

Article

Advancing the Analysis of Resilience of Global Phosphate Flows

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Abstract

This paper introduces a novel method for estimating material flows, with a focus on tracing phosphate flows from mining countries to those using phosphate in agricultural production. Our approach integrates data on phosphate rock extraction, fertilizer use, and international trade of phosphate-related products. A key advantage of this method is that it does not require detailed data on material concentrations, as these are indirectly estimated within the model. We demonstrate that our model can reconstruct country-level phosphate flow matrices with a high degree of accuracy, thereby enhancing traditional material flow analyses. This method bridges the gap between conventional material flow analysis and the economic analysis of resilience of national supply chains, and it is applicable not only to phosphorus but also to other resource flows. We show how the estimated flows can support country-specific assessments of supply security: while global phosphate flows appear moderately concentrated, country-level analyses reveal significant disparities in import dependencies and, in some cases, substantially higher supplier concentration.

Keywords: mineral resources; material flow analysis; hidden trade of materials; supply chains



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1. Introduction

Phosphorus (P) is a critical element in fertilizer production and, by extension, global food supply. Because agricultural practices continuously remove phosphorus from the soil, a stable supply of phosphate-based fertilizers is essential for both food security and economic development. While efforts to close phosphorus cycles at local and global scales are ongoing, agriculture will remain heavily dependent on phosphate fertilizers for the foreseeable future [1,2].

These fertilizers are primarily produced from mined phosphate rock—mainly sedimentary, with a smaller share from igneous sources. Production is concentrated in a few countries, creating a complex and potentially fragile trade network. This network is susceptible to global supply and demand shocks, with implications for international stability.

Although phosphate rock is not currently scarce at the global level and future supply is expected to meet demand, this is contingent on largely unrestricted trade. However,

given that the top four producers—China, the United States, Morocco, and Russia—are geopolitically influential, the risk of politically motivated trade disruptions cannot be ignored [3–6].

As a result, phosphate trade—including phosphate rock, fertilizers, and related products—has been widely studied for its implications in supply chain vulnerabilities and price volatility [7–11]. In parallel, phosphorus flows within ecosystems—through biomass production and food trade—are also significant [12–14], as are losses during mining, fertilizer production, and agricultural use, all pointing to opportunities for improving efficiency [15–19].

Agricultural use remains the dominant driver of global phosphorus demand. Imbalances in fertilizer use across countries reveal opportunities not only for optimizing crop yields but also for mitigating environmental impacts such as freshwater pollution. Additionally, projected increases in food demand will intensify challenges around sustainable phosphorus management [20–22]. This has led to the development of footprint metrics that assess local phosphorus demand against globally sustainable levels, accounting for the full production chain; see, e.g., [23].

This paper, however, focuses on the supply security of phosphorus used in fertilizers. Such an assessment of resilience includes economic and geopolitical aspects and requires a slightly different focus with respect to how we analyze flows compared to a traditional material flow analysis. Assessing supply security requires detailed knowledge of flows at the country level, has to incorporate a wide range of pathways, and has to be able to identify ultimate sources of materials no matter what path they have taken. While trade data on phosphate-related products is widely available, conventional methods struggle to translate this information into precise material flow models with these characteristics. Part of the problem is that trade data typically refer to products rather than the materials they contain, and existing methods often rely on product-specific concentration values to estimate physical flows. However, such concentration data are frequently incomplete or unavailable, especially for diverse products.

To address this, we propose a new top-down method that estimates material flows without requiring detailed concentration data. Instead of calculating flows from known concentrations (a bottom-up approach), we start from known extraction volumes and fertilizer use, and we estimate the material content of traded goods by fitting them within a global flow model. In this framework, the system boundaries are defined by phosphate rock mining and fertilizer application.

Our model allows us to estimate, for the first time, the global, trade-based flows of phosphorus prior to biomass production. It captures transfers of P—whether in raw phosphate rock, intermediates like phosphoric acid, or final fertilizer products—between countries for agricultural use. This approach enables a detailed reconstruction of the first round of global phosphorus flows, forming a foundation for more accurate assessments of supply security and system resilience. Furthermore, the method is generalizable and can be adapted to other resource flows beyond phosphorus.

2. Materials and Methods

2.1. Overview

It is important to note that at the global level, the most reliable component of trade data is the monetary value of traded goods. This is because in most countries, trade data originates from customs declarations, where monetary values are essential for determining tariffs and duties. While quantity data is often included, it can be less reliable and has only been systematically available since 2006—insufficient for the longitudinal analysis conducted in this study.

Traditional material flow analysis typically relies on physical quantity data combined with estimates of material concentrations to derive flows. Monetary-based flows are more common when multi-regional input–output data is used (MRIO). This allows the disaggregation of flows on a sectoral level—but for many applications, including the P flows before biomass production, it is not detailed enough, see also [24,25]. In contrast, our method is designed to work directly with monetary trade values. Since we aim to estimate relative shares of global trade rather than absolute quantities, using value data is sufficient for our purposes, as detailed in Section 2.3. Additionally, trade values often implicitly reflect product quality or concentration (e.g., higher-grade materials usually command higher prices), which can serve as a proxy for material content.

Trade data is reported at varying levels of detail. For cross-country comparability, we use the Harmonized System (HS) at the 6-digit level, which includes about 5400 product categories. While this level ensures broad international comparability, individual product categories still contain a degree of heterogeneity.

Trade data is not without its challenges: gaps, inconsistencies, and valuation differences—including those arising from exchange rate fluctuations—are well-documented [26,27]. To address these issues, we use a cleaned and reconciled version of the UN Comtrade database, published as Atlas [28], where import and export values are harmonized and reported on an FOB (free on board) basis.

In our analysis, we approximate the flow of phosphorus between countries using annual aggregate trade values. To derive physical flows, we estimate the average phosphorus content per USD for each relevant product category. These estimates allow us to convert value-based flows into material flows. The total of these category-specific flows is constrained to match known global phosphate flows for each year, as defined by the boundaries of our system.

Our system boundaries are on the one side set by P production, approximated by phosphate rock mining data by country. On the other side, they are set by the amount of P used in fertilizer application by country. To align data across production, trade, and use, we normalize country-level values relative to total global values in each year. This produces a flow matrix F_{ij} where each entry in row i represents the fraction of global phosphorus mined in country i that is ultimately used in country j . Row sums of F represent the share of global phosphorus mined in a given country. Column sums represent the share of global phosphorus used in a given country. The entire matrix is normalized such that all elements sum to 1. To convert these shares into absolute quantities (e.g., in metric tons of P_2O_5), the values can be multiplied by the total global phosphate availability in each year (e.g., as reported by a geological survey). This yields a detailed country-by-country breakdown of the origins and destinations of phosphorus applied as fertilizer.

2.2. Data

Data on the mining of phosphate rock (in the following abbreviated as PR) for the period from 2001 to 2022 was obtained from the World Mining database [29]. This dataset contains information on global mining activity; in particular, this includes 39 countries with the current ability to mine PR, of which 37 reported mining in 2022. We are aware that other data sources exist, especially for data on mining, yet we choose World Mining because this source is very comprehensive, especially for smaller countries. For an overview of data sources on phosphate and the related problems, the reader is referred to [30]. The total amount mined in 2022 was 71.1 million metr. t of P_2O_5 , see the left panel of Figure 1.

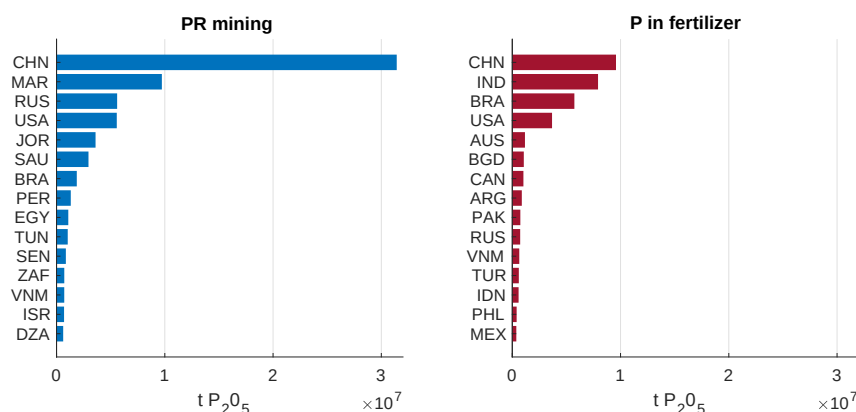


Figure 1. World's largest producers of phosphate rock (**left panel**) and largest phosphoric fertilizer users (**right panel**) in 2022 according to World Mining data and the FAO.

For the data on trade, we utilize the Comtrade database [31] in the version provided as Atlas [28]. We use data from those product categories that are known to contain significant amounts of P (verified in discussions with industry experts). We utilize data on the trade of products classified (according to the HS classification) in the categories 251010, 251020, 280910, 280920, 283510, 283521, 283522, 283523, 283524, 283525, 283526, 283529, 283531, 283539, 310310, 310320, 310390, 310510, 310520, 310530, 310540, 310551, 310559, 310560, and 310590. These 25 categories can be hierarchically aggregated into 5 more general categories, namely, natural calcium phosphate (phosphate rock), phosphoric acid, phosphates (mostly industrial use), phosphatic fertilizers, and mixed fertilizers.

The database contains information on the amounts traded on a bilateral basis in USD for 234 countries. For example, in 2022, the total trade volume for all the goods in the categories mentioned above amounted to USD 62.1 billion. Of this, USD 4.68 billion was traded in natural calcium phosphates, USD 7.25 billion was traded in phosphoric acid, USD 5.66 billion was traded in phosphates, USD 3.72 billion was traded in phosphatic fertilizers, and USD 40.82 billion was traded in mixed fertilizers. However, in this study, we will consider a weighted sum of these categories (details in Section 2.4). For an overview of global trade, the reader is referred to Figure A1 in the Appendix.

The use of phosphate can be approximated by data from the FAO [32]. This dataset contains information on the import, export, production, and agricultural use of fertilizer in 167 countries (these countries are responsible for roughly 95% of P-related trade). This data is typically available with a delay of 2 years, which determines that the current endpoint for our analysis is 2022. For example, the agricultural use of P in fertilizer for 2022 is reported at 41.9 million metr. t of P₂O₅, see also the right panel of Figure 1. Hence, when one compares the figures of PR mining and P fertilizer use (and averages these over a few years), one could come to the conclusion that about 70% of mined phosphate rock ends up as fertilizer. Considering losses in the production processes of fertilizer and a tendency toward under-reporting in fertilizer use, we know that the actual share is in fact higher. Therefore, studies have looked at the technical processes that are involved in fertilizer production. For example, we know that about 90% of processed mined phosphate is used in a chemical wet process and mostly converted to phosphoric acid, out of which about 82% is used to produce fertilizer. Considering further that 15% of P fertilizers are not made from phosphoric acid, we can approximate a lower bound of 80% of total P used in fertilizer [33]. Other studies estimate a higher fraction of P fertilizer use; at the upper end of the spectrum, the FAO estimated that 90% of mined PR is used by the fertilizer industry [34]. These differences can partly be explained by slightly varying approximations of the losses in the

fertilizer production processes, as well as by differences in the accounting for animal feed supplements ($\sim 7\%$).

In any case, we note that in our analysis we make the simplifying assumption that the entire PR production (and no other source) is used as fertilizer. This means that the P used for other purposes, e.g., via phosphorus compounds, see [35], is handled as if it flows in the same way. We also implicitly assume that mining and use take place in the same year, and we neglect the effect of changes in stocks as well as losses.

2.3. Trade-Based Flows

The phosphate trade network reflects large global dissimilarities between the mining and the agricultural uses of P. The shares in P-related trade over time are visualized in Figure 2. China, Morocco, and Russia are large exporters of P-related goods. India and Brazil are the largest importers. The position of the USA is unique because of the very high share of locally used P. Still, the USA is a net exporter, since it exports large amounts of fertilizer, which dominates its value-based P trade statistics.

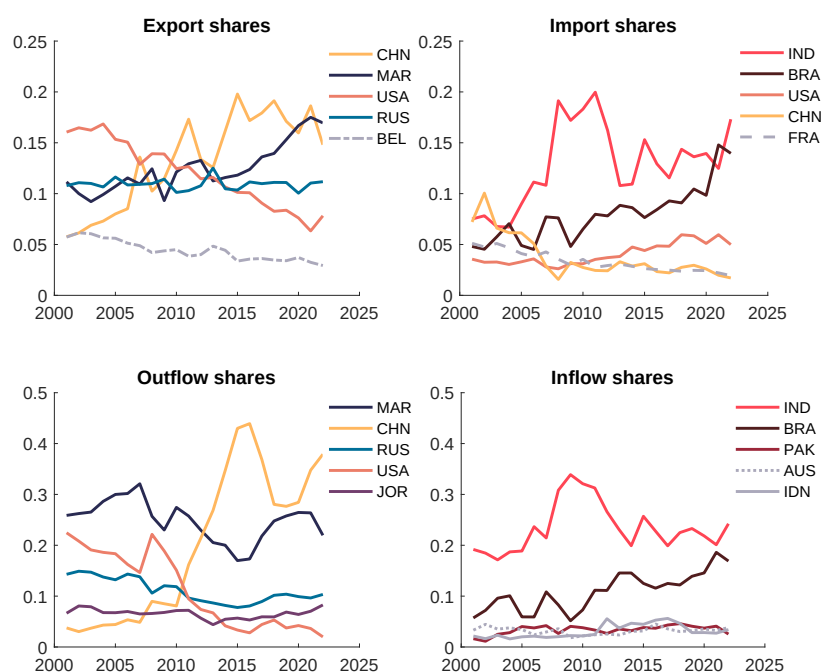


Figure 2. Shares in P-related trade by country over time. The top panels show the five largest exporters and importers of P-related goods. The United States and China are the only countries that appear in both panels. The bottom panels show the largest exporters and importers in a material sense, as derived from our analysis (F^{M5}). The rise and fall back of the Chinese outflow share is the most noticeable change over time.

The trade network is, however, not sufficient to draw conclusions from about the flow of P in a material sense (see the bottom panels of Figure 2). One reason is that goods in the different product categories contain P in very different amounts per USD value. The second reason is that countries can appear as net exporters of P while not mining any phosphate rock at all. This can happen because they act as a hub for the trade and production of P fertilizer. Third, we must account for flows within countries; this concerns fertilizer that is used in the same country where phosphate rock is mined.

In the following, we will show that these problems can, however, be overcome by transforming the matrix of imports and exports into a matrix of shares of net flows. We achieve this by applying some accounting identities and by re-evaluating indirect P flows between countries where necessary.

First of all, let us start by defining two vectors that carry the information on PR mining and on the agricultural use of P-based fertilizer by country, M^* and U^* . The data is taken from the World Mining and FAOSTAT databases, respectively. Both row vectors contain N entries, where N is the number of countries, in our case 234, plus 1 dummy for trades to undeclared places. For further calculations, it will be useful to normalize these vectors such that they represent the shares in global mining and use, respectively. For the countries for which no data on fertilizer use is available we assume that their share is the same as their share of P net imports. Hence, we define

$$M_i = \frac{M_i^*}{\sum_{i=1}^N M_i^*} \quad (1)$$

and

$$U_i = \frac{U_i^*}{\sum_{i=1}^N U_i^*}. \quad (2)$$

For each pair of countries, the dataset contains the traded value in USD for the $C = 25$ product (goods) categories. These can be represented by separate matrices $G_{1...C}$ with dimensions $N \times N$. In these matrices, each entry in row i represents exports of country i towards the country in column j . Since the imports and exports in the database have been harmonized, the matrices can equivalently be interpreted in a column-wise fashion; thus, entries in column j represent imports to country j from country i .

To utilize the information on P trade to inform us about actual P flows, it is useful to first consider only the net in P trade. For this, we can first calculate a matrix of net exports by subtracting imports from exports for each pair of countries and by dropping negative values; hence,

$$G_{i,j}^{net} = \max(0, (G - G')_{i,j}) . \quad (3)$$

To account for the fact that each of these categories represents goods with a specific average P content, a weighting for these categories is necessary. Hence, in the following we will work with matrices of weighted P trade T^{net} ,

$$T^{net} = \sum_{c=1}^C w_c G_c^{net}, \quad (4)$$

where w_c is the weight given to product category c and $\sum_c w_c = 1$. For the moment, however, we assume equal weights for all product categories. We will discuss optimized weighting schemes in Section 2.4.

We further remove reciprocal flows between countries from T^{net} through different product categories by applying Equation (3) equivalently. We then normalize the matrix of net exports by the total and obtain

$$T^{norm} = \frac{T^{net}}{\sum_{i=1}^N \sum_{j=1}^N T_{i,j}^{net}}. \quad (5)$$

To derive a complete picture of trade-based flows, we further must realize that we are missing information on P that is not traded but that stays within the country where it is mined. We can, however, approximate this data by assuming that exported P must originate from mined P that has not been used domestically or from net imports Im_i from other countries. The net imports can be calculated from $Im_i = \gamma_{tr} \sum_j T_{i,j}^{net}$, where γ_{tr} corrects for the overall share of traded vs. locally used P. A value of $\gamma_{tr} = 0.6$ was approximate from the aggregate data.

Hence, we can calculate a vector with the implied share of exported P, $\hat{E}$ as

$$\hat{E}_i = \max(0, M_i - U_i + Im_i) . \quad (6)$$

From this we can calculate a vector $\hat{L}$ with implied shares of P that remain locally as

$$\hat{L} = M - \hat{E} . \quad (7)$$

This now gives us the opportunity to include local P use as the diagonal entries into the normalized trade matrix, which (after re-scaling) results in the flow matrix F^{M1} , the first version of a P flow representation. In this matrix, each element represents the material share of P moved from country i to country j .

$$F^{M1} = T^{norm} \left(1 - \sum_{i=1}^N \hat{L}_i \right) + \hat{L}I , \quad (8)$$

where I is an $N \times N$ identity matrix.

2.4. Optimal Category Weights and Fit

To validate whether any flow matrix F is a good approximation of the true flow of materials in the system, we have to evaluate if it resembles the distribution of PR mining and P used in agriculture correctly. Note that a mathematical solution for an optimal flow is $F^{opt} = M U'$, which would imply flows proportional to local use from all countries that mine PR. We are, however, interested in a flow matrix that resembles the actual material flows, which are distinct from F^{opt} and for which trade flows are known to be a latent version.

Hence, we will assume that the reported data on PR mining and the data on agricultural use of P represent the true shares of P origination and use, which of course is a simplification. For the analysis of the fit, it makes sense to use the relationships between the matrix F and the vectors representing the shares of P mining and use, M and U . We can derive a vector of predicted P use $\hat{U}$ by multiplying with the flow matrix

$$\hat{U} = J F , \quad (9)$$

where J is a vector of ones with dimensions $1 \times N$. Similarly, we can predict the implied mining by using the transposed value of F and calculating

$$\hat{M} = J F' . \quad (10)$$

These relationships can also be expressed as the row and column sums of F . We note that Equation (7) implies that the entries on the main diagonal of F contain information on U and M by construction. We can use the predictions and compare $\hat{U}$ with U and $\hat{M}$ with M to evaluate the accuracy of F . We can in fact use this evaluation to solve one remaining problem in the calculation of F in the first place.

In particular, we have to investigate if the weighting scheme in the calculation of the trade matrix (see Equation (4)) can be improved. In an ideal setting, we would try to calculate the exact P content of each trade relationship that each country has with each other country for each product category. This, however, is not feasible, due to resource constraints and data availability. We can, however, obtain the approximate P content indirectly by estimating the optimal weighting scheme that results in the flow matrix that gives us the most likely actual P flows between countries.

For this purpose, we define a function D that evaluates the difference between the estimated and the observed quantities in terms of a weighted sum of absolute errors.

$$D = \alpha_U \sum_{i=1}^N |\hat{U}_i - U_i| + \alpha_M \sum_{i=1}^N |\hat{M}_i - M_i| \quad (11)$$

Since we are interested in minimizing the misallocation of P flows globally, we found that absolute errors are in this case a better choice than squared errors, since the latter would (due to the size distribution of countries) lead to an undesirable focus mainly on fitting a few large countries' P data. We obtain optimal weights by employing a non-linear optimization of D by choosing positive weights c in Equation (4) such that D is minimized. Repeating the calculations described in Section 2.3 generates an improved flow matrix F^{M2} .

We found that it is useful to give the mining part of Equation (11) a slightly higher weight than the use part. This is caused by the fact that the fertilizer use data is rather noisy, because for many countries figures are estimated or approximated. In particular, we chose $\alpha_M = \frac{2}{3}$ and $\alpha_U = \frac{1}{3}$. We found that the exact weighting of $\alpha_{U,M}$ has only negligible effects on our results (see also Section 2.8). Values of $\alpha_U > 0.5$ will, however, lead to noisy estimation results. Product categories that contain only very few entries were omitted to guarantee that an optimum for (11) could be found. We found that it is sufficient to include the 11 product categories with the most volume (which account for 90 % of the overall trade in the 25 P-related categories). While it is numerically possible to include up to around 16 categories in the estimation, this does not improve the overall fit of the estimated P flows.

The difference between the flow matrices F^{M1} and F^{M2} is that the latter is now based more heavily on product categories that are responsible for a high material P flow, irrespective of the monetary value. In the calculation of the flow, we now mainly rely on the information from the trade in phosphoric acid, DAP and MAP fertilizers, and calcium phosphate. To a lesser degree, superphosphates, sodium triphosphate, and other fertilizer forms are also considered. The optimal weighting scheme shows some variation from year to year. For an example, see Figure A2 in the Appendix.

Table 1 gives an overview of the fit. We note that in all our analyses, we separately estimate the weights and calculate the flow matrices for the years 2001–2022. While using net exports already produces a good fit of the flow matrix with the data, we observe that just by optimizing the weights, we can improve the average R^2 from 94% to 98% (first vs. second column). In the following, we will investigate how much further adjustments to the trade data can improve these results.

Table 1. Fit of the flow matrix with observed PR mining and P use. The table shows the average R^2 value (for the years 2001–2022) for the fit of F with M and U separately as well as combined, as well as the standard deviation. Further, we show the average D as well as its standard deviation. Note that F^{M2} to F^{M6} were calculated based on weights optimized for each model.

Model	F^{M1} Trade	F^{M2} Opt. Weights	F^{M3} Corr. Origin	F^{M4} Corr. Trade	F^{M5} Corr. M	F^{M6} Weights α_M
$\langle R^2_{min} \rangle$	0.9229	0.9770	0.9835	0.9863	0.9977	0.9980
$\langle R^2_{use} \rangle$	0.9537	0.9758	0.9840	0.9866	0.9896	0.9762
$\langle R^2 \rangle$	0.9383	0.9762	0.9837	0.9865	0.9937	0.9871
$\pm$	0.0183	0.0079	0.0062	0.0057	0.0045	0.0053
$\langle D \rangle$	0.3721	0.2092	0.1588	0.1493	0.0823	0.1079
$\pm$	0.0350	0.0273	0.0309	0.0287	0.0260	0.0236

2.5. Correcting for PR Origination

In our analysis, we rely on the fact that overall, the recorded net exports must resemble the actual flow of P to a large extent. Some distortion by trade activity, i.e., the fact that P may travel through several countries and possibly several product categories before

being used, is inevitable. While we cannot correct for the entirety of these effects, it is possible to make noticeable improvements by using information on the mining activity in different countries.

When we evaluate the row sums of F^{M2} , we observe that some countries show up as net exporters of P without having sufficient mining activity. To derive a flow matrix that is consistent with the qualitative aspects of the mining data, this aspect must be corrected. This means that we have to shift these exports to the most likely actual origin, i.e., the countries that mine PR.

To achieve this, we use the following algorithm. For each country i that is not mining PR, we consider its excess P exports x_i given by entries in row i in F^{M2} ,

$$x_i = \sum_{j=1}^N F_{i,j}^{M2}. \quad (12)$$

We then calculate the import shares of country i from countries j that do mine. We define the set of these countries as $j \in m$.

$$s_{m,i}^{imp} = \frac{F_{m,i}^{M2}}{\sum_m F_{m,i}^{M2}}, \quad (13)$$

Equivalently, the export shares to all countries j are given by

$$s_{i,j}^{exp} = \frac{F_{i,j}^{M2}}{\sum_j F_{i,j}^{M2}}. \quad (14)$$

Further, we calculate the amount of imports into country i that are used locally and are not exported, which is

$$l_i = \max(0, \sum_{i=1}^N F_{i,j}^{M2} - \sum_{i=1}^N F_{j,i}^{M2}). \quad (15)$$

In the flow matrix, we then add the excess exports of country i to the exports of countries that mine PR, given by $x_i(s_i^{imp} s_i^{exp})$. Here we make use of the fact that s_i^{imp} is a row vector and s_i^{exp} is a column vector. We then remove these exports from the export of the non-mining countries. Further, we must scale down the imports from the mining countries to the excess exporter by multiplying these imports by $l_i(\sum_i F_{i,j}^{M2})^{-1}$, which means that we correct the imports to the amount that the country itself uses. We denote the resulting matrix as F^{M2*} . In total, this procedure removes about 5% of the flows accounted for in F^{M2} . Since this matrix was normalized (see Equation (8)), we must reinstate this normalization after our correction algorithm. To achieve this and to derive our improved flow matrix F^{M3} , we have to consider that we should only re-scale the trade (off-diagonal) part of F^{M2*} , since the entries on the main diagonal were calculated from sources for which the absolute value in terms of P was known. The normalization that takes this into account is given by

$$F^{M3} = \frac{F^{M2*} - \text{diag}(F^{M2*})}{\sum_i \sum_j F_{ij}^{M2*}} \left(1 - \text{tr}(F^{M2})\right) + \text{diag}(F^{M2}). \quad (16)$$

The statistics in Table 1 show that these approximate corrections do in fact improve the fit of the model significantly. Interestingly, the fit improves not only with the mining data but also with the use data, which indicates that the correction also has a positive indirect effect on the accuracy of the column sums of the flow matrix.

2.6. Correcting for Trade

In the previous section, we showed how we correct the data for countries that do not mine phosphate rock. For these countries, it was self-evident that they could not be the source of relevant phosphate flows. For countries that do mine PR, a similar procedure can be used to approximately correct for trade flows where an intermediary is involved in a trade chain. The most relevant case here is probably the USA, which is both an importer and an exporter of phosphate, as well as a producer. Until now, our calculations implicitly assumed that, for example, imports to the USA have completely been used in the USA and that all exports from the USA originate from locally mined PR. A more realistic assumption is, of course, that imported P is both used domestically and re-exported (albeit likely in processed form). The share that is re-exported must be attributed to the original source country.

To analyze such trade chains, it is useful to look at a flow matrix with the domestic markets removed and start by defining a matrix $F^{D3} = F^{M3} - \text{diag}(F^{M3})$. We will now look at all the countries with PR mining (countries with less than 1% of global PR production were excluded from this correction) and again label this set of countries as m . We can calculate how much P can *potentially* flow through a country i as

$$p_i = \min \left(\sum_{j=1}^N F_{ij}^{D3}, \sum_{i=1}^N F_{ij}^{D3} \right). \quad (17)$$

The in- and outflows for a country i in terms of shares of the total flow are given by the vectors

$$f_i^{\text{in}} = \frac{F_{m,i}^{D3}}{\sum_{i=1}^N F_{m,i}^{D3}} \quad (18)$$

and

$$f_i^{\text{out}} = \frac{F_{i,j}^{D3}}{\sum_{j=1}^N F_{i,j}^{D3}}. \quad (19)$$

We define the share of the potential through-flow that we think should be re-accounted for as γ_p . We can now correct the flows by adding the through-flow of each country under consideration to the outflow of the original exporter by the operation

$$F^{M3*} = F^{M3} + \gamma_p p_i (f_i^{\text{in}} f_i^{\text{out}}). \quad (20)$$

We then have to reduce the outflow of country i by $\gamma_p p_i f_i^{\text{out}}$ and reduce the inflow by $\gamma_p p_i f_i^{\text{in}}$. Re-normalization of the resulting matrix (see Equation (16)) gives F^{M4} .

The parameter γ_p can be approximated by evaluating the fit of the model for values $0 \leq \gamma_p \leq 1$. We found the optimum to be 0.4, which means that countries that mine PR re-export on average 40% of the P that they import in addition to their own production. We note that in reality, longer chains of trade than considered here exist; however, we found that these are very likely not relevant for our results. This has two reasons. The first is that our analysis is already based on shares of net exports. The second reason is that for longer chains to be relevant, we would have to observe two countries with large trade volume in the middle of such a chain, which we do not. In fact, the only case where we do suspect longer chains of trade are smaller, remote countries (for example in Africa), which have only small P inflow. Also, for such countries, the trade data is often inaccurate, which makes 2nd-order corrections impractical.

The statistics of the improvement in fit from this step are shown in Table 1. The difference between F^{M3} and F^{M4} is, in fact, relatively small compared with the previous correction steps.

2.7. Scaling Outflow to Mining Data

The last correction deals with the overall differences between the PR production data and the implied mining of F^{M4} . Assuming that the PR mining data has a good overall level of accuracy (and is less distorted by price variations than the trade data), we can scale the entries in the rows of the mining countries in F^{M4} in such a way that their sum will closely match M . This operation is, of course, only useful as long as we do not negatively impact the column sums in terms of its prediction of fertilizer use. We note that this optional step is, in principle, an extension to the steps taken in Section 2.3, with the difference that here we condition the entire row sums (and not only the diagonal elements) of the flow matrix on M .

Again, we define a partial flow matrix without the local use as $F^{D4} = F^{M4} - \text{diag}(F^{M4})$. We then calculate how much P outflow should be available in each country. This share is given by

$$\hat{f}_i^{\text{out}} = M_i - F_{ii}^{M4}, \quad (21)$$

i.e., the mining in country i minus the local use. We then calculate a correction factor r_i based on the ratio of observed versus expected outflow of country i , given by

$$r_i = \left(\frac{\sum_{j=1}^N F_{ij}^{D4}}{\hat{f}_i^{\text{out}}} - 1 \right) \gamma_r + 1, \quad (22)$$

where γ_r is a damping factor. $\gamma_r = 1$ in this case. The damping factor is an optional parameter that can protect against adverse effects on the fit with the use data if necessary, see also the next section. A new flow matrix F^{M5} can now be calculated by dividing the entries of rows i in F^{M4} by the corresponding correction factor r_i . We avoid correcting countries with very low PR production and trade flows by demanding that $M_i > 0.005$ and $\hat{f}_i^{\text{out}} > 0.003$. The matrix is then re-normalized equivalent to Equation (16). The statistics in Table 1 show that this correction in fact does improve the overall fit significantly. In particular, we increase the consistency of the flow matrix with the PR mining data without losing consistency with the fertilizer use data. We note that when comparing the fit with other models, one should consider that in this step, we endogenized M_i .

2.8. Simplifying the Estimation

A final consideration is whether the setup for finding the optimal weights of the product categories can be simplified. This is important in order to gain insights about the applicability of this method to other resources or goods. While for the case of P both the origin and the (preliminary) end use are relatively easy to determine, we can assume that for many other cases, use data will not be available in comparable accuracy, since the variety in terms of applications is typically much higher than it is for P.

This means that one will typically be in a situation where a product category weighting will have to be estimated based only on data on the origination. For the case of P, this would mean that we would modify Equation (11), i.e., set the weight for the fertilizer use part α_U to 0.

We re-estimated the model described in Section 2.7 with this setting and found that the resulting flow matrix F^{M6} has a fit that is comparable with variants discussed in previous sections. We found that in this case, a slight dampening of the correction factor in Equation (22) is useful by setting $\gamma_r = 0.9$. The fit with the mining data is very similar to that of F^{M5} , while the fit with the use data is only slightly worse. This might be seen as a good indication that an application of the presented model to other cases with more limited data quality should be feasible.

3. Results

3.1. Global P Flow Network

While the original trade data already provides a useful approximation of the P flows per se, it is worth noting that the ranking of the countries in terms of exports and imports differs from the ranking in terms of the material flow. This can already be observed from the aggregated data presented in the bottom panels of Figure 2. For example, we observe that Belgium appears among the P exporters but not in the panel summarizing P outflow. Similarly, the USA does not appear in the panel describing inflow, since from the perspective of material flow, only a little P used in the USA originates from outside the country. Also, the massive changes with respect to the Chinese contribution to global phosphate flows become much clearer by looking at the material flow of P, see also [36].

The flow of P is visualized in more detail in Figure 3. The diagram shows the flow of P based on the derived flow matrix for 2022 (F^{M5}). All data on the approximated flows for 2001–2022 is available for download in spreadsheet form (<https://cloud.tugraz.at/index.php/s/dH43JQgAfB4c65r> (accessed on 20 July 2025)). Color-coded arrows show the flow of P between as well as within countries. The cumulative amounts for each country are shown around the circle. These have been calculated by multiplying the shares of the flow by the total amount of PR mined. Note that by design, all flows are counted twice, once in the country of origin and once in the country of use.

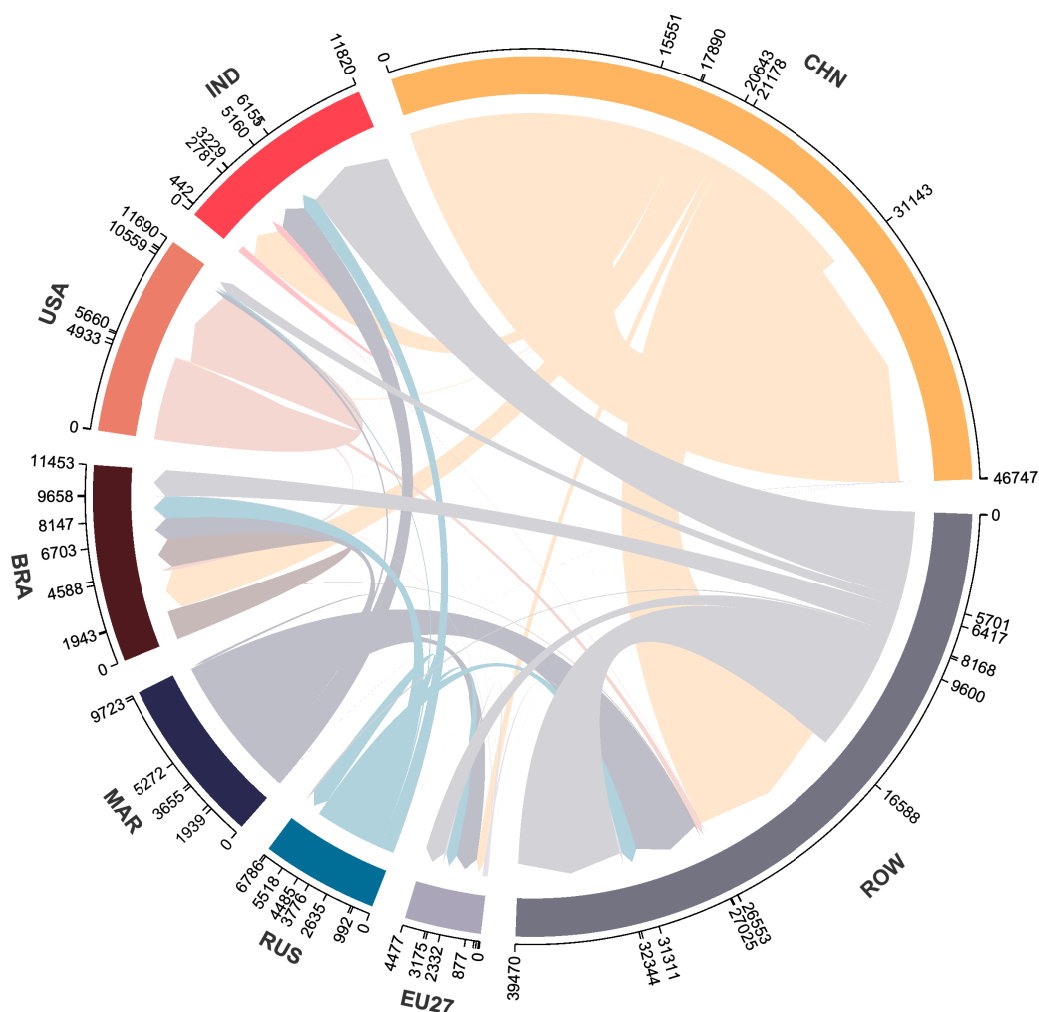


Figure 3. P flow diagram based on F^{M5} for 2022 for the six single countries with the largest flows as well as for the EU27 and the rest of the world (ROW), P_2O_5 (thousands of tons).

China is the country that is involved in the largest amount of P flow. It supplies almost all the P for its own consumption while also being a large supplier for the rest of the world. The other large supplier is Morocco, whose domestic demand is negligible. Also, the USA mines enough PR to cover its P demand, and additional inflows roughly cancel out its outflow to Brazil and some other countries. The other large consumers, India, the EU, and Brazil, differ significantly in their mix of P source countries. Brazil has some mining of its own, and it meets the rest of its demand by inflow from a mix of countries. India's mining is (relative to its size) almost negligible. It relies on inflow from Jordan (here shown as part of ROW), China, Morocco, Saudi Arabia and Russia. The EU27 relies almost entirely on imports; among the most important sources are Morocco and Russia. For a visualization of the flows at an earlier point in time (2001), the reader is referred to Figure A5 in the Appendix.

A more detailed breakdown of the in- and outflows of the most important countries is provided in Figure 4. Here, flows within a country are omitted. The two top panels show the P outflows of China and Morocco, while the two bottom panels show the inflows of Brazil and India.

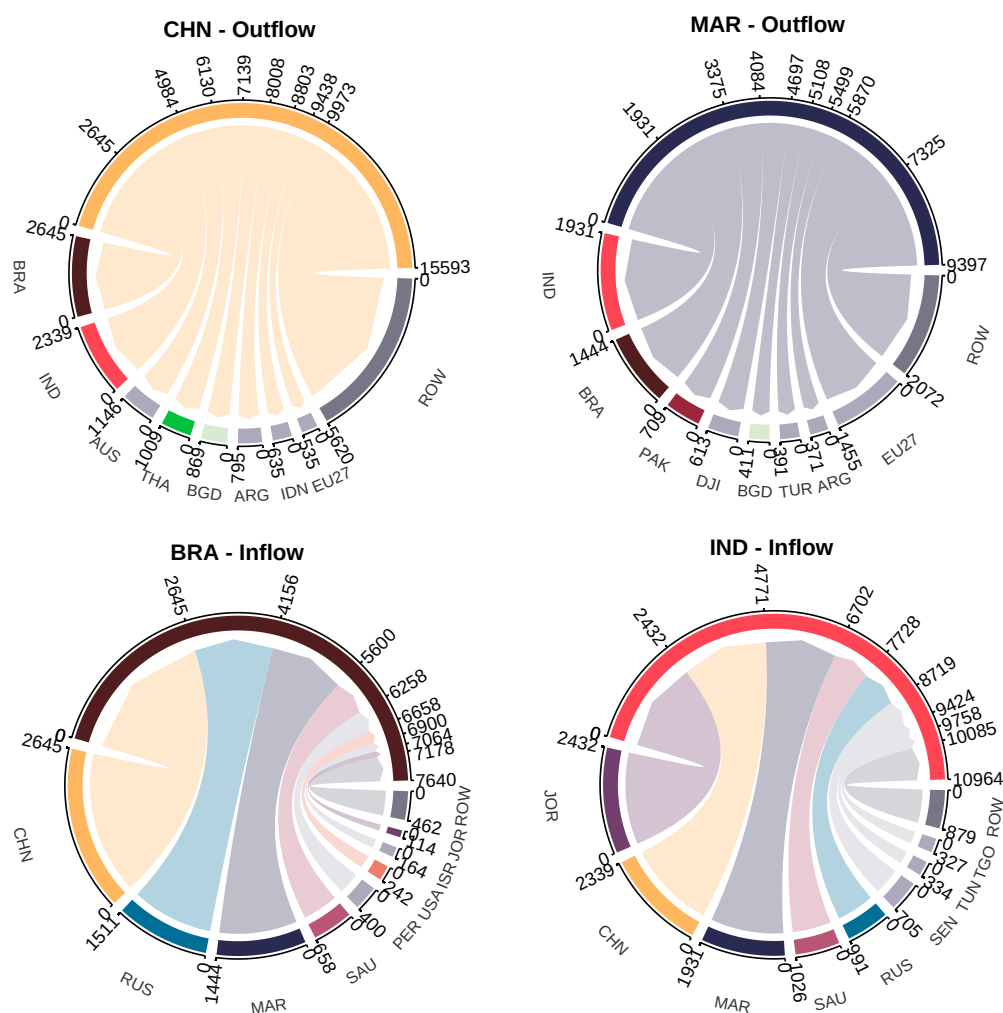


Figure 4. Outflows of P for China and Morocco (top panels) and inflows of P for Brazil and India (bottom panels) for 2022, P_2O_5 (thousands of tons).

The estimated P flows can serve as the foundation for an analysis of counterfactual supply shortfalls. The reasons for such shortfalls can be environmental. Recently, however, intended disruptions caused by trade wars or armed conflict have also gained relevance.

For example, we can verify that the countries most affected by a shortfall in Chinese supply would be Brazil, India, and Australia. Similarly, in the case of a Moroccan shortfall, the countries most affected (in terms of absolute P_2O_5 inflow in 2022) would be India, Brazil, and Pakistan. In the case of Russia, the most affected countries would be Brazil, India, and Belgium.

An additional application of these short-run projections (outside the scope of this paper) could be the approximation of effects on regional biomass and, consequently, food production. Such an analysis would need to consider data on fertilizer demand (taking into account soil conditions and P accumulation) and the ability of farmers to pass on fertilizer price increases together with potential shortfalls in P inflows. In the medium to long run, adjustments in P markets, crop selection, and recycling potentials would also have to be taken into account [37–39].

3.2. Validation

Since there are no previous studies with comparable coverage, the validation of our estimated material P flows relies on two parts. The most important part is the analysis of the fit between the estimated flows and data on mining and fertilizer use, as described in Section 2.4 and Table 1. For an analysis of the fit at the country level, the reader is referred to Figure A3 in the Appendix. In general, we find that the fit—especially for the four largest PR producers—is reasonable. The fit of the P use data shows more variation. We find that our estimates for countries where FAO data is based on official statistics tend to be fairly accurate, while countries where the data is based on surveys or estimates exhibit more outliers. The second part of the validation is a comparison with existing data on P-related trade. The dataset that is currently closest to ours is the Fertilizer Trade Matrix of FAOSTAT [32,40]. This dataset contains estimates as well as imputed values of P_2O_5 equivalents of straight and compound fertilizers. However, it does not include traded phosphoric acid or domestic P flows, and it is not necessarily consistent with fertilizer use and production data. Overall, we estimate that this dataset covers about 40% of global P flows before biomass production. We used this dataset to qualitatively validate the pairwise flows between countries, assuming that the net exports derived from it are representative of total pairwise flows. In particular, we analyzed the 200 largest flows estimated in our model and compared the flows for corresponding country pairs with the Fertilizer Trade Matrix data. These flows are in reasonable alignment and show rank correlations of about 0.77; for details, see Figure A4 in the Appendix.

3.3. Dynamics of Flows

Besides looking at the flows for a particular year, it is necessary to look at the dynamics of these flows. We measure the year-by-year changes in the flow matrix by calculating the weighted Jaccard similarity [41] between matrices as

$$J_{t,t-1} = \frac{\sum_{i=1}^N \sum_{j=1}^N \min(F_{i,j,t}, F_{i,j,t-1})}{\sum_{i=1}^N \sum_{j=1}^N \max(F_{i,j,t}, F_{i,j,t-1})}. \quad (23)$$

Hence, a value of J equal to 1 would indicate identical flow in successive years, while a value of 0 would indicate that they are completely different.

The left panel of Figure 5 shows the year-to-year changes of the flow matrix. They vary around a value of 0.75, with the lowest around the years 2007–2008, which coincides with a time when P prices peaked, imports to India increased, and China's exports were volatile, see also Figures 2 and A1 as well as [42]. More changes, and thus a drop in similarity is also observed in 2022, which coincides with the start of the Ukraine war and also higher, more volatile prices (see also Figure A1 in the Appendix).

It is obvious that P flows show some persistence over time, and we can analyze this in more detail by looking at the decay of the Jaccard similarity. This means that we calculate J for flow matrices which are an increasing number of years apart. The results in the right panel of Figure 5 indicate that Jaccard similarity for P flows decays slowly. This gives an indication of the predictability of future P flows and the speed with which changes in P flows occur.

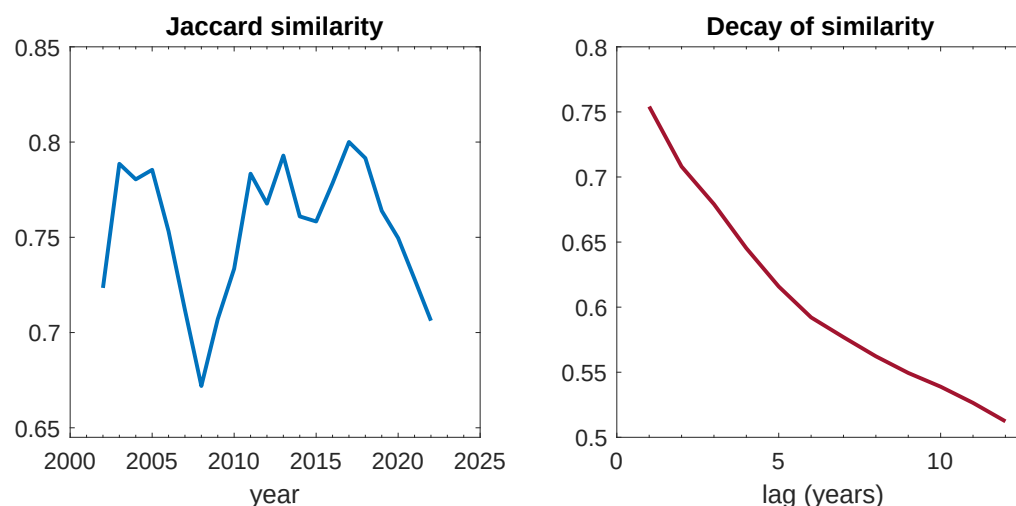


Figure 5. Jaccard similarity for successive years of the flow matrix F^{M4} (left panel) and decay (right panel).

3.4. Resilience

One important application of country-level material flow analysis is the assessment of supply security and resilience. A widely used metric for this purpose is the Herfindahl–Hirschman Index (HHI), which quantifies market concentration based on the distribution of market shares [43,44]. In the context of raw materials, the HHI is typically calculated using each country's share in global production. For a more comprehensive view of supply security, this measure should ideally be combined with other country-level risk factors.

Let s_i represent the market share of country i (in percentage terms). The HHI is then calculated as

$$HHI = \sum_{i=1}^N s_i^2. \quad (24)$$

The HHI ranges from just above 0 (perfect competition) to 10,000 (monopoly). Conventionally, HHI values between 1500 and 2500 indicate moderate market concentration, while values above 2500 signal high concentration. These thresholds stem from USA antitrust guidelines on horizontal mergers. While recent revisions have made the thresholds more stringent [45], the older limits are still commonly used in raw material supply assessments.

The top panel of Figure 6 illustrates the HHI for phosphate based on mine production. Our results replicate the findings of [46], showing that the global HHI for phosphate has gradually increased—from values just below 1800 to around 2500—with some year-to-year fluctuations. When using our own model-based country-level estimates of phosphate flows, we find qualitatively similar results (partly by construction).

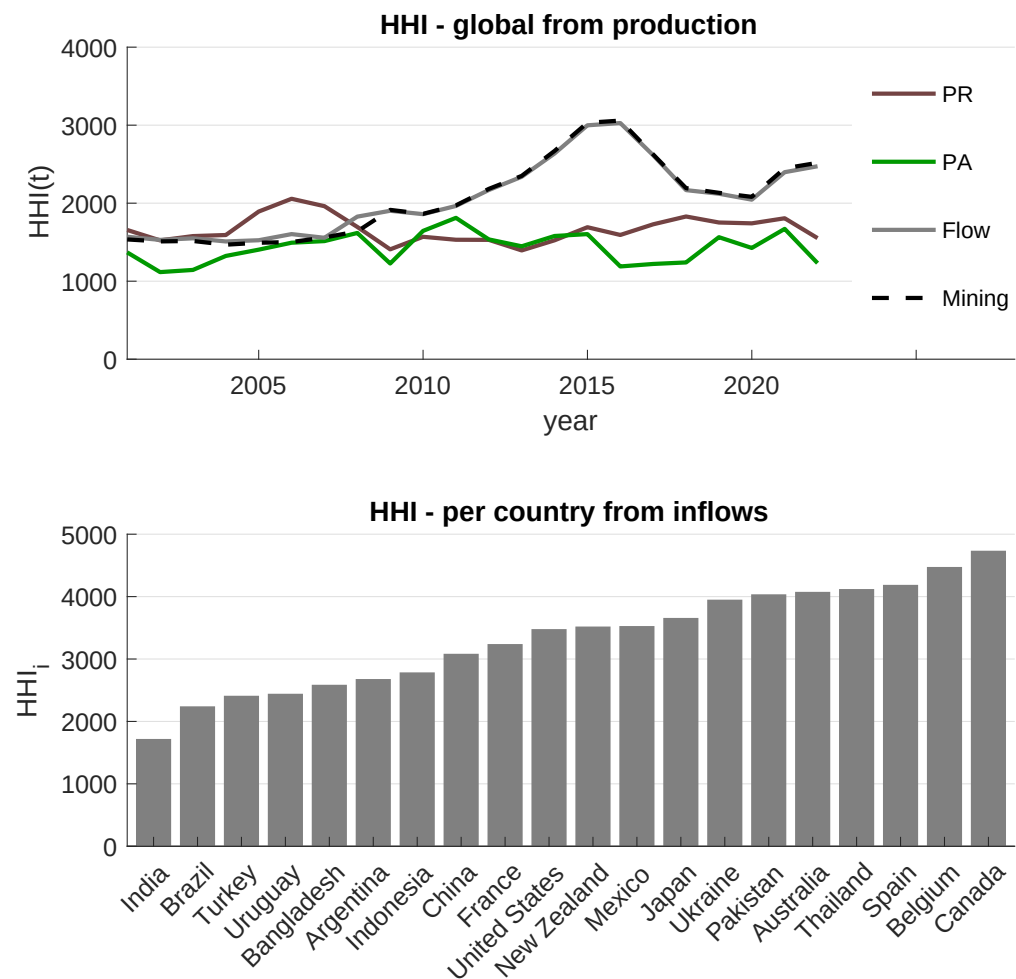


Figure 6. HHI index for P over time on the global level (**top panel**) and Inflow-HHI per country (median values for the same time period, **bottom panel**).

To provide further context, we also computed HHIs based on export market shares for phosphate rock and phosphoric acid. Up until 2011, these results closely tracked the production-based HHI. However, post-2011, they began to diverge. The rising HHI for mine production reflects the sharp increase in China's phosphate rock production between 2010 and 2016. Interestingly, this rise did not correspond to a similar increase in China's share of P-related exports. One plausible explanation is that the reported Chinese mining figures during that period may have been slightly overstated. Supporting this, we also observe a discrepancy between global mining and fertilizer use data during the same time frame, likely reflecting the same underlying issue.

More importantly, our estimated P flow data allows us to calculate a country-specific version of the HHI, which we refer to as the Inflow-HHI. This metric captures the concentration of phosphorus supply sources for each importing country. To compute it, we normalize each country's total phosphorus inflow (based on F^{M5}) to 100% and calculate the HHI based on the shares of imports from individual source countries, using the same formula as above.

The bottom panel of Figure 6 presents Inflow-HHI values for the 20 largest importing countries. Two key insights emerge. First, country-level HHIs are generally much higher than the global HHI, indicating greater concentration and thus higher vulnerability for individual countries. Second, there is significant variation among countries. For example, major importers like India and Brazil have Inflow-HHIs around 2000, suggesting moderate

concentration. In contrast, countries such as Spain, Belgium, and Canada exhibit HHIs exceeding 4000, indicating high dependency on a limited number of suppliers.

It is important to note that this Inflow-HHI reflects only the concentration of external supply sources. For countries with significant domestic phosphate production—such as the United States and China—the Inflow-HHI should be interpreted in the context of their overall import dependence.

4. Conclusions

This study demonstrates that trade data, when combined with other relevant data sources, such as extraction and use data, can be effectively used to approximate the flow of mineral resources—even with only limited prior knowledge about material concentrations. Specifically, our approach provides a meaningful representation of global phosphorus flows—encompassing phosphate rock, fertilizers, and related products—prior to biomass production. This offers a valuable foundation for analyzing vulnerabilities of country-level supply relationships, particularly relevant with respect to food security.

A key contribution of this work is the translation of nominal bilateral trade data into material flows of phosphorus, which enhances the accuracy of supply chain assessments. This is achieved through a top-down approach, involving the indirect estimation of material concentrations in traded goods, as well as by algorithms that correct data on net exports such that they can be interpreted as flows. Our method yields insights into the following:

- The origin of phosphorus flows;
- Their destinations and approximate material content;
- The resilience of national supply structures;
- The complex web of global dependencies in phosphorus trade.

We show that the resulting flows can be used for a significantly improved analysis of the resilience of phosphate supply, exemplified by the calculation of Inflow-HHIs at the country level. A more detailed analysis of potential crisis scenarios and the effects of supply disruptions on agricultural production remains for future research.

Further, the integration of multiple data sources also allows for the identification of inconsistencies between reported data and model-based expectations, offering a way to validate and improve existing datasets.

Finally, the approach developed here is generalizable. While demonstrated using phosphorus, it can be extended to other critical raw materials—such as sulfur, nitrogen, or potassium—that are essential for agriculture and industry.

Author Contributions: Conceptualization, M.R., M.B., and G.S.; Methodology, M.R.; Formal Analysis, M.R.; Data Curation, M.R.; Writing—Original Draft Preparation, M.R., M.B. and G.S.; Writing—Review and Editing, M.R., M.B. and G.S.; Visualization, M.R. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The flow matrices are available for download at <https://cloud.tugraz.at/index.php/s/dH43JQgAfB4c65r> (accessed on 20 July 2025). Source code is available upon request. All used data is publicly available.

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Appendix A

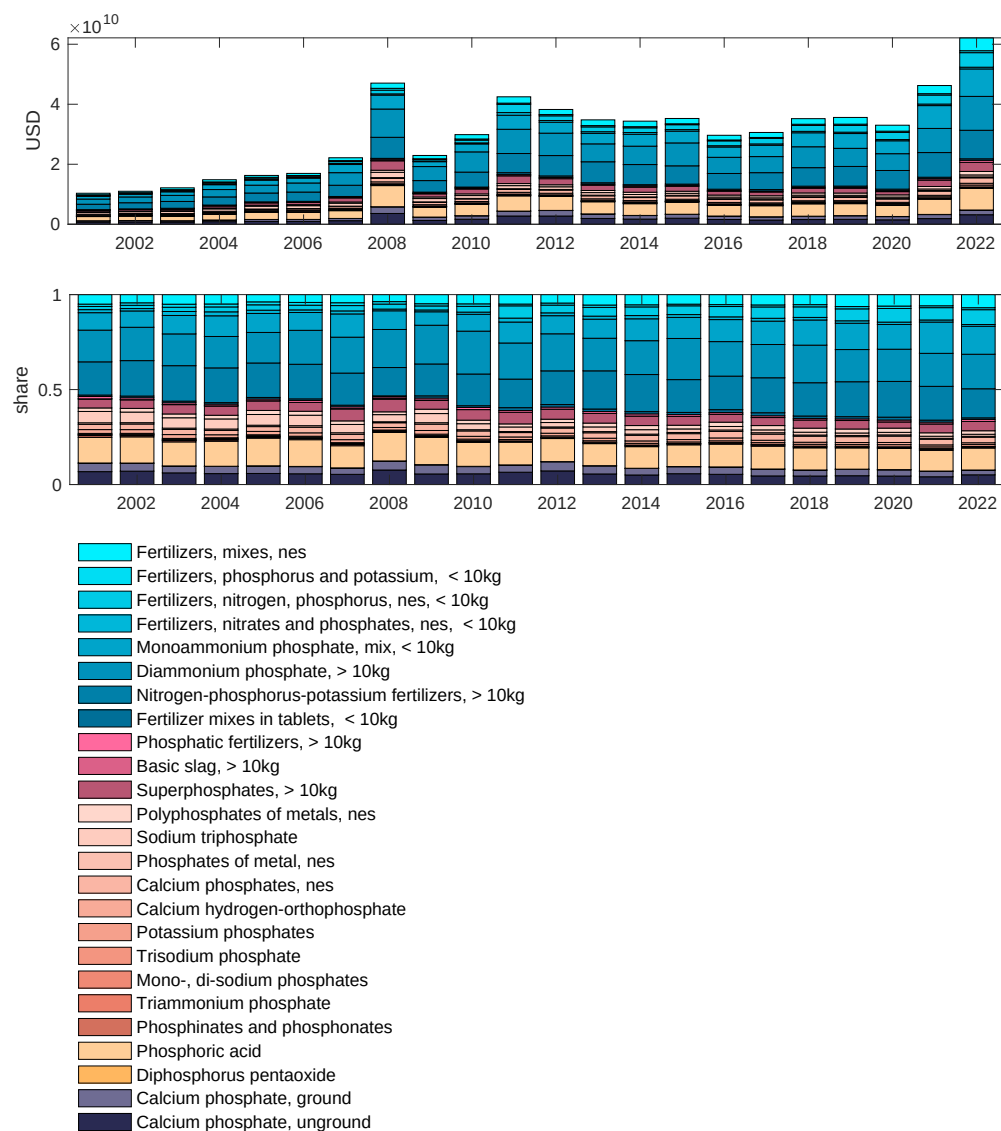


Figure A1. Trade in P-related goods, 2001–2022. The top panel shows the USD amounts of trade in P-related goods, disaggregated into the 25 6-digit HS categories. The bottom panel shows the fractions of these 25 goods categories over time.

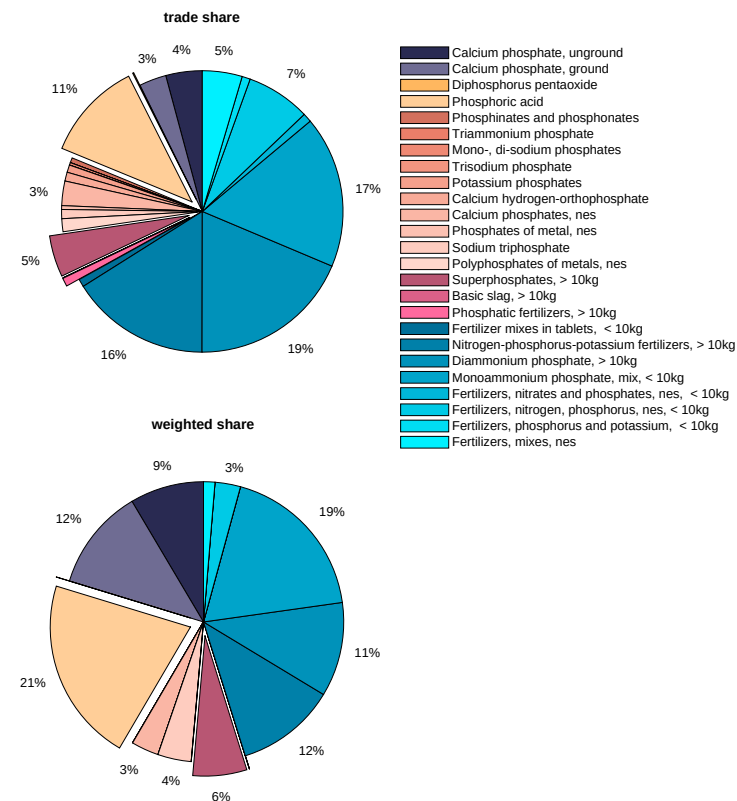


Figure A2. Contributions of product categories. The top chart shows the shares of the different product categories in terms of USD of net trade in 2021. The bottom chart shows the shares based on weighted net trade as used in the estimation of the flow matrix F^{M5} . The legend shows the 25 disaggregated product categories. (Shares for the categories $\leq 1\%$ omitted.)

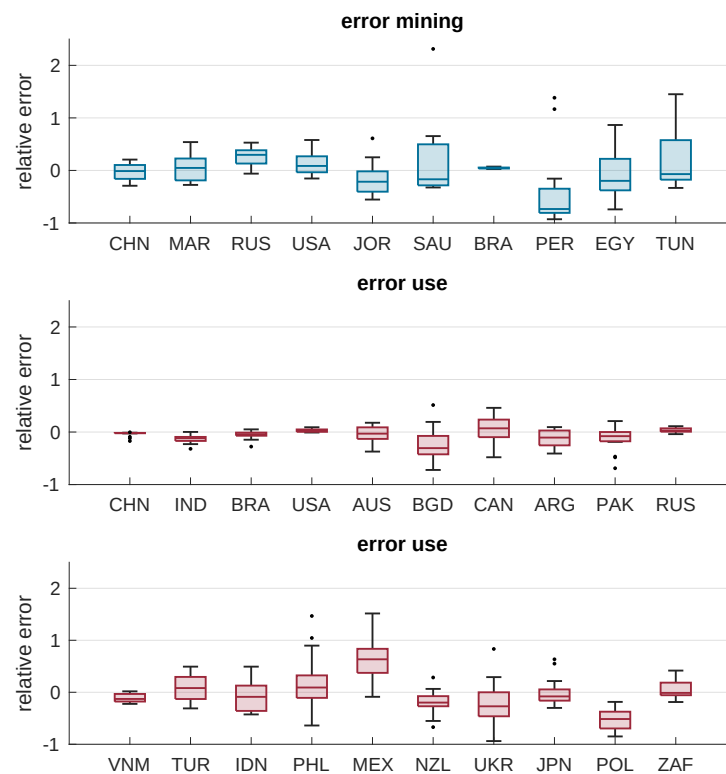


Figure A3. Box-plots of the deviations of the estimated PR mining (top panel) and P use (middle and bottom panels) relative to the empirical data (2001–2022), i.e., M and U for the 10 largest producer and 20 largest P fertilizer user countries, respectively, based on F^{M4} .

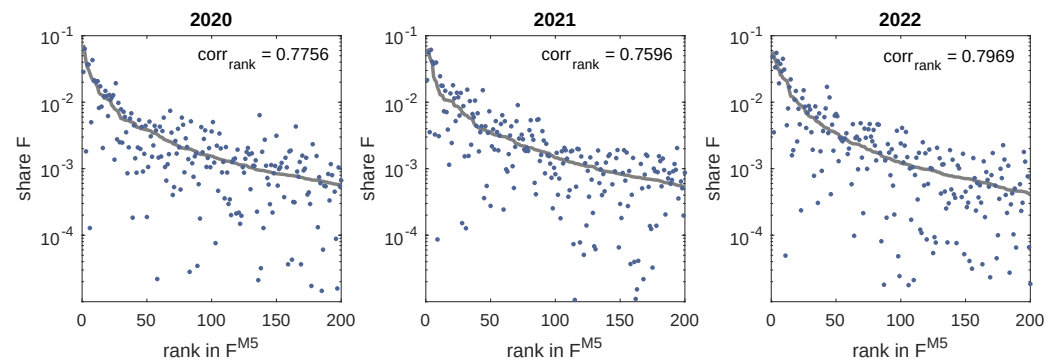


Figure A4. Comparison of top 200 pairwise flows for 2020–2022 based on F^{M5} with FAO data. We utilize data from the FAOSTAT Fertilizers Trade Matrix. We calculate shares of net exports in terms of P_2O_5 based on reported imports and exports of straight phosphatic fertilizers and compound fertilizers. The plots show the shares ordered according to our estimates (gray lines) versus the calculated shares based on the FAO data (blue dots). The estimates are in reasonable agreement, as also indicated by the reported values of the rank correlation. Note that the FAO data does not include traded phosphoric acid or domestic P flows, and it is not necessarily consistent with fertilizer use and production data.

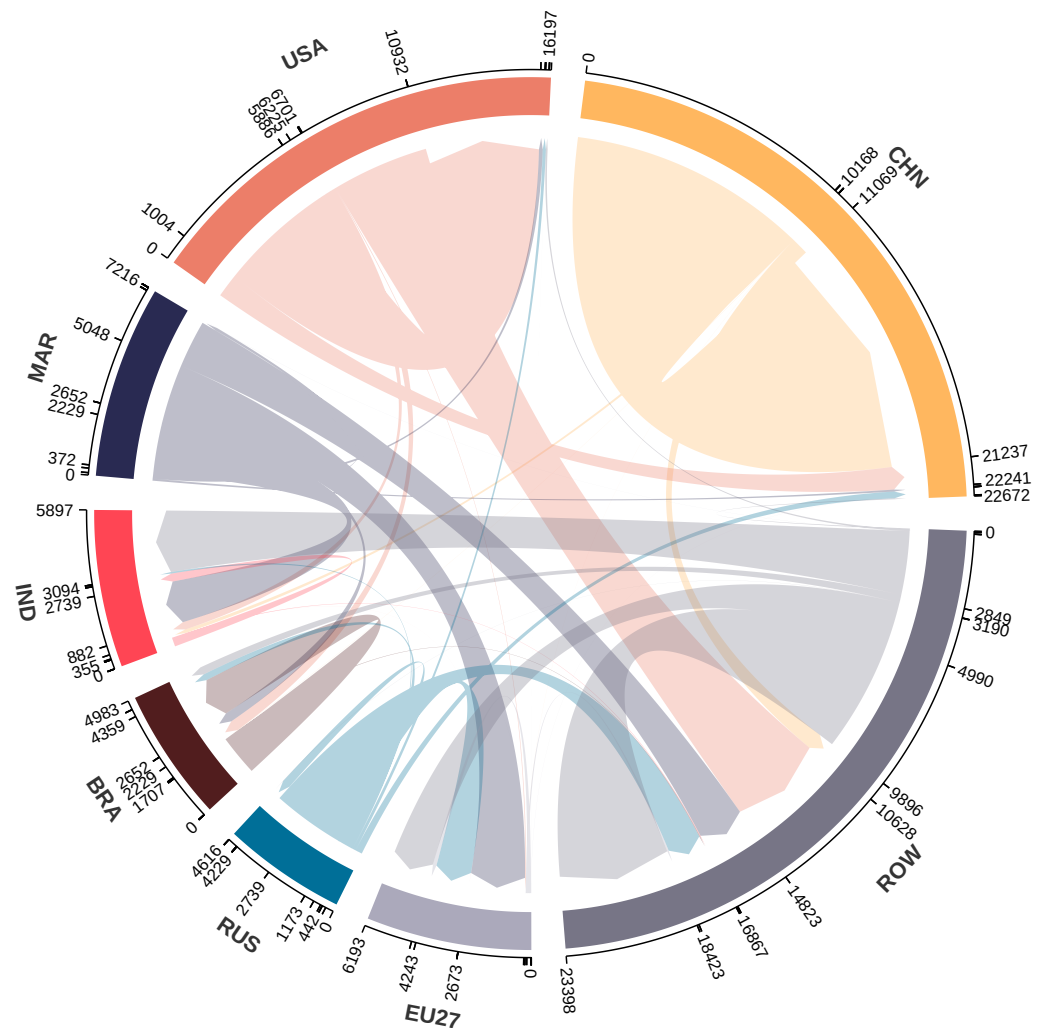


Figure A5. P flow diagram based on F^{M5} for 2001 for the six single countries with the largest flows as well as for the EU27 and the rest of the world (ROW), P_2O_5 (thousands of tons).

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