Network resilience of phosphorus cycling in China has shifted by natural flows, fertilizer use and dietary transitions between 1600 and 2012

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Abstract

The resilience of the phosphorus (P) cycling network is critical to ecosystem functioning and human activities. Although P cycling pathways have been previously mapped, a knowledge gap remains in evaluating the P network's ability to withstand shocks or disturbances. Applying principles of mass balance and ecological network analysis, we examine the network resilience of P cycling in China from 1600 to 2012. Results show that changes in network resilience have shifted from being driven by natural P flows for food production to industrial P flows for chemical fertilizer production. Urbanization has intensified the one-way journey of P, further deteriorating network resilience. Over 2000–2012, the network resilience of P cycling has decreased by 11% due to dietary changes towards more animal-based foods. A trade-off between network resilience improvement and increasing food trade is also observed. These findings can support policy decisions for enhanced P cycling network resilience in China.

Main

The element phosphorus (P) is central to food security. Approximately 90% of global phosphate rock demand is for food production[1]. Access to P is pressured by population growth[1,2], limited P recycling and reuse[3], and finite P mining resources. In addition to access, the network resilience of P cycling (i.e., a system attribute[4] that ensures continuous access of P within the network and is critical for sustainable P management) is vulnerable to socio-environmental shocks and disturbances[5,6]. To eradicate hunger and achieve food security, it is essential to better understand the metabolic network of P flows.

Existing studies mainly focus on P flow pathways[7-10] and the planetary boundary of P resources5, and lack a system-level perspective of network resilience of P cycling. This would lead to the risk of ignoring opportunities or costs from indirect-network effects arising from the metabolic flows of P. A network approach can better enable our societies in taking a collective, holistic, and long-term responsibility of the governance of P flows – especially in light of significant changes that anthropogenic activities have posed to the P cycling patterns within socio-ecological systems[10,11].

During 1600–2012, the population of China has grown approximately 10-fold and P supplies of arable land have increased by approximately 13-fold[12,13]. Despite having the second-largest P mining resources in the world[12,14], at the current rates of extraction, China would face P scarcity in the next three generations[15]. As a cautionary policy against peak P, the government of China imposed a 135% export tariff on P products in 2008[15]. Existing studies have revealed primary P flow pathways at China's regional[16-25] and national levels[12,26-31]. They have led to the identification of key processes for the consumption and loss of this critical element.

Here we provide a network perspective of P metabolism in China and examine the configurations of this network for the resilience of its flows. We constructed the 149-

node P cycling networks (the nodes can be found in Supplementary Table 1) in China for each year during 1600–2012, using the methods of Liu et al.[12] and the principle of mass balance (see *Methods*). We apply ecological network analysis (ENA)[32] to evaluate the network resilience of P cycling in China and reveal its underlying determinants. Besides exploring how major determinant factors have changed over time, our analysis allows the quantification of the effects of China's rapid urbanization and dietary changes on decreasing network resilience.

Results

Evolution of P cycling network resilience

Resilience measures were based on the proposed *alpha* indicator, which considers two sides of the system-level properties of a network[33] – namely efficiency and redundancy (see *Methods*). Network efficiency reflects the constraints among resource flow pathways, i.e., higher efficiency describes flow pathways with higher intensity and specialization[33]. In contrast, network redundancy indicates the diversity of resource flow pathways, which is necessary for mitigating the impacts of shocks and disruptions to a system. Based on the model proposed by Goerner et al.[34], we assume that an alpha higher than the optimal value indicates an overly efficient network (high specialization but also highly brittle and vulnerable to shocks), while an alpha lower than the optimal value indicates an overly redundant network (low specialization but also less vulnerable to shocks). According to Ulanowicz[4], we assume the optimal value of alpha to be 1/e = 0.3679 (see Supplementary Notes).

Our results reveal that the P cycling network in China was in an overly efficient state during the study period of 1600–2012 (see Figure 1 and Extended Data Figure 1), being most efficient and therefore most vulnerable to shocks or disruptions to P flows at the very end (2000–2012). The resilience of the P cycling network in China was below the optimal value throughout the entire study period; it has decreased by 18%, reaching its maximum value in 1950 and its minimum value in 2012. Given that the resilience indicator tends to be insensitive to large internal structural changes within the network, such a decrease is significant (see Supplementary Notes).

The evolution of the resilience of the P cycling network in China (Figure 1) can be generally divided into three stages: the 1600-1911, 1911-1950, and 1950-2012 periods. In the first and second stages, there was no chemical P fertilizer use in China and the resilience of the P cycling only had a slight increase of 0.9%. It is noteworthy that during the second stage, the value of resilience exhibited high volatility. This high volatility can be arguably attributed to the socio-political turmoil and wars in China and its effects on agriculture and P usage, e.g., the Chinese Revolution of 1911, the Anti-Japanese War during 1937–1945, and the People's Liberation War of 1945–1949. In the third stage, China begins to increasingly rely on chemical P fertilizers in its agricultural production. This increasing dependence on chemical P fertilizers has subsequently decreased the resilience of the P cycling network by 18%. The third stage can be viewed through three phases corresponding with major socio-economic milestones in China: (1) during 1950-1978 (before the Reform and Opening-up policy), resilience decreased by 9.8%; (2) during 1978–2000 (before China's accession to the World Trade Organization), resilience increased slightly by 1.9%; and (3) during 2000–2012 (the acceleration of urbanization and P intensive food demand in China), resilience sharply decreased by 11.1%. The future continuation of a declining trend would indicate that the P cycling network would be increasingly vulnerable to random or targeted socio-economic shocks. This would mean that the access of P flows to the network's nodes may be disrupted. Subsequently, P shortages would ensue, therefore putting the sustainability and security of China's food and agricultural system at risk.

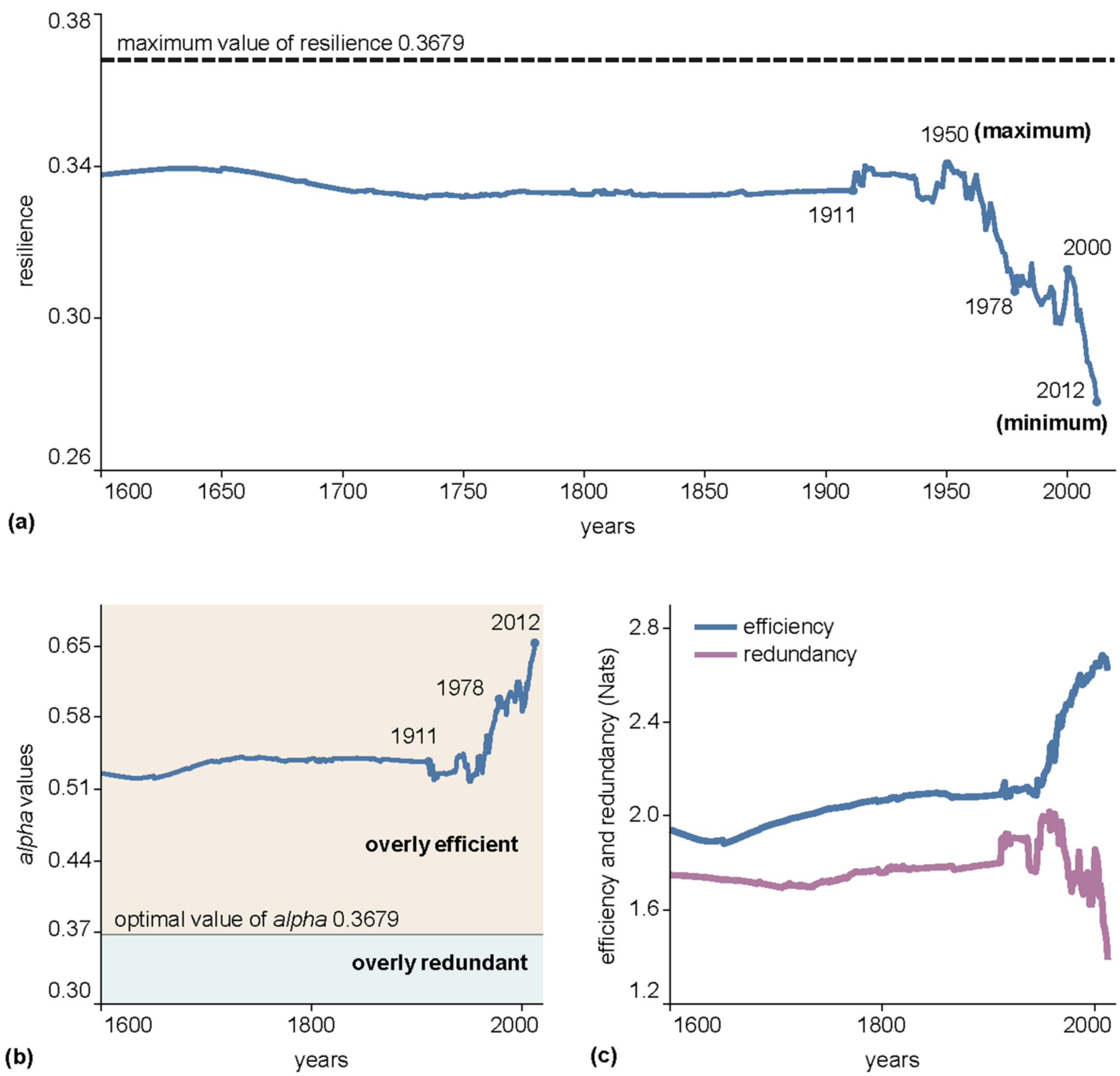

Figure 1. The evolution of resilience, *alpha*, and efficiency & redundancy of the P cycling network in China during 1600–2012. Graphs *a*, *b*, *c* show the evolution of resilience, *alpha*, and efficiency & redundancy, respectively. Efficiency and redundancy are measured in Nat – a unit of information[35]. The optimal values of *alpha* and resilience are both 0.3679 (see Supplementary Notes).

Socio-economic and network transitions

Network resilience has been dominated by redundancy changes throughout the entire period of 1600–2012 (Figure 2). For example, during 1600–1950, network resilience slightly increased by 0.003 (from 0.3378 to 0.3408). This is because changes in network efficiency decreased the resilience by 0.0089 (-297%), while changes in network redundancy increased the resilience by 0.1119 (397%). Before the year 2000, changes in efficiency decreased network resilience, while changes in redundancy mostly increased network resilience. However, during 2000–2012, the impacts of changes in efficiency and redundancy have reversed. Changes in efficiency increased resilience by 3%, while changes in redundancy decreased resilience by 103%.

Socio-economic factors considered in this study include: (1) the demand-side socio-economic factors, including human P demand, food structure (indicated by the sum of P content in all foods, except for grain, divided by P content in grain), and the urbanization ratio; and (2) the supply-side structural factors, including fertilizer P use proportion (indicated by the amount of chemical fertilizer P used in arable land divided by the total amount of P used in arable land) and the P recycling rate (indicated by the proportion of renewable P, such as human and animal excreta, flowing to arable land divided by the total amount of P flowing to arable land).

To investigate how these socio-economic factors affect the network resilience, we (1) proposed a hypothesis on the mechanism of resilience changes; (2) conducted correlation analysis among the socio-economic factors (to eliminate the co-varying effects) and selected relevant indicators in the regression model; and (3) constructed multilinear regression models to evaluate this hypothesis during different time periods. Detailed information is provided in Supplementary Methods. Results confirm our hypothesis that the resilience of P cycling network in China is influenced by human food demand (scale and structure) through structural changes (e.g., P fertilizer proportion) of the P cycling network. In particular, during 1950–2012, the resilience of P cycling network in China was negatively correlated with human P demand (or fertilizer P use proportion) and food structure. This is because, accompanying population growth and per capita food demand, food consumption continued to increase, which consequently increased the scale of human P demand. To meet this demand, the P cycling network changed its structure through more efficient transfers of P via pathways with higher intensities and specializations (e.g., industrial P production and fertilizer P use). Subsequently, the network resilience decreased.

During 2000–2012, the resilience of P cycling network in China was mainly determined by dietary changes. This is because, after the year 2000, urbanization accelerated in China and higher living standards were adopted. Although the scale of food P demand slightly decreased (see Extended Data Figure 2), food consumption went from a modest, mostly vegetarian-based diet to a more complex diet (i.e., more animal-based foods with higher P content) (see Extended Data Figure 3). To meet this demand, the animal husbandry and aquaculture sectors expanded their production, subsequently increasing the demand for agricultural products such as grains and beans and P fertilizer use in the cultivation sector. All of these activities changed the network structure (e.g., increasing the fertilizer P use proportion and decreasing the P recycling rate) and reduced the flow diversity of the P cycling network. Furthermore, unlike in rural areas, P-rich waste from urban households (e.g., human excreta) are much harder to be re-used as organic fertilizers for food production. This is primarily due to insufficient technologies in recycling P from wastewater and solid wastes[3]. Therefore, urbanization, as opposed to traditional agrarian living, reduced the proportion of recycled P for food production and intensified P utilization – ultimately decreasing network resilience.

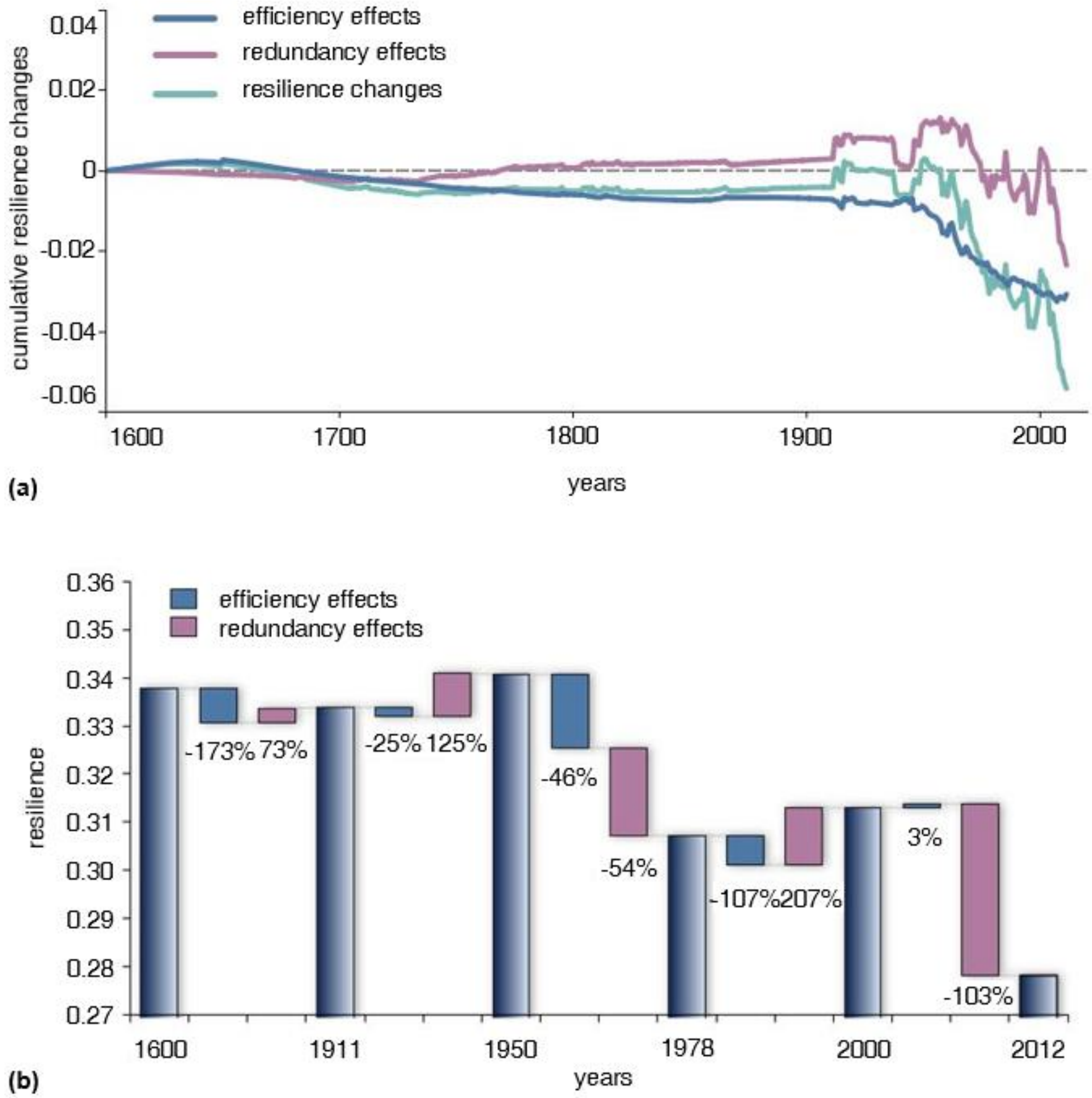

Figure 2. Relative contributions of changes in efficiency and redundancy to changes in the resilience of the phosphorus cycling network in China. Graph *a* shows results for 1600-2012, and graph *b* shows results for specific time periods.

To investigate critical internal structural factors influencing changes in the efficiency, redundancy, and resilience of China's P cycling network, we decomposed resilience changes into the contributions of three internal factors (see *Methods*). These comprised: (1) the concentration degree of P flows (i.e., the proportion of a given P flow relative to the total system throughflow, where a higher value indicates a higher P flow intensity); (2) node inter-dependency (i.e., the degree of dependence between any two nodes, where higher values indicate a higher probability of a flow between two given nodes); and (3) node inter-independency (i.e., the degree of freedom between any two nodes, where higher values indicate higher diversity for the destination and origin of flows between two nodes). Using these factors, it is also possible to describe changes in network efficiency and redundancy. Specifically, efficiency changes can be decomposed into the contribution of the concentration degree of P flows and that of the node inter-dependency, while redundancy changes can be decomposed into the contribution of the concentration degree of P flows and that of node inter-independency. In essence, the system-level variables of efficiency, redundancy, and resilience are composed of individual node-to-node relationships, including the dependency degree, freedom degree, and the concentration of these relationships in the entire network.

Changes in the concentration degree of P flows have dominated the changes in network resilience, efficiency, and redundancy during 1600–2012 (Figure 3). Changes in the concentration degree of P flows increased network efficiency during 1600–2012, but their effects on changes in network redundancy and resilience have been diverse. It is worth noting that during 2000–2012 changes in concentration degree of P flows have decreased network efficiency, redundancy, and resilience by 144%, 102%, and 102%, respectively. This is consistent with our above findings with regard to influencing socio-economic factors; to satisfy the increasing human P demand, the economic metabolic system would increase its concentration degree of P flow pathways to enhance its efficiency. However, with the increase in the concentration degree of P flows, more and more P flows are concentrated in the node of P extraction and the P cycling network becomes less redundant. Accelerated by the urbanization process, the increase in concentration degree of P flows hampers the network redundancy and thus decreases network resilience. As a result, to maintain a relatively high-level resilience of the P cycling network, we need to optimize the concentration degree of P flows in particular nodes. Specifically, nodes of P recycling should have higher concentration levels of P flows, such as nodes related to the recycling of excreta, wastewater, and solid wastes. These nodes present significant opportunities for increasing P recycling, which can in turn increase network resilience.

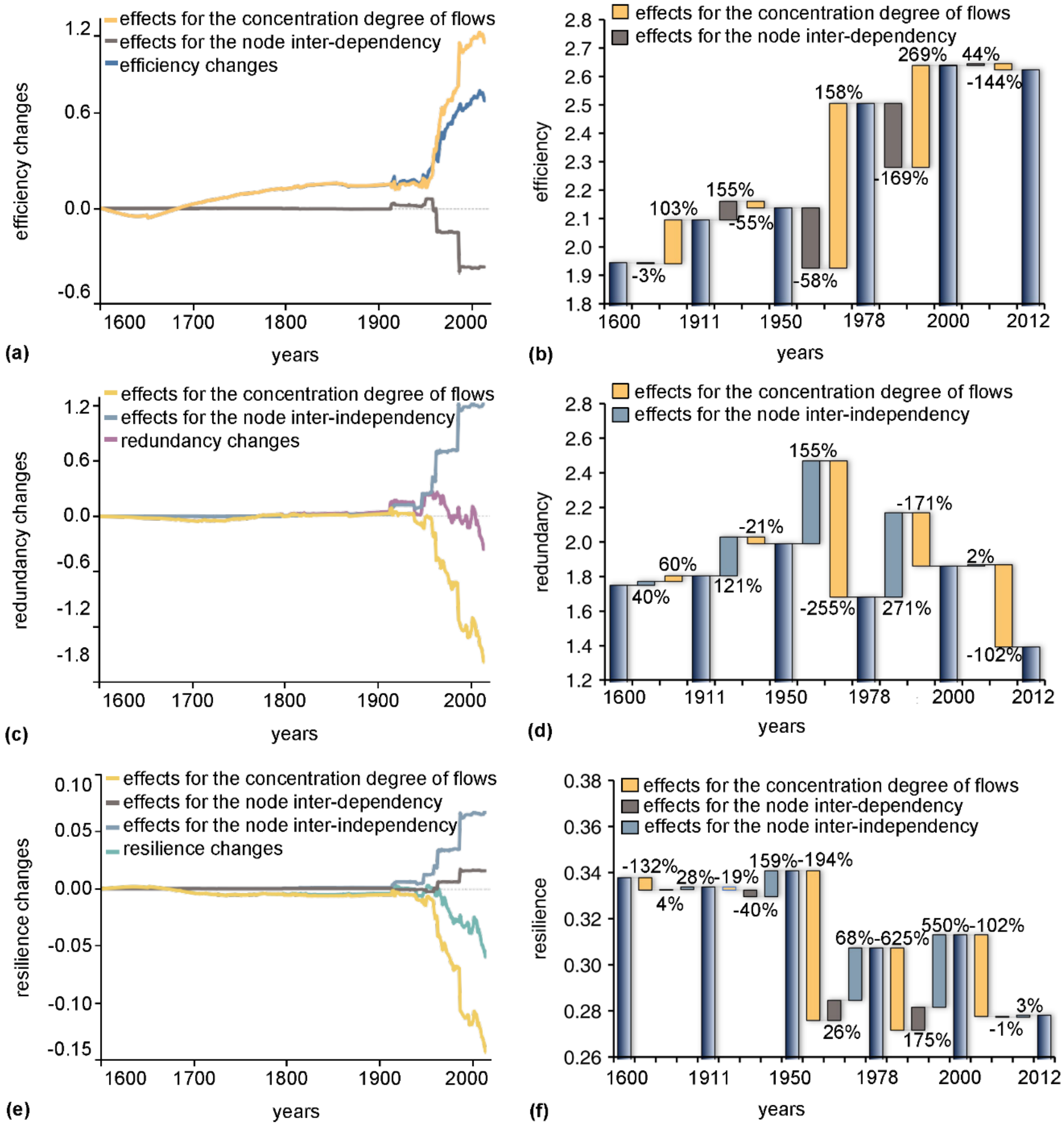

Figure 3. Relative contributions of changes in concentration degree of P flows, node inter-dependency, and node inter-independency to changes in efficiency, redundancy, and resilience of the P cycling network in China during 1600–2012. Graphs *a* and *b* are for efficiency; graphs *c* and *d* are for redundancy; and graphs *e* and *f* are for resilience. Efficiency and redundancy indicators are measured in Nat – a unit of information[35].

Critical links and nodes

This study further explored how changes in individual links and nodes have affected the resilience of the P cycling network in China (see Figure 4 and Supplementary Tables 2–6). For better illustration, we aggregated the 149-node results to 16-node results (see Supplementary Table 1). During 1600–1950, the increase of network resilience was mainly influenced by changes in P flow from *Stock* to *Cultivation* (i.e., P fixation by plants from soil), which contributed 125% of the changes in network resilience. This P flow reflects the natural pathway of P from soil (without fertilizer P) used for food production. This finding indicates that network resilience changes are driven by the changes of natural P flows (without fertilizer P) for food production, as has been the case in China's agrarian society. However, in the modern era, resilience changes are primarily dominated by P flows from *Stock* to *Non-arable land* (i.e., the extraction of P rocks). This flow represents P mining for the production of chemical fertilizers. It contributed 18%, 84%, and 15% of network resilience changes during 1950–1978, 1978–2000, and 2000-2012, respectively**.**

The long term dataset employed here suggests that changes in network resilience of P cycling in China shifted from being driven by natural P flows (without fertilizer P) for food production in the historical agrarian age, to being driven by industrial P flows for chemical fertilizer production in the modern era. This phenomenon became more prominent during 2000–2012, when the decline of network resilience was dominated by the P flow pathway of *Stock*→*Non-arable land*→*P rocks from mining*→*Fertilizers*. Such a shift is strongly correlated with population growth and urbanization.

We also investigated the critical nodes influencing changes in the resilience of the P cycling network in China during 2000–2012 (see Figure 4 and Supplementary Tables 7-

11). From the viewpoint of P inflows to nodes (i.e., P use perspective), network resilience changes are primarily due to node clusters of mining (34%), non-arable land (20%), cultivation (17%, including nodes of beans, wheat, rice, etc.), agricultural product processing (15%, including nodes of grains, feed processing, etc.), and chemical production (10%). From the viewpoint of P outflows from nodes (i.e., P supply perspective), network resilience changes are mainly due to node clusters of non-arable land (21%), stock (19%), cultivation (16%, including nodes of crop straws, maize, beans, rice, etc.), animal husbandry (14%, including nodes of excreta from cattle, excreta from pig, etc.), and mining (14%). These nodes are mostly located in the upstream stages of food supply chains. However, nodes located in the downstream stages of food supply chains (e.g., wastewater treatment and solid waste disposal) play minimal roles in network resilience changes.

Currently, due to the insufficient development and diffusion of P recovering technologies[1], P outflows from the downstream nodes are not closely connected with P inflows from the upstream nodes of food supply chains. Thus, P recovery and reuse from downstream nodes to upstream nodes of food supply chains are crucial for improving the resilience of the P cycling network in China.

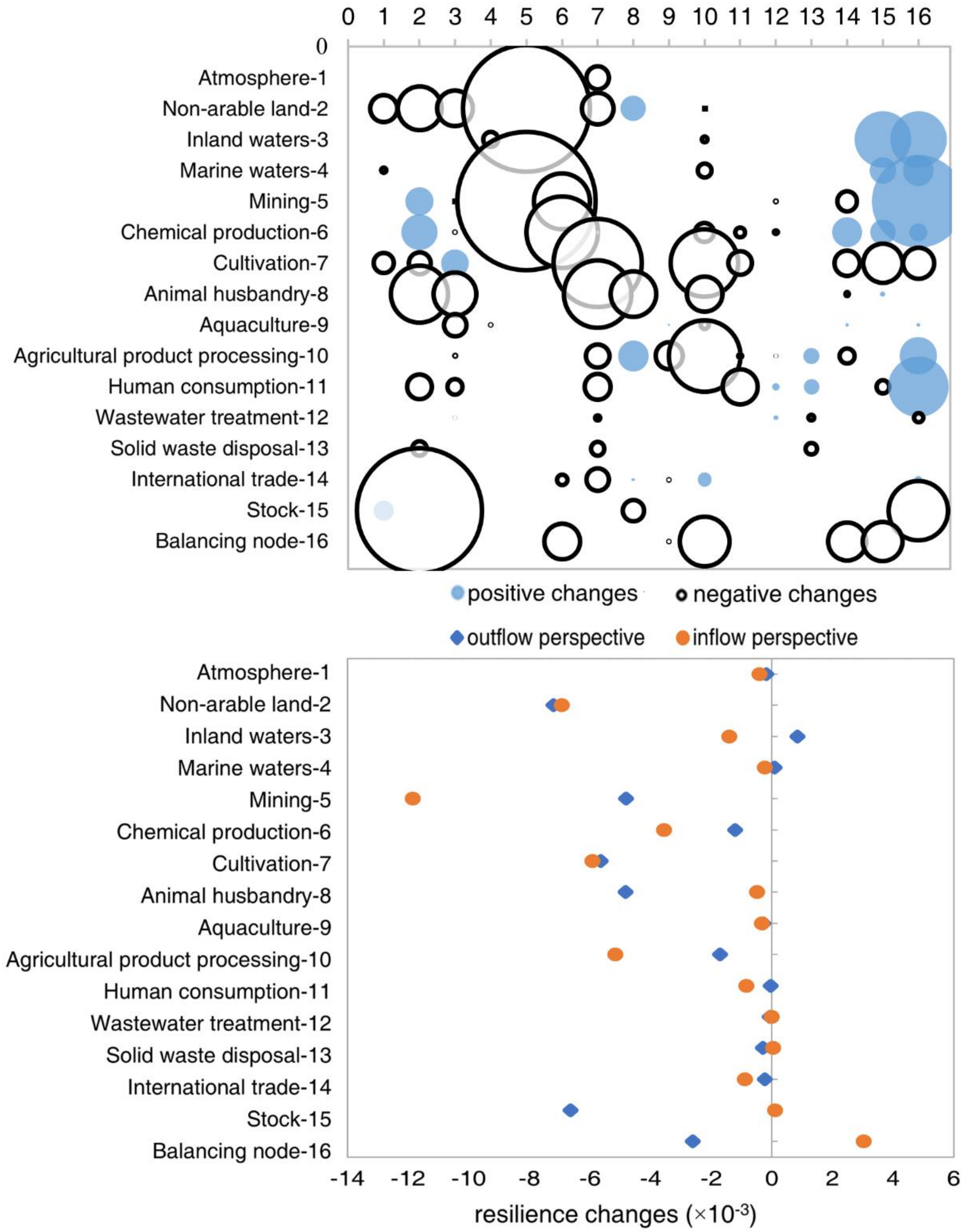

Figure 4. Critical links and nodes influencing the resilience of the P cycling network in China during 2000–2012. Graph *a* is for links, and graph *b* is for nodes. The absolute values of network resilience changes in graph *a* are indicated by the areas of circles. For better illustration, we aggregated the 149-node results to 16-node results (see Supplementary Table 1).

Discussion

This study evaluates the evolution of the resilience of the P cycling network in China over four centuries (1600–2012), as well as its underlying determinants. Our results reveal that, in the most recent decades, the network resilience of the P cycling in China has declined. This trend is reinforced as the traditional pathway of P from soil to food production shifted to an anthropogenic intensive pathway of P mining to food production. The key factors underlying this trend include the growth of food demand and the changes of the food structure from a modest, mostly vegetarian-based diet to a more complex diet (i.e., more animal-based foods with higher P content), made possible through rising societal affluence[36]. Should this trend persist, China's food security shall be increasingly vulnerable to P availability under socio-environmental shocks and disturbances to its P cycling network.

An ecocentric viewpoint may prescribe the replacement of P rocks and chemical fertilizers by organic fertilizers and the embrace of an agrarian-based society. However, this vision may face strong resistance from socio-economic driving forces. Furthermore, while a network perspective considers the resource distribution, the eco-centric viewpoint would be effective only with a lower scale of overall P demand. To satisfy the increasing food demand and guarantee sustainable development, we should not only rely on P rocks to maintain the high efficiency of P cycling, but also improve the network resilience through P recycling and P productivity improvement in food supply chains.

During 2000-2012, network resilience is mainly determined by dietary changes. It is worth noting that urbanization significantly influenced food consumption patterns. In 2012, the urbanization ratio in China was only 53%, which the United Nations projects will reach 80% by 2050[37]. Future predictions also indicate that urbanization will continue to increase the proportion of animal-based products in human diets. This will consequently decrease the resilience of the P cycling network and make it more vulnerable to socio-environmental shocks and disturbances.

The fact that only 14% of P extraction was found to be used for China's food consumption indicates that the current P cycling network is actually a 'one-way journey', where most of P is directly deposited in the soil or discharged into water bodies or solid wastes. In addition to increasing the risk of P rock scarcity, this trend undermines the health of water bodies through e.g., eutrophication.

Increasing the resilience of the P cycling network will enhance the system's ability to deal with disturbances, which benefits the maintenance of food security. As previously stated, network resilience declined due to changes in the quantity and quality of human diets. To simultaneously increase the network resilience and satisfy food demand, we provide the following suggestions.

The first suggestion is to reduce food loss and food wastes. Roughly one-third of global food is lost in the supply side or wasted in the demand side every year[38]. Our study reveals that households in China consumed 1.8 Mt of P in 2012. If food loss and waste can be completely avoided, then household P consumption will be only 1.2 Mt of P. In this avenue, based on the correlation between resilience and its socio-economic drivers (i.e., human P demand and food structure changes), the resilience of the P cycling network in China would increase by 9.3% if food consumption patterns remain stable.

The second suggestion is to improve the "farm to fork efficiency" (i.e., P productivity) in food supply chains. The concentration degree of P flows is the primary structural factor influencing network resilience. A promising solution to optimize the concentration of P flows is to reduce the intensity of P flow pathways through improving P productivity in food supply chains. There are significant potentials for China to improve P productivity in fertilizer production, crop production, food processing, food consumption, and composting[19,39,40]. Given the importance of the P cycling networks to ecological and human systems, P productivity in food supply chains should be a priority. Possible measures in this avenue include setting guidance limits and standards for P fertilizer use, promoting advanced technologies to reduce food loss during food processing, and reducing food wastage during food consumption through education and public awareness campaigns.

The third suggestion is to reduce fertilizer use. We found that the proportion of P mineral fertilizer used in China relative to the total amount of P used in arable land has increased from 0.2% in 1950 to 76% in 2012, indicating the country's high dependence on P mineral fertilizers. The average proportion of P mineral fertilizer use in the world was about 54% in 2013[7]. According to the correlation between the resilience of P cycling network and the proportion of P mineral fertilizer, the resilience of China's P cycling network would increase by 8.1%, if the fertilizer P use proportion could be reduced to the global average level with the food structure remaining stable. A potential measure to achieve this is developing technologies to enhance fertilizer use efficiency. Currently, only 15–30% of applied P fertilizer is utilized through the harvest of crops[41]. Approaches to increase fertilizer use efficiency range from high-tech solutions (e.g., precision agriculture) to organic farming techniques aimed at optimizing soil conditions to increase

P availability of soil. Other approaches focus on the addition of microbial inoculants to increase the P availability of soil[1].

An alternative for decreasing the proportion of mineral P fertilizer use is to increase the P recycling rate. The current recycling of P mainly comes from animal excreta and human excreta in rural areas. In addition, there are lots of other measures to recover and reuse P, such as ploughing crop residues back into the soil; composting food wastes[39,40]; and P recovery from sewage sludge[42], steelmaking slags[43], and wastewater[1]. Our results reveal that actions for improving the resilience of the P cycling network in China should also focus on nodes in the downstream stages of food supply chains, such as nodes related to wastewater treatment and solid waste disposal. Two socio-technical pathways to increase P recycling would thus be the recovery of P from wastewater and the reuse of food wastes and sludge to produce organic fertilizers for cultivation. It should be noted that changes in diets also affect how much P can be recycled and could be viewed as another potential avenue for increasing the network resilience.

In 2015, the Ministry of Agriculture (MOA) in China launched a plan to promote zero increase in fertilizer use by enhancing fertilizer use efficiency, and to promote the usage of renewable P (e.g., animal excreta and crop straws) by 2020[44]. It is forecasted that the proportion of P mineral fertilizer use in China will decrease in the near future, thereby increasing the network resilience of P cycling in China.

The measures proposed above for improving the network resilience are also solutions for P resource conservation. As a result, improving the resilience of the P cycling network by these measures have co-benefits with P resource conservation. Yet, it should be noted that increases in network resilience may have trade-offs with other goals.

An example involves increasing production of agricultural products domestically. In 2012, China imported a significant quantity of beans for food production. According to our calculations, the P contents of imported beans and domestically produced beans are 348 thousand tonnes (kt) and 104 kt, respectively. If all of the demand for beans were satisfied by China's domestic production, the relevant flows of the P cycling network (e.g., P extraction and waste discharge) would be increased and the network resilience would decrease by 0.8% from the 2012 level. Contrary to beans, in 2012, the demand for maize was met by domestic production in China. If the total demand for maize was met through imports, the network resilience would increase by 3.0% from the 2012 level. Such findings also apply to other food commodities internationally traded, such as meat, dairy, and fish, reinforcing the need to balance network resilience improvements and food supply independence (i.e. less trade).

Our results also show that reducing China's excessive production of P fertilizers will improve the network resilience. In 2012, China produced 8.5 Mt of fertilizer P, while only 7.5 Mt were used by the cultivation and the rest 1 Mt were exported to other nations. If the production of P fertilizers could perfectly match the domestic demand, then network resilience would improve by 0.3% from the 2012 level. Similar findings may apply in the case of P rock extraction.

The framework and metrics presented here are widely applicable to resource management at various spatial scales. For example, the International Resource Panel[45] could apply them to evaluate the network resilience of global resource cycling and identify its underlying determinants – both key to the implementation of global sustainability goals.

Methods

This study constructs the P cycling network in China during 1600–2012, using the methods of Liu et al.[12] and the principle of mass balance. We analyze the resilience of the network in China, based on the network configurations of efficiency and redundancy. We also identify potential external socio-economic factors, internal structural factors, and critical links and nodes influencing the functioning of the network. Theoretical resilience is assessed using the ecological network analysis (ENA). The potential impact of external socio-economic factors on network resilience are analyzed through a set of regression analyses. The contributions of structural factor changes to network resilience changes are calculated through index decomposition analysis. Critical links and nodes are identified based on the results of structural factors.

The P cycling network

A network consists of nodes and links. The P cycling network in China comprises 149 nodes, including 43 sectors and 106 products (see Figure 5 and Supplementary Table 1). We obtained raw data for P flows from the study of Liu et al.[12]. Using the principle of mass balance, we constructed the 149-node networks in this study.

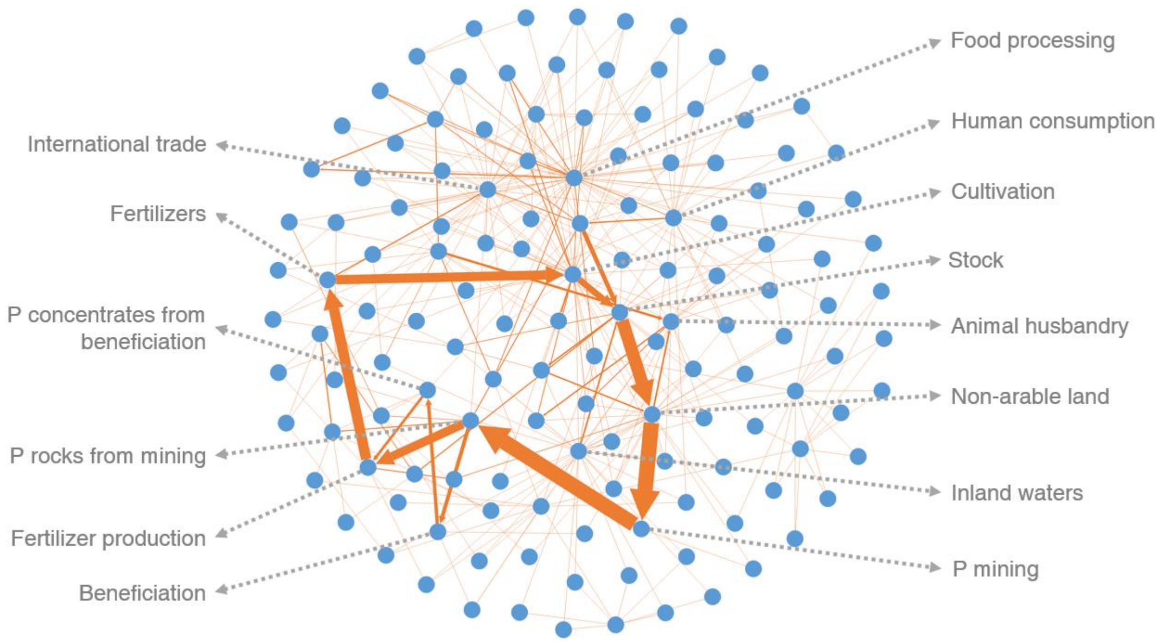

Figure 5. The phosphorus cycling network of China in 2012.

The resilience of a network

The concept of resilience indicates the ability of a network to maintain continuous operations in case of shocks, and has been used in assessing the performances of various human-natural systems[46-48]. The resilience of a system is composed of two opposing properties of a network system: system efficiency and redundancy[33].

System efficiency reflects the development of constraining resource flow pathways, i.e., flow pathways with higher intensity and specialization[33]. Efficiency indicates the degree of concentration of resource flow pathways and the ability to efficiently transmit information/resources within the system. For example, nations tend to pursue preferential interactions in international trade, which would increase productivity but probably reduce the diversity of trade partners and commodity flow pathways.

In contrast, system redundancy indicates the diversity of resource flow pathways, which is beneficial to mitigate the impacts of shocks and faults within a system. Diversity reflects a system's capacity to adapt to changing environmental conditions[4,33]. For example, sectors with more diverse pathways have been found to grow again after a global financial crisis (i.e., have higher growth resilience)[33].

Whereas higher efficiency may indicate higher growth, it may also indicate higher vulnerability within a system. On the other hand, while greater redundancy may indicate slower growth, it may benefit network resilience.

$$efficiency = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{f(i,j)}{T(\cdot,\cdot)} \times ln\frac{f(i,j)\times T(\cdot,\cdot)}{T(\cdot,j)\times T(i,\cdot)} \quad (1)$$

$$redundancy = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{f(i,j)}{T(\cdot,\cdot)} \times ln\frac{T(\cdot,j)\times T(i,\cdot)}{f(i,j)^2} \quad (2)$$

In the above equations, $f(i,j)$ indicates flows from node *i* to node *j*; $T(i,\cdot) = \sum_{j=1}^{n} f(i,j)$ indicates total outflows of node *i*; $T(\cdot,j) = \sum_{i=1}^{n} f(i,j)$ indicates total inflows of node *j*; $T(\cdot,\cdot) = \sum_{i=1}^{n}\sum_{j=1}^{n} f(i,j)$ indicates the total system throughflow; *n* indicates the number of nodes in the network; and the notation *ln* indicates the natural logarithm.

The *alpha* metric *α* is proposed to reflect the trade-off between efficiency and redundancy, as shown in equation (3)[33]. It is a more comprehensive metric to measure the order of a network. We can define the *resilience* of a network based on the *alpha* metric, as shown in equation (4)[33,34].

$$\alpha = \frac{efficiency}{efficiency + redundancy} \quad (0 \le \alpha \le 1) \quad (3)$$

$$resilience = -\alpha \, ln\,(\alpha) \quad (4)$$

The optimal value of α is 0.3679, where the maximum value of resilience is 0.3679[34]. If α is smaller than 0.3679, the network is overly redundant, whereas α larger than 0.3679 indicates the network is overly efficient. An overly redundant network has low productivity and low vulnerability, while an overly efficient network has high productivity and high vulnerability. Comparatively, the overly efficient network can more efficiently transmit information/resources within the network but is usually more vulnerable to shocks. Since network resilience incorporates two opposing properties of a network, i.e., efficiency and redundancy, it is not always beneficial for enhancing network resilience to simply increase redundancy or reduce efficiency. If α is too high (α ≈ 1) due to the increase of redundancy, the system will become brittle and the inflexible pathways can become vulnerable to perturbations. More detailed information on the theoretical foundations of ENA, mathematical formulas, interpretations of these indicators, and optimal value of α are provided in the Supplementary Notes.

Relative contributions of efficiency and redundancy changes

Assuming $y = theoretical\ resilience$, $e = efficiency$ and $r = redundancy$, we can write equations (3)-(4) as

$$y = -\frac{e}{e+r} ln(\frac{e}{e+r}) \tag{5}$$

The resilience changes with time *t* can be expressed as

$$\frac{dy}{dt} = \frac{1-log(e+r)+log\ (e)}{(e+r)^2}\left(e\frac{dr}{dt} - r\frac{de}{dt}\right) \tag{6}$$

During a certain time period from 0 to *t*, one can substitute $\frac{dy}{dt}$, $\frac{dr}{dt}$, and $\frac{de}{dt}$ with Δy, Δr, and Δe. The equation (6) can be re-written as

$$\Delta y = \frac{1-log(e+r)+log\ (e)}{(e+r)^2}(e\Delta r - r\Delta e) = \Delta_r y + \Delta_e y \tag{7}$$

where $\Delta_r y$ and $\Delta_e y$ indicate the relative contributions of redundancy changes and efficiency changes to network resilience changes, respectively.

$$\Delta_r y = \frac{1-log(e+r)+log(e)}{(e+r)^2} e\Delta r \tag{8}$$

$$\Delta_e y = \frac{1-log(e+r)+log(e)}{(e+r)^2}(-r)\Delta e \tag{9}$$

We define a ratio as

$$ratio \equiv \frac{\Delta_r y}{\Delta_e y} = \frac{e\Delta r}{-r\Delta e} = \frac{\frac{1}{2}(e_t+e_0)\Delta r}{-\frac{1}{2}(r_t+r_0)\Delta e} = \frac{(e_t+e_0)(r_t-r_0)}{-(r_t+r_0)(e_t-e_0)} \tag{10}$$

As a result, $\Delta_r y$ and $\Delta_e y$ can be written as

$$\Delta_r y = (y_t - y_0)\frac{\Delta_r y}{\Delta_r y+\Delta_e y} = (y_t - y_0)\frac{ratio}{1+ratio} \tag{11}$$

$$\Delta_e y = (y_t - y_0)\frac{\Delta_e y}{\Delta_r y+\Delta_e y} = (y_t - y_0)\frac{1}{1+ratio} \tag{12}$$

Based on the above formulas, one can calculate the relative contributions of efficiency and redundancy changes to the changes in network resilience during a certain time period.

The influence of structural factors

According to equation (1), we can decompose network efficiency into two structural factors: the concentration degree of flows (W) and node inter-dependency (a.k.a. Point-wise Mutual Information, PMI[49]). The element w_{ij} of matrix W, shown in equation (13), means the portion of the flow from node *i* to node *j* in the total system throughflow. The element pmi_{ij} of matrix PMI, shown in equation (14), indicates the degree of dependence between nodes *i* and *j*. A high value of pmi_{ij} can indicate a high probability of a flow from node *i* to node *j*. For example, oil flows from Saudi Arabia to the U.S. reveal one of the highest PMIs within all oil trade partners[49]. Subsequently, the network efficiency can be expressed as equation (15).

$$w_{ij} \equiv \frac{f(i,j)}{T(\cdot,\cdot)} \tag{13}$$

$$pmi_{ij} \equiv ln\frac{f(i,j)\times T(\cdot,\cdot)}{T(\cdot,j)\times T(i,\cdot)} \tag{14}$$

$$e = efficiency = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \times pmi_{ij} \tag{15}$$

We apply the index decomposition analysis[50] to reveal the contributions of changes in W and PMI to the changes in network efficiency, as shown in equation (16).

$$\Delta e_{ij} = \Delta w_{ij} \times pmi_{ij} + w_{ij} \times \Delta pmi_{ij} \tag{16}$$

The notation Δe_{ij} means network efficiency changes caused by changes in the link from node *i* to node *j*; Δw_{ij} means the changes in concentration degree of P flow from node *i* to node *j*; Δpmi_{ij} means the changes in node inter-dependency between node *i* and node *j*. The first item in the right-hand side of equation (16) indicates the contribution of the changes in the concentration degree of P flows from node *i* to node *j* to network efficiency changes, and the second item stands for the contribution of the changes in node inter-dependency between node *i* and node *j* to network efficiency changes.

There are two decomposition forms that are equally valid for equation (16) during the period of 0 to t[37]. The superscripts 0 and t in equations (17) and (18) indicates the time points.

$$\Delta e_{ij\_1} = \Delta w_{ij} \times pmi_{ij}^{0} + w_{ij}^{t} \times \Delta pmi_{ij} \tag{17}$$

$$\Delta e_{ij\_2} = \Delta w_{ij} \times pmi_{ij}^{t} + w_{ij}^{0} \times \Delta pmi_{ij} \tag{18}$$

Subsequently, the equation (16) can be re-written in the following form.

$$\Delta e_{ij} = \frac{1}{2}\left(\Delta w_{ij} \times pmi_{ij}^{0} + \Delta w_{ij} \times pmi_{ij}^{t}\right) + \frac{1}{2}\left(w_{ij}^{t} \times \Delta pmi_{ij} + w_{ij}^{0} \times \Delta pmi_{ij}\right) =$$

$$\Delta w_{ij} \times \frac{1}{2}\left(pmi_{ij}^{0} + pmi_{ij}^{t}\right) + \frac{1}{2}(w_{ij}^{t} + w_{ij}^{0}) \times \Delta pmi_{ij} \tag{19}$$

Consequently, at the system level, the contribution of the changes in concentration degree of all P flows to network efficiency changes ($\Delta_w e$) and the contribution of the changes in node inter-dependency to network efficiency changes ($\Delta_{pmi} e$) can be quantified by equations (21) and (22), respectively. The notation Δe indicates network efficiency changes.

$$\Delta e = \Delta_w e + \Delta_{pmi} e \tag{20}$$

$$\Delta_w e = \sum_{i=1}^{n}\sum_{j=1}^{n} \Delta_w e_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} \Delta w_{ij} \times \frac{1}{2}\left(pmi_{ij}^{0} + pmi_{ij}^{t}\right) \tag{21}$$

$$\Delta_{pmi} e = \sum_{i=1}^{n}\sum_{j=1}^{n} \Delta_{pmi} e_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{1}{2}(w_{ij}^{t} + w_{ij}^{0}) \times \Delta pmi_{ij} \tag{22}$$

Similar to network efficiency, we can also decompose network redundancy into two structural factors according to equation (2): the concentration degree of flows (W) and node inter-independency (i.e., the point-wise mutual redundancy (PMR), which indicates the degree of freedom between any two nodes). A higher value of PMR between node *i* and *j* (pmr_{ij}) can indicate a more diversity of destinations of a flow from node *i* to other nodes excluding node *j*. For example, nations embroiled in a trade war (most notably China and the U.S.) would seek to increase their PMR, that is, their flexibility in avoiding the other warring side.

$$w_{ij} \equiv \frac{f(i,j)}{T(\cdot,\cdot)} \tag{23}$$

$$pmr_{ij} \equiv ln\frac{T(\cdot,j) \times T(i,\cdot)}{f(i,j)^2} \tag{24}$$

$$r = redundancy = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \times pmr_{ij} \tag{25}$$

Similarly, network redundancy changes caused by changes in the flow from node *i* to node *j* (Δr_{ij}) can be decomposed into the contributions of the changes in the concentration degree of the flow from node *i* to node *j* ($\Delta_w r_{ij}$) and changes in node inter-independency between node *i* and node *j* ($\Delta_{pmr} r_{ij}$).

$$\Delta r_{ij} = \Delta_w r_{ij} + \Delta_{pmr} r_{ij} \tag{26}$$

$$\Delta_w r_{ij} = \Delta w_{ij} \times \frac{1}{2}\left(pmr_{ij}^0 + pmr_{ij}^t\right) \tag{27}$$

$$\Delta_{pmr} r_{ij} = \frac{1}{2}(w_{ij}^t + w_{ij}^0) \times \Delta pmr_{ij} \tag{28}$$

Consequently, at the system level, the contribution of the changes in concentration degree of all P flows to network redundancy changes ($\Delta_w r$) and the contribution of the changes in node inter-independency to network redundancy changes ($\Delta_{pmr} r$) can be quantified by equations (30) and (31), respectively. The notation Δr indicates network redundancy changes.

$$\Delta r = \Delta_w r + \Delta_{pmr} r \tag{29}$$

$$\Delta_w r = \sum_{i=1}^{n} \sum_{j=1}^{n} \Delta_w r_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{n} \Delta w_{ij} \times \frac{1}{2}\left(pmr_{ij}^0 + pmr_{ij}^t\right) \tag{30}$$

$$\Delta_{pmr}r = \sum_{i=1}^{n}\sum_{j=1}^{n}\Delta_{pmr}r_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n}\frac{1}{2}(w_{ij}^{t} + w_{ij}^{0}) \times \Delta pmr_{ij} \tag{31}$$

To quantify how W, PMI, and PMR affects network resilience, we define two new variables.

$$pry \equiv \frac{\Delta_r y}{\Delta r} = \frac{y_t - y_0}{r_t - r_0} \times \frac{ratio}{1+ratio} \tag{32}$$

$$pey \equiv \frac{\Delta_e y}{\Delta e} = \frac{y_t - y_0}{e_t - e_0} \times \frac{1}{1+ratio} \tag{33}$$

The notation *pry* indicates network resilience changes due to unitary redundancy changes, and *pey* represents network resilience changes due to unitary efficiency changes. As a result, we can derive the following equations.

$$\Delta_r y = pry \times \Delta r = pry \times \left(\Delta_w r + \Delta_{pmr} r\right) \tag{34}$$

$$\Delta_e y = pey \times \Delta e = pey \times \left(\Delta_w e + \Delta_{pmi} e\right) \tag{35}$$

$$\Delta y = \Delta_r y + \Delta_e y = (pry \times \Delta_w r + pey \times \Delta_w e) + pry \times \Delta_{pmr} r + pey \times \Delta_{pmi} e \tag{36}$$

$$\Delta y = \Delta_w y + \Delta_{pmr} y + \Delta_{pmi} y \tag{37}$$

The notations $\Delta_w y$, $\Delta_{pmr} y$, and $\Delta_{pmi} y$ indicate the contributions of changes to network resilience respectively by W, PMR, and PMI. They are expressed by equations (38) to (40), respectively.

$$\Delta_w y = pry \times \Delta_w r + pey \times \Delta_w e \tag{38}$$

$$\Delta_{pmr} y = pry \times \Delta_{pmr} r \tag{39}$$

$$\Delta_{pmi} y = pey \times \Delta_{pmi} e \tag{40}$$

In essence, the three system-level variables (i.e., efficiency, redundancy, and resilience) are composed by individual node-to-node relationships: the degree of dependencies (PMI), the degree of freedom (PMR), and the concentration of these relationships (W) over the entire network. The PMI, PMR, and W are independent from each other. Thus, it is valid to conduct the index decomposition analysis to quantify the relative contributions of the changes in W, PMI, and PMR to the changes in network efficiency, redundancy, and resilience.

Effects of link and node changes

According to the above calculations, the effects of changes in the flow from node *i* to node *j* (Δf_{ij}) to changes in network efficiency, redundancy, and resilience can be quantified by equations (41) to (43).

$$\Delta e_{ij} = \Delta w_{ij} \times \frac{1}{2}\left(pmi_{ij}^{0} + pmi_{ij}^{t}\right) + \frac{1}{2}\left(w_{ij}^{t} + w_{ij}^{0}\right) \times \Delta pmi_{ij} \quad (41)$$

$$\Delta r_{ij} = \Delta w_{ij} \times \frac{1}{2}\left(pmr_{ij}^{0} + pmr_{ij}^{t}\right) + \frac{1}{2}\left(w_{ij}^{t} + w_{ij}^{0}\right) \times \Delta pmr_{ij} \quad (42)$$

$$\Delta y_{ij} = (pry \times \Delta_{w} r_{ij} + pey \times \Delta_{w} e_{ij}) + pry \times \Delta_{pmr} r_{ij} + pey \times \Delta_{pmi} e_{ij} \quad (43)$$

Summing up the results for all the inflows to node *j*, we can calculate the contribution of changes in node *j* to changes in network efficiency, redundancy, and resilience.

$$\Delta e_{\cdot,j} = \sum_{i=1}^{n} \Delta e_{ij} \quad (44)$$

$$\Delta r_{\cdot,j} = \sum_{i=1}^{n} \Delta r_{ij} \quad (45)$$

$$\Delta y_{\cdot,j} = \sum_{i=1}^{n} \Delta y_{ij} \quad (46)$$

The notations $\Delta e_{\cdot,j}$, $\Delta r_{\cdot,j}$, and $\Delta y_{\cdot,j}$ indicate the contributions of changes in node *j* to changes in network efficiency, redundancy, and resilience, respectively, from the inflow perspective.

Similarly, summing up the results for all the outflows from node *i*, we can calculate the contribution of changes in node *i* to changes in network efficiency, redundancy, and resilience.

$$\Delta e_{i,\cdot} = \sum_{j=1}^{n} \Delta e_{ij} \quad (47)$$

$$\Delta r_{i,\cdot} = \sum_{j=1}^{n} \Delta r_{ij} \quad (48)$$

$$\Delta y_{i,\cdot} = \sum_{j=1}^{n} \Delta y_{ij} \quad (49)$$

The notations $\Delta e_{i,\cdot}$, $\Delta r_{i,\cdot}$, and $\Delta y_{i,\cdot}$ indicate the contributions of changes in node *i* to changes in network efficiency, redundancy, and resilience, respectively, from the outflow perspective.

Uncertainty analysis

The variety of raw data sources[12] may bring uncertainties into the results of this study. We used Monte Carlo simulation sampling 10,000 times (the same sampling methods as Liu et al.[12]) to calculate uncertainties in efficiency, redundancy, *alpha*, and resilience of the P cycling network in China during 1600–2012 (see Extended Data Figure 4 and Supplementary Discussions). Uncertainties are relatively large before 1949. Taking resilience as an example, we see that, compared to its calculation values, maximum and minimum uncertainties before 1949 are 2.6% and −7.6%, respectively. In contrast, its maximum and minimum uncertainties after 2000 are 2.2% and −3.8%, respectively. These results indicate that better statistical systems in recent years have significantly improved the quality of data sources[12], thereby reducing uncertainties in results. This underscores the need to improve P-related statistics in future research for obtaining more accurate P cycling estimates.

We conducted uncertainty analysis for the aggregation of nodes. Specifically, we constructed two networks of China's P cycling: one with 16 nodes and the other with 149 nodes. We calculated and compared the key indicators of the two networks, including efficiency, redundancy, *alpha*, and resilience (see Extended Data Figures 5-6 and Supplementary Discussions). Results have showed that both the 16-node and 149-node networks demonstrate almost the same evolution trend in these indicators during 1600–2012. However, in the 16-node network, the P cycling system was in an overly redundant state during 1742–1974 and generally in an overly efficient state during the remaining period. However, in the 149-node network, the P cycling system was in an overly efficient state during 1600–2012. Moreover, changes between the maximum and minimum values for the resilience of the 149-node network is 22.5%, which is much larger than that of the 16-node network (1.2%). Thus, the resolution of networks will significantly influence the results of this study. More accurate networks require more high-resolution data. Future studies in this avenue should be cautious on node aggregation.

Data and code availability

Calculations to generate 149-node P flow networks used data from Liu et al.[12] and were processed in MATLAB 2019a and R version 3.6.1. All data and computer codes generated for this study are available from the corresponding authors upon reasonable request.

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Contributions

S.L., Y.Y., A.K., and Z.M. designed the study. S.L. and Y.Y. collected data and conducted calculations. S.L., Y.Y., A.K., B.F., G.D., and S.C. led the analysis. S.L., Y.Y., A.K., B.F., C.F., G.D., S.C., T.M., B.Z., Z.M., and Z.Y. contributed to the writing. S.L. and Y.Y. contributed equally.

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Ethics declaration

Competing interests

The authors declare no competing interests.

Supplementary information

Supplementary information: supplementary tables 1-11, notes, methods, discussions and references. Supplementary table 1 is listed in Additional Supplementary Table.