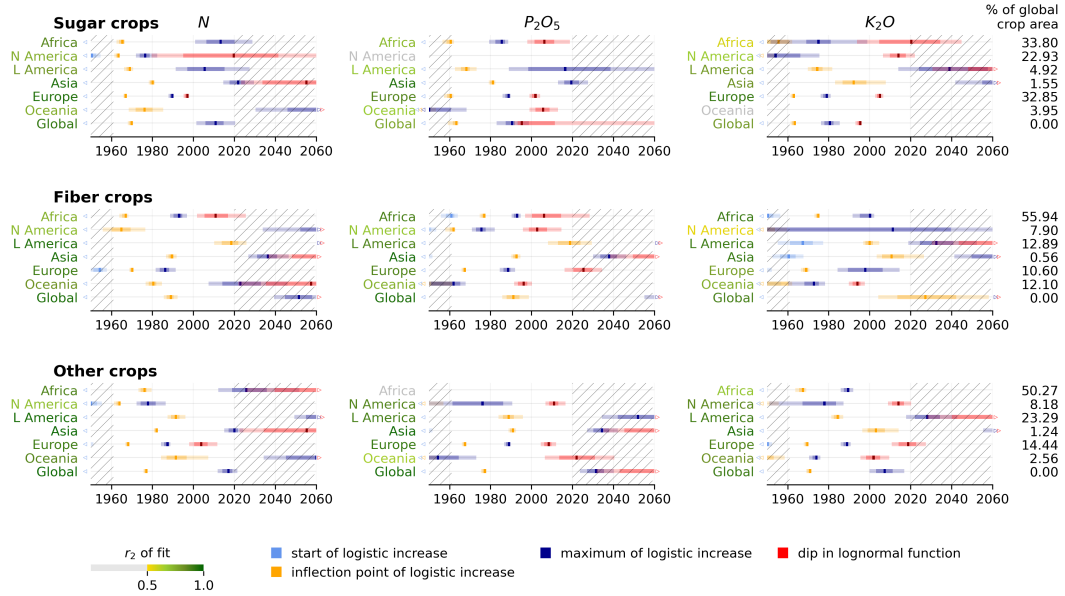


Figure C.15. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the global and regional intensification of fertilizer use for sugar crops, fiber crops and other crops. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

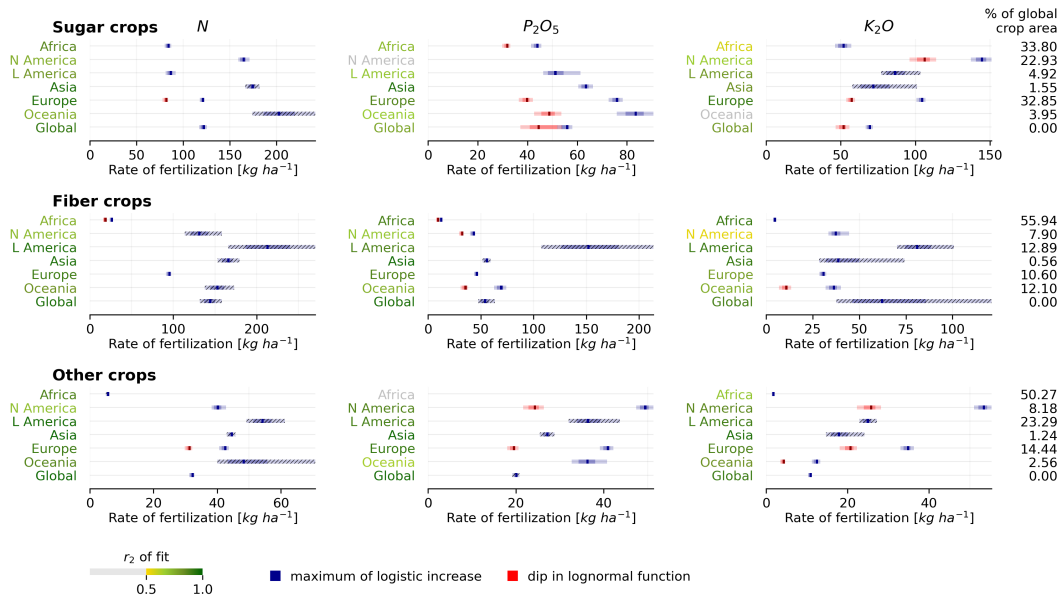


Figure C.16. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the global and regional intensification of fertilizer use for sugar crops, fiber crops and other crops. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the region names with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

C.4.4 National rates of fertilization

C.4.4.1 Peak rates of fertilization for crop classes *other cereals*, *oil-palm fruit*, *other oilseeds*, *vegetables*, *fruits*, *roots and tubers*, *sugar crops*, *fiber crops* and *other crops*

The timing and fertilization rates of the peaks in the country level application rates of N, P_2O_5 and K_2O, for the crop classes *other cereals*, *oil-palm fruit*, *other oilseeds*, *vegetables*, *fruits*, *roots and tubers*, *sugar crops*, *fiber crops* and *other crops*, are summarized in Figs. C.17 and C.18. The shaded areas are the 95% credible ranges, which are defined as the highest posterior density ranges, i.e. the smallest (disconnected) two dimensional interval that contained 95% of the posterior samples. Given that the data span from 1961 to 2019, caution is warranted when interpreting peak values estimated beyond this temporal range.

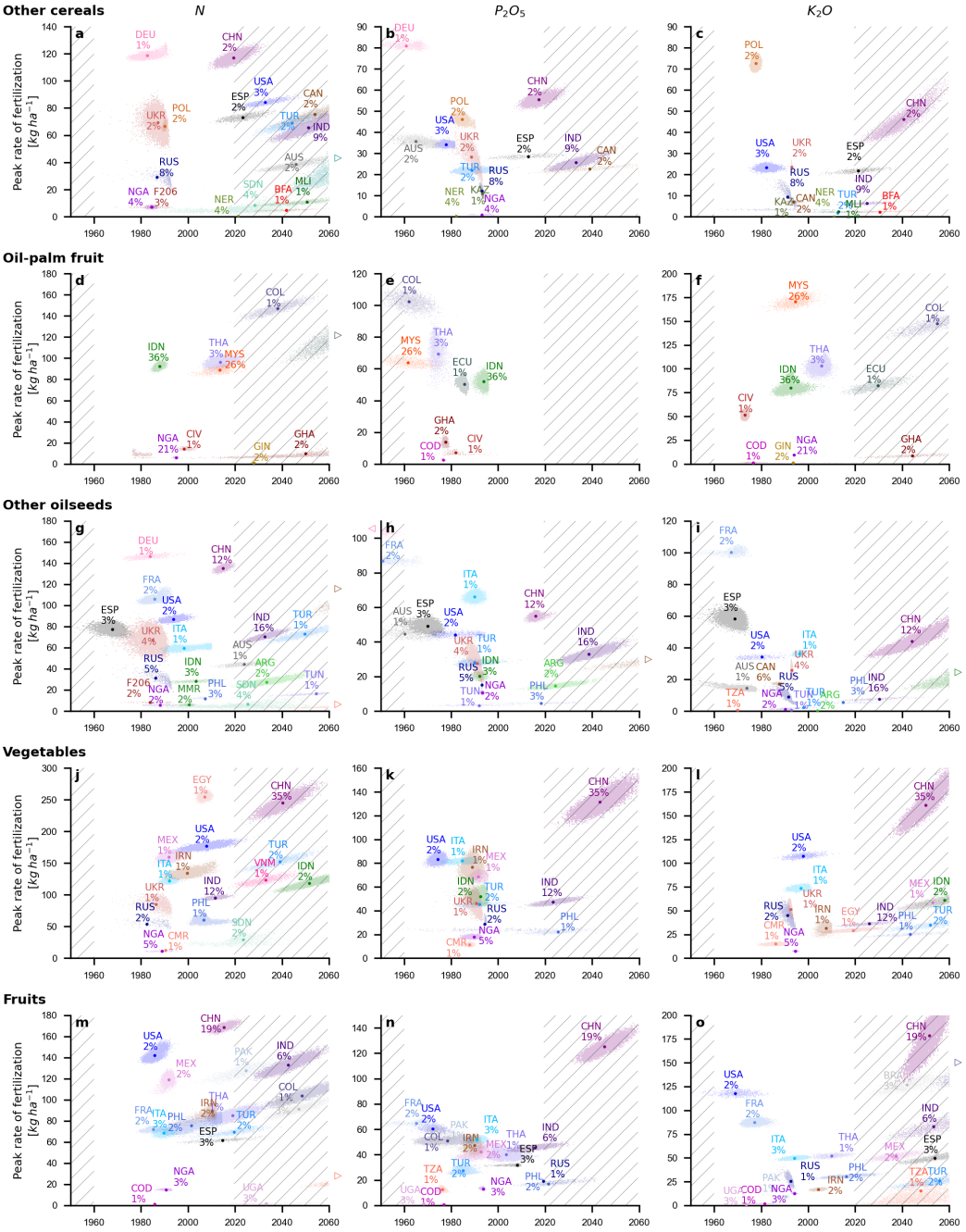


Figure C.17. Peaks in intensities of N, P_2O_5 and K_2O use for other cereals (a-c), oil-palm fruit (d-f), other oilseed crops (g-i), vegetables (j-l) and fruits (m-o) for the countries with more than 1% of the harvested area of the crop since 1990. Geometric medians and 95% highest posterior density intervals are indicated by dots and shaded areas, respectively. Countries are abbreviated using their three-letter ISO codes [355]. The percentages are the average areas of harvested crop in the countries since 1990, relative to the global average areas. Estimated peaks after 2060 are indicated with arrows.

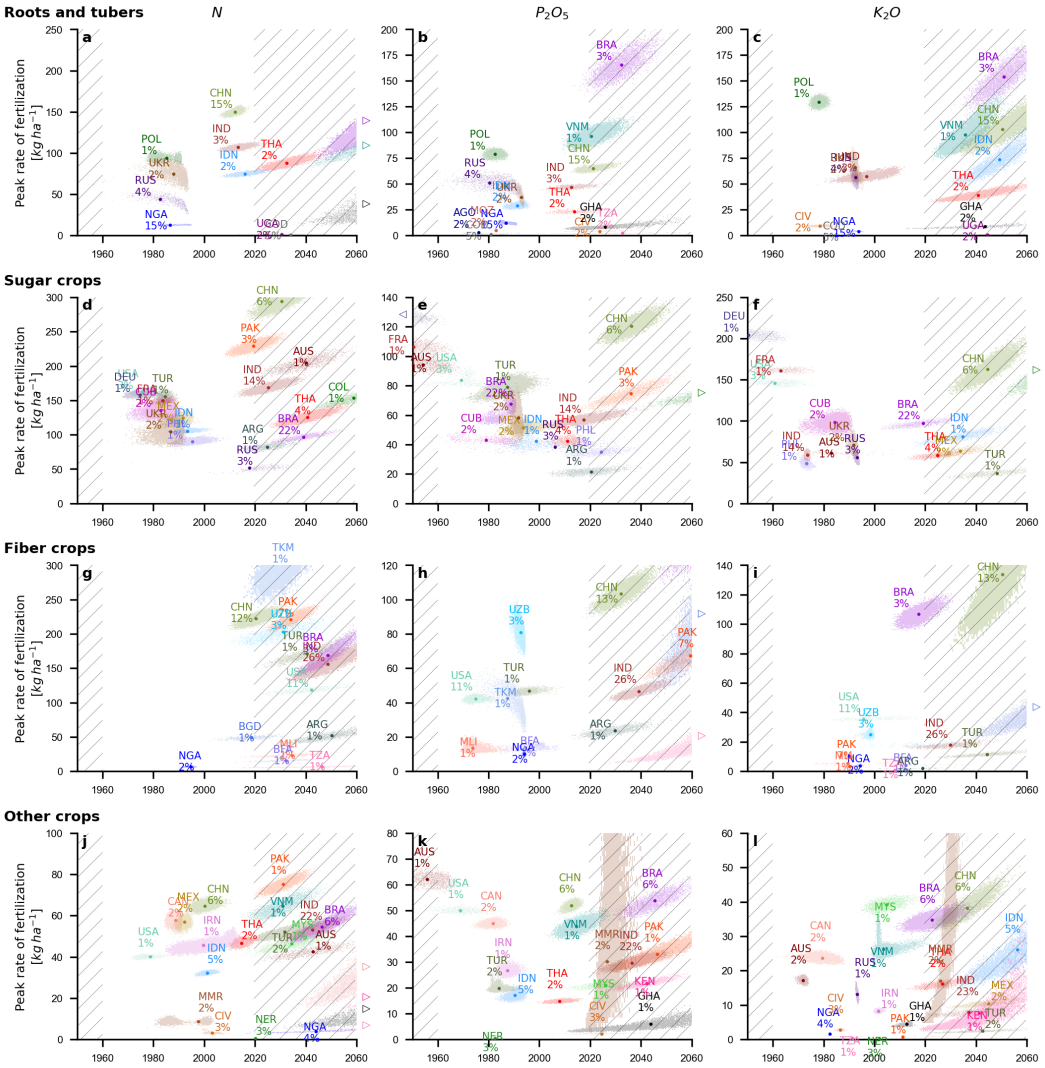


Figure C.18. Peaks in intensities of N, P_2O_5 and K_2O use for roots and tubers (a-c), sugar crops (d-f), fiber crops (g-i) and other crops (j-l) for the countries with more than 1% of the harvested area of the crop since 1990. Geometric medians and 95% highest posterior density intervals are indicated by dots and shaded areas, respectively. Countries are abbreviated using their three-letter ISO codes [355]. The percentages are the average areas of harvested crops in the countries since 1990, relative to the global average harvested crop areas. Estimated peaks after 2060 are indicated with arrows.

C.4.4.2 Start, peak and dip of the trajectories of the intensity of fertilizer use

The following figures compare the timings (Figs. C.19, C.21, C.23 and C.25) and fertilization rates (Figs. C.20, C.22, C.24 and C.26) of the start of the logistic increase, the peak and the lognormal dip of fertilizer use for each fertilizer (N, P_2O_5 and K_2O) for the 13 crop classes (wheat, maize, rice, other cereals, soybean, oil-palm fruit, other oilseeds, vegetables, fruits, roots and tubers, sugar crops, fiber crops and other crops) and for all countries with an average area of harvested crops after 1990 > 1% of the global crop area. The rates of fertilizer use at the lognormal dips are only shown when the dip was sufficiently defined by the data (see Appendix C.3.2).

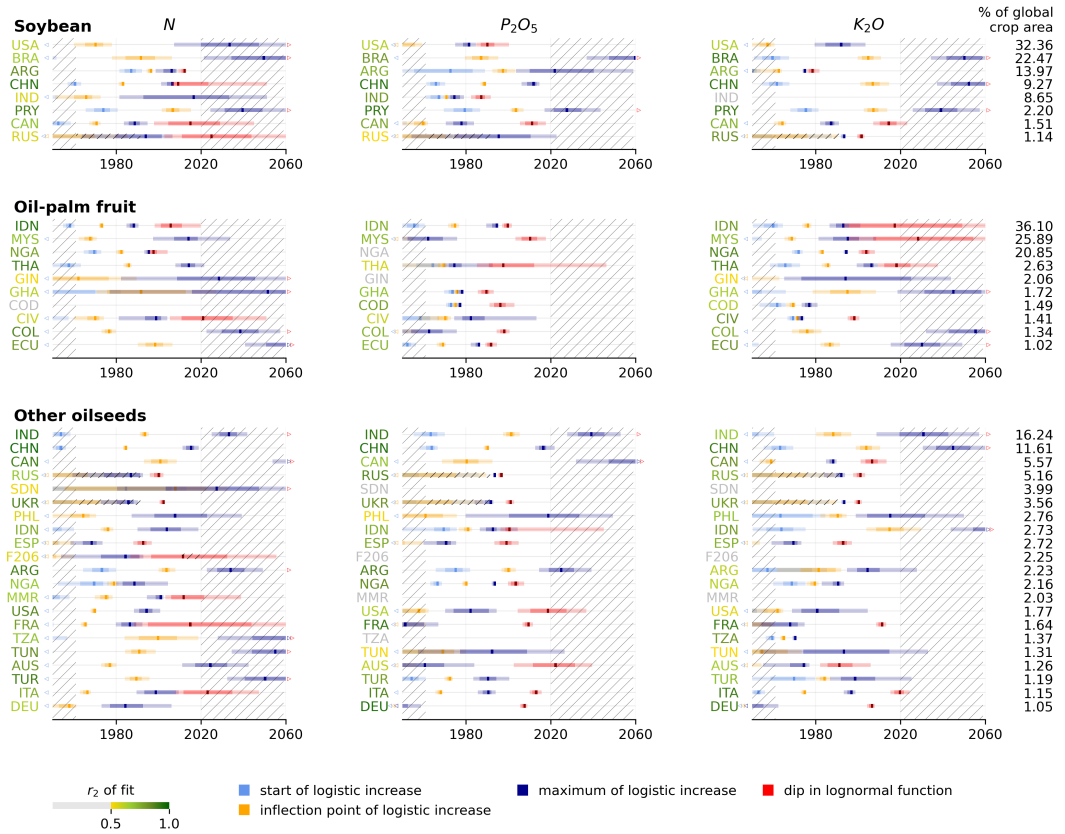


Figure C.21. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the intensification of fertilizer use for soybean, oil-palm fruit and other oilseeds in countries with > 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis display ISO3 codes of the countries, with the colors representing the R^2 value of the model fit. Labels in gray indicate model fits with $R^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

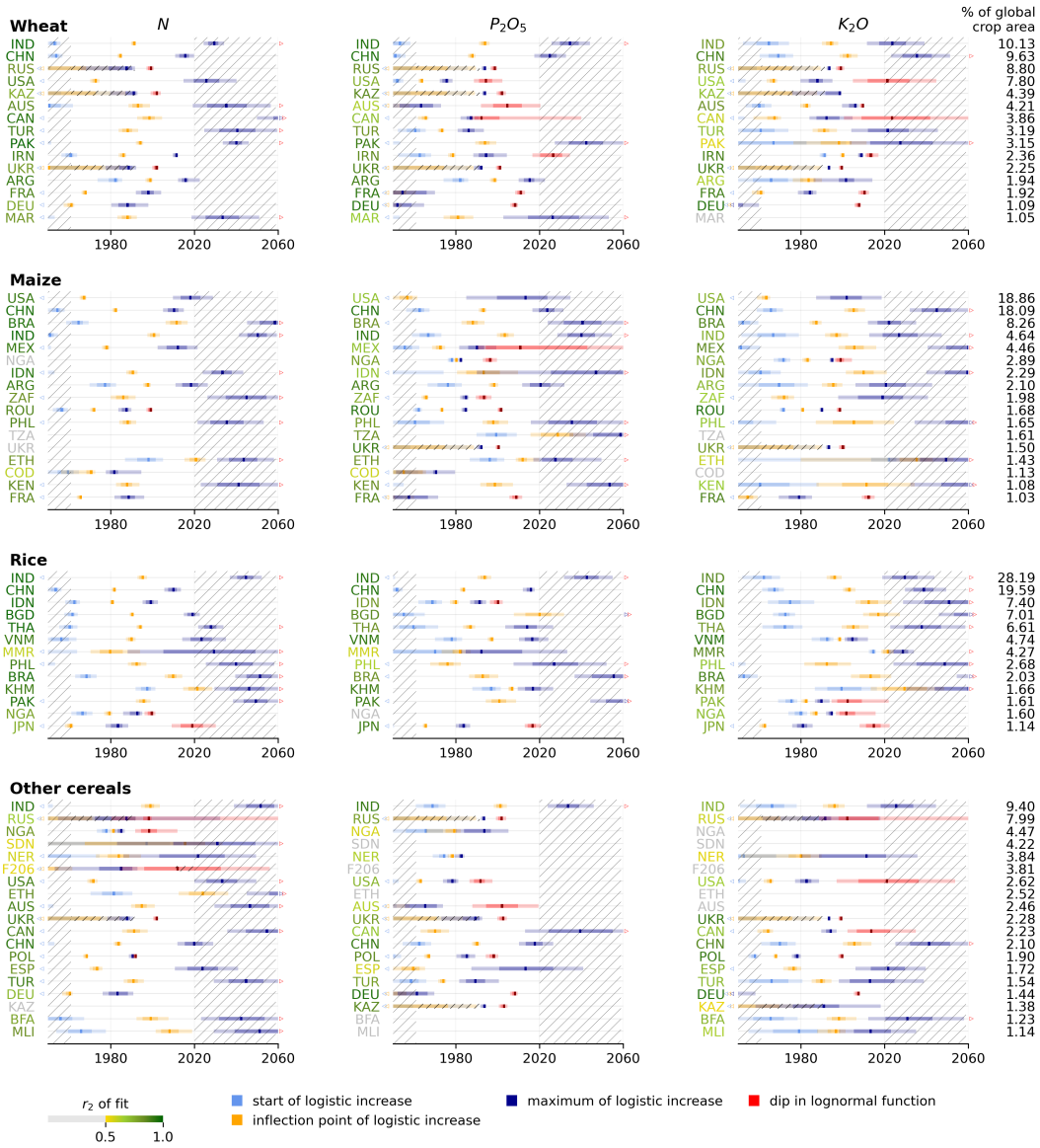


Figure C.19. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the intensification of fertilizer use for wheat, maize, rice and other cereals in countries with > 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis displays the ISO3 codes of the countries, with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

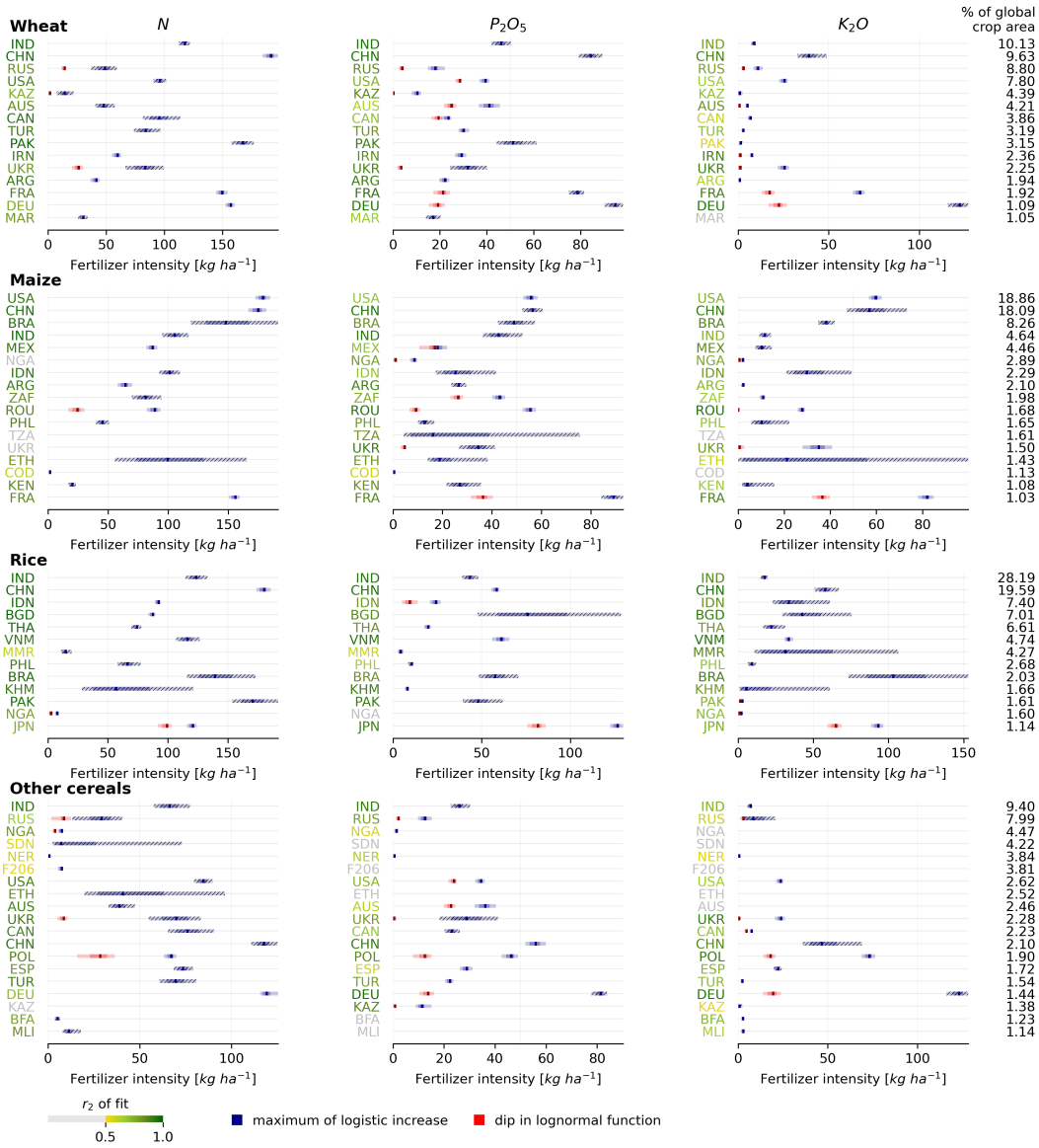


Figure C.20. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the intensification of fertilizer use for wheat, maize, rice and other cereals in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the ISO3 codes of the countries, with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

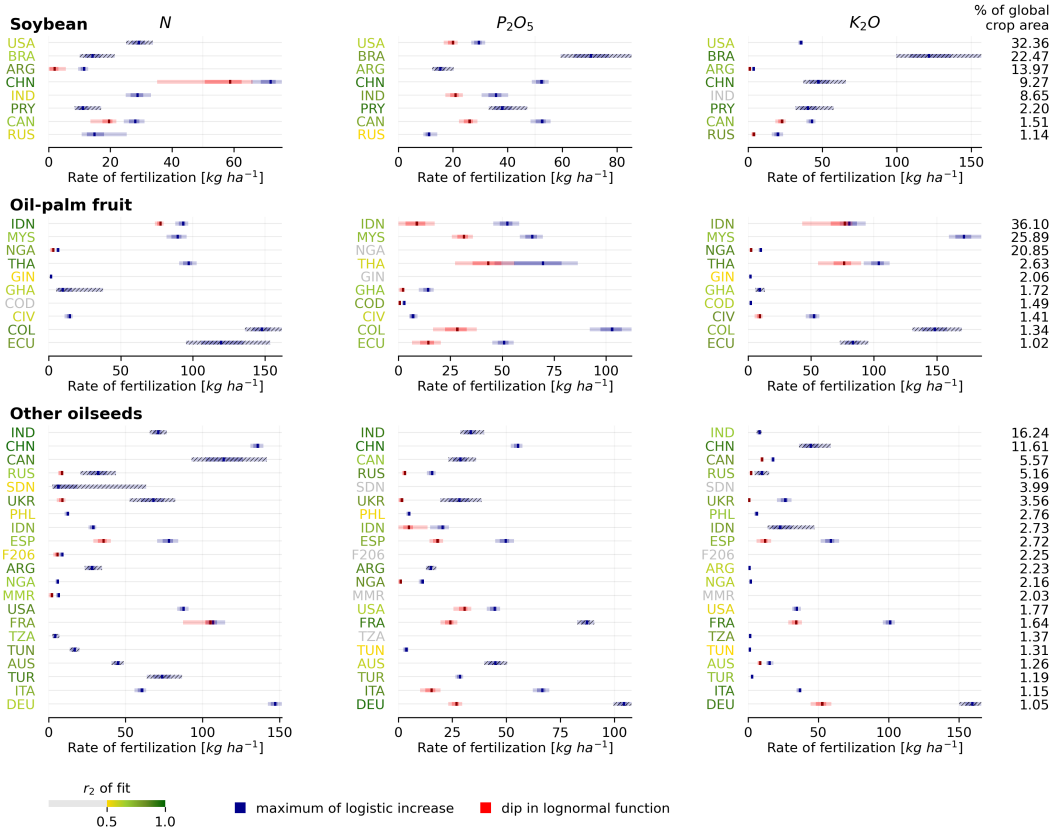


Figure C.22. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the intensification of fertilizer use for soybean, oil-palm fruit and other oilseeds in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the ISO3 codes of the countries, with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

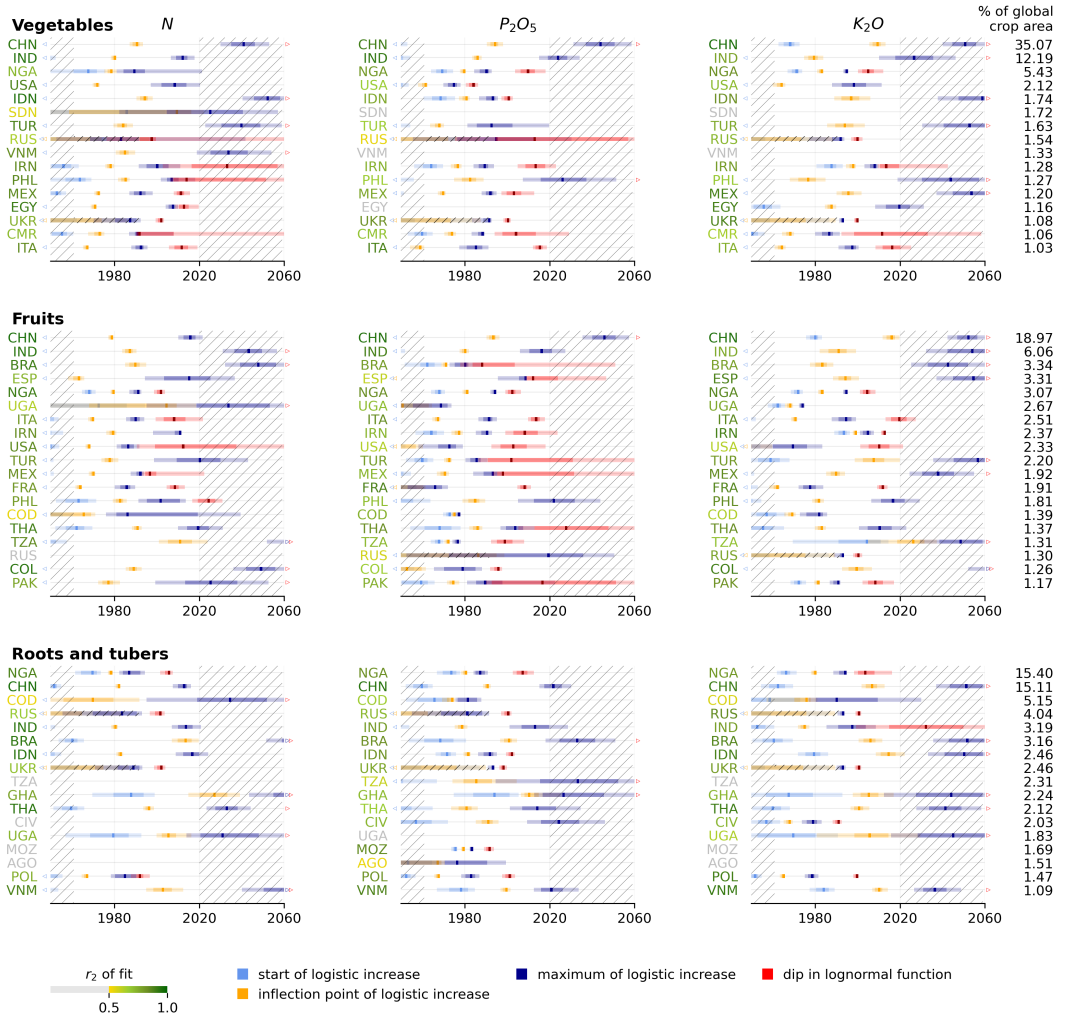


Figure C.23. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the intensification of fertilizer use for vegetables, fruits and roots and tubers in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis display ISO3 codes of the countries, with the colors representing the R^2 value of the model fit. Labels in gray indicate model fits with $R^2 <$ 0.5 or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

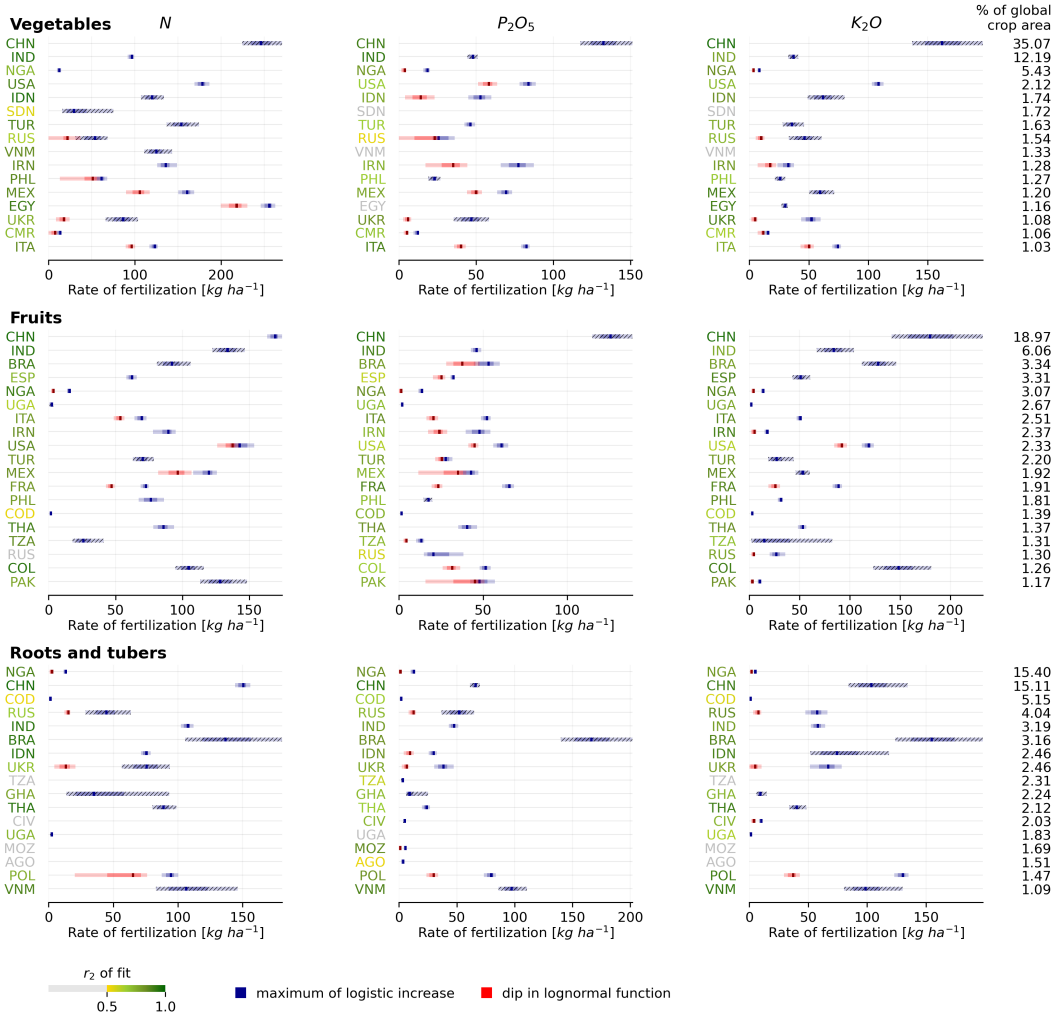


Figure C.24. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the intensification of fertilizer use for vegetables, fruits and roots and tubers in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the ISO3 codes of the countries, with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

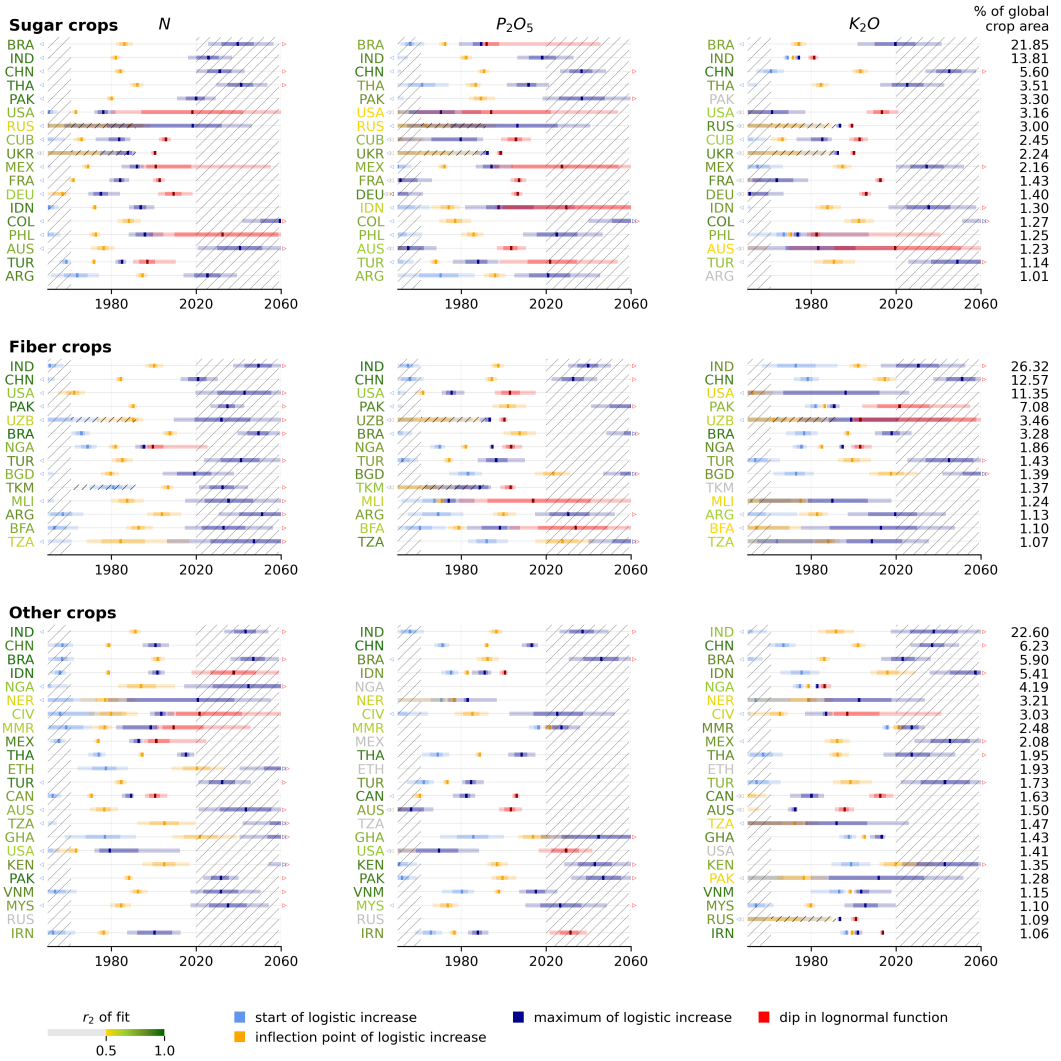


Figure C.25. Start of the logistic increase (X_{start}, light blue), saturation point (X_{max}, blue), and decay location (X_D, red) in the intensification of fertilizer use for sugar crops, fiber crops and other crops in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. The striped areas denote temporal ranges outside the study period. The y-axis display ISO3 codes of the countries, with the colors representing the R^2 value of the model fit. Labels in gray indicate model fits with $R^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

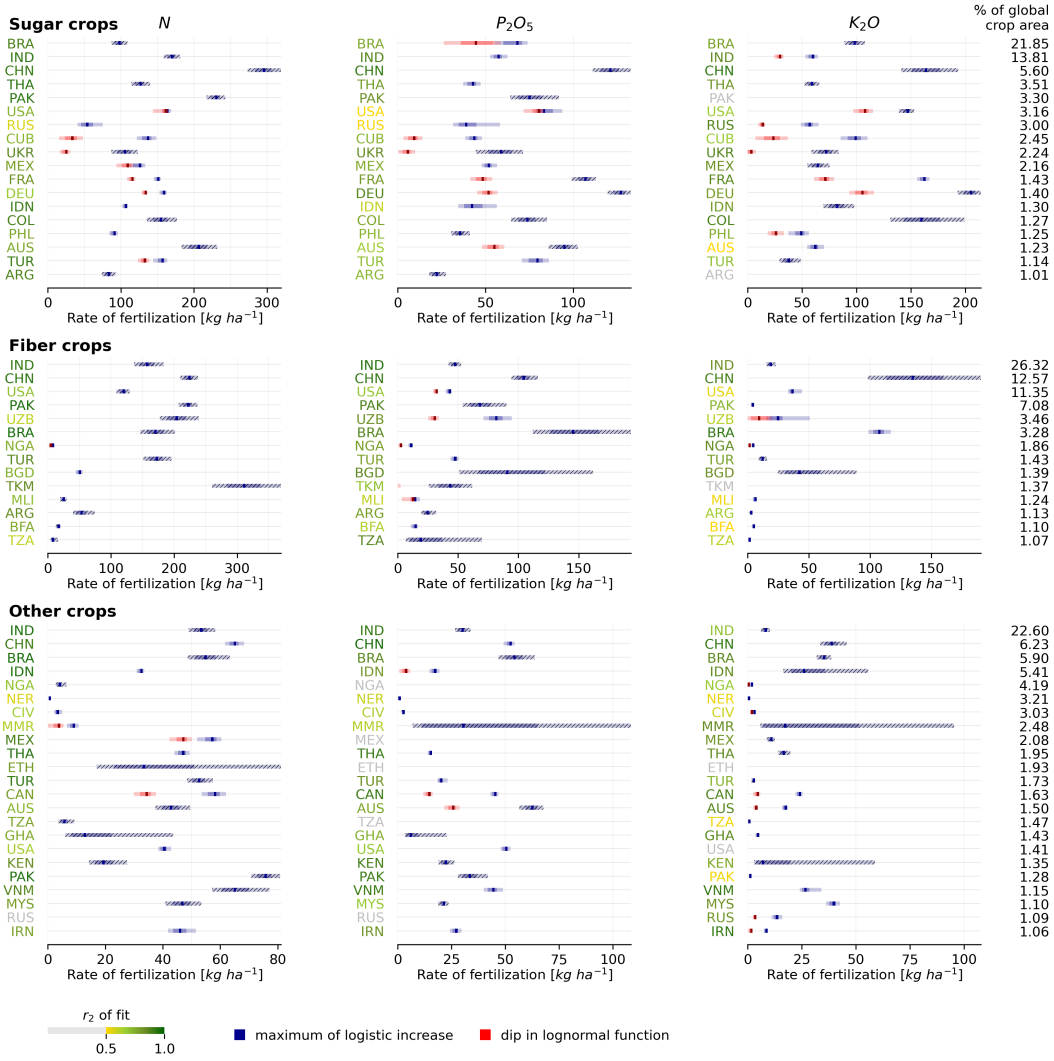


Figure C.26. Peak rate ($0.99A$, blue) and dip of the lognormal decay (D, red) in the intensification of fertilizer use for sugar crops, fiber crops and other crops in countries with $>$ 1% of the global harvested area of each crop since 1990. The median and the 68% and 95% credible interval are shown for all estimates. Striped lines indicate cases where the parameter A is reached outside the study period. Parameter D is not shown if it is outside the study period. The y-axis displays the ISO3 codes of the countries, with the colors representing the determination coefficient (r^2) of the model fit. Labels in gray indicate model fits with $r^2 < 0.5$ or those not meeting the quality standards described in the Methods section. The left, middle and right panels show the results for N, P_2O_5 and K_2O, respectively.

Appendix D

Supplementary information:

A multidecadal analysis of fertilizer use and allocation

D.1 Extended Results

D.1.1 Food *vs* Feed

In this section, we compare the national values of the ratio between fertilizer use for *feed* and fertilizer use for *food* (fertilizer used for *feed* relative to *food* (FFR)) for the 1960s and the 2010s. Countries without data for these exact decades, but with available data for both *food* and *feed* in two different decades within the study period, were also included in the figures (Figs. D.1 to D.4). While the main manuscript shows results only for the top 50 national fertilizer consumers, this section includes all countries for which data are available.



Figure D.1. Ratios between the amount of fertilizer used for *feed* and *food* (FFR) in the African countries. Each arrow represents the change in FFR between the 1960s (arrow start) and the 2010s (arrow end) for each country. Red and blue arrows indicate an increase and decrease, respectively. Gray lines represent global changes in the ratios over time, with the right end marking the 2010s for all three nutrients. The left, middle, and right panels display data for Nitrogen (N), Phosphorus (P), and Potassium (K), respectively. Colors indicate broader Food and Agriculture Organization (FAO) regions, as used throughout the plots. Country labels indicate the ISO3 code of the country, and all ISO3 codes are defined in Table A4. 3. Labels indicate the absolute value of Cliff's delta (black > 0.474; blue > 0.33; yellow > 0.147; light grey < 0.147). Asterisks mark countries where the first decade shown is not the 1960s or the last is not 2010s.

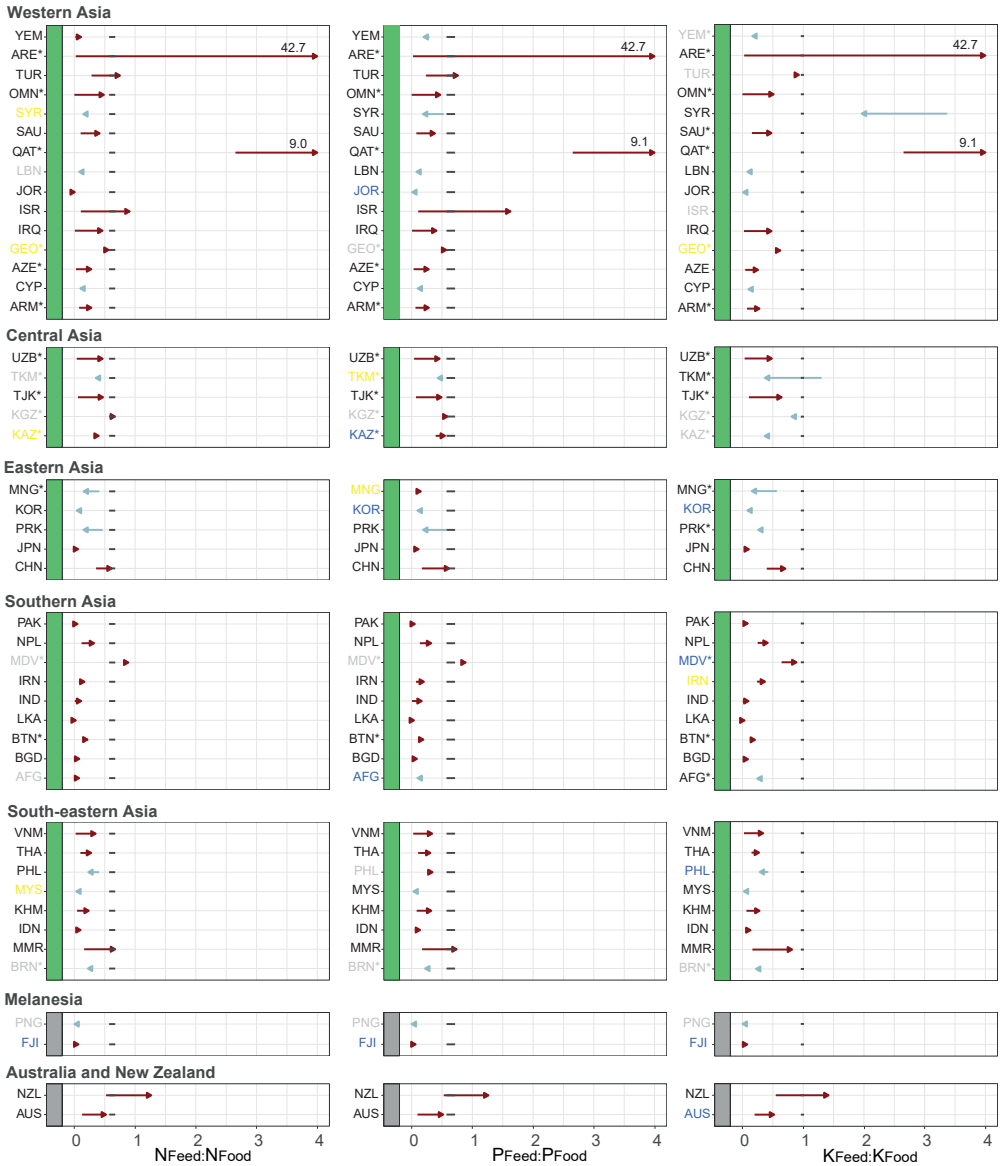


Figure D.2. Ratios between the amount of fertilizer used for *feed* and *food* (FFR) in the Asian and Oceanic countries countries. Each arrow represents the change in FFR between the 1960s (arrow start) and the 2010s (arrow end) for each country. Red and blue arrows indicate an increase and decrease, respectively. Gray lines represent global changes in the ratios over time, with the right end marking the 2010s for all three nutrients. The left, middle, and right panels display data for N, P, and K, respectively. Colors indicate broader FAO regions, as used throughout the plots. Country labels indicate the ISO3 code of the country, and all ISO3 codes are defined in Table C.1. Labels indicate the absolute value of Cliff's delta (black > 0.474; blue > 0.33; yellow > 0.147; light grey < 0.147). Asterisks mark countries where the first decade shown is not the 1960s or the last is not 2010s. Numbers indicate FFR above 4.

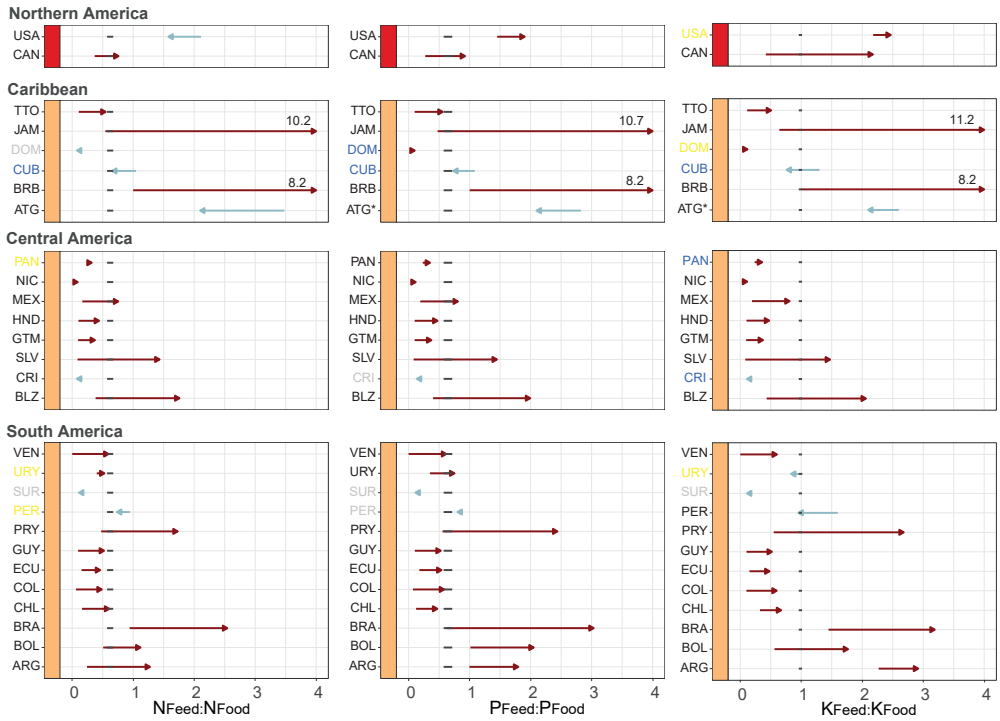


Figure D.3. Ratios between the amount of fertilizer used for *feed* and *food* (FFR) in the American countries countries. Each arrow represents the change in FFR between the 1960s (arrow start) and the 2010s (arrow end) for each country. Red and blue arrows indicate an increase and decrease, respectively. Gray lines represent global changes in the ratios over time, with the right end marking the 2010s for all three nutrients. The left, middle, and right panels display data for N, P, and K, respectively. Colors indicate broader FAO regions, as used throughout the plots. Country labels indicate the ISO3 code of the country, and all ISO3 codes are defined in Table C.1. Labels indicate the absolute value of Cliff's delta (black > 0.474; blue > 0.33; yellow > 0.147; light grey < 0.147). Asterisks mark countries where the first decade shown is not the 1960s or the last is not 2010s. Numbers indicate FFR above 4.

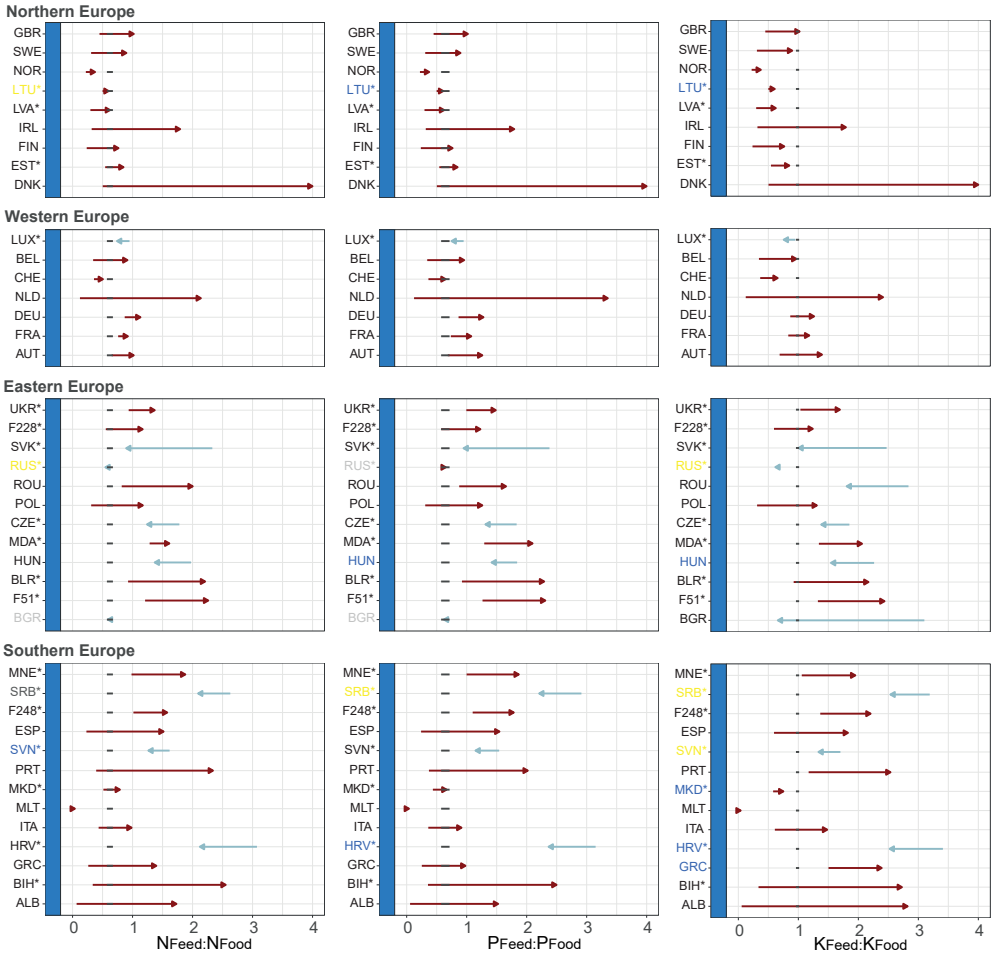


Figure D.4. Ratios between the amount of fertilizer used for *feed* and *food* (FFR) in the European countries countries. Each arrow represents the change in FFR between the 1960s (arrow start) and the 2010s (arrow end) for each country. Red and blue arrows indicate an increase and decrease, respectively. Gray lines represent global changes in the ratios over time, with the right end marking the 2010s for all three nutrients. The left, middle, and right panels display data for N, P, and K, respectively. Colors indicate broader FAO regions, as used throughout the plots. Country labels indicate the ISO3 code of the country, and all ISO3 codes are defined in Table C.1. Labels indicate the absolute value of Cliff's delta (black > 0.474; blue > 0.33; yellow > 0.147; light grey < 0.147). Asterisks mark countries where the first decade shown is not the 1960s or the last is not 2010s. Numbers indicate FFR above 4.

D.1.2 Virtual NPK fertilizer traded across major crops

In this section, we include additional figures on virtual NPK fertilizer trade referenced in the main text but not included there due to space limitations.

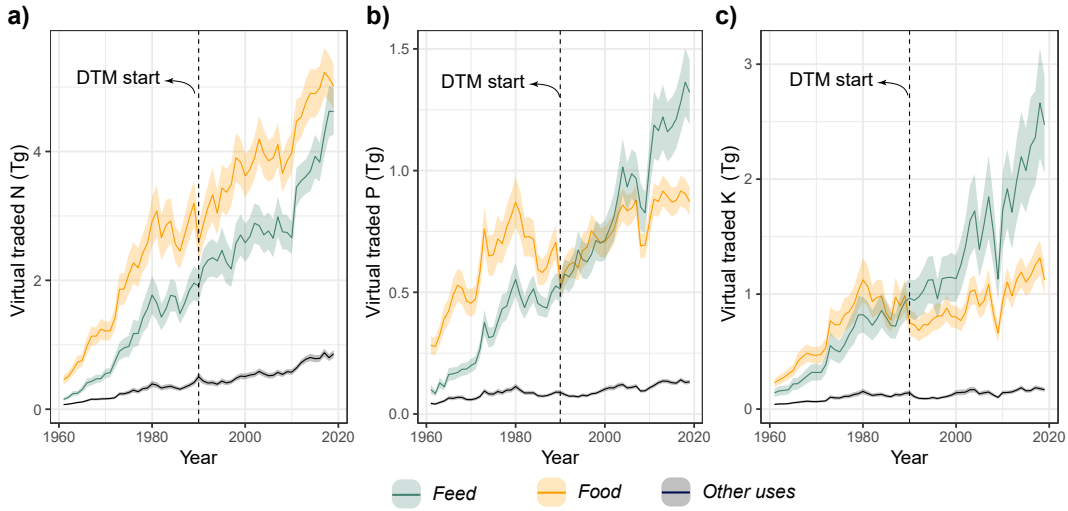


Figure D.5. Global virtually traded flows of: a) N, b) P, and c) K fertilizers for major crop products used for *food* (orange), *feed* (green), and *other uses* (black) between 1961 and 2019. The solid lines indicate the mean of the 500 Monte Carlo (MC) simulations, and the shaded areas indicate the *sd* of the simulations. The dashed line indicates the initial year where annual data of the Detailed Trade Matrix (DTM) of Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) has been used.

D.1.3 Crops behind the changes in global fertilizer use

The additive decomposition of total changes for each use, based on inputs for the four crops reveals different patterns across nutrients, crops and periods (Fig. D.12). Most of the changes in the *food* use category are associated with changes in wheat and rice (Fig. D.12 a-c). However, while the positive contribution of rice extends until 2005, the positive contribution of wheat is primarily concentrated before 1990 (Fig. D.12 a-c). For the *feed* category, maize and soybean were the main contributions (Fig. D.12 d-f). However, while for P and K the long-term contribution of both crops was similar, for N, the contribution of maize is clearly larger (Fig. D.12 d). The short-term results show that soybean's contribution is concentrated in the more recent periods (since 1990), whereas the contributions from maize are more evenly distributed over the entire study period (Fig. D.12 d-f). Changes for the *other uses* category are related to changes associated with maize, and particularly in the 2006-2019 period (Fig. D.12 g-i).

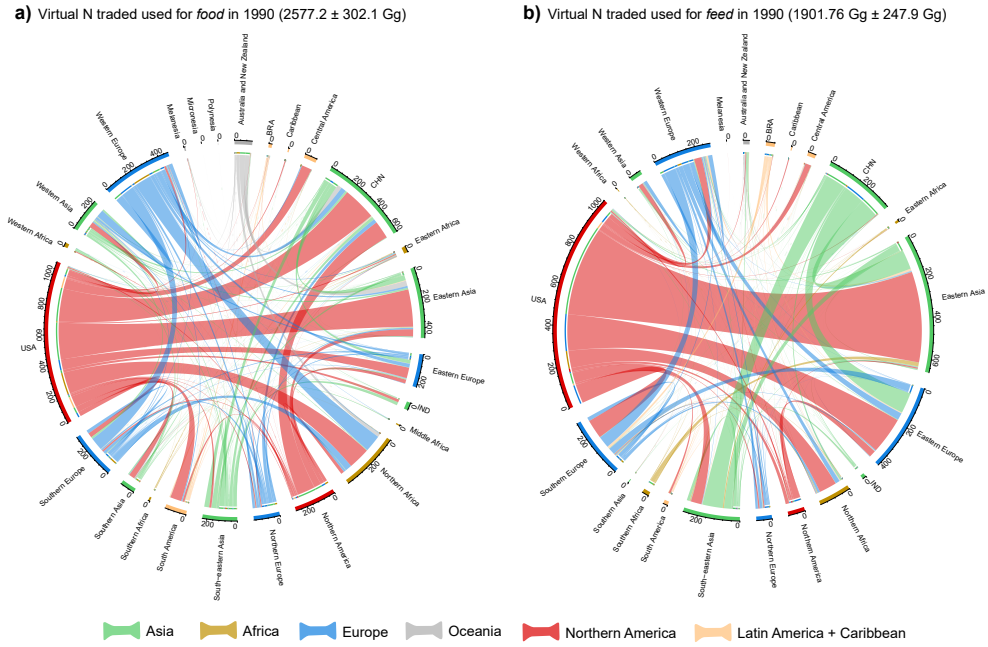


Figure D.6. Global flows of N fertilizer traded for major crops used for *food* (a) and *feed* (b) in 1990. The outer rings indicate the total flow of N fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

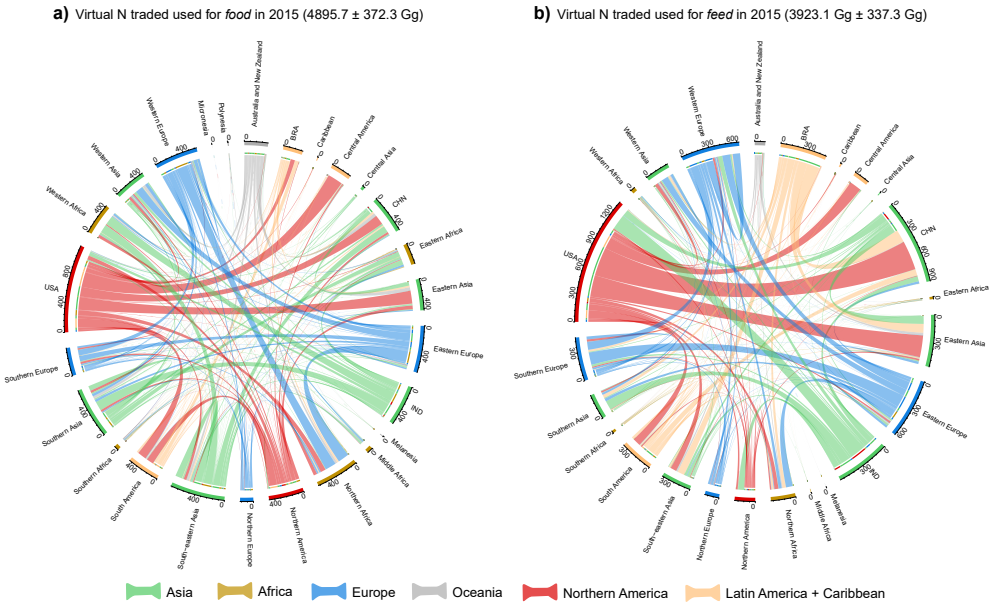


Figure D.7. Global flows of N fertilizer traded for major crops used for *food* (a) and *feed* (b) in 2015. The outer rings indicate the total flow of N fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

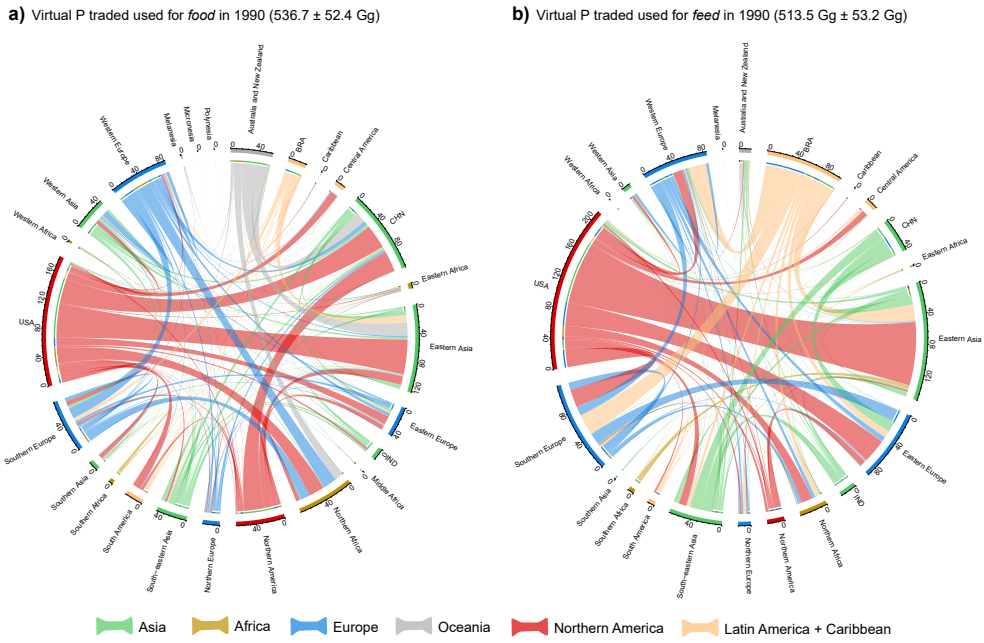


Figure D.8. Global flows of P fertilizer traded for major crops used for *food* (a) and *feed* (b) in 1990. The outer rings indicate the total flow of P fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

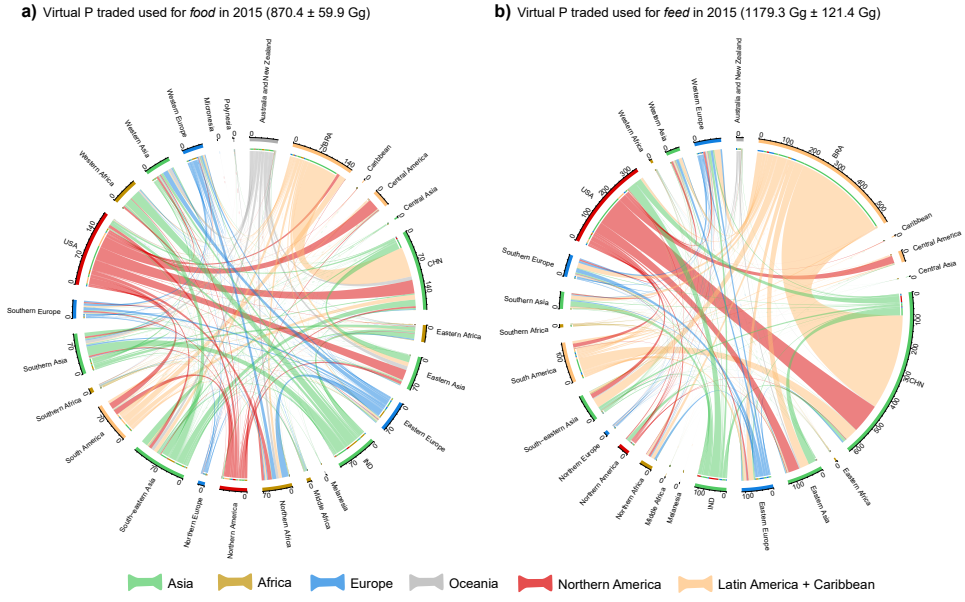


Figure D.9. Global flows of P fertilizer traded for major crops used for *food* (a) and *feed* (b) in 2015. The outer rings indicate the total flow of P fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

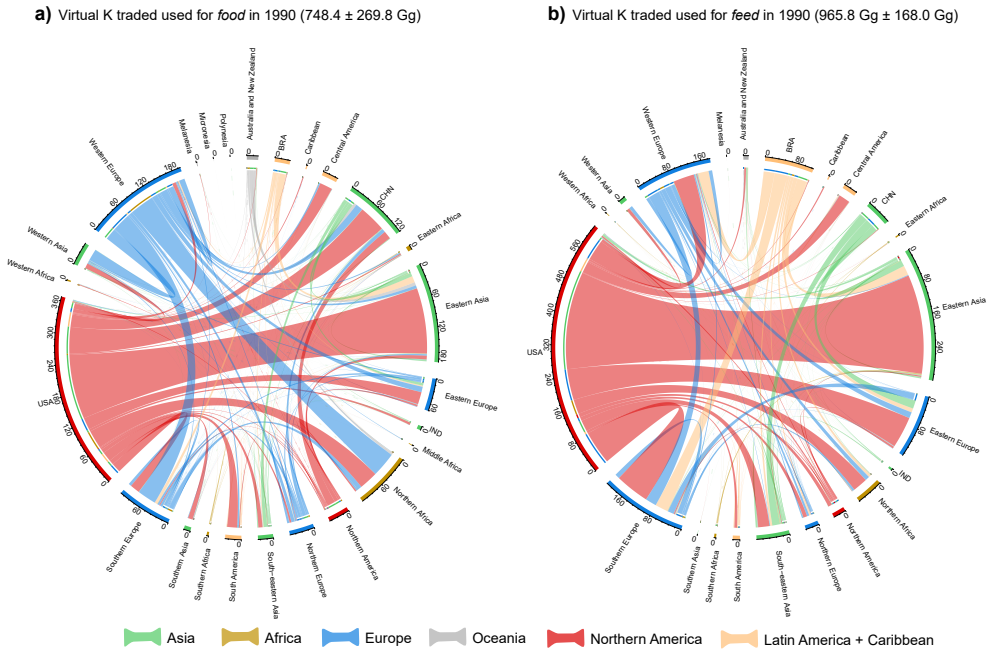


Figure D.10. Global flows of K fertilizer traded for major crops used for *food* (a) and *feed* (b) in 1990. The outer rings indicate the total flow of K fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

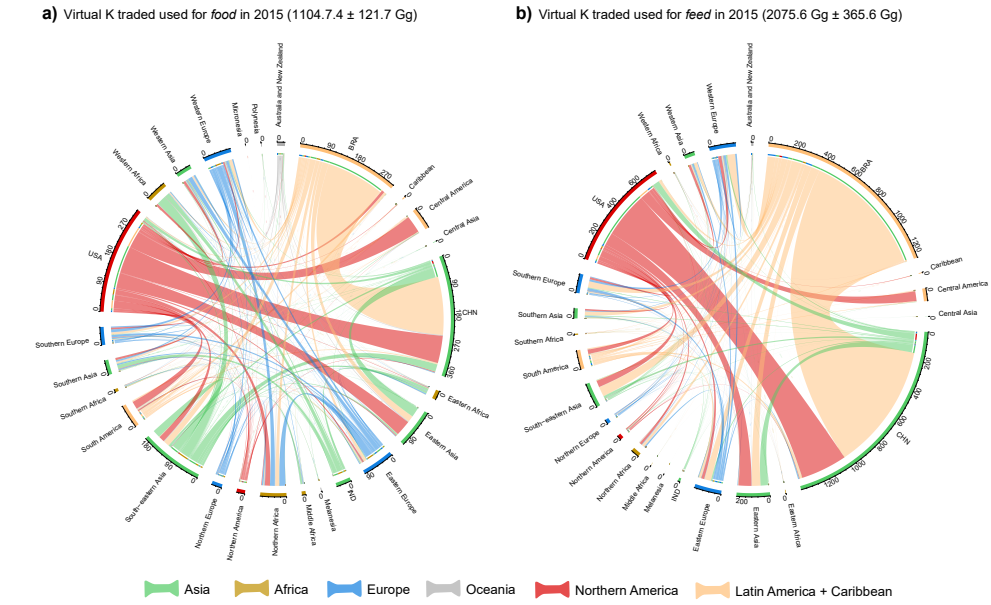


Figure D.11. Global flows of K fertilizer traded for major crops used for *food* (a) and *feed* (b) in 2015. The outer rings indicate the total flow of K fertilizer for each region in Gg, and the inner rings indicate the regions of the exports/imports. The colors of the flows represent the exporter regions, and the color coding corresponds to the continents indicated at the bottom.

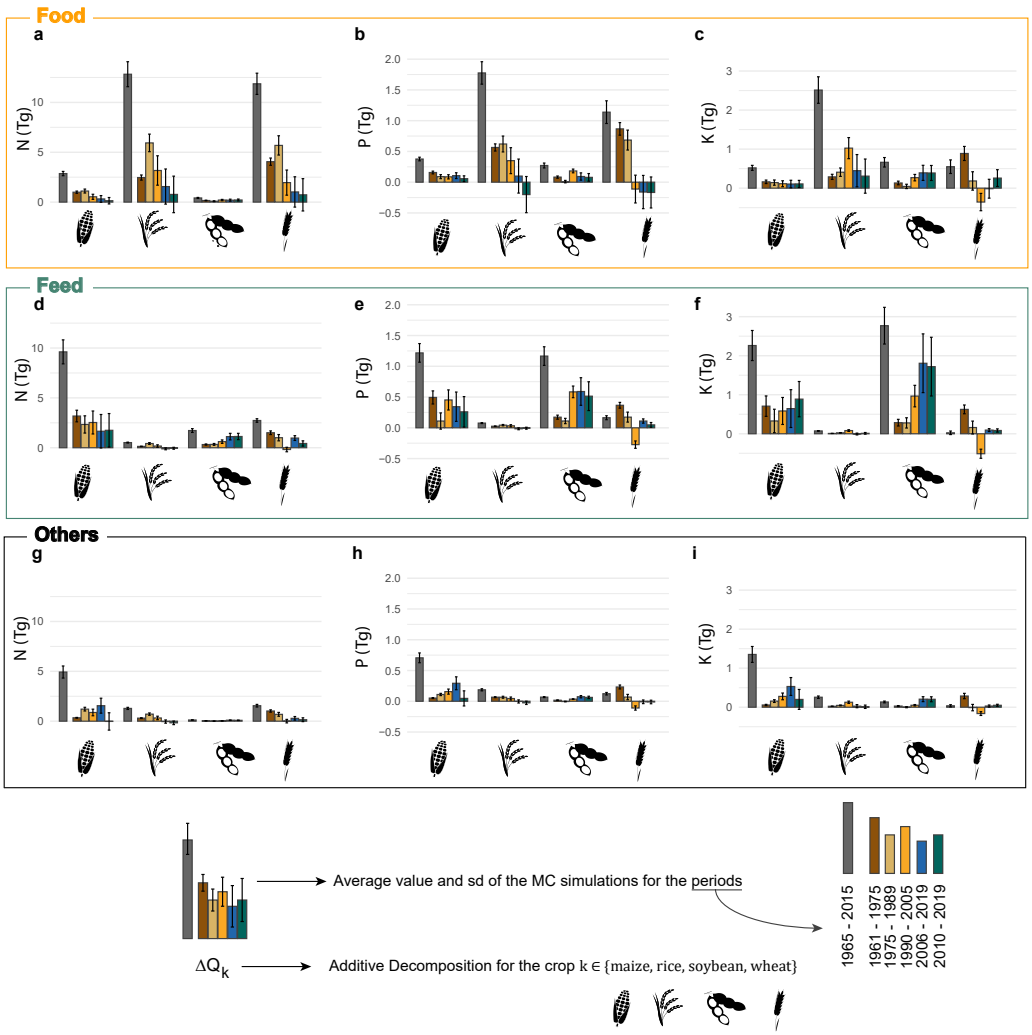


Figure D.12. Additive factor decomposition of changes in total N, P, and K inputs between 1965-2015 (grey), 1961-1975 (dark brown), 1975-1989 (light brown), 1990-2005 (yellow), 2006–2019 (blue), 2010–2019 (green). Bars represent the contributions of the four crops, maize, rice, soybean and wheat. Top row shows the results for the fertilizer allocated to *food*: (a) Nitrogen, (b), Phosphorus, (c) Potassium. Middle row, fertilizer allocated to *feed*: (d) Nitrogen, (e), Phosphorus, (f) Potassium. Bottom plots, fertilizer allocated to *other uses*, (g) Nitrogen, (h), Phosphorus, (i) Potassium. The bars indicate the average of the Monte Carlo simulations, and the error bars the standard deviation (*sd*). The results for 1965-2015 are based on the 500 simulations; 200 were used for the other periods.

D.1.4 Fertilizer Use for *other uses*

As indicated in the previous subsection and Fig. D.12, most of the increase in fertilizer use for the *other uses* category was due to inputs for maize. This increase began primarily after 2000, when the total N consumed for maize and allocated to *other uses* increased from2.0 ± 0.3 Tg in 2000 to 7.1 ± 1.1 Tg in 2015. This increase occurred with the growth in global bioethanol production, which increased more than five-fold during this 15-year period (Fig. D.13). Two countries, the United States of America (USA) and Brazil, accounted for > 80% of global bioethanol production [69]. Brazil, however, consumed <5% (Fig. D.13 a, c), and the USA consumed approximately 50% of the fertilizer allocated to the *other uses* category (Fig. D.13 a, c). These results are also represented by the ratios between NPK consumption for *other uses* for maize and bioethanol production. These ratios in the USA ranged between 0.08 and 0.21 kg NPK fertilizer per kg of oil equivalent, while they did not exceed 0.02 in Brazil. We also used linear models to analyze the relationship between NPK consumption for the *other uses* category and bioethanol production to confirm this correlation in the three regions analyzed: the world, the USA, and Brazil. The temporal series of both values were correlated in the three regions (Fig. D.13), the amounts of variance explained (R2) were higher in the global and USA models.

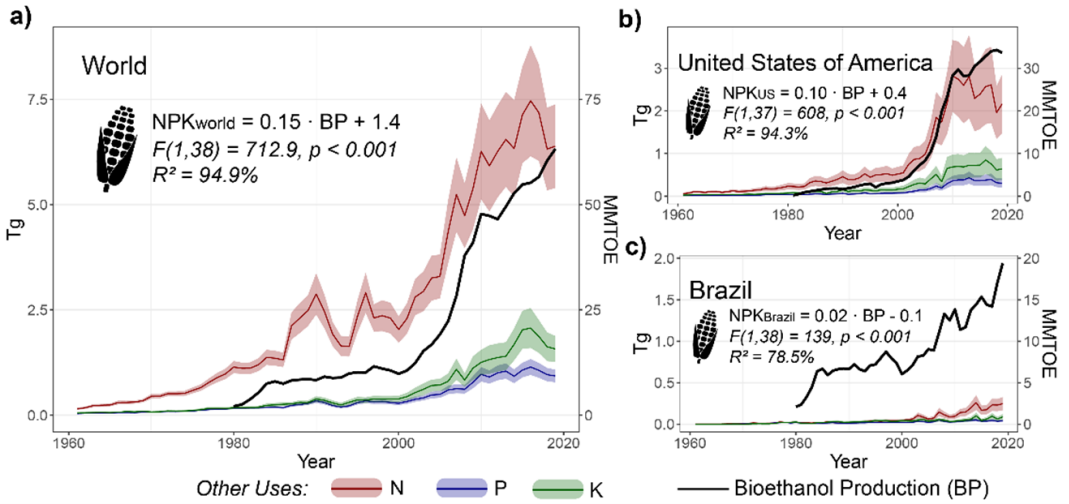


Figure D.13. Fertilizer consumption for maize production (y-axes) allocated to the *other uses* category is shown in Tg. The red, blue, and green lines represent N, P, and K, respectively, average of the MC simulations. The shaded areas indicate the sd of the MC simulations. The black lines indicate the million metric tonnes of oil equivalent (MMTOE) of bioethanol produced. The statistical results correspond to the linear model between the summed average NPK fertilizer consumption for *other uses* and bioethanol production. a) World results, b) USA results (the largest bioethanol producer), and c) Brazil results (the second largest bioethanol producer).

D.2 Extended Discussion

D.2.1 Fertilizer use for *other uses*

The *other uses* category includes various subcategories, such as losses, seeds, and industrial uses unrelated to food. Drawing strong conclusions from our results in this category is therefore challenging, because it was not the primary focus of this study. Some observations, however, could be made: fertilizer consumption for *other uses* across the four crops was almost entirely linked to maize production (Fig. D.12), and its consumption was strongly correlated with bioethanol production (Fig. D.13 a). Correlation does not imply causation, but these findings support the idea that maize production for bioethanol drove fertilizer consumption in the *other uses* category.

Comparing our results with previous studies on the two main bioethanol producers, the USA and Brazil, also reinforces these ideas. For example, we estimated that 0.22 ± 0.06 Tg of P fertilizers were used for the *other uses* category in the USA in 2008, which was slightly higher than the 0.15 Tg for bioethanol production alone during the 2007/2008 cropping season estimated by Hein and Leemans (2012) [391] or the 0.19 Tg estimated for 2007 by MacDonald, Bennett and Carpenter (2012) [389]. The estimated ratios for NPK fertilizer used for *other uses* relative to bioethanol produced in the USA. since 2000 (ranging between 0.08 and 0.21 kg NPK per kg of oil equivalent) were slightly higher but remained within the same order of magnitude as the values reported by Lee et al. (2021) [482] (approximately 0.08 kg NPK per kg of oil equivalent, based on 25.4 kg per bushel and 15.4 MJ per kg of maize). Bioethanol production in Brazil is primarily derived from sugarcane rather than maize [391]. Our results support this observation, because the ratio of NPK fertilizer used for maize in the *other uses* category relative to bioethanol production was at least five-fold lower than in the USA Maize is not extensively used for bioethanol production in Brazil, but the consumption of fertilizers for sugarcane production intended for bioethanol, especially N and K, was high, exceeding 60 kg ha^{-1} y^{-1} [483], and therefore likely had an impact of a similar magnitude to that for maize.

D.2.2 Discussion of the main limitations of the study

As explained in the main text, this study aimed to provide an initial overview of the trends of fertilizer use since 1960. Nevertheless, it presents several limitations arising from the assumptions and the sources. The two main assumptions of the publication are: I) that crops are fertilized similarly, regardless of their final use, and II) that trade patterns for crop products between 1961 and 1990 have remained consistent with those since 1990. In addition, the uncertainty associated with the databases employed, especially with the fertilizer use by crop (FUBC) database is large [331]. It was the main reason we conducted the uncertainty analysis, although here we will give further details of the implications of this uncertainty. In this section we include more information regarding the first assumption, and the uncertainty of the fertilizer use.

D.2.2.1 Analysis of the assumption 1: Same fertilization levels independently of the final crop use

Addressing the first assumption, a key advantage is that most of the four crops are primarily directed toward a single purpose in most countries, with some notable exceptions, such as

the consumptions of soybean in Japan, maize in Mexico, and wheat in Australia [379, 380]. For example, >70% of the combinations of crop, year, and country in this study based on Food Balances (FB) from FAOSTAT [379, 380] were in a primary-use category with percentages exceeding 75% of total crop consumption.

This assumption can reasonably hold at extreme bounds, when one use accounts for most of the crop end use. Nevertheless, we here have performed a sensitivity analysis to address what is the effect of the changes in fertilization intensity for an individual use on the others, depending on the percentage of the production allocated to the dominant use. Then we reviewed the existing knowledge regarding fertilizer applications for the different uses of the four crops.

Sensibility Analysis: Propagation of a change in fertilizer use for the dominant use

We performed several calculations to assess how flexible the system is in allowing variation in the average fertilizer use per hectare within a country across different uses.

To simplify notation, we first consider a hypothetical situation without trade. Nevertheless, this procedure would be the same considering trade. In this case, for each crop and year we have three percentages representing the share of production allocated to *food*, *feed*, and *other uses*. For each use (u), we estimate the amount of fertilizer applied as:

$$Q(u) = Q \cdot P_u = A \cdot F \cdot P_u \tag{D.1}$$

where Q is the total fertilizer consumed for the crop–country–year combination, calculated as the product of crop area (A) and the average fertilizer application rate (F); and P_u is the proportion of production allocated to use u.

The total fertilizer consumption can also be written as the sum of all uses:

$$Q = \sum_{u \in U} Q_u \tag{D.2}$$

where U is the set of uses. Thus, if the average fertilizer use per hectare (F) varies between uses and we increase or decrease F for one particular use ($u1$), this will directly affectQ_1 and consequently alter the values across the other uses Q_2, and Q_3.

Since crop area (A) and the proportion of the production allocated to each use (P) are fixed for a given country–crop–year combination, the only factor that can vary is F. How much can this value differ between uses? This is the question we address below, crop by crop. This point also relates to the assumption that $F1 = F2 = F3$.

Let P_1 denote the share of dominant and $x_1 = F1'/F$ the relative use change in the average fertilizer rate of the use.

As we have three uses, we will start with a case where the amount for one use is equal to 0: $(Q_2 = 0) \bigvee (Q_3 = 0)$

For this case, the relative change in the average fertilizer use required for the second use when $P_3 = 0$ is:

$$x_2 = \frac{1 - x_1 \cdot P_1}{1 - P_1} \tag{D.3}$$

Therefore, the relative change in fertilizer use for the dominant use determines the relative change in the second use (x_2). Based on these relative changes in fertilization, the percentages of total fertilizer consumed for each use can be estimated as (PF'_u):

$$PF'_u = P_u \cdot x_u \tag{D.4}$$

We performed simulations varying the relative change in the average fertilizer application rate per hectare for the dominant use ($x_1 \in [-50, 50\%]$), considering the following values of P_1 : $70\%, 80\%, 90\%, 95\%, 99\%$. In Fig. D.14 , we included a shaded region were $x_2 \in [-50, 50\%]$. We added this band because we consider it unlikely that the fertilizer rate for either the dominant or the secondary uses (Fu) would be more than 50% lower or higher than the country-crop-year average (F).

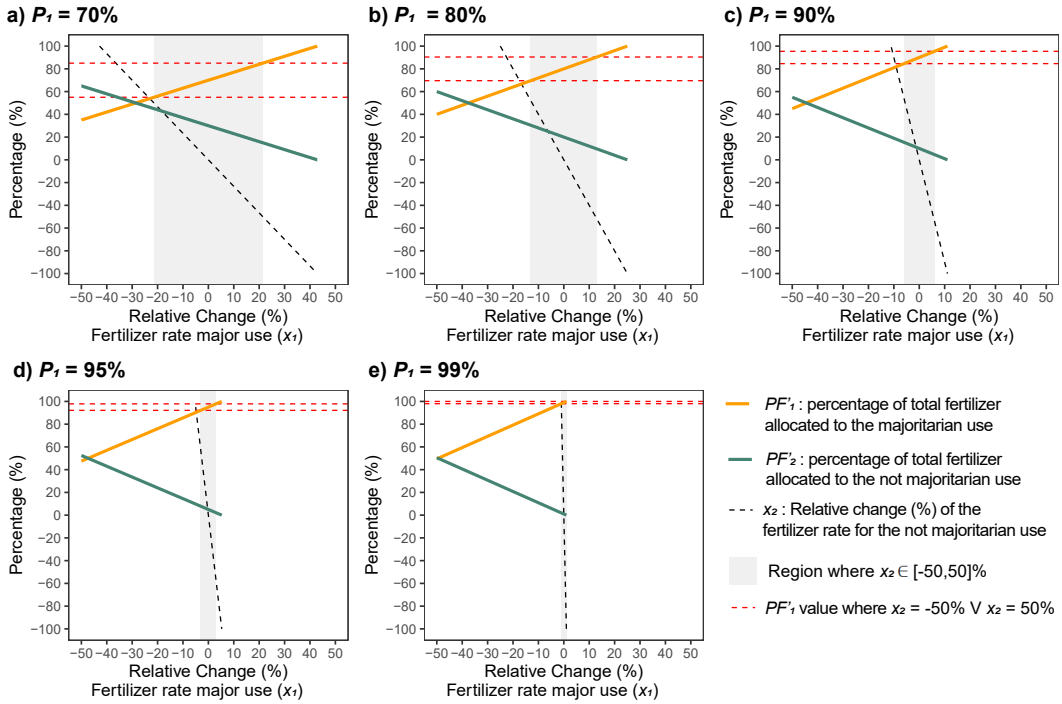


Figure D.14. Percentage of the total fertilizer use (PF') allocated to the dominant (orange line) and non-dominant (green line) uses, considering a relative change of the average fertilizer rate for the dominant use between -50% and +50% (x-axis). Panels (a) to (e) show results obtained by fixing the proportion of production allocated to the majoritarian use at 70%, 80%, 90%, 95% and 99% respectively. The dashed black line represents the relative change in fertilizer rate for the non-majoritarian use ($x2$), and the red dashed lines indicate the PF' values for the dominant use when $x2$ is equal to -50% or +50%.

The results shown in Fig. D.14 illustrate that a change in the average fertilizer rate for the dominant use (F'_1) has a stronger impact on the average fertilizer rate for the non-dominant (F'_2) use when the proportion of the allocation of the majoritarian use ($P1$) is higher. For example, when 80% of the production is allocated to one use, an increase of 12.5% in the average fertilizer rate for that use (relative to the crop-country-year average) would result in a 50% reduction in the fertilizer rate for the non-dominant use (x_2), together with a 10% increase in the share of fertilizer allocated to the dominant use (PF'_1) and a proportional reduction for the non-dominant one PF'_2.

If we cap the two non-dominant uses' relative changes $x_2, x_3 \in [0.5, 1.5]$ (i.e. $\pm 50\%$), then under fixed crop area (A), fixed allocation of the production among uses (P_u) and total conservation of fertilizer consumption ($Q' = Q$) then the largest shifts in the share of fertilizers for the dominant use (PF'_1) occurred when both non-dominant uses have the same

relative change of fertilizer rate (both -50% or +50%).

With this idea in mind, that when a large proportion of production is allocated to one use, a relative change in the average fertilizer rate for the dominant use impact strongly the relative changes in the non-dominant uses, we will discuss crop by crop the potential biases arising from considering equal the fertilization rate for all uses. We would like to emphasize that a huge bias is impossible when $P1 \geq 90\%$ (since with a $x_u = \pm 50\%$, $PF'_1 = P_1 \pm 5\%$), and unlikely when $P1 \geq 80\%$ (as with a $x_u = \pm 25\%$, $PF'_1 = P_1 \pm 5\%$).

Crop Fertilization Review: Analysis of crop utilization and review of fertilization depending on the use

Rice: The rice products and by-products used for livestock feeding include rice straw, rice bran, broken rice, polish rice, and in some cases the grain itself. Rice straw, used as roughage especially in Asia [484, 485], is not included in the FB (Table D.2); therefore, it is not accounted for in our calculations, and it does not contribute to fertilizer use allocated to *feed*. We support this differentiation because straw is a by-product that cannot be used for human consumption. In addition, it has not been discussed in this section.

Beyond rice straw, in most countries where rice products are used for livestock feeds, the primary materials are by-products such as rice bran, rice polish or broken rice, rather the full grain [485–487]. Therefore, it is unlikely that fertilization levels would differ between rice grown for *food* and that grown for *feed*. Some regional studies have likewise assumed same fertilization levels for both uses [487].

In addition to the previous argument, a small number of countries would be vulnerable to the assumption of same fertilization rates across uses (Fig. D.15). Particularly, the countries where the dominant use present values below 70%, 80% and 90% in less degree respectively. This analysis was performed both including (Fig. D.15 a) and excluding Fig. D.15 b) losses and seed category, which we initially allocated to *other uses*. We did this differentiation because we consider that fertilization of seeds and losses may not follow different patterns to overall patterns.

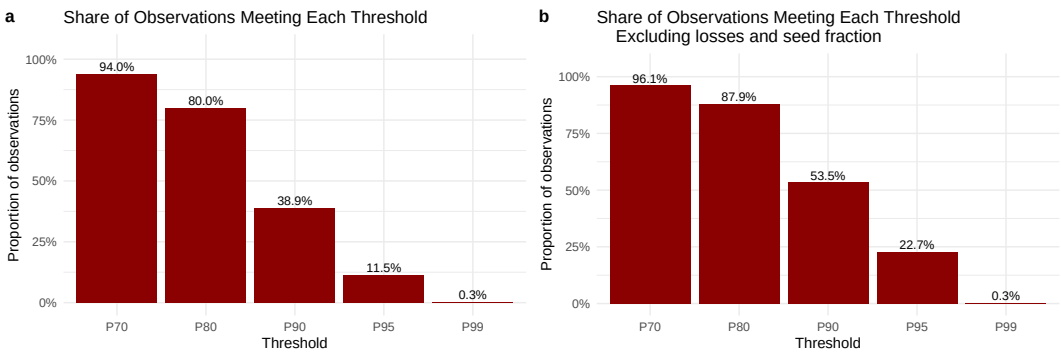


Figure D.15. Proportion of country–year combinations in which more than 70% (P70), 80% (P80), 90% (P90), 95% (P95), or 99% (P99) of the production was allocated to a single category, among the top 50 consumers of N,phosphorus pentoxide (P_2O_5), and potassium oxide (K_2O) for rice production. a) Using the original use classification from the paper, b) Excluding the percentages allocated to seed and losses, which were originally included under *other uses*.

The most vulnerable country to this assumption was Myanmar which represents 33% of the data points below the 70% in the Fig. D.15 b. The rice products and by-products used in Myanmar for livestock feeding are primarily broken rice and rice bran [486], both of which

are milling by-products that can also be consumed by humans. Nevertheless, the kernel is not commonly used as a livestock feeding [486]. Other countries below this percentage were Cambodia or Surinam (31% of the data points below the 70% in the Fig. D.15b). Although, information regarding feedstuff is limited for these two countries, they represent only on annual average 0.6% of the N-fertilizer consumption for rice.

From the top ten consumers of N-fertilizers for rice, that represent > 90% of N-fertilizer consumption global consumption (based on the average of all years), only Vietnam and Indonesia present > 10% of the years (but < 25%) with the dominant use below the 80% of production allocation. In both countries like in Myanmar rice products used for feeding livestock are rice bran and broken rice [488, 489]. The two major consumers China and India presented average allocation fraction for *food*, the main use, of 84% and 94% respectively.

Based on all this information, we argue that assuming similar average fertilizer application rates for rice used for *feed* and for *food* is reasonable, because: (i) rice feedstuffs typically originate from by-products such as rice bran or broken rice, which cannot be independently fertilized, (ii) the major fertilizer-consuming countries for rice generally have a large share of production consumed as *food* (> 80%).

Wheat: The wheat products and by-products used for livestock feed and industrial uses include wheat straw, wheat bran, wheat middling and the by-products derived from biofuel production, distillers dried grain with soluble (DDGS) 15. As in the case of rice, wheat straw is not included in the FB, or DDGS (Table D.2); therefore, it is not accounted for in our calculations, and it does not contribute to fertilizer use allocated to *feed*. In the contrary, wheat grain is used directly is used directly in livestock feed mixtures in several countries, primarily in European nations and Australia.

The assessment of the frequency of the dominant use above different thresholds indicates that, unlike rice, wheat production is more evenly distributed among uses (Fig. D.16). Countries where wheat production does not have a clearly dominant use include most European nations, the former Soviet Union, Australia, Canada, and, to a lesser extent, the USA ($\bar{P_{Food}}$ = 80.0%). In contrast, major wheat producers such as China, India, Argentina, and Pakistan show values above 85%.

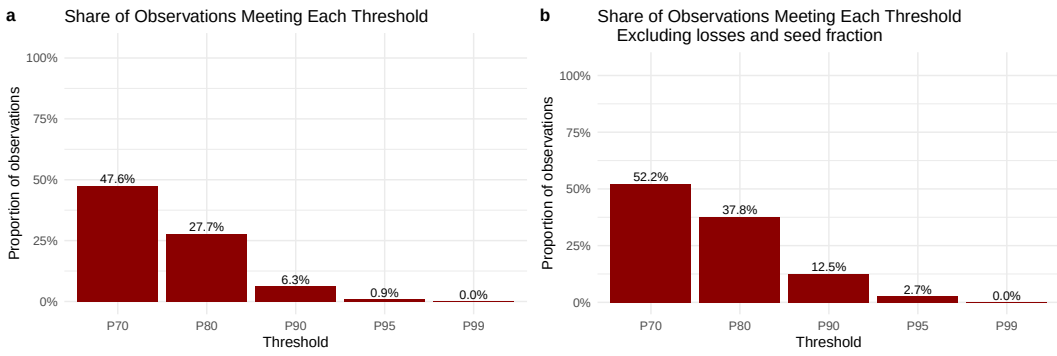


Figure D.16. Proportion of country–year combinations in which more than 70% (P70), 80% (P80), 90% (P90), 95% (P95), or 99% (P99) of the production was allocated to a single category, among the top 50 consumers of N,P_2O_5, and K_2O for wheat production. a) Using the original use classification from the paper, b) Excluding the percentages allocated to seed and losses, which were originally included under *other uses*.

Sources for comparing fertilization rates between different uses or practices are rare. One

source with temporal resolution is the British survey for fertilizer practice [490]. Although, it does not differ between the final use of wheat, it gives average fertilization rate for winter wheat, milling and non-milling [490]. Milling wheat in the United Kingdom and Northern Ireland (UK) is completely used for human consumption while non-milling primarily for livestock feeding [491]. Although the by-products of the milling process are used for feeding livestock [491]. The data of this database (Fig. D.17) suggests that fertilization rate for P and K for both uses are equivalent, while N fertilization rate for milling winter wheat is slightly higher (13.5% between the two end markets) than the use for non-milling winter wheat.

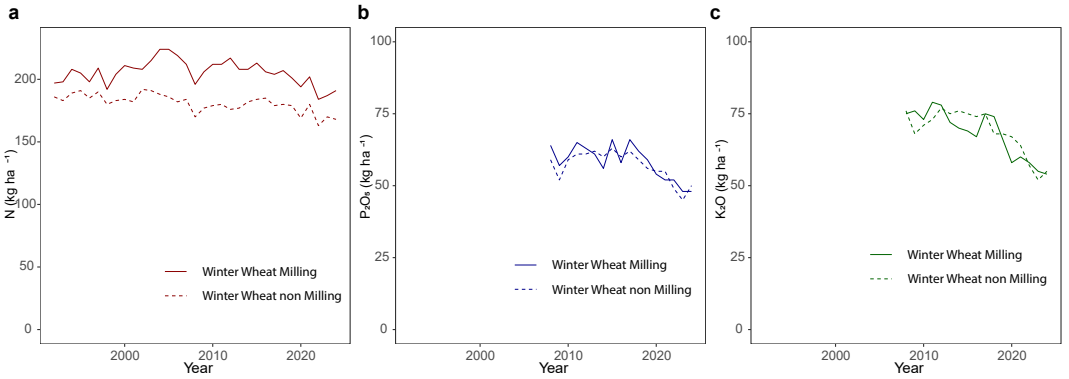


Figure D.17. Average fertilizer application rate (kg per ha) for winter wheat milling (solid line) and non-milling (dashed lines) in the UK. Panels show the results for Nitrogen (a), phosphorus pentoxide (b), potassium oxide (c)

Considering the variation for N observed in the UK, we conducted a theoretical sensitivity analysis by considering $P3 = 0\%$. In the worst-case scenario ($P1 = 50\%$), the resulting bias in a country's total fertilizer allocation for that use is about 4.5% for the use (Fig. D.18).

Therefore, although this assumption may introduce some bias by considering fertilizer use to be the same across different end uses, we consider it reasonable for wheat because: (i) some of the largest fertilizer-consuming wheat producers (China, India, and the USA) typically have more than 80% of their total wheat production allocated to a single use, reducing the impact in total estimations, (ii) a significant fraction of wheat used for feed and industrial purposes originates from the wheat milling by products, for which fertilization application should be the same as for grain, (iii) the limited data available to infer differences among uses suggest that fertilization levels for P and K are equivalent, while N rates tend to be slightly higher for wheat destined for milling (Fig. D.17). These differences introduced a potential maximum bias of $< 5\%$ (Fig. D.18).

We therefore conclude that, although N-fertilization rates for food products may be slightly higher than those for *feed* or *other uses*, there is insufficient data to conduct a precise assessment. The potential bias is expected to be low, as the available data for the UK indicates.

Maize: The maize and products included in the FB databases of FAOSTAT include grain, germ, flour, bran, gluten, starch, and feed and meal gluten (Table D.2). They did not include the straw nor the forage (silage) maize. The estimations of fertilizer rate included in the FUBC dataset also exclude the forage maize [331]. We note this because numerous sources [132, 195, 492] report differences between fertilizer rates for forage and grain maize; however,

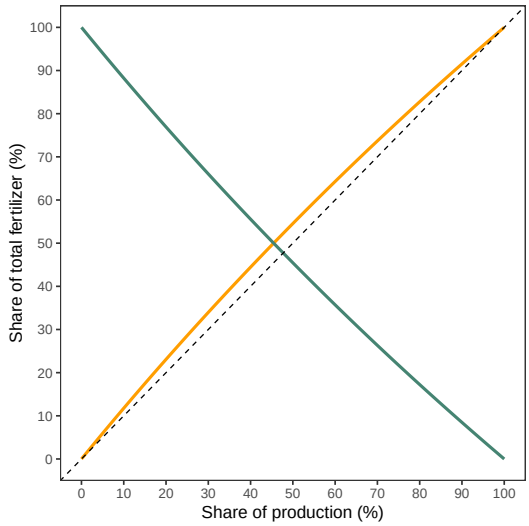


Figure D.18. Sensitivity analysis based on the difference between milling and non-milling winter wheat in the UK, showing the total fraction of fertilizer use allocated to two uses (y-axis) as a function of the share of production destined for each use (x-axis).

we here are not comparing these differences.

As in the case of wheat, for a great proportion of country-year combinations (> 50%) of the top 50 countries by fertilizer consumption for maize (Fig. D.19), less than 80% of the production is allocated to dominant use. If we focus on the top ten N-fertilizer consumers (Table D.1), we see countries with a majoritarian use for *feed* (e.g. Brazil and China) and some countries with a dominant use for *food* (e.g. India or Mexico).

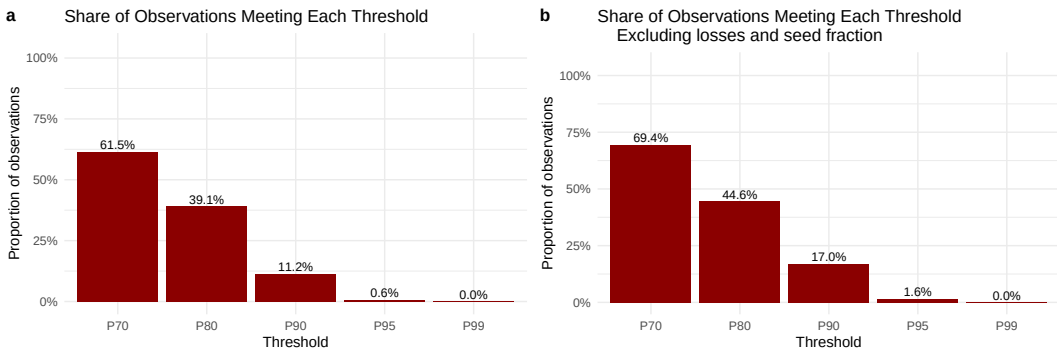


Figure D.19. Proportion of country–year combinations in which more than 70% (P70), 80% (P80), 90% (P90), 95% (P95), or 99% (P99) of the production was allocated to a single category, among the top 50 consumers of N,P_2O_5, and K_2O for maize production. a) Using the original use classification from the paper, b) Excluding the percentages allocated to seed and losses, which were originally included under *other uses*.

Regarding maize used for *feed*, we reviewed the available literature for these ten countries. Although we found differences in fertilizer rate statistics and recommendations between silage maize and grain maize [132, 195, 492], we did not find any specific statistics or recommendations distinguishing different uses of grain maize [132, 155–161, 223, 250, 254].

Table D.1. Average proportion of maize production allocated to *feed* (P_{feed}), *food* (P_{food}), and *other uses* (P_{others}), and number of years in which the dominant use exceeds 80% (>P80). Results shown for the top ten consumers of nitrogen fertilizer for maize (on average), which together account for over 90% of global N fertilizer consumption for maize

ISO3	P_{feed}	P_{food}	P_{others}	> 80
BRA	77.89%	17.79%	4.30%	23.73%
CHN	76.48%	11.35%	12.16%	37.29%
EGY	40.82%	54.77%	4.41%	0.00%
USSR	77.05%	9.77%	13.17%	13.56%
FRA	77.00%	15.73%	5.74%	35.59%
IDN	13.41%	70.98%	15.61%	50.85%
IND	23.74%	70.15%	6.11%	50.85%
MEX	27.93%	67.46%	4.61%	10.17%
UKR	72.05%	21.44%	6.51%	5.08%
USA	70.99%	15.14%	13.82%	22.03%

In addition, some important countries for maize production such as Mexico, where it is easy to differentiate maize production as they destined most white production towards human consumption, and yellow production [493] towards livestock feeding don't give different recommendations based on the variety.

Regarding maize used for industrial purposes, in the best of our knowledge there is not specific information suggesting different fertilization rate levels. In addition, although this may not be the strongest argument, previous life cycle assessment studies of bioethanol production have made the same assumption, applying the average fertilizer rate for corn (at the national or state level) as the rate used for maize cultivated for bioethanol production [389, 391, 482].

We consider that the assumption for maize can be held as: (i) there are not any statistics nor recommendations for the reviewed top consumer countries suggesting that different fertilizer practices occurred depending on the end market of the maize production, (ii) previous research assessing the impact of the industrial uses of maize has also assumed that the fertilization levels were the same to the national, or state-level rates.

Soybean: In the case of soybeans, most of the production is crushed: the oil is generally used for human consumption, while the resulting soybean cakes are primarily used for livestock feed [35]. Consequently, this significant fraction cannot be fertilized independently. When we exclude the oil, seed, and losses fractions from total soybean production, the remaining portion indicates that, like rice, most of the production is effectively allocated to a single product (Fig. D.20).

Among the top soybean producers and excluding oil, only Asian countries, such as China, or Japan present in the first decades of the study important shares (> 20%) for *food* production. However, we did not find any information in the known statistics [132] nor the scientific papers suggesting different fertilization rates depending on the use [494].

We consider it reasonable to assume similar fertilization rates across soybean uses because: (i) A large percentage of soybeans are crushed and then divided between different

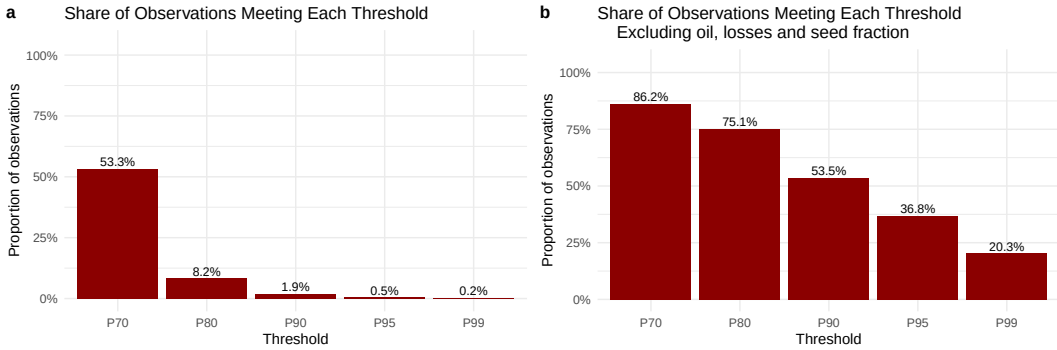


Figure D.20. Proportion of country–year combinations in which more than 70% (P70), 80% (P80), 90% (P90), 95% (P95), or 99% (P99) of the production was allocated to a single category, among the top 50 consumers of N,P_2O_5, and K_2O for soybean production. a) Using the original use classification from the paper, b) Excluding the percentages allocated to seed and losses, which were originally included under *other uses*.

end uses. Therefore, the fertilization rate applied to the crushed fraction, the largest portion of production is independent of its final use, (ii) in countries where soybeans are a traditional crop, production is more evenly distributed among uses. However, we did not find any statistics or recommendations suggesting different fertilizer practices according to the final market of the product.

D.2.2.2 Uncertainty linked to the FUBC [331] data

A critical point of the study, and the basis for the annual estimation of FUBC [331] (hereinafter 'SD publication') for all countries. We performed an uncertainty analysis completely focused on the uncertainty of this dataset. One of the critical points of the methodology used in the creation of the database is whether national totals are more reliable than the FUBC databases. In the database creation machine learning (ML) predictions were forced to match FAOSTAT totals, and we acknowledge that this procedure has both advantages and disadvantages.

We chose this approach because we considered national totals to be more reliable than FUBC. Although this may not hold true in all situations, we provide here a comparison between the two existing databases with national resolution on total fertilizer consumption (FAO-International Fertilizer Association (IFA)), as well as a comparison between FUBC values contained in national databases and those in the global databases included in the SD publication (All references are cited in the validation section of the SD publication). We would like to make clear, however, that this may not be a fully fair comparison, since it involves data from two international organizations (FAO-IFA) at the national-total level, and global data sources versus national databases at the crop level. Nonetheless, an important share of FAOSTAT data is derived from questionnaires to national agencies and we considered that compiling national databases on total consumption for a set of countries to be beyond the scope of this paper at this stage.

Based on the results shown in Fig. D.21, we consider that forcing the results to match FAOSTAT totals is not intrinsically negative. Although the amount of data available to assess the true uncertainty of the sources is limited, it appears that FUBC datasets are likely less reliable than total consumption datasets (Fig. D.21). Thus, we believed the few available

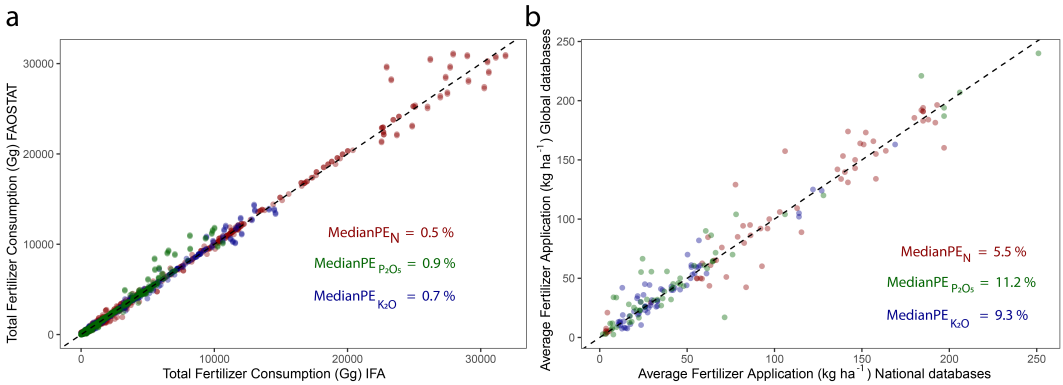


Figure D.21. a) Comparison of shared data points for total fertilizer consumption (Gg) across all countries and years between the IFA database (x-axis) and FAOSTAT (y-axis); b) Comparison of shared data points for fertilizer use by crop (kg ha^{-1}) across all countries and years between global databases (y-axis) and national databases compiled in Coello and Decorte et al. (2025) [331] (x-axis). In both panels, red points represent N, blue points represent P_2O_5, and green points represent K_2O. Median Percentage Errors (MedianPE) are reported for each nutrient.

data support our decision. In addition, past research, when it has performed an assessment at crop level usually has realized the same adjustment, relying on country totals [127, 142].

Nevertheless, we also note that is not possible to reach a strict conclusion on this debate. To address this point, we repeated part of the analysis using the ML predictions directly, without adjustment to match FAOSTAT totals, in order to compare both results. This task was quite time-consuming, and although we could extend it to all results if required, we limited it to the first figure and to 100 MC repetitions instead of the 500 used with the original data source.

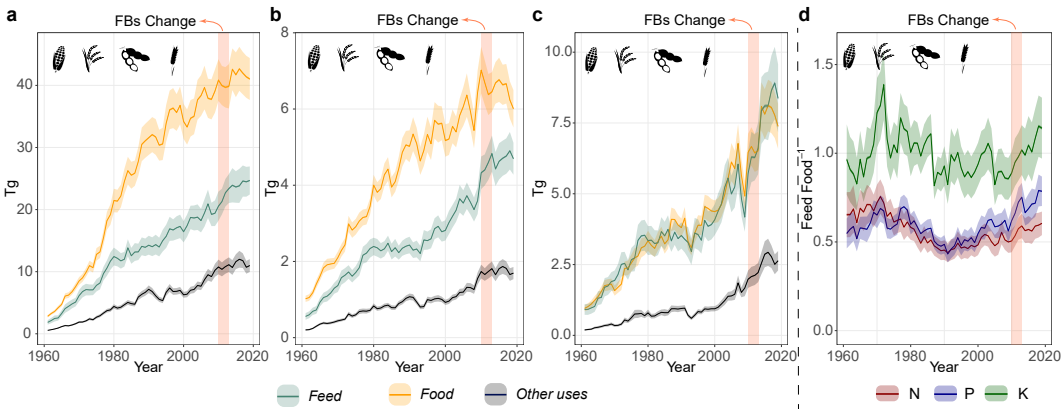


Figure D.22. Fertilizer used for producing maize, rice, wheat, and soybean for *food*, *feed*, and *other uses* based on the fertilizer used by crop data used in the main text. The solid line represents the average, and the shaded areas the sd of 500 MC simulations. a) Nitrogen, b) phosphorus, c) potassium, and d) ratios between the fertilizer used for *food* and *feed* for the three nutrients.

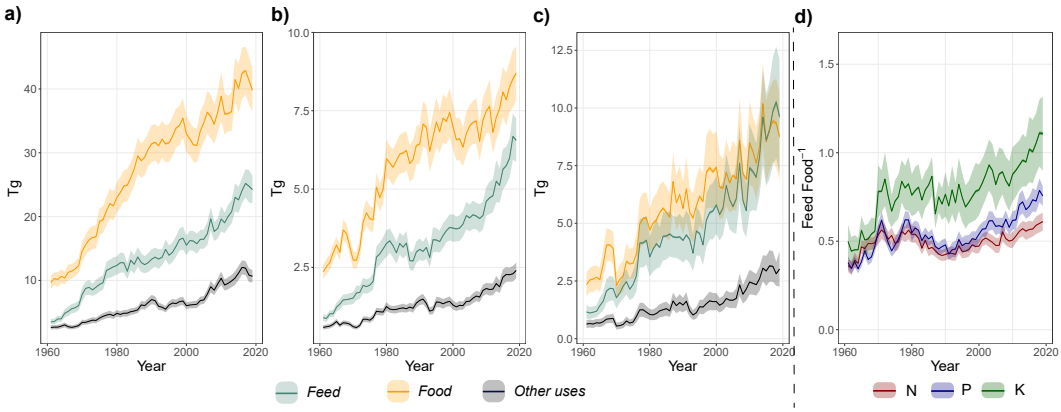


Figure D.23. Fertilizer used for producing maize, rice, wheat, and soybean for *food*, *feed*, and *other uses* based on the fertilizer used by crop data resulting from using the Machine Learning predictions of the Coello and Decorte et al. (2025) [331] publication. The solid line represents the average, and the shaded areas the sd of 100 MC simulations. a) Nitrogen, b) phosphorus, c) potassium, and d) ratios between the fertilizer used for *food* and *feed* for the three nutrients

As shown Figs. D.22 and D.23, there are differences between the two approaches. Nevertheless, the main message, the growing trend in fertilizer uses for *feed* compared to *food* since 1990 is even reflected at global level. This occurs primarily because a larger figure of fertilizers was used for *food* in the earlier decades (1960-1990) when using the ML predictions (Fig. D.23) instead of the adjusted values (Fig. D.22). The main reason for this is that ML predictions tend to overestimate the fertilizer use by crops during the first decades in countries with a higher share of crops used for *food*, primarily the Union of Soviet Socialist Republics (USSR) and in several Asian countries (Fig. D.24). Therefore, although we recognize that deciding whether to use the adjusted predictions by national totals or the raw ML outputs is not straightforward, we consider that the potential biases are smaller when using the adjusted values.

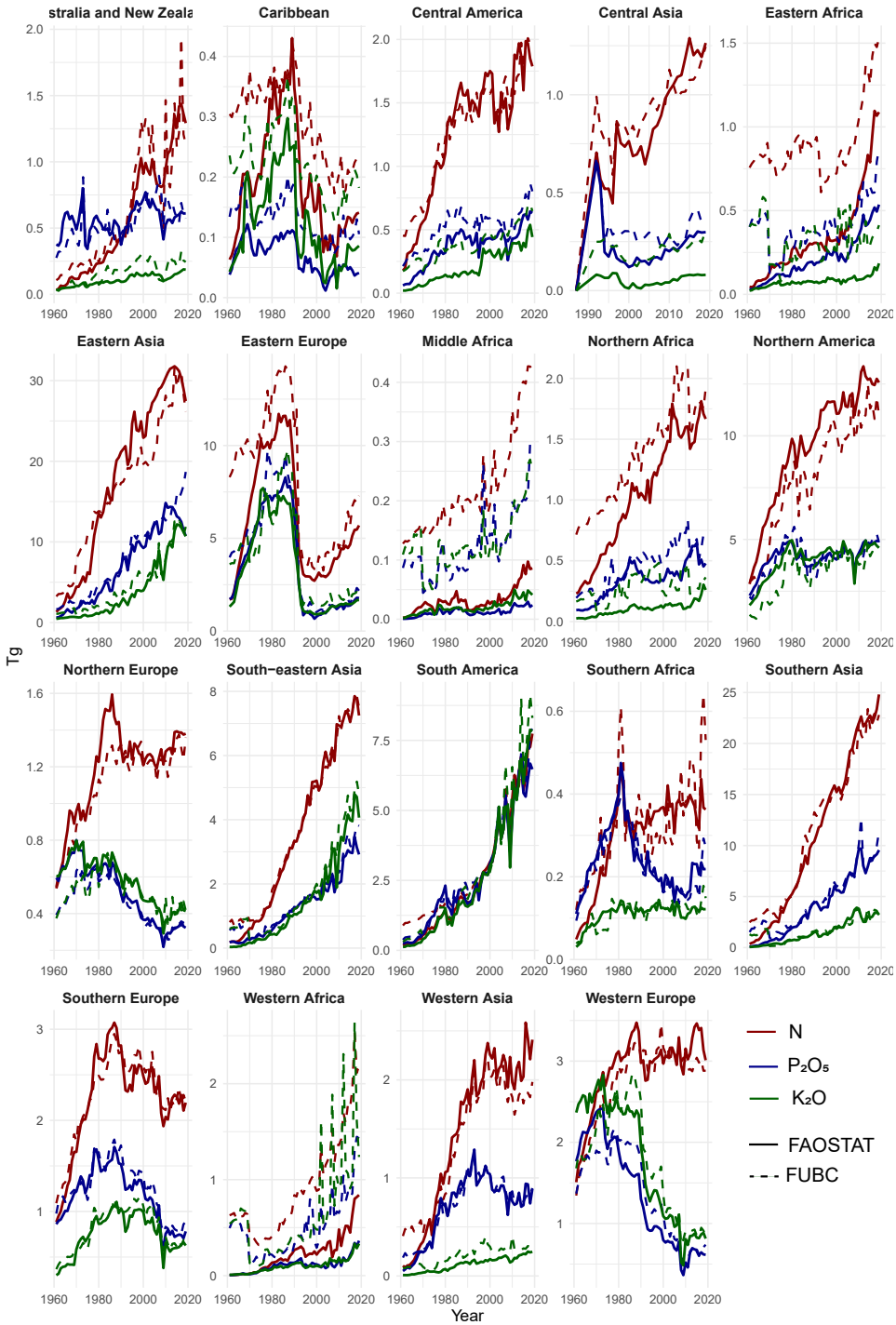


Figure D.24. Comparison between the total fertilizer consumption derived from the Machine Learning predictions of the Coello and Decorte et al. (2025) [331], combined with the FAOSTAT harvested area [163] (dashed lines), and total national fertilizer consumption from FAOSTAT [68] after removing the fraction used for fodder crops and grasslands [331] (solid lines). Red lines represent the results for nitrogen (N), blue lines P_2O_5, and green lines K_2O.

D.3 Extended Data Sources

The Food Balance (FB) databases from FAOSTAT [379, 380] were the main sources used for developing this study. Understanding the limitations and differences between the FB databases and the definitions of the items used are important for accurately interpreting our results and their implications, despite the extensive amount of data provided by these databases since 1961.

The FAOSTAT FB [379, 380] provided information about the production, trade, consumption, and use of different items (crops and livestock products) since 1961. FAOSTAT changed the methodology for compiling and validating the data set at the beginning of the 2010s. They indicated that the "key difference between the new and old FB methodologies is the absence of a balancer variable". In the new methodology, a balancing mechanism spreads the imbalances across all components, whereas in the old methodology, the stock, industrial use, and feed classes usually absorbed all potential errors. We thus decided to compare the crop allocation figures between the three uses resulted from the two FB data sets from the available years with data from the two data sets (2010-2013). Before assessing the differences in the results using both data sets, we will describe the items used for evaluating domestic consumption, the exported fraction, and all uses (food, feed, seed, losses, processing, and industrial non-food).

D.3.1 Definitions of FB items

The FB items used for assessing the four main crops in the analysis are described in Table D.2. Both FB used the same items for reporting the data for wheat, maize, and soybean production Table D.2. They changed the items for rice, but the default composition of both classes is the same in Table D.2.

Table D.2. Items of the FAOSTAT FB used in the analyses, and the commodities included in each item.

Crop	FAOSTAT FB Item	FB data set	Item description
Wheat	Wheat and products (2511)	Both [379, 380]	Default composition: 15 Wheat; 16 Flour, wheat; 17 Bran, wheat; 18 Macaroni; 19 Germ, wheat; 20 Bread; 21 Bulgur; 22 Pastry; 23 Starch, wheat; 24 Gluten, wheat; 41 Cereals, breakfast; 110 Wafers; 114 Mixes and doughs; 115 Food preparations, flour, malt extract
Maize	Maize and products (2514)	Both [379, 380]	Default composition: 56 Maize; 57 Germ, maize; 58 Flour, maize; 59 Bran, maize; 63 Gluten, maize; 64 Starch, maize; 846 Feed and meal, gluten
Rice	Rice and products (2807)	2010–2019 [379]	Default composition: 27 Rice, paddy; 28 Rice, husked; 29 Rice, milled/husked; 31 Rice, milled; 32 Rice, broken; 33 Gluten, rice; 34 Starch, rice; 35 Bran, rice; 38 Flour, rice
Rice	Rice (milled equivalent) (2805)	1961–2013 [380]	Default composition: 27 Rice, paddy; 28 Rice, husked; 29 Rice, milled/husked; 31 Rice, milled; 32 Rice, broken; 33 Gluten, rice; 34 Starch, rice; 35 Bran, rice; 38 Flour, rice
Soybean	Soybean (2555)	Both [379, 380]	Default composition: 236 Soybean; 239 Soya sauce; 240 Soya paste; 241 Soya curd

D.3.2 Comparison between the two FB data sets

The differences in estimating the percentages for the three uses (*food*, *feed*, and *other uses*) between the two FB databases were small. The three linear models comparing all shared data points identified strong relationships between the two FB databases (Fig. D.25).

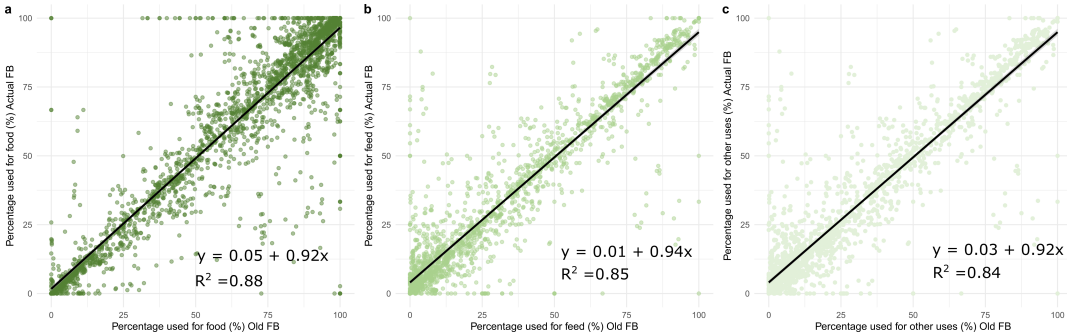


Figure D.25. Relationships between the two FB databases [379, 380]. a) Linear model comparing all shared data points for the percentage used for food across the four crops, b) linear model comparing all shared data points for the percentage used for feed across the four crops, and c) linear model comparing all shared data points for the percentage used for *other uses* across the four crops

D.3.3 Dry-matter contents of the items in the FAOSTAT Detailed Trade Matrix (DTM)

The FAOSTAT DTM 36 includes similar items to the FB data sets, although they are not identical. To develop the bilateral trade matrix for each crop, we grouped information for all products and by-products (items) of each crop based on their Dry matter content (DMC). Table D.3 summarizes the information for the items used for each crop, the DMC of each item, and the reference considered for the DMC information. Information about the DMC for soybean cake and soybean oil was not required as they were the only item considered for analyzing the trade of both classes.

Table D.3. Items from DTM used for creating the bilateral trade matrix for each crop, including their dry-matter content (DMC) and its reference. We assumed that rice oil contained no water, as for the other oils. For some items, we used closely related by-products or the average of different types of the items.

FAOSTAT DTM item	Crop	DMC (%)	Source
Bran of maize (59)	Maize	90.9	[495]
Cake of maize (61)	Maize	91.6	Average classes [496]
Flour of maize (58)	Maize	89.0	[497]
Forage and silage, maize (636)	Maize	30.3	[498]
Germ of maize (57)	Maize	93.2	Average classes [496]
Green corn (maize) (446)	Maize	30.1	[499]
Maize (corn) (56)	Maize	86.3	[495]
Oil of maize (60)	Maize	100	[497]
Bran of rice (35)	Rice	93.9	[497]
Cake of rice bran (37)	Rice	94.2	[497]
Flour of rice (38)	Rice	89.2	[497]
Husked rice (28)	Rice	89.1	(Brown rice) [497]
Oil of rice bran (36)	Rice	100	–
Rice (27)	Rice	88.0	(Rice, paddy) [495]
Rice, broken (32)	Rice	87.6	[495]
Rice, milled (31)	Rice	87.5	(Rice, polished) [497]
Rice, milled (husked) (29)	Rice	87.5	(Rice, polished) [497]
Rice, paddy (rice milled equivalent) (30)	Rice	88.0	[495]
Rice-fermented beverages (39)	Rice	22.1	[500]
Soya beans (236)	Soybean	91.5	[501]
Soya curd (241)	Soybean	23.1	[497]
Soya paste (240)	Soybean	47.0	[497]
Soya sauce (239)	Soybean	29.0	[497]
Soya bean oil (237)	Soybean oil	–	–
Cake of soya bean (238)	Soybean cake	–	–
Germ of wheat (19)	Wheat	93.3	[497]
Wheat (15)	Wheat	87.4	[495]
Wheat and meslin flour (16)	Wheat	87.4	[497]
Bran of wheat (17)	Wheat	91.7	[497]

D.3.4 Diagram of the methods

Fig. D.26 summarizes the methodology we have followed for estimating the amount of fertilizer use for each country, year, crop (maize, rice, wheat and soybean), and category of use (*feed*, *food*, *other uses*).

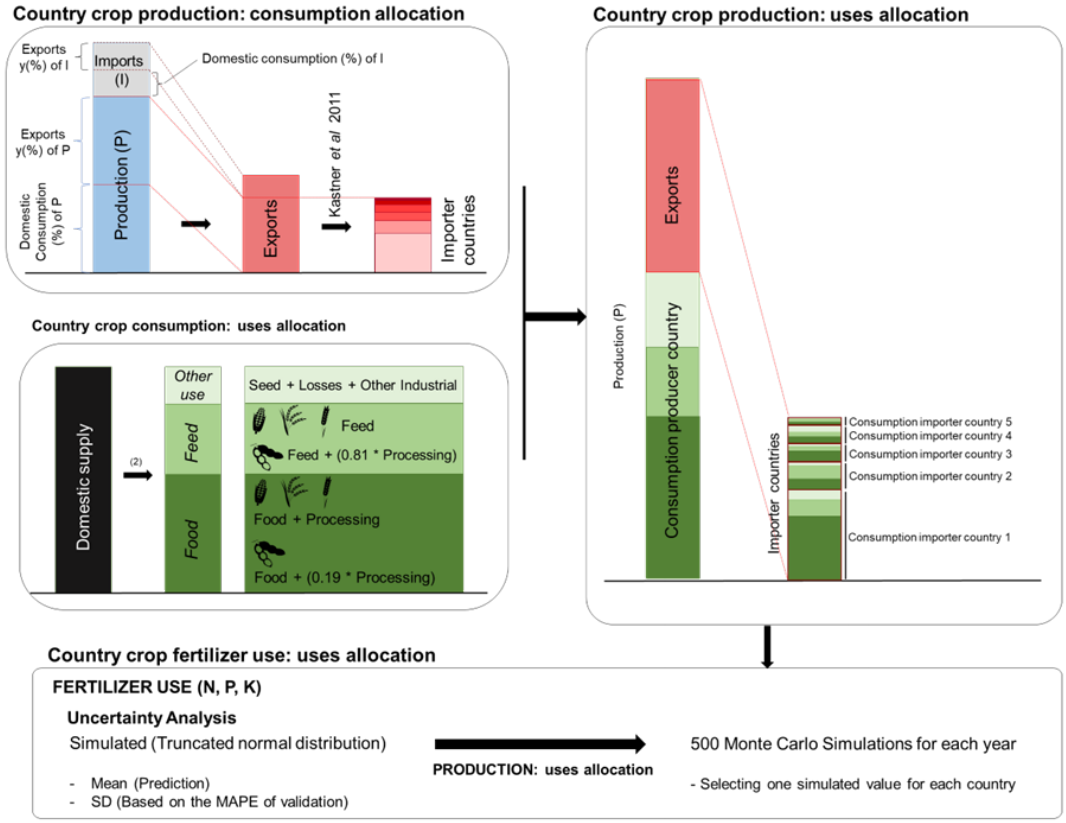


Figure D.26. Methodological flowchart for estimating the amount of fertilizer used due to *food*, *feed*, and *other uses*.

Appendix E

Supplementary information:

Crop demand limits gains in global fertilizer use efficiency: A global analysis at crop level since 1961

E.1 Extended Data Sources and Methods

E.1.1 Energy content and Protein Concentration

To estimate the energy and proteins produced from crops allocated for food, and the proteins produced due to the livestock products produced due to the crops used for feed, we used data about the energy content and the protein concentration of crops and animal products. In this sub-section the median values and the standard deviation from the sources used (Table E.1)

E.1.2 Livestock Data Sources and Methods

To estimate the energy and proteins produced from crops allocated for livestock feed we combined multiple data sources, estimations and assumptions to obtain results for each crop, year and country. This section of the extended methods provides additional details to complement the description presented in the main "Sources and Methods" section. The main assumption underlying this section of the methods concerns the livestock products included in the analysis. We limited our estimates to five major animal products: hen eggs, chicken meat, pork, dairy milk, and beef. These five products represent the primary source of animal-derived food globally, accounting in 2010 for 99% of grain and oilseed cakes used for feed demand [385]. Although production for other livestock, such as goats and buffaloes is important in specific regions, data of their production systems, Feed Conversion Ratios (FCR) is scarcer than for the other livestock products. A detailed diagram of the data used about livestock and the procedure to estimate the proteins and energy produced by the crop used for feed can be check in the Fig. E.1.

Table E.1. Nutritional composition of selected crop and livestock products, including their average and standard deviation of dry-matter content (DMC), energy, proteins and their references. We assumed that rice oil contained no water, as for the other oils.

Crop/ Livestock Product	DMC (%)	$\widetilde{\textbf{Energy}}$ (kcal/100g)	SD(Energy) (kcal/100g)	$\widetilde{\textbf{Protein}}$ (g/100g)	SD(Protein) (g/100g)	References
Maize	86.30	361.00	50.00	8.10	1.18	[495, 497, 502, 503]
Rice	88.00	358.00	49.93	11.00	1.25	[495, 497, 502, 503]
Wheat	86.90	343.00	23.25	7.94	1.30	[497, 502, 503]
Soybean	89.50	449.00	110.52	38.48	1.96	[495, 497, 502, 503]
Egg (hen)	–	139.00	2.65	12.30	0.95	[497, 503, 504]
Chicken meat	–	148.00	36.77	15.15	4.03	[497, 503, 504]
Pork meat	–	362.00	–	13.40	–	[503]
Dairy milk	–	61.00	1.15	3.30	0.07	[497, 503, 504]
Beef meat	–	150.00	–	18.50	–	[503]

The first step in the livestock component of the method estimates the fraction of each crop consumption attributed to each livestock product (Fraction of feed allocated to different animal products). To estimate this, we based our calculations on the annual feed requirements of the five major livestock products in each country. The equations used in this step are described in the Materials and Methods of the main text; however, the sources and preprocessing procedures have not yet been detailed. In this step, we used data on: (i) production of all livestock products (P), (ii) the share of the production of each livestock product produced under different Livestock Systems (LS), (iii) the FCR of each livestock product under each LS and (iv) the Feed Rations (FR) associated with each product and system. These variables are also used in subsequent steps of the method; therefore, their sources and preprocessing are described in more detail in the relevant sections that follow.

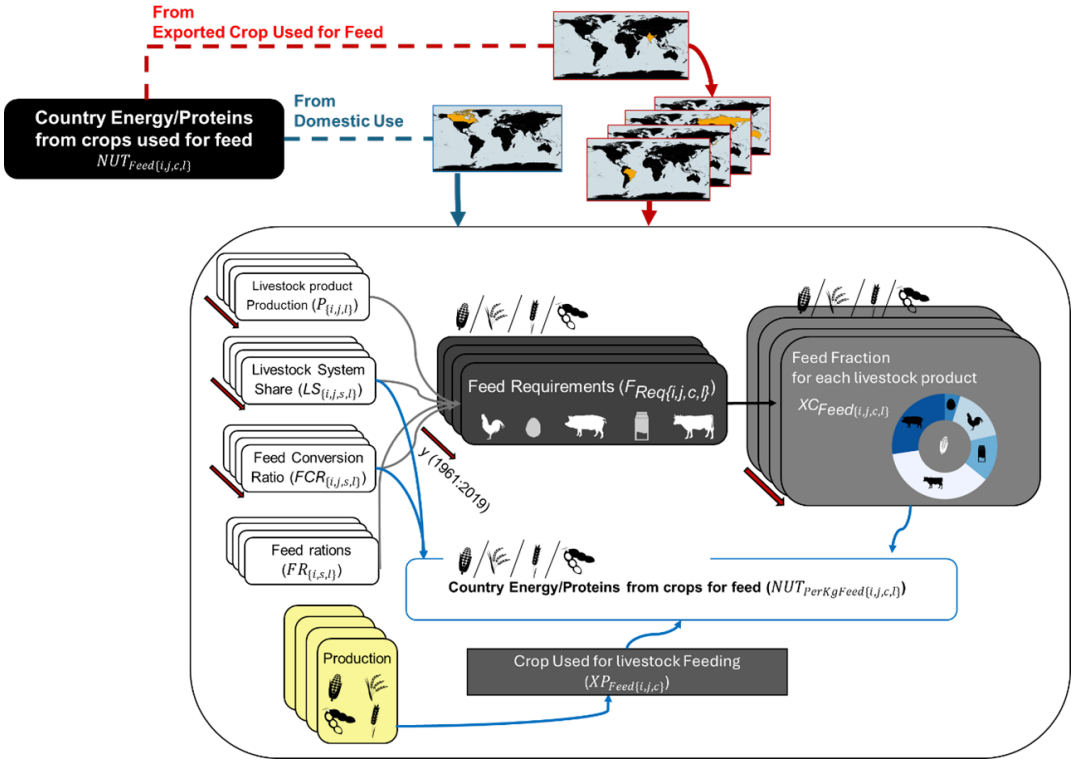


Figure E.1. Diagram of the methods applied to estimate the number of proteins and energy produced by the crop used for livestock feeding.

E.1.2.1 Livestock products: production (P)

The annual data on production for the five major livestock products considered (hen eggs, chicken meat, pork meat, dairy milk and beef) was obtained from Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) [163]. The Food and Agriculture Organization (FAO) database provides annual data on the production of the five products since 1961 for most world countries.

E.1.2.2 Livestock system shares (LS)

Livestock system shares ($LS_{\{i,j,s,l\}}$) are defined here as the fraction of the production of a livestock product produced under extensive (grazing/backyard), semi-intensive (mixed) or intensive (industrial) systems for each country, and year. Data about spatial or temporal evolution of livestock system shares is very limited [447–449, 505]. However there are enough evidences and data confirming that livestock production have shifted towards more intensive systems during the study period [447–449].The sources depending on the livestock product changed both the temporal and the spatial resolution; therefore, we have performed a different procedure for each product trying to use the best possible source and estimation in each case.

Chicken broiler and hen layer:

In 2015, Gilbert et al. (2015) [505] published global raster maps of chicken broiler production by system for the year 201013, which we have adopted as the foundation for our national-level system-share estimates. From these grid maps we extracted, for each country, the total head counts under the two production systems considered in the study by summing the values of all grid cells classified as intensive, or extensive (backyard), respectively. These values serve as the baseline inputs ($LS_{\{i,2010,s,chi\}}$)) for our subsequent piecewise projection of livestock system dynamics. We assumed that the number of animals under each livestock system implies the same proportion of production between both systems.

To generate annual time series from 1961 to 2019, we used the regional growth rates for broiler-chicken systems in the 1980s and 1990s reported by Seré and Steinfeld (1996) [447]. Because Gilbert et al. (2015) [505] distinguish between extensive and other systems, whereas Seré and Steinfeld (1996) [447] provide separate rates for extensive, mixed, and intensive systems, we defined one composite intensive and mixed growth parameter for each region. To accomplish this, we first computed the weighted average of the reported annual growth rate ($g_{Sere\{r,s,chi\}}$) of mixed and intensive systems, by using the system's share of broiler production under each system (s) within each region (r) ($LS_{\{s,r,1995,chi\}}$). Then, for each year we project the percentage of broiler production under extensive (ext) or intensive+mixed (mix+int) systems by using the Eqs. (E.1) and (E.2) respectively:

$$LS_{\{i,j,\text{ext},chi\}} = LS_{\{i,2010,\text{ext},chi\}} \cdot \left(1 + g_{\{r,\text{ext},chi\}}\right)^{(j-2010)} \text{ if } s = \text{ext} \tag{E.1}$$

$$LS_{\{i,j,\text{mix+int},chi\}} = LS_{\{i,\text{mix+int},2010,chi\}} \cdot \left(1 + g_{\{r,\text{mix+int},chi\}}\right)^{(j-2010)} \text{ if } s = \text{mix+int} \tag{E.2}$$

$$LS^{*}_{\{i,j,s,chi\}} = \frac{LS_{\{i,j,s,chi\}}}{\sum_{s'} LS_{\{i,j,s',chi\}}} \tag{E.3}$$

Where i indexes' countries and$r$ the corresponding Seré and Steinfeld region (See Table E.3 for country and region correspondence). This method yields two unnormalized estimates per country–year: one for the extensive system and one for the combined intensive+mixed share. We then normalized the shares to sum up 1 (100%) for each country i and each year j by using the Eq. (E.3).

For disaggregating the intensive+mixed category into two distinct categories, we calculated, for each region (Seré and Steinfeld (1996) [447] regions) the ratio between intensive and mixed system shares ($R_r^{(int/mix)}$), as well as the ratio between their growth rates ($g_r^{(int/mix)}$) (Eqs. (E.4) and (E.5)).

$$R_{\{r\}}^{(\text{int/mix})} = \frac{LS_{\{r,\text{int}\}}}{LS_{\{r,\text{mix}\}}} \tag{E.4}$$

$$g_{\{r\}}^{(\text{int/mix})} = \frac{g_{\{r,\text{int}\}} \cdot LS_{\{r,\text{int}\}}}{g_{\{r,\text{mix}\}} \cdot LS_{\{r,\text{mix}\}}} \tag{E.5}$$

If any system's weighted-growth term was zero (resulting in a zero numerator or denominator), we replaced it with one to avoid division-by-zero artifacts. We then took each region's 1995 ratio $R_r^{(int/mix)}$ and its growth rate $g_r^{(int/mix)}$ for generating a continuous time series by using the same equation as in previous steps. Finally, we used this time varying $R_{r,j}^{(int/mix)}$ to disaggregate the $LS_{i,j,mix+int,chi}$ into separate intensive and mixed components by Eqs. (E.6) and (E.7):

$$LS_{\{i,j,\text{int},chi\}} = LS_{\{i,j,\text{mix+int},chi\}} \cdot \frac{R_{\{r,j\}}^{(\text{int/mix})}}{1 + R_{\{r,j\}}^{(\text{int/mix})}} \tag{E.6}$$

$$LS_{\{i,j,\text{mix},chi\}} = LS_{\{i,j,\text{mix+int},chi\}} - LS_{\{i,j,\text{int},chi\}} \tag{E.7}$$

To our knowledge, no national-level data exists for hen egg production. The comparison of regional broiler and layer estimates from Seré and Steinfeld (1996) [447] (Fig. E.2) reveals a strong correlation between chicken and hen egg production system shares across regions. Consequently, we applied the same national-level system shares estimated for broilers to hen layers.

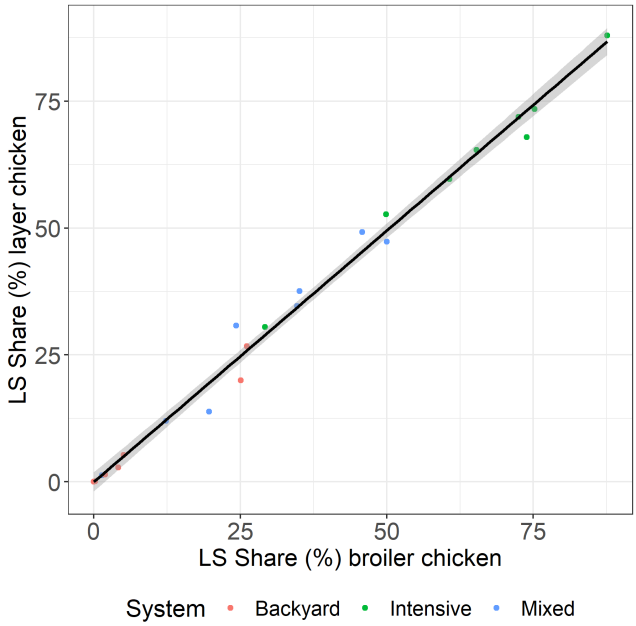


Figure E.2. Scatterplot comparing Seré and Seinfeld 1996 regional livestock-system shares for broiler chicken and layer hens. The solid line represents the fitted linear regression, and the grey area the confidence interval, which has an $R^2 > 0.99$, $p < 0.001$, and a slope of 0.99, indicating an almost perfect correspondence between broiler and layer livestock system shares.

Pigs, pork meat:

In 2015, Gilbert et al. (2015) [505] published global raster maps of pig production by system for the year 2010 13, which we have adopted as the foundation for our national-level system-share estimates. From these grid maps, we extracted, for each country, the total head counts under the three production systems (industrial, semi-intensive or extensive (backyard)) by summing the values of all grid cells classified accordingly. We then computed the corresponding system-share variables by dividing each system's total head count by the aggregate pig population, assuming that the share of animals under each system reflects the same proportion of total production. These three share variables serve as the baseline inputs (LSi,2010,s,pig) for our subsequent piecewise projection of livestock system dynamics.

To generate annual time series from 1961 to 2019, we used the regional growth rates reported by Lassaletta et al. (2019) [449]. Based on the system share proportions reported for the years 1970, 1990, and 2015, we estimated two regional growth rates (g), one for the period 1970-1990 ($g_{1970\rightarrow1990s,r}$), and other for the period 1990-2005 ($g_{1990\rightarrow2005s,r}$). We then, applied the $g_{1990\rightarrow2005s,r}$ to the national livestock system share of the year 2010 to estimate the share of the year 1990 (Eqs. (E.8) and (E.9)).

$$LS_{\{i,1990,s,pig\}} = LS_{\{i,2010,s,pig\}} \cdot \left(1 + g_{1990\rightarrow2005\{s,r,pig\}}\right)^{(1990-2010)} \tag{E.8}$$

$$LS^{\text{norm}}_{\{i,1990,s,pig\}} = \frac{LS_{\{i,1990,s,pig\}}}{\sum_{s'} LS_{\{i,1990,s',pig\}}} \tag{E.9}$$

By using the normalized estimation for the year 1990, and the two growth rates s, we extended the system-share estimates across the full period (Eqs. (E.10) and (E.11)), finally normalizing the annual results (Eq. (E.12)):

$$S_{\{i,j,s,pig\}} = LS_{\{i,j,s,pig\}} \cdot \left(1 + g_{1970\rightarrow1990\{s,r\}}\right)^{(j-1990)} \text{ if } j < 1990 \tag{E.10}$$

$$LS_{\{i,j,s,pig\}} = LS_{\{i,j,s,pig\}} \cdot \left(1 + g_{1990\rightarrow2005\{s,r\}}\right)^{(j-1990)} \text{ if } j > 1990 \tag{E.11}$$

$$LS^{\text{norm}}_{\{i,j,s,pig\}} = \frac{LS_{\{i,j,s,pig\}}}{\sum_{s'} LS_{\{i,j,s',pig\}}} \tag{E.12}$$

Beef and dairy milk:

The availability of data of livestock systems for dairy cattle and beef is more limited than for pigs or poultry, with no estimates at national al level. To generate a continuous country-level estimates from 1961 to 2019, we combined two sources: the regional livestock system shares for 2010 from GLEAM v.2 [450], and the growth rates estimated for Seré and Steinfeld (1996) [447].

We began by extracting the amount of dairy protein produced in 2010 by production system (grazing and mixed) for each GLEAM region (See Table E.3). For each region, we calculated the share of protein from each system relative to the total protein from dairy cattle assuming identical protein concentration across systems. This yielded a 2010 baseline estimate of regional system shares ($LS^{GLEAM}_{r,2010,s,milk}$). We then used historical system share estimates and growth rates from Seré and Steinfeld (1996) [447]. We extracted growth rates (g) for backyard (extensive) and intermediate (mixed) systems. These rates were applied to project system shares forward and backward from the 1995 reference year (Eq. (E.13))

$$LS^{\text{S\&S}}_{\{r,j,s,milk\}} = LS^{\text{S\&S}}_{\{r,1995,s,milk\}} \cdot \left(1 + g_{1990\rightarrow2005\{s,r,milk\}}\right)^{(j-1995)} \tag{E.13}$$

To translate these regional results to national level estimates (assigning the same values to all countries within a GLEAM region) we calculated a correction factor ($\alpha_{i,s,milk}$) for each country (i) and system (s). This factor reflects the ratio between the GLEAM 2010 ($LS^{\text{GLEAM}}_{r,2010,s,milk}$) share and projected estimation from Seré and Steinfeld (1996) [447] ($LS^{\text{S\&S}}_{r,2010,s,milk}$). We applied this correction because GLEAM provides higher spatial resolution, its regions aggregate fewer countries than those defined by Seré and Steinfeld (1996) [447].

$$\alpha_{\{i,s,milk\}} = \frac{LS^{\text{GLEAM}}_{\{r,2010,s,milk\}}}{LS^{\text{S\&S}}_{\{r,2010,s,milk\}}} \tag{E.14}$$

$$LS_{\{i,j,s,milk\}} = \alpha_{\{i,s,milk\}} \cdot LS^{\text{S\&S}}_{\{r,j,s,milk\}} \tag{E.15}$$

To ensure consistency and prevent division by 0 or artificial inflation, we enforced a minimum regional share of 1% when applying the correction factor. We also constrained grazing (extensive) share to prevent increases relative to mixed systems after 1995, based on the assumption that further extensification is unlikely under global intensification trends. Finally, we normalized all shares to ensure they summed to 100% (Eq. (E.16))

$$LS^{\text{norm}}_{\{i,j,s,milk\}} = \frac{LS_{\{i,j,s,milk\}}}{\sum_{s'} LS_{\{i,j,s',milk\}}} \tag{E.16}$$

To estimate the LS for beef cattle production we applied a methodology similar to that used for dairy milk, due to the absence of country-level data. We combined the regional system shares for 2010 from GLEAM v2, and the growth rates reported by Seré and Steinfeld (1996) [447]. We began by calculating the regional shares ($LS^{GLEAM}_{r,2010,s,beef}$) of each livestock system (extensive (grazing), intermediate (mixed) and intensive (feedlot)) from the GLEAM v2 [450]. We assumed that protein production shares by system reflects overall production shares. Then, using the shares ($LS^{S\&S}_{r,1995,s,beef}$) and the annual growths ($g_{1990\rightarrow2005s,r,beef}$) reported by Seré and Steinfeld (1996) [447], we projected the regional shares backward to 1961 and forward to 2019 by using Eq. (E.17).

$$LS^{\text{S\&S}}_{\{r,j,s,beef\}} = LS^{\text{S\&S}}_{\{r,1995,s,beef\}} \cdot \left(1 + g_{1990\rightarrow2005\{s,r,beef\}}\right)^{(j-1995)} \tag{E.17}$$

To downscale these regional results to national level estimates (assigning the same values to all countries within a GLEAM region) we calculated a correction factor ($\alpha_{i,s,beef}$,Eq. (E.18)) for each country (i) and system (s), and we projected this correction factor over the period, as we did for dairy milk (Eq. (E.19)).

$$\alpha_{\{i,s,beef\}} = \frac{LS^{\text{GLEAM}}_{\{r,2010,s,beef\}}}{LS^{\text{S\&S}}_{\{r,2010,s,beef\}}} \tag{E.18}$$

$$LS_{\{i,j,s,beef\}} = \alpha_{\{i,s,beef\}} \cdot LS^{\text{S\&S}}_{\{r,j,s,beef\}} \tag{E.19}$$

To ensure consistency and prevent division by 0 or artificial inflation, we enforced a minimum regional share of 1% when applying the correction factor.

GLEAM groups all intensive production into a single non-grazing category. We disaggregated the mixed and feedlot shares using their 2010 ratio based on Seré and Steinfeld (1996) [447] projections. We then used this ratio for calculating the $LS_{i,j,intermediate,beef}$ and $LS_{i,j,intensive,beef}$ solving the Eqs. (E.20) and (E.21).

$$LS_{\{i,j,\text{intermediate},beef\}} = \frac{1 - LS_{\{i,j,\text{grazing},beef\}}}{1 + \frac{LS^{\text{S\&S}}_{\{r,j,\text{intermediate},beef\}}}{LS^{\text{S\&S}}_{\{r,j,\text{intensive},beef\}}}} \tag{E.20}$$

$$LS_{\{i,j,\text{intensive},beef\}} = 1 - LS_{\{i,j,\text{grazing},beef\}} - LS_{\{i,j,\text{intermediate},beef\}} \tag{E.21}$$

We ensured that the industrial (feedlot) share never exceeded plausible trends by capping the values when the ratio of intermediate to feedlot dropped below 2010 levels for the period 2010-2019 to 2010 levels. Additionally, we also enforced a monotonic decrease in grazing shares over time using a cumulative minimum filter based on the assumption that further extensification is unlikely under global intensification trends. Finally, we normalized the results to sum up 100%.

E.1.2.3 Feed Conversion Ratios (FCR)

We defined the FCR as the kg of feed, measured in Dry matter content (DMC), required to produce one kilogram of edible animal product. Our main source is the global compilation by Sandström et al. (2022) [452], which aggregates FCR values for different livestock systems and regions based on prior literature. However, evidence from earlier studies shows that FCRs, particularly in intensive systems, have declined over time due to improvements in feed efficiency and animal genetics [404, 506–513]. To account for this, we compiled global and national data to estimate the average rate of FCR decline in intensive systems ($g_{\bar{FCR}}$) throughout the study period. Due to lack of available data, we assumed FCRs in extensive systems remained constant, while FCRs in intermediate (mixed) systems declined at the same rate as those in intensive systems. Although the data available was very scarce we found at least one study for each livestock product (Table E.2).

Table E.2. Average growth rates of feed conversion ratio (g_{FCR}) and their *standard deviation (SD)* for livestock products

Livestock Product	$\bar{g}_{FCR}$	SD(g_{FCR})	References
Hen eggs	-0.0110	–	[507]
Broiler chicken	-0.0081	0.0033	[510, 512–514]
Pig meat	-0.0088	0.0004	[404, 511, 512]
Dairy milk	-0.0232	–	[508]
Beef	-0.0068	–	[509]

E.1.2.4 (Feed Rations (FR)

Feed rations for each livestock product under each production system were assessed at the regional level without temporal variation, as no consistent time-series data were available for the full study period. Consequently, we assumed that feed rations remained constant over time. This variable is only used to estimate the fraction of each crop allocated to different livestock products, consequently, we assumed that there is no changes due to the feed rations in these proportions. We used the information compiled by [452] for the different GLEAM regions.

E.1.3 Country (Areas) Regional Classifications

As a starting point, we used the countries and areas listed in the FAOSTAT database, together with the FAOSTAT regional classification [285]. For China, we considered FAO data separately for China, Taiwan, and mainland China. Belgium and Luxembourg were combined into a single entry before 2000. However, some of the sources used employed different regional classification that we have considered in some of the steps of the process. Table E.3 includes all territorial units considered together with the corresponding region for the different sources.

Table E.3. Countries (areas) included in the study and their corresponding ISO3 code [355], M49 code [481], region from FAO classification (R_FAO), region from GLEAM v2 [450], region from Lassaletta et al. (2019) [449], and region from Seré and Steinfeld (1996) [447]

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
ARM	Armenia	51	WAS	NENA	Russia +	CIS AND EUROPE
AFG	Afghanistan	4	SAS	SA	Rest Southern Asia	ASIA
ALB	Albania	8	SEU	WE	Central Europe	CIS AND EUROPE
DZA	Algeria	12	NAF	NENA	Northern Africa	WANA
ASM	American Samoa	16	OCE	OCE	Oceania	OECD
AND	Andorra	20	SEU	WE	Western Europe	OECD
AGO	Angola	24	MAF	SSA	Rest Southern Africa	SSA
ATG	Antigua and Barbuda	28	CAR	LAC	Rest Central America	CSA
ARG	Argentina	32	SAM	LAC	Rest South America	CSA
AUS	Australia	36	OCE	OCE	Oceania	OECD
AUT	Austria	40	WEU	WE	Western Europe	OECD
BHS	Bahamas	44	CAR	LAC	Rest Central America	CSA
BHR	Bahrain	48	WAS	NENA	Middle East	WANA
BRB	Barbados	52	CAR	LAC	Rest Central America	CSA
F15	Belgium-Luxembourg	58	WEU	WE	Western Europe	OECD
BGD	Bangladesh	50	SAS	SA	Rest Southern Asia	ASIA
BMU	Bermuda	60	NAM	NAM	Rest Central America	OECD
BTN	Bhutan	64	SAS	SA	Rest Southern Asia	ASIA
BOL	Bolivia (Plurinational State of)	68	SAM	LAC	Rest South America	CSA
BWA	Botswana	72	SAF	SSA	Rest Southern Africa	SSA
BRA	Brazil	76	SAM	LAC	Brazil	CSA
ABW	Aruba	533	CAR	LAC	Rest Central America	CSA
BLZ	Belize	84	CAM	LAC	Rest Central America	CSA
IOT	Chagos Archipelago	86	EAF	SSA	#N/D	SSA
SLB	Solomon Islands	90	OCE	OCE	Oceania	WORLD
BRN	Brunei Darussalam	96	SEAS	ESEA	Southeastern Asia	ASIA
BGR	Bulgaria	100	EEU	EE	Central Europe	CIS AND EUROPE
MMR	Myanmar	104	SEAS	ESEA	Southeastern Asia	ASIA
BDI	Burundi	108	EAF	SSA	Eastern Africa	SSA
BVT	Bouvet Island	74	SAM	LAC	Rest South America	CSA
CMR	Cameroon	120	MAF	SSA	Western Africa	SSA
CAN	Canada	124	NAM	NAM	Canada	OECD
CPV	Cabo Verde	132	WAF	SSA	Western Africa	SSA
CYM	Cayman Islands	136	CAR	LAC	Rest Central America	CSA

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
CAF	Central African Republic	140	EAF	SSA	Western Africa	SSA
LKA	Sri Lanka	144	SAS	SA	Rest Southern Asia	ASIA
TCD	Chad	148	EAF	SSA	Western Africa	SSA
CHL	Chile	152	SAM	LAC	Rest South America	CSA
CHN	China, mainland	156	EAS	ESEA	China +	ASIA
CXR	Christmas Island	162	OCE	OCE	Oceania	WORLD
CCK	Cocos (Keeling) Islands	166	OCE	OCE	Oceania	WORLD
COL	Colombia	170	SAM	LAC	Rest South America	CSA
COM	Comoros	174	EAF	SSA	Eastern Africa	SSA
COG	Congo	178	EAF	SSA	Western Africa	SSA
COK	Cook Islands	184	OCE	OCE	Oceania	WORLD
CRI	Costa Rica	188	CAM	LAC	Rest Central America	CSA
CUB	Cuba	192	CAR	LAC	Rest Central America	CSA
CYP	Cyprus	196	WAS	NENA	Central Europe	WANA
F51	Czechoslovakia	200	EEU	EE	Central Europe	OECD
AZE	Azerbaijan	31	WAS	NENA	Russia +	CIS AND EUROPE
BEN	Benin	204	WAF	SSA	Western Africa	SSA
DNK	Denmark	208	NEU	WE	Western Europe	OECD
DMA	Dominica	212	CAR	LAC	Rest Central America	CSA
DOM	Dominican Republic	214	CAR	LAC	Rest Central America	CSA
BLR	Belarus	112	EEU	EE	Ukraine +	CIS AND EUROPE
ECU	Ecuador	218	SAM	LAC	Rest South America	CSA
EGY	Egypt	818	NAF	NENA	Northern Africa	WANA
SLV	El Salvador	222	CAM	LAC	Rest Central America	CSA
GNQ	Equatorial Guinea	226	MAF	SSA	Western Africa	SSA
F62	Ethiopia PDR	230	EAF	SSA	Eastern Africa	SSA
EST	Estonia	233	NEU	WE	Central Europe	CIS AND EUROPE
FRO	Faroe Islands	234	NEU	WE	Western Europe	OECD
FLK	Falkland Islands (Malvinas)	238	SAM	LAC	Rest South America	CSA
FJI	Fiji	242	OCE	OCE	Oceania	WORLD
FIN	Finland	246	NEU	WE	Western Europe	OECD
FRA	France	250	WEU	WE	Western Europe	OECD
GUF	French Guiana	254	SAM	LAC	Rest South America	CSA
PYF	French Polynesia	258	OCE	OCE	Oceania	WORLD
ATF	French Southern Territories	260	EAF	SSA	Oceania	SSA

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
DJI	Djibouti	262	EAF	SSA	Eastern Africa	SSA
GEO	Georgia	268	WAS	NENA	Russia +	CIS AND EUROPE
GAB	Gabon	266	MAF	SSA	Western Africa	SSA
GMB	Gambia	270	WAF	SSA	Western Africa	SSA
F77	Germany Nl	278	EEU	EE	#N/D	
F78	Germany Fr	280	WEU	WE	#N/D	
DEU	Germany	276	WEU	WE	Western Europe	OECD
BIH	Bosnia and Herzegovina	70	SEU	WE	Central Europe	CIS AND EUROPE
GHA	Ghana	288	WAF	SSA	Western Africa	SSA
GIB	Gibraltar	292	SEU	WE	Western Europe	OECD
KIR	Kiribati	296	OCE	OCE	Oceania	WORLD
GRC	Greece	300	SEU	WE	Western Europe	OECD
GRL	Greenland	304	NAM	NAM	#N/D	WORLD
GRD	Grenada	308	CAR	LAC	Rest Central America	CSA
GLP	Guadeloupe	312	CAR	LAC	Rest Central America	CSA
GUM	Guam	316	OCE	OCE	Oceania	WORLD
GTM	Guatemala	320	CAM	LAC	Rest Central America	CSA
GIN	Guinea	324	WAF	SSA	Western Africa	SSA
GUY	Guyana	328	SAM	LAC	Rest South America	CSA
HMD	Heard and McDonald Islands	334	OCE	OCE	Oceania	WORLD
HTI	Haiti	332	CAR	LAC	Rest Central America	CSA
VAT	Holy See	336	SEU	WE	#N/D	
HND	Honduras	340	CAM	LAC	Rest Central America	CSA
HKG	China, Hong Kong SAR	344	EAS	ESEA	China +	ASIA
HUN	Hungary	348	EEU	EE	Central Europe	CIS AND EUROPE
HRV	Croatia	191	SEU	WE	Central Europe	CIS AND EUROPE
ISL	Iceland	352	NEU	WE	Western Europe	OECD
IND	India	356	SAS	SA	India	ASIA
IDN	Indonesia	360	SEAS	ESEA	Indonesia +	ASIA
IRN	Iran (Islamic Republic of)	364	SAS	SA	Middle East	ASIA
IRQ	Iraq	368	WAS	NENA	Middle East	WANA
IRL	Ireland	372	NEU	WE	Western Europe	OECD
ISR	Israel	376	WAS	NENA	Middle East	OTHER DEVELOPED
ITA	Italy	380	SEU	WE	Western Europe	OECD
CIV	Côte d'Ivoire	384	WAF	SSA	Western Africa	SSA
KAZ	Kazakhstan	398	CAS	NENA	Asia-Stan	CIS AND EUROPE
JAM	Jamaica	388	CAR	LAC	Rest Central America	CSA
JPN	Japan	392	EAS	ESEA	Japan	OECD
JOR	Jordan	400	WAS	NENA	Middle East	WANA
KGZ	Kyrgyzstan	417	CAS	NENA	Asia-Stan	CIS AND EUROPE
KEN	Kenya	404	EAF	SSA	Eastern Africa	SSA

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
KHM	Cambodia	116	SEAS	ESEA	Southeastern Asia	ASIA
PRK	Democratic People's Republic of Korea	408	EAS	ESEA	Korea	ASIA
KOR	Republic of Korea	410	EAS	ESEA	Korea	ASIA
KWT	Kuwait	414	WAS	NENA	Middle East	WANA
LVA	Latvia	428	NEU	WE	Central Europe	CIS AND EUROPE
LAO	Lao People's Democratic Republic	418	SEAS	ESEA	Southeastern Asia	ASIA
LBN	Lebanon	422	WAS	NENA	Middle East	WANA
LSO	Lesotho	426	SAF	SSA	Rest Southern Africa	SSA
LBR	Liberia	430	WAF	SSA	Western Africa	SSA
LBY	Libya	434	NAF	NENA	Northern Africa	WANA
LIE	Liechtenstein	438	WEU	WE	Western Europe	OECD
LTU	Lithuania	440	NEU	WE	Central Europe	CIS AND EUROPE
MHL	Marshall Islands	584	OCE	OCE	Oceania	WORLD
MAC	China, Macao SAR	446	EAS	ESEA	China +	ASIA
MDG	Madagascar	450	EAF	SSA	Eastern Africa	SSA
MWI	Malawi	454	EAF	SSA	Rest Southern Africa	SSA
MYS	Malaysia	458	SEAS	ESEA	Southeastern Asia	ASIA
MDV	Maldives	462	SAS	SA	Rest Southern Asia	ASIA
MLI	Mali	466	WAF	SSA	Western Africa	SSA
MLT	Malta	470	SEU	WE	Central Europe	CIS AND EUROPE
MTQ	Martinique	474	CAR	LAC	Rest Central America	CSA
MRT	Mauritania	478	WAF	SSA	Western Africa	SSA
MUS	Mauritius	480	EAF	SSA	Eastern Africa	SSA
MEX	Mexico	484	CAM	LAC	Mexico	OECD
MID	Midway Island	488	OCE	OCE	Oceania	WORLD
MCO	Monaco	492	WEU	WE	Western Europe	OECD
MNG	Mongolia	496	EAS	ESEA	China +	ASIA
MSR	Montserrat	500	CAR	LAC	Rest Central America	CSA
MAR	Morocco	504	NAF	NENA	Northern Africa	WANA
MOZ	Mozambique	508	EAF	SSA	Rest Southern Africa	SSA
FSM	Micronesia (Federated States of)	583	OCE	OCE	Oceania	WORLD
MDA	Republic of Moldova	498	EEU	EE	Ukraine +	CIS AND EUROPE
NAM	Namibia	516	SAF	SSA	Rest Southern Africa	SSA
NRU	Nauru	520	OCE	OCE	Oceania	WORLD
NPL	Nepal	524	SAS	SA	Rest Southern Asia	ASIA

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
NLD	Netherlands (Kingdom of the)	528	WEU	WE	Western Europe	OECD
ANT	Netherlands Antilles (former)	530	CAR	LAC	Rest Central America	CSA
NCL	New Caledonia	540	OCE	OCE	Oceania	WORLD
MKD	North Macedonia	807	SEU	WE	Central Europe	CIS AND EUROPE
VUT	Vanuatu	548	OCE	OCE	Oceania	WORLD
NZL	New Zealand	554	OCE	OCE	Oceania	OECD
NIC	Nicaragua	558	CAM	LAC	Rest Central America	CSA
NER	Niger	562	WAF	SSA	Western Africa	SSA
NGA	Nigeria	566	WAF	SSA	Western Africa	SSA
NIU	Niue	570	OCE	OCE	Oceania	WORLD
NFK	Norfolk Island	574	OCE	OCE	Oceania	WORLD
NOR	Norway	578	NEU	WE	Western Europe	OECD
MNP	Northern Mariana Islands	580	OCE	OCE	Oceania	WORLD
F164	Pacific Islands Trust Territory	582	OCE	OCE	Oceania	WORLD
PAK	Pakistan	586	SAS	SA	Rest Southern Asia	ASIA
PAN	Panama	591	CAM	LAC	Rest Central America	CSA
CZE	Czechia	203	EEU	EE	Central Europe	OECD
PNG	Papua New Guinea	598	OCE	OCE	Indonesia +	WORLD
PRY	Paraguay	600	SAM	LAC	Rest South America	CSA
PER	Peru	604	SAM	LAC	Rest South America	CSA
PHL	Philippines	608	SEAS	ESEA	Southeastern Asia	ASIA
PCN	Pitcairn	612	OCE	OCE	Oceania	WORLD
POL	Poland	616	EEU	EE	Central Europe	CIS AND EUROPE
PRT	Portugal	620	SEU	WE	Western Europe	OECD
GNB	Guinea-Bissau	624	WAF	SSA	Western Africa	SSA
TLS	Timor-Leste	626	SEAS	ESEA	Indonesia +	ASIA
PRI	Puerto Rico	630	CAR	LAC	Rest Central America	CSA
ERI	Eritrea	232	EAF	SSA	Eastern Africa	SSA
QAT	Qatar	634	WAS	NENA	Middle East	WANA
PLW	Palau	585	OCE	OCE	Oceania	WORLD
ZWE	Zimbabwe	716	EAF	SSA	Rest Southern Africa	SSA
REU	Réunion	638	EAF	SSA	Eastern Africa	SSA
ROU	Romania	642	EEU	EE	Central Europe	CIS AND EUROPE
RWA	Rwanda	646	EAF	SSA	Eastern Africa	SSA

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
RUS	Russian Federation	643	EEU	RUS	Russia +	CIS AND EUROPE
SCG	Serbia and Montenegro	891	SEU	WE	Central Europe	CIS AND EUROPE
KNA	Saint Kitts and Nevis	659	CAR	LAC	Rest Central America	CSA
LCA	Saint Lucia	662	CAR	LAC	Rest Central America	CSA
SPM	Saint Pierre and Miquelon	666	NAM	NAM	USA	OECD
VCT	Saint Vincent and the Grenadines	670	CAR	LAC	Rest Central America	CSA
SMR	San Marino	674	SEU	WE	Western Europe	OECD
STP	Sao Tome and Principe	678	MAF	SSA	Western Africa	SSA
SAU	Saudi Arabia	682	WAS	NENA	Middle East	WANA
SEN	Senegal	686	WAF	SSA	Western Africa	SSA
SYC	Seychelles	690	EAF	SSA	Eastern Africa	SSA
SLE	Sierra Leone	694	WAF	SSA	Western Africa	SSA
SVN	Slovenia	705	SEU	WE	Central Europe	CIS AND EUROPE
SVK	Slovakia	703	EEU	EE	Central Europe	CIS AND EUROPE
SGP	Singapore	702	SEAS	ESEA	Southeastern Asia	ASIA
SOM	Somalia	706	EAF	SSA	Eastern Africa	SSA
ZAF	South Africa	710	SAF	SSA	Southern Africa	OTHER DEVELOPED
ESP	Spain	724	SEU	WE	Western Europe	OECD
ESH	Western Sahara	732	NAF	NENA	Northern Africa	WANA
F206	Sudan (former)	736	NAF	NENA	Eastern Africa	WANA
SUR	Suriname	740	SAM	LAC	Rest South America	CSA
TJK	Tajikistan	762	CAS	NENA	Asia-Stan	CIS AND EUROPE
SWZ	Eswatini	748	SAF	SSA	Rest Southern Africa	SSA
SWE	Sweden	752	NEU	WE	Western Europe	OECD
CHE	Switzerland	756	WEU	WE	Western Europe	OECD
SYR	Syrian Arab Republic	760	WAS	NENA	Middle East	WANA
TKM	Turkmenistan	795	CAS	NENA	Asia-Stan	CIS AND EUROPE
TWN	China, Taiwan Province of	158	EAS	ESEA	China +	ASIA
TZA	United Republic of Tanzania	834	EAF	SSA	Rest Southern Africa	SSA
THA	Thailand	764	SEAS	ESEA	Southeastern Asia	ASIA
TGO	Togo	768	WAF	SSA	Western Africa	SSA
TKL	Tokelau	772	OCE	OCE	Oceania	WORLD
TON	Tonga	776	OCE	OCE	Oceania	WORLD

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
TTO	Trinidad and Tobago	780	CAR	LAC	Rest Central America	CSA
OMN	Oman	512	WAS	NENA	Middle East	WANA
TUN	Tunisia	788	NAF	NENA	Northern Africa	WANA
TUR	Türkiye	792	WAS	NENA	Turkey	WANA
TCA	Turks and Caicos Islands	796	CAR	LAC	Rest Central America	CSA
ARE	United Arab Emirates	784	WAS	NENA	Middle East	WANA
UGA	Uganda	800	EAF	SSA	Eastern Africa	SSA
TUV	Tuvalu	798	OCE	OCE	Oceania	WORLD
F228	USSR	810	EEU	RUS	Russia +	CIS AND EUROPE
GBR	United Kingdom of Great Britain and Northern Ireland	826	NEU	WE	Western Europe	OECD
UKR	Ukraine	804	EEU	EE	Ukraine +	CIS AND EUROPE
USA	United States of America	840	NAM	NAM	USA	OECD
UMI	United States Minor Outlying Islands	581	OCE	OCE	USA	OECD
BFA	Burkina Faso	854	WAF	SSA	Western Africa	SSA
URY	Uruguay	858	SAM	LAC	Rest South America	CSA
UZB	Uzbekistan	860	CAS	NENA	Asia-Stan	CIS AND EUROPE
VEN	Venezuela (Bolivarian Republic of)	862	SAM	LAC	Rest South America	CSA
VNM	Viet Nam	704	SEAS	ESEA	Southeastern Asia	ASIA
ETH	Ethiopia	231	EAF	SSA	Eastern Africa	SSA
VGB	British Virgin Islands	92	CAR	LAC	Rest Central America	CSA
VIR	United States Virgin Islands	850	CAR	LAC	Rest Central America	CSA
WAK	Wake Island	872	OCE	OCE	Oceania	WORLD
WLF	Wallis and Futuna Islands	876	OCE	OCE	Oceania	WORLD
WSM	Samoa	882	OCE	OCE	Oceania	WORLD
F246	Yemen Ar Rp	886	WAS	NENA	Middle East	WANA
F247	Yemen Dem	720	WAS	NENA	Middle East	WANA
F248	Yugoslav SFR	890	SEU	WE	Central Europe	CIS AND EUROPE
YEM	Yemen	887	WAS	NENA	Middle East	WANA
COD	Democratic Republic of the Congo	180	MAF	SSA	Western Africa	SSA
ZMB	Zambia	894	EAF	SSA	Rest Southern Africa	SSA
BEL	Belgium	56	WEU	WE	Western Europe	OECD

ISO3	Country	M49	R_FAO	R_GLEAM	R_Lassaletta_2019	R_Sere_1996
LUX	Luxembourg	442	WEU	WE	Western Europe	OECD
AIA	Anguilla	660	CAR	LAC	Rest Central America	CSA
CHA	Channel Islands	830	NEU	WE	#N/D	WORLD
SJM	Svalbard and Jan Mayen Islands	744	NEU	WE	#N/D	WORLD
IMN	Isle of Man	833	NEU	WE	Western Europe	OECD
MYT	Mayotte	175	EAF	SSA	Eastern Africa	SSA
SGS	South Georgia and the South Sandwich Islands	239	SAM	LAC	Rest South America	CSA
SRB	Serbia	688	SEU	WE	Central Europe	CIS AND EUROPE
MNE	Montenegro	499	SEU	WE	Central Europe	CIS AND EUROPE
GGY	Guernsey	831	NEU	WE	Western Europe	OECD
F275	Kosovo	412	SEU	WE	Central Europe	CIS AND EUROPE
SDN	Sudan	729	NAF	NENA	Eastern Africa	WANA
SSD	South Sudan	728	EAF	SSA	Eastern Africa	SSA
CUW	Curaçao	531	CAR	LAC	Rest Central America	CSA
SXM	Sint Maarten (Dutch part)	534	CAR	LAC	Rest Central America	CSA
MAF	Saint Martin (French part)	663	CAR	LAC	Rest Central America	CSA
BLM	Saint Barthélemy	652	CAR	LAC	Rest Central America	CSA
JEY	Jersey	832	NEU	WE	Western Europe	OECD
ALA	Åland Islands	248	NEU	WE	Western Europe	OECD
PSE	Palestine	275	WAS	NENA	#N/D	WANA

E.2 Extended Results

E.2.1 Global Partial Factor Productivity (PFP_{energy}) at crop level

This section presents Global Partial Factor Productivity (PFP_{energy}) at crop level

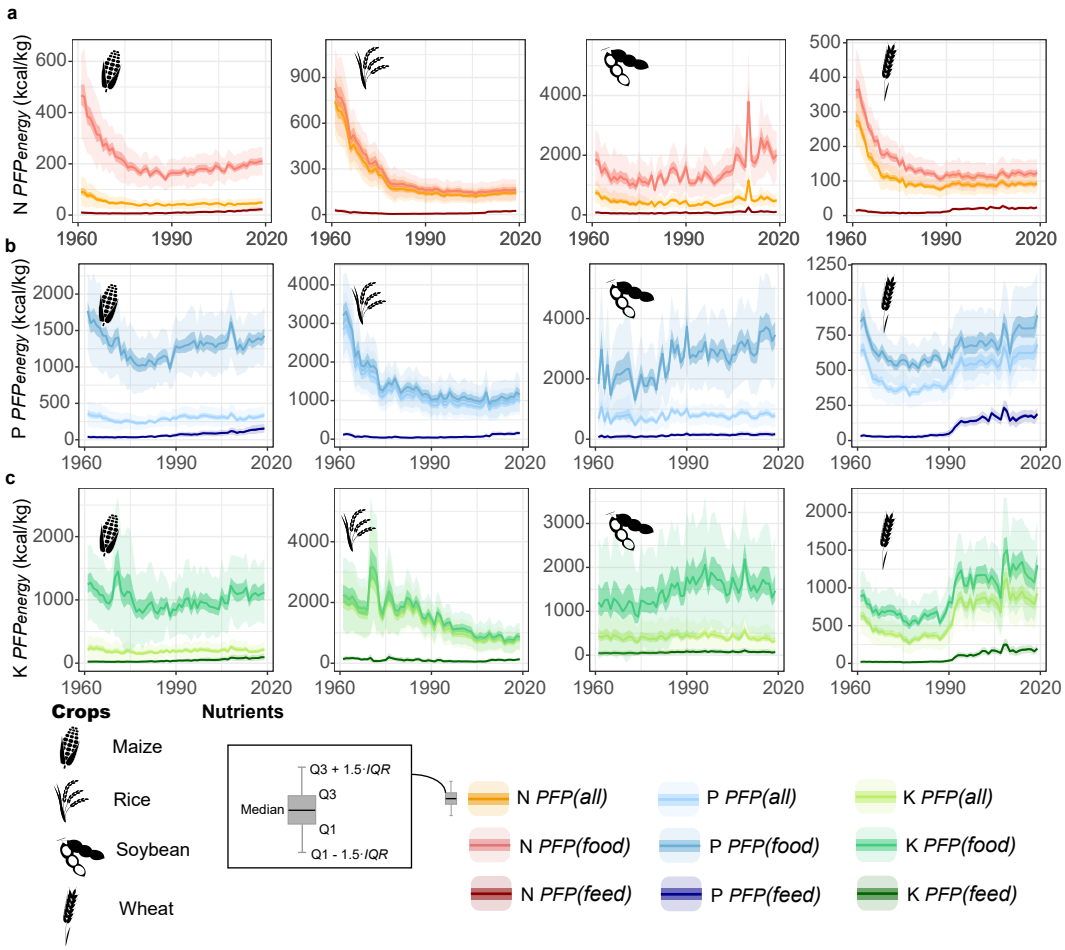


Figure E.3. Diagram of the methods applied to estimate the number of proteins and energy produced by the crop used for livestock feeding.

E.2.2 Fertilizer Potential Savings (FPS) equalized by protein

This section presents the fertilizer potential savings (FPS), equalized by protein, for the ten countries with the highest Fertilizer Potential Savings (FPS) in each of three decades: 1961–1969, 1985–1995, and 2010–2019 (Fig. E.4).

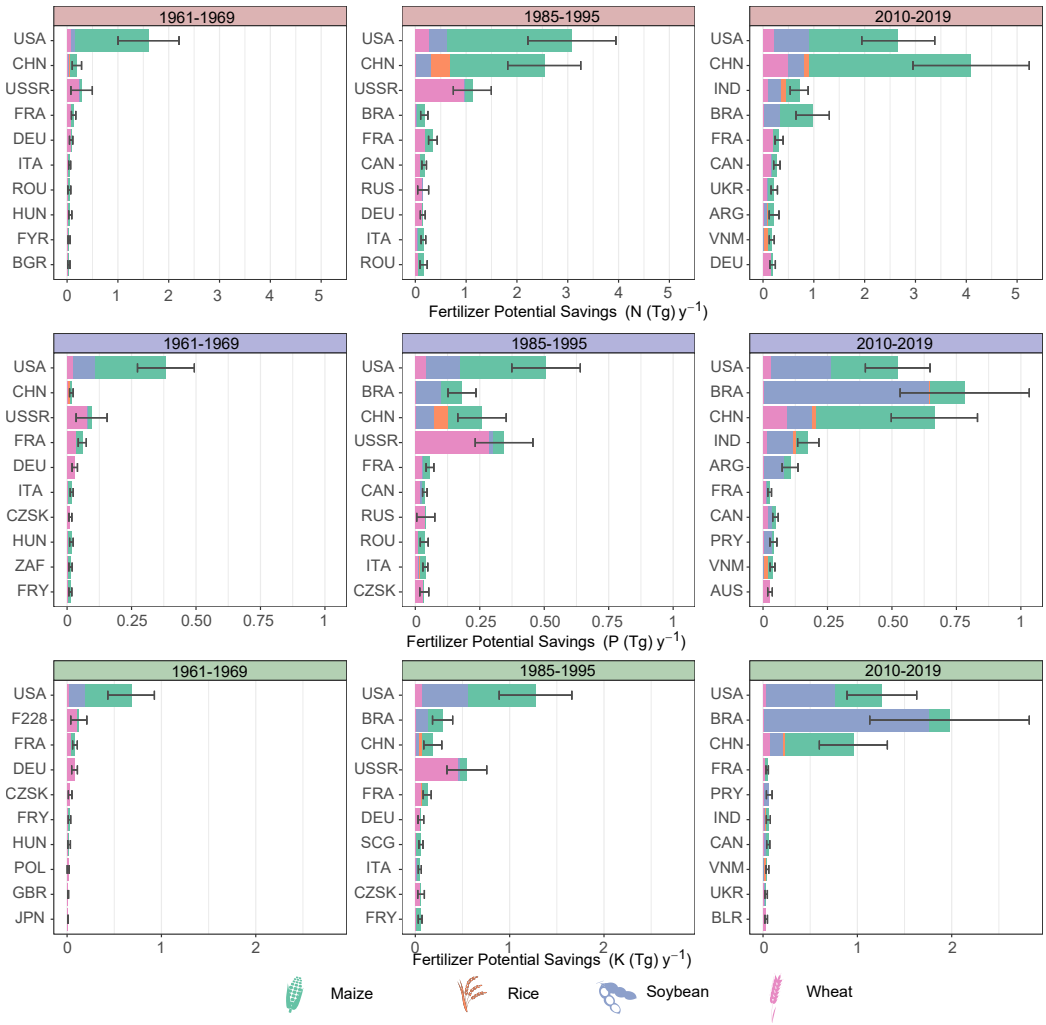


Figure E.4. Mean Fertilizer Potential Savings (FPS) by decade for the top 10 countries per nutrient and decade equalized by protein production. Bars show the mean FPS from all Monte Carlo simulations, disaggregated by crop (maize in green, rice in orange, soybean in blue, wheat in pink). Error bars indicate the sum of the standard deviations of the Monte Carlo simulations for each crop within the decade. Top panels show the results for Nitrogen, middle panels show the results for Phosphorous and bottom panels show the results for Potassium.

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Research Outputs

This section summarizes the main research outputs developed during the doctoral period that are not presented as the core of the thesis, which is composed of the previous seven section of the main text

Publications related to this thesis

- Coello, F.*, Decorte, T.*, Janssens, I., Mortier, S., Sardans, J., Peñuelas, J., & Verdonck, T. (2025). *Global Crop-Specific Fertilization Dataset from 1961–2019*. *Scientific Data*, 12, Article 40. https://doi.org/10.1038/s41597-024-04215-x.

Other publications developed during the PhD

- Peguero, G.*, **Coello, F.***, Sardans, J., Asensio, D., Grau, O., Llusià, J., Ogaya, R., Urbina, I., Van Langenhove, L., Verryckt, L. T., Stahl, C., Bréchet, L., Courtois, E. A., Chave, J., Hérault, B., Janssens, I. A., & Peñuelas, J. (2023). *Nutrient-based species selection is a prevalent driver of community assembly and functional trait space in tropical forests*. *Journal of Ecology*, 111, 1218–1230. https://doi.org/10.1111/1365-2745.14089. *These authors contributed equally to this work.
- Peñuelas, J., **Coello, F.**, & Sardans, J. (2023). *A better use of fertilizers is needed for global food security and environmental sustainability*. *Agriculture & Food Security*, 12, 5. https://doi.org/10.1186/s40066-023-00409-5
- Rodeja, J., **Coello, F.**, Sardans, J., & Peñuelas, J. (2025). *The Potash Trilemma: Geopolitics, Market Dynamics, and Global Food Security*. *Journal of Sustainable Agriculture and Environment*, 4, e70050. https://doi.org/10.1002/sae2.70050
- Liu, J., Wang, H., Peñuelas, J., Mou, J., Delgado-Baquerizo, M., Sardans, J., **Coello, F.**, Quan, Z., Qiu, T., Li, Y., Guo, Y., Hu, Z., Ying, Y., Lv, J., Zhang, Y., Tan, W., Zhou, G., Li, L.-J., & Fang, L. (2025). *Global-scale prevalence of low nutrient use efficiency across major crops*. *Nature Communications*, 16, 11036. https://doi.org/10.1038/s41467-025-66019-w

Other research outputs

- **Coello, F.**, Sardans, J., & Peñuelas, J. (2025). *Why have we fertilized the world? Global drivers of NPK fertilization in major crops since 1961* [Highlighted]. Oral presentation at the EGU General Assembly 2025, Vienna, Austria, 27 April–2 May 2025. https://doi.org/10.5194/egusphere-egu25-15675
- Research stay of three months at the University of Antwerp, Antwerp, Belgium (2023).

