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Key Points:

- Over one third of global AGHG emissions can be linked with intermediate trade (64.2%) and final trade (35.8%)
- Trade-related virtual AGHG emission transfers shape a highly heterogeneous network
- The hub economies are of great importance on global AGHG emission mitigation

Supporting Information:

- Supporting Information S1

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Linking Agricultural GHG Emissions to Global Trade Network

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Abstract As part of the climate policy to meet the 2 °C target, actions in all economic sectors, including agriculture, are required to mitigate global greenhouse gas emissions. While there has been an ever-increasing focus on agricultural greenhouse gas (AGHG) emissions, limited attention has been paid to their economic drivers in the globalized world economy and related mitigation potentials. This paper makes a first attempt to trace AGHG emissions via global trade networks using a multiregional input-output model and a complex network model. Over one third of global AGHG emissions in 2012 can be linked with products traded internationally, of which intermediate trade and final trade contribute 64.2% and 35.8%, respectively. Japan, the United States, Germany, the United Kingdom, and Hong Kong are the world's five largest net importers of embodied emissions, while Ethiopia, Australia, Pakistan, India, and Argentina are the five largest net exporters. Some hunger-afflicted developing countries in Asia and Africa are important embodied emission exporters, due to their large-scale exports of agricultural products. Trade-related virtual AGHG emission transfers shape a highly heterogeneous network, due to the coexistence of numerous peripheral economies and a few highly connected hub economies. The network clustering structure is revealed by the regional integration of several trading communities, while hub economies are collectors and distributors in the global trade network, with important implications for emission mitigation. Achieving AGHG emission reduction calls for a combination of supply- and demand-side policies covering the global trade network.

1. Introduction

Agriculture plays a fundamental role in supporting the global economy, meeting the demands of a growing population, changing diets, evolving lifestyles, and increasing biofuel production. Ensuring food security has been included in the sustainable development goals (SDGs) set by the United Nations. Global agri-food production has witnessed a rapid expansion since the 1980s (Davis et al., 2015). The worldwide production of meat, for example, rose from 71.4 Mt in 1961 to 307.5 Mt in 2012 (Caro et al., 2014). However, a great challenge confronts the agriculture sector to reconcile food supply expansion and the consequential climate impact (Frank et al., 2017; Valin et al., 2013). Agriculture is one of the most important economic sectors producing greenhouse gas (GHG) emissions (FAO, 2017; IPCC, 2014), including a dominant share of global CH₄ and N₂O emissions (Tubiello et al., 2013). The total GHG emissions from global agriculture were 6029.1 Mt CO₂-eq in 2012, approximately 11.2% of the world's total anthropogenic GHG emissions (Tubiello et al., 2015). In the context of global efforts to mitigate climate change, reducing GHG emissions from agriculture has been extensively investigated at various scales (Frank et al., 2017; Wollenberg et al., 2016).

The supply of agricultural products and corresponding AGHG emissions are linked with not only domestic markets for final consumption but also foreign markets and consumers via international trade (Dalin & Rodríguez-Iturbe, 2016; Schierhorn et al., 2016). International trade of agricultural products has been exponentially increasing at an even greater rate than production itself, yielding a significant extension of global food supply chains. The ratio of global agri-food export to production value surged from 10% in the 1970s to more than 50% in the 2010s (Ercsey-Ravasz et al., 2012). The total trade volume of agricultural products grew from 433.2 billion USD in 2000 to 1310.8 billion USD in 2016

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(FAO, 2017). Notwithstanding the growing significance of international agri-food trade, no research has specially focused on AGHG emissions caused by the trade demands, which are also directly linked with the intermediate trade and final trade. Intermediate trade activities refer to the trade of goods and services for intermediate production, including the processing of intermediate goods such as primary products and other raw materials, and final trade activities are the trade of goods and services for final consumption (e.g., household consumption, government consumption, and investment).

Top-down methods through multiregional input-output (MRIO) analysis can be employed to account for consumption-related emissions embodied in bilateral trade and multilateral trade (Wiedmann & Lenzen, 2018). For the world economy, the spatial linkages of different industrial sectors are depicted by global MRIO models (Chen & Wu, 2017; Lenzen et al., 2012a; Lenzen et al., 2013). As a result, the virtual transfer of GHG emissions among different countries or regions can be revealed (Davis & Caldeira, 2010; Jakob & Marschinski, 2013; Moran & Wood, 2014; Peters et al., 2011). Previous studies have contributed significantly to a consumption-oriented understanding on the origin of environmental and climate challenges (e.g., Arto & Dietzenbacher, 2014; Hertwich & Peters, 2009; Kanemoto et al., 2014, 2016; Malik et al., 2016; Pan et al., 2017; Zhang et al., 2018). For instance, Kanemoto et al. (2016) and Jiang and Green (2017) quantified global carbon footprints in some earlier years covering AGHG emissions with limited inventory data. Recently, because of the growing concerns over sustainable development of agriculture at a macroscale, substantial literature has been developed to extend the application of the global MRIO method to arable land use, agricultural water consumption, nitrogen pollution, and biodiversity threats (e.g., Chen et al., 2018a; Chen & Han, 2015; Hamilton et al., 2018; Lenzen et al., 2012b; Oita et al., 2016; Wood et al., 2018; Yu et al., 2013), yet the linkages of AGHG emissions with global trade networks remain to be systematically revealed.

Embodied AGHG emission flows, obtained via the global input-output modeling, form a web of interactions and further evolve into a complex network, where the countries are treated as network nodes and the emission flows as edges. Network characterization of global agri-food trade has caught increasing attention during the last few years (Ercsey-Ravasz et al., 2012; Lin et al., 2014; Sartori & Schiavo, 2015; Shuttters & Muneepeerakul, 2012; Torreggiani et al., 2018), yet their attention is confined to food trade itself, emphasizing either domestic food flows (Lin et al., 2014), national food security (Ercsey-Ravasz et al., 2012; Sartori & Schiavo, 2015), or international agri-food trade groups (Shuttters & Muneepeerakul, 2012; Torreggiani et al., 2018). A notable exception is Konar et al. (2011), which investigated virtual water network behind international food trade. In spite of the abundant literature on agri-food trade network, none of them have paid attention to the intricate network of embodied AGHG emissions in international trade. This paper advances the research in this area. Network analysis on the structure of interwoven AGHG emission flows can help understand the global food supply chains from a new angle. It not only sheds light on the regional and clustering features of AGHG emission flows but also identifies the hub economies as collectors and distributors in the global food trade, which are critical for implementing targeted mitigation policies on AGHG emissions. Although other tools like linkage analysis in MRIO models can also identify the key economies (Lenzen, 2003), complex network analysis is a more powerful instrument in the sense that it exploits the relation between a node and its neighbors, as well as the further relation between its neighbors and their own neighboring nodes. Moreover, compared with linkage analysis, it produces extra insight on overall properties and grouping structures of the network, enhancing the comprehensive understanding over global AGHG emissions.

This paper aims to link on-site AGHG emissions to global trade networks, adopting the Eora global MRIO model and the FAOSTAT emission database. We explore the characteristics of embodied AGHG emission transfers through international trade covering both the intermediate trade and final trade, because intermediate trade occupies a considerable share in global trading activities (Johnson & Noguera, 2012; Wu & Chen, 2017; Zhang et al., 2018). Network analysis is further conducted to reveal the hub economies and community structures of embodied AGHG emission flows. The results can help stakeholders better understand the complex relationship between agricultural production and final consumption. Furthermore, the opportunities to reduce global AGHG emissions in the international trade are addressed from the demand-driven perspective.

2. Methods and Data

2.1. The Global MRIO Model

The Global MRIO table describes the economic structure of a globalized world economy. Over the last decade, many institutions and experts have been engaged in the compilation of global economic input-output tables. In this study, the MRIO table for 2012 is chosen and extracted from the Eora MRIO Database (Lenzen et al., 2013), which is currently the largest database covering the most regions among existing input-output databases. A total of 188 economies are included, and 25 sectors are covered for each region, with the original two sectors of Agriculture and Fishing merged into one to fit the emission data. The extensive coverage of EORA enables us to trace embodied emissions for each region and identify the whole AGHG trade network. In most countries, agriculture is recorded as a single sector in their official input-output tables. Treating agriculture as a single sector can provide more accurate and convincing results in this study, which aims to draw the overall picture of embodied GHG emissions in global trade, instead of highlighting emissions from specific agricultural commodities.

The basic framework of a revised global MRIO table is shown in Figure S1 in the supporting information, which illustrates the input-output balance and the trade for intermediate production and final consumption/use. Detailed sectoral and regional information is shown in Tables S1 and S2, respectively. Other MRIO databases, such as EXIOBASE, offer more detailed sector classifications and have been used to uncover material and emission footprints (e.g., Hamilton et al., 2018; Moran & Wood, 2014; Wood et al., 2018; Zheng et al., 2018). However, these databases only cover the large economies, while many developing countries are important exporters of agricultural products but are absorbed into the rest of world. The EORA MRIO table nevertheless makes it feasible to identify GHG flows from those developing countries and presents the panorama of global trade network.

Sectoral biophysical balance implies emissions embodied in total outputs equals direct biophysical emissions plus indirect emissions embodied in intermediate inputs, with consideration of the AGHG emissions embodied in both final uses and intermediate inputs for all sectors linked with the environment and the economy (Wu & Chen, 2017; Zhang et al., 2018). Therefore, the emission balance in the global MRIO model can be expressed as

$$E_i^S + \sum_{R=1}^m \sum_{j=1}^n (\epsilon_j^R \times Z_{ji}^{RS}) = \epsilon_i^S \times X_i^S, \quad (1)$$

where E_i^S is the direct or on-site AGHG emissions of sector i in region S ; m stands for the number of regional economies; n refers to the number of economic sectors; ϵ_j^R represents the embodied (direct and indirect) AGHG emission intensity of the output from sector j in region R ; Z_{ji}^{RS} is the intermediate input of global economy, representing the economic fluxes from sector j in region R to sector i in region S ; ϵ_i^S represents the embodied (direct and indirect) AGHG emission intensity of the output from sector i in region S ; and X_i^S represents the total economic output from sector i in region S .

The compressed matrix form of the balance equation can then be shown as

$$\mathbf{E} + \boldsymbol{\varepsilon} \times \mathbf{Z} = \boldsymbol{\varepsilon} \times \hat{\mathbf{X}}, \quad (2)$$

$$\boldsymbol{\varepsilon} = \mathbf{E} (\hat{\mathbf{X}} - \mathbf{Z})^{-1}, \quad (3)$$

where $\hat{\mathbf{X}}$ is the diagonal matrix of \mathbf{X} . Under the condition that the matrix $(\hat{\mathbf{X}} - \mathbf{Z})$ is reversible, the embodied AGHG emission intensity ($\boldsymbol{\varepsilon}$) can be obtained. The AGHG emissions embodied in different economic activities can then be calculated by multiplying the monetary value of the products required in the activities with the corresponding sectors' embodied emission intensities.

The AGHG emissions embodied in intermediate trade and final trade are considered separately in this study, as the trade volumes in intermediate goods and final goods contribute with comparable importance to economies at different levels (Johnson & Noguera, 2012; Meng et al., 2018; Wu & Chen, 2017). Intermediate trade refers to intermediate producers' production-driven intermediate import and export,

while final trade covers final users' consumption-driven final import and export. Correspondingly, EEI_p^R , EEX_p^R , EEI_f^R , and EEX_f^R are specifically defined as the embodied AGHG emissions in intermediate imports, intermediate exports, final imports, and final exports of region R , respectively.

$$EEI_p^R = \sum_{S=1(S \neq R)}^m \sum_{i=1}^n \sum_{j=1}^n (\epsilon_i^S \times Z_{ij}^{SR}), \quad (4)$$

$$EEX_p^R = \sum_{j=1}^n \sum_{S=1(S \neq R)}^m \sum_{i=1}^n (\epsilon_j^R \times Z_{ji}^{RS}), \quad (5)$$

$$EEI_f^R = \sum_{S=1(S \neq R)}^m \sum_{i=1}^n \sum_{t=1}^l (\epsilon_i^S \times Y_{it}^{SR}), \quad (6)$$

$$EEX_f^R = \sum_{j=1}^n \sum_{S=1(S \neq R)}^m \sum_{t=1}^l (\epsilon_j^R \times Y_{jt}^{RS}). \quad (7)$$

2.2. The Complex Network Model

This section describes how we conduct complex network analysis based on the embodied AGHG emissions from the global MRIO model. Blöchl et al. (2011) first interpreted the input-output table as a weighted directed network and applied a complex network model to analyze its centrality. Inspired by this, researchers began to combine input-output models with the complex network models to study the trade networks of embodied carbon dioxides (Liang et al., 2015), energy (Chen et al., 2018b; Gao et al., 2018), rare earth (Wang et al., 2017), and minerals (Jiang et al., 2018). Our methods are in line with those studies except that we the conduct analysis on both intermediate and final trade networks.

2.2.1. Degree and Degree Distribution

In the unweighted AGHG network, the out-degree and in-degree represent the number of economies that a given economy is exporting AGHG to or importing AGHG from

$$k_i^{out} = \sum_{j=1(i \neq j)}^n a_{ij}, \quad (8)$$

$$k_i^{in} = \sum_{j=1(i \neq j)}^n a_{ji}, \quad (9)$$

where a_{ij} is a dummy variable indicating whether there are embodied AGHG flows from economy i to economy j , n is the total number of economies, and k_i^{out} and k_i^{in} represent the out-degree and in-degree, respectively. As for the weighted AGHG network, links connecting any two economies are weighted in proportion to the AGHG flows between them. Out-strength and in-strength in the weighted AGHG network represent the amounts of exported and imported AGHG emissions.

To analyze the scale-free structure of the AGHG network, we calculate the probability distribution of degree k as $p(k) = n_k/n$, where n_k is the number of economies that have the same degree k . The network can be characterized as a scale-free network if its degree distribution is well fitted by a power law distribution, that is, $p(k) \propto k^{-\lambda}$.

2.2.2. Network Distance

The shortest path between any two nodes is a path of edges that connect the nodes, and it is the shortest path possible in number of edges or weighted distances. Let d_{ij} be the shortest path from nodes i to j . The average path length is defined as the average shortest path:

$$L = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1(i \neq j)}^n d_{ij}. \quad (10)$$

Define m_i as the number of neighbors of node i and E_i as the actual number of edges among the m_i neighbors. Clustering coefficient measures the extent of node connections and clusters by the probability that any two neighbors of a given node are connected:

$$C = \frac{1}{n} \sum_{i=1}^n \frac{E_i}{m_i \times (m_i - 1)}. \quad (11)$$

2.2.3. Node Centrality

As a measure of node connectivity and intermediarity, betweenness centrality reflects the importance of a given node as the role of bridging other nodes by the number of shortest paths that go through it:

$$b_k = \sum_{i=1}^n \sum_{j=1}^n \sigma_{ij}(k) / \sigma_{ij}, \quad (12)$$

where σ_{ij} is the number of shortest paths between economy i and economy j , $\sigma_{ij}(k)$ is the number of shortest paths between i and j that pass through economy k , and b_k is the betweenness centrality of economy k . This measure indicates if economy k is on the shortest path between i and j , and then it counts in the betweenness centrality of economy k . In the AGHG network, an economy with high betweenness centrality implies its crucial bridging roles in transferring AGHG-embodied goods. For the weighted AGHG network, the path length between two economies is defined by the reciprocal embodied AGHG flows, with which we likewise obtain the weighted betweenness centrality.

Eigenvector centrality is another widely used centrality measure, which is defined as

$$v_i = \lambda^{-1} \sum_{j=1}^{n_i} a_{ij} v_j, \quad (13)$$

where λ and v_j are the largest eigenvalue and the associated eigenvector, respectively. Eigenvector centrality measures the node influence based on its neighbors. A node has large eigenvector centrality if it is connected with many other high-centrality nodes.

2.2.4. Community Partition

A community is a set of nodes that are more tightly connected internally than to the nodes outside of the community. Community partition is to divide the network into groups of nodes based on node connection. The detection of communities can shed light on the underlying function of the whole network system, where each community serves as a functional unit of the network. In order to better visualize the clustering structure of the AGHG network, we divide it into several submodules or communities; that is, the economies in the same community are densely linked but sparsely connected with the economies in other communities. We apply the modularity maximization method introduced by Girvan and Newman (2002) to find the optimal community partition. The modularity Q is defined by

$$Q = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n \left[w_{ij} - \frac{p_i p_j}{2m} \right] \delta(c_i, c_j), \quad (14)$$

where $w_{ij} = q_{ij} + q_{ji}$ is the amount of AGHG flows between economy i and economy j ; $p_i = \sum_{j=1}^n w_{ij}$ is the sum of AGHG flows attached to economy i ; c_i is the community to which economy i is assigned; $\delta(c_i, c_j)$ is an indicator function, which equals to 1 if $c_i = c_j$ and 0 otherwise; and $m = \sum_{i=1}^n \sum_{j=1}^n w_{ij} / 2$.

The modularity of partition compares the compactness of the links inside communities with that of the links between communities. A higher value of modularity suggests better quality of community partition. We use the algorithm proposed by Blondel et al. (2008) to implement this method and extract the community structure of the AGHG network.

2.3. Data Sources

The FAOSTAT emission database, including all the GHGs from global agriculture, is maintained by the Food and Agriculture Organization of the United Nations (FAO, 2017). This database can ensure the consistency with previous global and regional estimates, as well as the comparability across regions. Main agricultural emission subdomains refer to enteric fermentation, manure management, rice cultivation, synthetic fertilizers, manure applied to soils, manure left on pastures, crop residues, cultivation of organic soils,

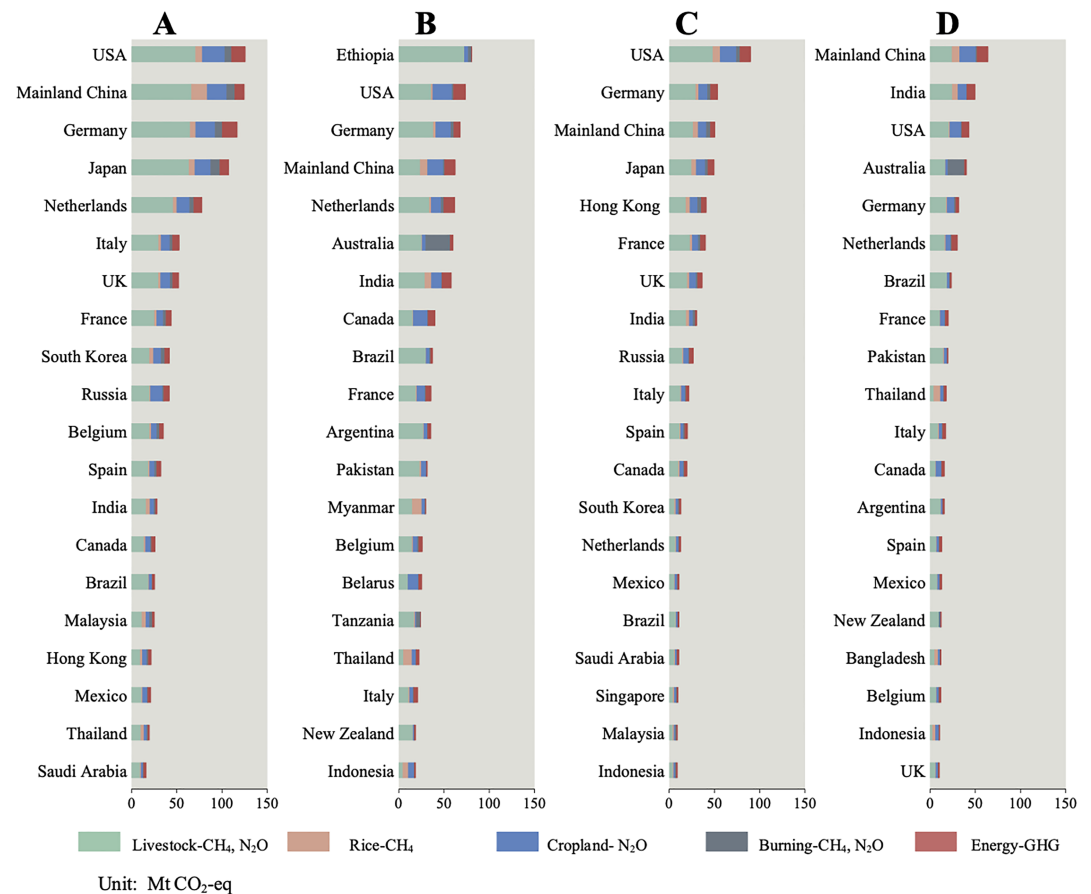


Figure 1. Embodied AGHG emissions in international trade of the top 20 intermediate importers (a), intermediate exporters (b), final importers (c), and final exporters (d).

burning of crop residues, burning of savanna, and energy use. The source categories of GHGs can be further divided into livestock-related CH₄ and N₂O emissions (52.3% of the total in 2012), rice cultivation-related CH₄ emissions, cropland-related N₂O emissions, burning-related CH₄ and N₂O emissions, and energy use-related GHG emissions. The latest complete data of AGHG emissions are for the year 2012, expressed in CO₂-equivalents according to the global warming potentials over a 100-year time horizon in the IPCC's Second Assessment Report. The population data are available from the statistical database of World Bank (2017).

3. Results

3.1. Substantial AGHG Emission Transfers via International Trade

The total embodied AGHG emissions in international trade are 2116.0 Mt CO₂-eq in 2012, equivalent to 35.1% of total global direct emissions. The United States has the largest volume of imported embodied AGHG emissions, accounting for 10.2% of global total import (40.6% of its total embodied emissions). Mainland China (8.3% of the total import or 19.4% of its total embodied emissions) ranks second, followed by Germany, Japan, and the Netherlands. The top five exporters of embodied AGHG emissions are Mainland China (6.0% of global total export or 14.0% of its total embodied emissions), the United States (5.5% of the total export or 22.0% of its total), India, Australia, and Germany, together accounting for 26.0% of the global trade-related emissions. Detailed trade-related embodied AGHG emissions are listed in Table S3.

Globally, intermediate trade and final trade account for 64.2% and 35.8% in international trade, respectively. For instance, intermediate imports account for 58.3% of the United States' total imported emissions while intermediate exports 63.1% of its exported emissions. As shown in Figure 1, the United States is the largest

intermediate importer and final importer of embodied AGHG emissions, while it is also the second largest intermediate exporters. Ethiopia is the largest intermediate exporters. Mainland China and India are the top two final exporters. In addition, Germany, Australia, and Netherlands have large embodied AGHG emissions in intermediate trade.

As to the emission source category, in the intermediate trade (see Table S4), the total transfer of embodied emissions from livestock-related CH_4 and N_2O , rice cultivation-related CH_4 , cropland- N_2O , burning-related CH_4 and N_2O , and energy use-related GHG reach 760.8, 93.9, 249.1, 95.7, and 159.6 Mt CO_2 -eq, respectively. In the final trade (see Table S5), the total transfers of embodied emissions from livestock-related CH_4 and N_2O , cropland- N_2O , and energy use-related GHG are 411.1, 140.7, and 97.2 Mt CO_2 -eq, respectively. As for the trading sectors, Agriculture and Food & Beverages contribute to 55.7% and 15.2% of the embodied AGHG emissions in intermediate trade, respectively. Also 37.9% and 30.8% of the embodied AGHG emissions in final trade are associated with Agriculture and Food & Beverages, respectively. In Japan, 55.4% of the total imported AGHG emissions are associated with the foreign supply into the sector of Agriculture, 23.0% into Food & Beverages, and 4.8% into Hotels & Restaurants.

Figure 2 further displays the trading transfers of embodied AGHG emissions via the intermediate trade and final trade among major economies (excluding intraregional trade within the economy). In Figure 2a, the largest intermediate trading flow is from Ethiopia to Japan among the top 20 economies. A total of 80.6 Mt CO_2 -eq of embodied emission is exported from Ethiopia, of which 32.8% and 28.1% are transferred to Japan and the EU27. The second largest flow is from Canada to the United States. The United States is the largest export market for Mexico and Canada, whose imports from these two countries contribute 17.0% of its total imports. The EU27 imports large quantities of agricultural products from other regions, and the emissions embodied in its import trade account for 20.4% of global total imports. As to the final trade of the 20 economies selected, the EU27 occupies the largest part in Figure 2b. The embodied emission from the EU27 imports is 1.9 times that from its exports, reflecting the extreme imbalance in its embodied emission trade. Meanwhile, China and India play the role as important embodied AGHG emission suppliers in the final trade.

The total net trade (total net imports or exports) of global embodied AGHG emissions reached 868.9 Mt CO_2 -eq. Japan, the United States, Germany, the United Kingdom, and Hong Kong are the world's five largest net importers. Meanwhile, Ethiopia, Australia, India, Pakistan, and Argentina are the five largest net exporters. Most of the direct emissions generated in Ethiopia and Belarus are to produce exports to meet the final demand in foreign countries. According to the "Global Hunger Index 2010" reported by the International Food Policy Research Institute (Grebmer et al., 2010), India, Ethiopia, and Pakistan continue to have hunger-afflicted areas. Nevertheless, these economies are net exporters of embodied AGHG emissions, owing to large-scale exports of agricultural products. Figure 3 presents the main trading flows of embodied AGHG emissions in the net trade among some major economies. In the intermediate net trade, the EU27, Japan, and China play the role of recipients because their imported embodied emissions are much larger than their exported embodied emissions. The net import of emissions in Japan is 99.7 Mt CO_2 -eq, of which 26.5% comes from Ethiopia and 12.0% from Australia. Russia is also a major net importer of embodied emissions, and Belarus and the EU27 are the largest net sources of its imports. In the final net trade, the EU27 and Japan remain recipients, with the net embodied emissions from final imports of 89.1 and 45.5 Mt CO_2 -eq, respectively. Note that the arrows connecting China and the United States flow in opposite directions. This can be partly explained by the fact that the United States exports intermediate goods such as soybeans to China for local production, but the United States imports final goods such as packaged foods and manufacturing commodities from China for local consumption.

3.2. Network Characteristics of Spatial AGHG Emission Outsourcing

International trade networks create complex links and feedback effects between geographically separated production and consumption locations. The interboundary flows of AGHG emissions are characterized by a complex network whose nodes are the 188 economies and edges are the embodied AGHG flows. The top 3,000 edges account for more than 95% of the AGHG flows, though the number of edges in each network is 35,156 (see Figure S2). This suggests the ubiquity of negligible edges and loosely connected nodes that are not neighboring many other nodes. To better understand the network characteristics of AGHG emission

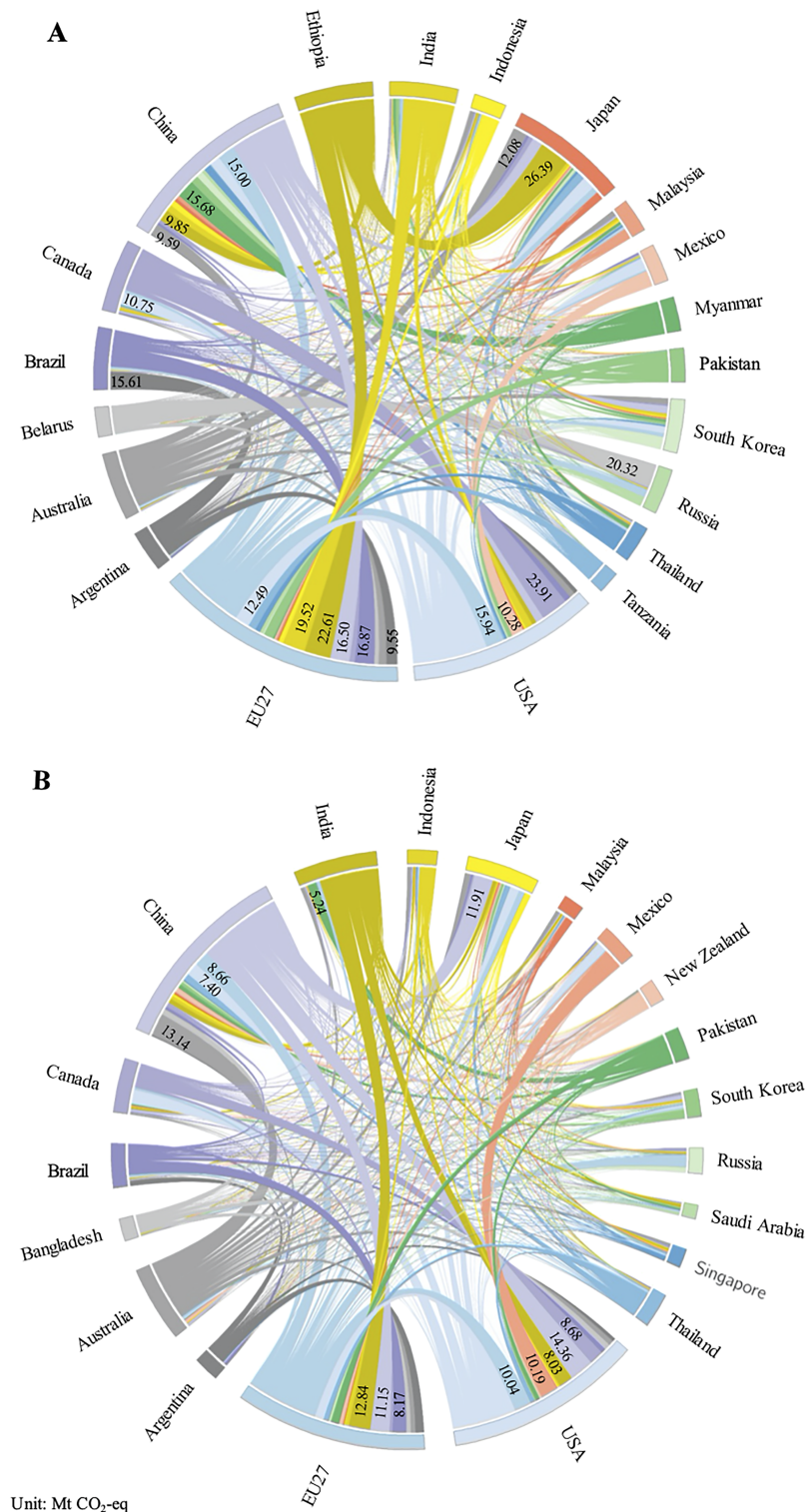


Figure 2. Interregional transfers of embodied AGHG emissions via intermediate trade (a) and final trade (b) among major economies. Note: The top 20 economies for the intermediate trade and final trade are selected in Figures 2a and 2b, respectively. Twenty-seven countries in the EU (excluding Croatia) are represented by EU27; China includes the mainland, Hong Kong, Macao, and Taiwan. The width of the connecting line represents the volume of trading flow. The connection between economies represents the trade transfer of embodied AGHG emissions, and the color of the connecting line is consistent with the exporter.

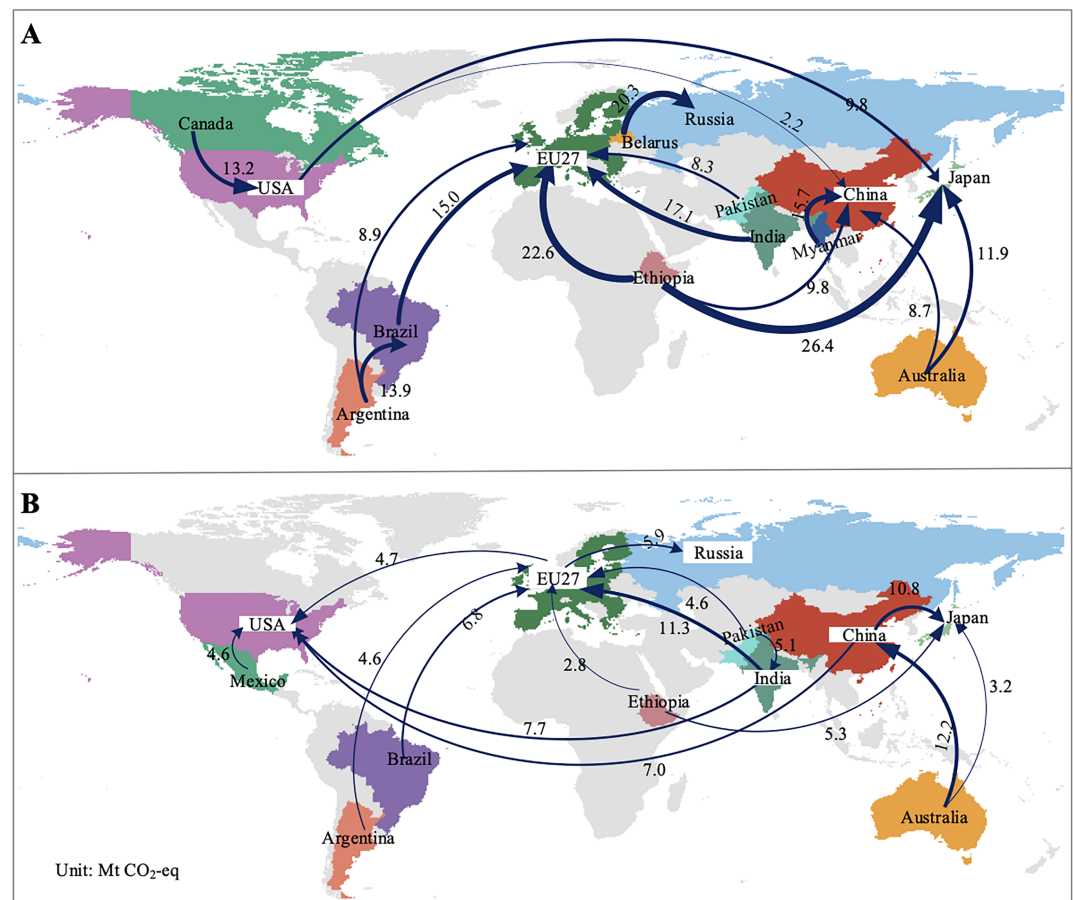


Figure 3. Main net trading flows of embodied AGHG emissions in terms of intermediate net trade (a) and final net trade (b). Note: 27 countries in the EU (excluding Croatia) are represented by EU27; China includes the mainland, Hong Kong, Macao, and Taiwan. The width of the blue line represents the net volume of trade-embodied emissions.

flows in interregional supply chains, we follow Nuss et al. (2016) and Chen et al. (2018b) to employ a filtering algorithm that removes the edges with weights less than a certain threshold (0.01 Mt CO₂-eq in our case). This procedure preserves all nodes but reduces edge numbers to 3,786 and 4,794, accounting for 97.0% and 97.4% of embodied AGHG flows in final trade and intermediate trade, respectively.

Before exploring detailed features of the AGHG network, we catch a glimpse on the overall network properties by discussing some network statistics (see Table S6). The link density for final trade is 0.107, lower than the density of intermediate trade (0.136), indicating the global intermediate trade of agricultural products involves more economies than the final trade. The clustering coefficients, which measure the probability of connection among neighboring nodes, are 0.374 and 0.458, suggesting economies are also more interconnected in intermediate trade than final trade. Those values of link densities and clustering coefficients are rather small even for intermediate trade, indicating that most economies are not directly linked with others. However, the average path length is 2.241 and 2.211, that is, only 2.2 steps to connect any two randomly selected nodes on average. This suggests most of the loosely connected economies can be indirectly linked with other nodes through their neighbors. The seeming contradiction between small link densities and clustering coefficients, and short characteristic path length is resulted from the coexistence of loosely connected economies and highly connected hub economies.

To further assess the network heterogeneity, Figure 4 shows degree distributions of the final-trade and intermediate-trade networks. There are a large number of peripheral economies that are loosely connected and a few hub economies that are highly connected with others. The in-degree and out-degree distributions for both intermediate and final trade are well fitted by power law distributions, suggesting the topology of the

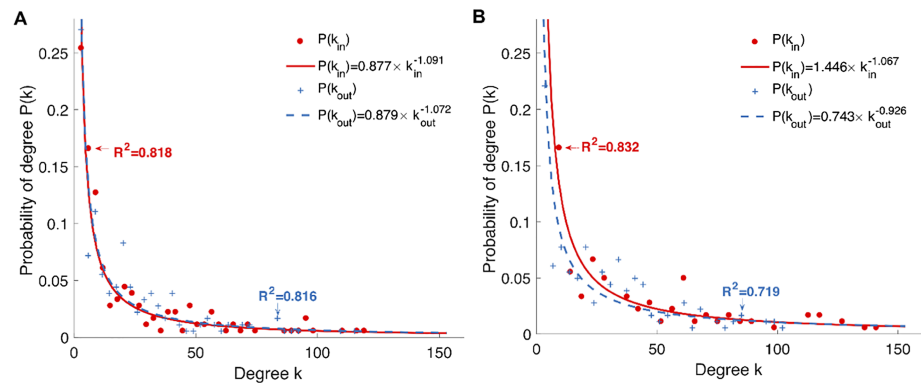


Figure 4. In-degree and out-degree distributions for final trade (a) and intermediate trade (b). Note: Power law distributions fit the final-trade in-degree, final-trade out-degree, intermediate-trade in-degree, and intermediate out-degree with high R^2 , implying the AGHG network is a scale-free network.

AGHG network approximately follows a scale-free network. The high R^2 highlights inherently heterogeneous roles of the 188 economies in the AGHG network.

After discussing the network heterogeneity, we shift our attention to clustering structures. Figure 5 visualizes the community partition with the Girvan-Newman algorithm. The final-trade network is characterized by six subgroups (see Table S7 for details). Community 1, dominated by European and North African countries, generates 474.7 Mt CO₂-eq flows and is the largest community in terms of both community members and aggregate flows. In spite that Community 2 is formed by 33 countries (Sub-Saharan African countries mainly), it generates the smallest AGHG flows (32.5 Mt CO₂-eq) among the six communities. Community 3 consists of countries in America and Community 4 of countries in East and Southeast Asia. The two communities are similar in the number of members and total AGHG flows. Twenty-five countries from South Asia and Middle East, for example, India, Pakistan, Iran, and Egypt, which are large exporters of agricultural products, form Community 5. The last community, led by Russia and Central Asian countries, consists of only 14 countries and generates 55.5 Mt CO₂-eq flows. On the other hand, the intermediate-trade network is divided into four communities. Communities 2 and 6 in the final-trade network are merged into one community. Communities 4 and 5 in the final-trade network are also combined together. This disparity in clustering structures implies that economies are more closely involved in the intermediate trade of agricultural products than the final trade. In order to check the robustness of our community partition, we follow the approach proposed by Carissimo et al. (2018), which examines partition stability against random perturbations. As depicted in Figure S3, the clustering distance (measured by Variation of Information) of our partition significantly departs from the random graph. This strongly supports the robustness of our community structure.

We further calculate the key network indicators (see Figures S4 and S5). For the final trade, Mainland China has the largest out-degree and out-strength. Ethiopia is the economy with the largest out-strength for intermediate trade while its out-degree is significantly smaller than other nodes with large out-strength, suggesting high concentration on the export destinations of its agricultural products. On the other hand, the final-trade in-strength of the United States is notably higher than other economies even though its in-degree is smaller than Germany and France. Except Mainland China and India, economies with large in-degree and in-strength are developed economies, especially those from West Europe. We also use betweenness centrality to assess the connectivity of each economy in the network. The United States and Mainland China are the two countries with the largest final-trade betweenness centrality. However, the intermediate-trade betweenness centrality of Mainland China becomes smaller while India has the largest weighted centrality, implying India is bridging many other economies as a trade junction in the intermediate trade of agricultural products. Countries like Argentina in South America, Belarus in East Europe, and South Africa and Tanzania in Africa also have large intermediate-trade betweenness centrality despite of their small total strength, because they are the leading countries that bridge other trade partners. Another centrality measure presented in Figures S4 and S5 is eigenvector centrality, which reflects the influence of a node by its neighboring nodes' importance. Because they are closely connected with the pivotal nodes

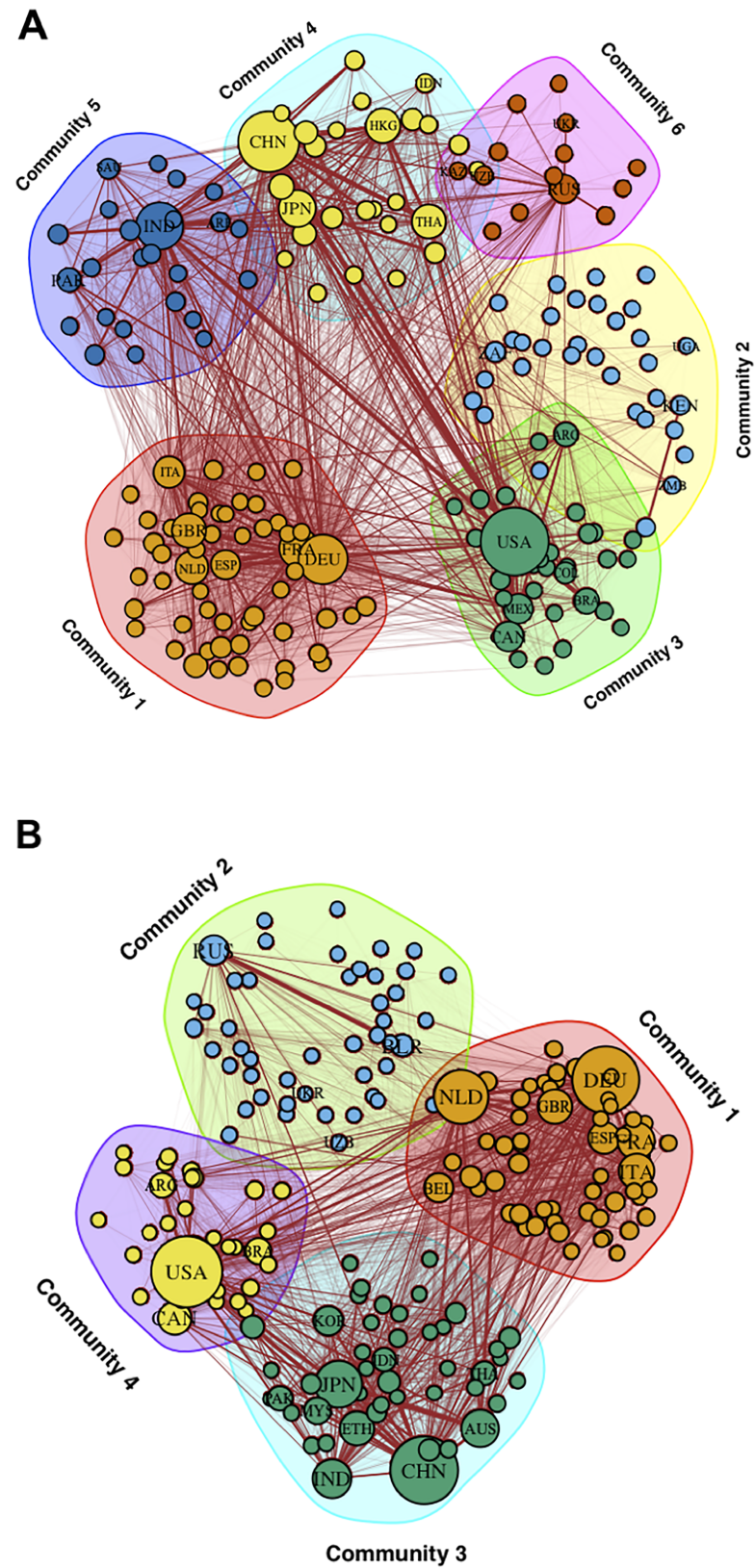


Figure 5. Regional community structures for final trade (a) and intermediate trade (b). Note: The circle size of each node represents its total strength. The thickness of each connecting line represents the edge weight, that is, the amount of AGHG flows. Community detection and partitions are based on the Girvan-Newman algorithm.

such as the United States, Mainland China, and India, countries like Brazil, Thailand, and Pakistan also hold large eigenvector centrality.

4. Discussions and conclusions

Global AGHG emissions are expected to increase steadily in the future (FAO, 2017; UNEP, 2012), because of the rising consumption of food products and growing agricultural industrialization (Davis et al., 2015; Havlik et al., 2014; Herrero et al., 2016; UNEP, 2012). The world average per capita embodied AGHG emission is 0.9 t CO₂-eq; the variation among economies nevertheless is very high (see Table S8). Of the 20 largest emitting economies, Australia, with the fourth and fifth largest out-strength in intermediate and final trade, has the largest per capita embodied AGHG emission of 5.2 t CO₂-eq. However, the per capita emissions in other economies with large out-strength, such as Mainland China, India, Indonesia, and Pakistan, are below the world-average level. Mainland China's total embodied emissions in final demand are 1.7 times greater than those of the United States (see Table S8), but its per capita emissions are only 39.6% of the United States. For many developing and emerging countries in Africa and Asia, the diversification and westernization of diets and lifestyles are leading to profound and long-term changes in the structure of food demand, which poses a potential warning on the increase of global animal food consumption and its associated AGHG emissions.

International trade can improve resource allocation for agricultural production and help to meet the food and nutritional demands of a growing population around the world (Fader et al., 2013; Torreggiani et al., 2018). Globalization has induced more economies to participate in the international trade of agricultural products, making up the peripheral regions of the virtual AGHG network. For most economies with large out-strength and out-degree, their embodied AGHG emission inventories are significantly different from the direct emission inventories owing to international trade. For instance, Australia's direct emissions are 70.6% more than its embodied emissions in final demand. Japan's embodied emissions are 182.8 Mt CO₂-eq, 4.9 times of its direct emissions. Major trading economies in either intermediate trade or final trade are identified, including the United States, Mainland China, Germany, Japan, India, Australia, and Netherlands. Japan, the United States, Germany, the United Kingdom, and Hong Kong are the top five net importers, while Ethiopia, Australia, India, Pakistan, and Argentina are the top five net exporters. Developing climate policies should take account of the structures of international trade, because the large-scale trade of agri-food products has a prominent impact on regional AGHG emissions (Caro et al., 2014; Schmitz et al., 2012; Yu et al., 2013).

Embodied AGHG emissions in intermediate trade (64.2%) almost doubles the emissions in final trade (35.8%). The network structures of intermediate and final trade imply differentiated responsibilities of each economy. For example, along with India, Pakistan and Saudi Arabia are also the leading countries in their community of intermediate trade, while their roles are much more trivial in final trade. This suggests the two countries need to put more efforts in emission mitigation of their trades of intermediate products. Moreover, the intermediate-trade AGHG network is revealed to be more densely connected and have shorter path length. The network heterogeneity meanwhile characterizes the existence of a few highly connected hub economies. Those features together imply any perturbation in the key nodes will spread rapidly over the network. The hub economies are of great importance on global AGHG emission mitigation, so identifying them through network indicators provides valuable policy implications. The priority of GHG mitigation shall be laid on those economies. The same livestock raised in different countries have different GHG emission intensities (Hawkins et al., 2016). Theoretically, the imports of agricultural commodities with lower embodied emission intensities will generate a global climate benefits (Caro et al., 2014; Havlik et al., 2014). Therefore, the benefits of GHG mitigation technologies, especially in producing intermediate agricultural products, adopted by hub economies can also be simultaneously shared by many other economies. In addition, the AGHG network is regionally integrated and partitioned by several communities, within which numerous of peripheral economies are connected by hub economies. This regional integration not only widens the scope of understanding how policy interventions structurally affect the AGHG network but also highlights the necessity of concerted efforts in each community to reduce GHG emissions.

The scale-free feature implies that global trade network is stable against random failures because the probability that a randomly removed node is a loosely connected economy is significantly large and removing

such a node has quite limited effects on the overall topology. However, the AGHG network is vulnerable to coordinated adjustments on key nodes; that is, adjustments in trade patterns and emission intensities of hub economies will reshape the network structure and generate profound impacts on global AGHG emissions. Similarly detected in the trade network of natural gas, oil, rare earths, and embodied energy (Chen et al., 2018b; Gao et al., 2015; Geng et al., 2014; Hou et al., 2018), this scale-free topology occurs as the results of preferential treatments and globalization trends. Comparative advantages such as natural resources, geographical location, and climate suitability promote positive feedbacks on the production of agricultural products, leading to preferential attachment that typically appears in the high-degree nodes (Serrano & Boguñá, 2003). As reflected by out-degree and out-strength, besides China and India, developing countries like Ethiopia, Pakistan, Thailand, and Myanmar are also major exporters in the AGHG network. However, huge obstacles exist in mitigating their AGHG emissions since agriculture is their pillar industry. Mitigation investments in those countries need technical and financial supports from developed economies, which on the contrary are revealed to be the chief importers of AGHG-embodied goods by in-degree and in-strength. Nonnegligible are the roles of bridging countries with large betweenness and eigenvector centrality, such as Belarus, Brazil, South Africa, and Tanzania. Reducing their emissions can contribute significantly to the mitigation of their neighboring hub economies like Mainland China, India, and the United States.

The global total export value of agricultural products is 1337.7 billion USD in 2012, mainly from large-size economies such as the United States (145.0), the Netherlands (86.6), Brazil (80.1), Germany (79.2), and France (70.2). However, the export values of many developing economies such as Mainland China, India, and Pakistan are relatively low, comparing to their high volumes of embodied AGHG emission exports. Policy makers should consider the trade-off between economic benefits and AGHG emissions of exported commodities. Demand-side interventions such as country-of-origin food labels and carbon certification schemes can also contribute to optimizing trade structure in the importing countries and adopting environmentally benign agricultural technologies in the exporting countries. Given the spillover effects of climate policies, the regionally integrated community structure necessitates greater intracountry cooperation within the same communities. Foreign consumers are incentivized to consume less emission-intensive agricultural products, adopt more climate-friendly diets, reduce food wastage, and in turn prompt upstream suppliers to minimize environmental impacts (Kastner et al., 2011; Pradhan et al., 2013; Yue et al., 2017). Realizing the full potentials to mitigate global AGHG emissions calls for a combination of supply- and demand-side policies and actions. Equipped with more concrete MRIO models and more specific data sources, future research on developing targeted policies should take account of specific agricultural commodities, different diet and other consumption demands, structural changes of agri-food trade, and their evolution trends among various countries.

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See Tables S1–S8 and Figures S1–S5 in the supporting information associated with this article. All the AGHG emission data can be available from the FAOSTAT Emissions Database (at <http://faostat.fao.org/>). This study has been supported by the National Natural Science Foundation of China (Grant 71774161 and 71804194) and the Yue Qi Young Scholar Project, China University of Mining and Technology (Beijing). Very helpful comments by the anonymous reviewers and the editor are highly appreciated.

References

- Arto, I., & Dietzenbacher, E. (2014). Drivers of the growth in global greenhouse gas emissions. *Environmental Science & Technology*, 48(10), 5388–5394. <https://doi.org/10.1021/es5005347>
- Blöchl, F., Theis, F. J., Vega-Redondo, F., & Fisher, E. O. N. (2011). Vertex centralities in input–output networks reveal the structure of modern economies. *Physical Review E* 2011, 83(4), 046127. <https://doi.org/10.1103/physreve.83.046127>
- Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 10, P10008. <https://doi.org/10.1088/1742-5468/2008/10/p10008>
- Carissimo, A., Cutillo, L., & De Feis, I. (2018). Validation of community robustness. *Computational Statistics & Data Analysis*, 120, 1–24. <https://doi.org/10.1016/j.csda.2017.10.006>
- Caro, D., LoPresti, A., Davis, S. J., Bastianoni, S., & Caldeira, K. (2014). CH₄ and N₂O emissions embodied in international trade of meat. *Environmental Research Letters*, 9(11), 114005. <https://doi.org/10.1088/1748-9326/9/11/114005>
- Chen, B., Han, M. Y., Peng, K., Zhou, S. L., & Chen, G. Q. (2018a). Global land-water nexus: Agricultural land and freshwater use embodied in worldwide supply chains. *Science of the Total Environment*, 613, 931–943. <https://doi.org/10.1016/j.scitotenv.2017.09.138>
- Chen, B., Li, J. S., Wu, X. F., Han, M. Y., Zeng, L., Li, Z., & Chen, G. Q. (2018b). Global energy flows embodied in international trade: A combination of environmentally extended input–output analysis and complex network analysis. *Applied Energy*, 210, 98–107. <https://doi.org/10.1016/j.apenergy.2017.10.113>
- Chen, G. Q., & Han, M. Y. (2015). Global supply chain of arable land use: Production-based and consumption-based trade imbalance. *Land Use Policy*, 49, 118–130. <https://doi.org/10.1016/j.landusepol.2015.07.023>
- Chen, G. Q., & Wu, X. F. (2017). Energy overview for globalized world economy: Source, supply chain and sink. *Renewable and Sustainable Energy Reviews*, 69, 735–749. <https://doi.org/10.1016/j.rser.2016.11.151>
- Dalin, C., & Rodríguez-Iturbe, I. (2016). Environmental impacts of food trade via resource use and greenhouse gas emissions. *Environmental Research Letters*, 11(3), 035012. <https://doi.org/10.1088/1748-9326/11/3/035012>

- Davis, F. K., Yu, K. L., Herrero, M., Havlik, P., Carr, J. A., & D'Odorico, P. (2015). Historical trade-offs of livestock's environmental impacts. *Environmental Research Letters*, 10(12), 125013. <https://doi.org/10.1088/1748-9326/10/12/125013>
- Davis, S. J., & Caldeira, K. (2010). Consumption-based accounting of CO₂ emissions. *Proceedings of the National Academy of Sciences of the United States of America*, 107(12), 5687–5692. <https://doi.org/10.1073/pnas.0906974107>
- Ercsey-Ravasz, M., Toroczka, Z., Lakner, Z., & Baranyi, J. (2012). Complexity of the international agro-food trade network and its impact on food safety. *PLoS ONE*, 7(5), e37810. <https://doi.org/10.1371/journal.pone.0037810>
- Fader, M., Gerten, D., Krause, M., Lucht, W., & Cramer, W. (2013). Spatial decoupling of agricultural production and consumption: quantifying dependences of countries on food imports due to domestic land and water constraints. *Environmental Research Letters*, 8(1), 014046. <https://doi.org/10.1088/1748-9326/8/1/014046>
- FAO (2017). FAOSTAT Emissions Database. Retrieved from (<http://faostat.fao.org/>)
- Frank, S., Havlik, P., Soussana, J. F., Levesque, A., Valin, H., Wollenberg, E., et al. (2017). Reducing greenhouse gas emissions in agriculture without compromising food security. *Environmental Research Letters*, 12(10), 105004. <https://doi.org/10.1088/1748-9326/aa8c83>
- Gao, C., Su, B., Sun, M., Zhang, X., & Zhang, Z. (2018). Interprovincial transfer of embodied primary energy in China: A complex network approach. *Applied Energy*, 215, 792–807. <https://doi.org/10.1016/j.apenergy.2018.02.075>
- Gao, C., Sun, M., & Shen, B. (2015). Features and evolution of international fossil energy trade relationships: A weighted multilayer network analysis. *Applied Energy*, 156, 542–554. <https://doi.org/10.1016/j.apenergy.2015.07.054>
- Geng, J. B., Ji, Q., & Fan, Y. (2014). A dynamic analysis on global natural gas trade network. *Applied Energy*, 132, 23–33. <https://doi.org/10.1016/j.apenergy.2014.06.064>
- Girvan, M., & Newman, M. E. (2002). Community structure in social and biological networks. *Proceedings of the National Academy of Sciences of the USA*, 99(12), 7821–7826. <https://doi.org/10.1073/pnas.122653799>
- Grebmer, K. V., Ruel, M. T., Menon, P., Nestorova, B., Olofinbiyi, T., Fritshel, H., Yohannes, Y. 2010. Global hunger index: The challenge of hunger. Available at: <http://www.ifpri.org/publication/2010-global-hunger-index-challenge-hunger>.
- Hamilton, H. A., Ivanova, D., Stadler, K., Merciai, S., Schmidt, J., Van Zelm, R., et al. (2018). Trade and the role of non-food commodities for global eutrophication. *Nature Sustainability*, 1(6), 314–321. <https://doi.org/10.1038/s41893-018-0079-z>
- Havlik, P., Valin, H., Herrero, M., Obersteiner, M., Schmid, E., Rufino, M. C., et al. (2014). Climate change mitigation through livestock system transitions. *Proceedings of the National Academy of Sciences of the USA*, 111(10), 3709–3714. <https://doi.org/10.1073/pnas.1308044111>
- Hawkins, J., Ma, C., Schilizzi, S., & Zhang, F. (2016). Apples to kangaroos: A framework for developing internationally comparable carbon emission factors for crop and livestock products. *Journal of Cleaner Production*, 139, 460–472. <https://doi.org/10.1016/j.jclepro.2016.08.060>
- Herrero, M., Henderson, B., Havlik, P., Thornton, P. K., Conant, R. T., Smith, P., et al. (2016). Greenhouse gas mitigation potentials in the livestock sector. *Nature Climate Change*, 6(5), 452–461. <https://doi.org/10.1038/nclimate2925>
- Hertwich, E. G., & Peters, G. P. (2009). Carbon footprint of nations: A global, trade-linked analysis. *Environmental Science & Technology*, 43(16), 6414–6420. <https://doi.org/10.1021/es803496a>
- Hou, W., Liu, H., Wang, H., & Wu, F. (2018). Structure and patterns of the international rare earths trade: A complex network analysis. *Resources Policy*, 55, 133–142. <https://doi.org/10.1016/j.resourpol.2017.11.008>
- IPCC (2014). IPCC fifth assessment report: Climate change 2013 (AR5). Retrieved from www.ipcc.ch/index.htm
- Jakob, M., & Marschinski, R. (2013). Interpreting trade-related CO₂ emission transfers. *Nature Climate Change*, 3(1), 19–23. <https://doi.org/10.1038/nclimate1630>
- Jiang, M., An, H., Guan, Q., & Sun, X. (2018). Global embodied mineral flow between industrial sectors: A network perspective. *Resources Policy*, 58, 192–201. <https://doi.org/10.1016/j.resourpol.2018.05.006>
- Jiang, X., & Green, C. (2017). The impact on global greenhouse gas emissions of geographic shifts in global supply chains. *Ecological Economics*, 139, 102–114. <https://doi.org/10.1016/j.ecolecon.2017.04.027>
- Johnson, R. C., & Noguera, G. (2012). Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics*, 86(2), 224–236. <https://doi.org/10.1016/j.jinteco.2011.10.003>
- Kanemoto, K., Moran, D., & Hertwich, E. G. (2016). Mapping the carbon footprint of nations. *Environmental Science & Technology*, 50(19), 10,512–10,517. <https://doi.org/10.1021/acs.est.6b03227>
- Kanemoto, K., Moran, D., Lenzen, M., & Geschke, A. (2014). International trade undermines national emission reduction targets: New evidence from air pollution. *Global Environmental Change*, 24, 52–59. <https://doi.org/10.1016/j.gloenvcha.2013.09.008>
- Kastner, T., Kastner, M., & Nonhebel, S. (2011). Tracing distant environmental impacts of agricultural products from a consumer perspective. *Ecological Economics*, 70(6), 1032–1040. <https://doi.org/10.1016/j.ecolecon.2011.01.012>
- Konar, M., Dalin, C., Suweis, S., Hanasaki, N., Rinaldo, A., & Rodriguez-Iturbe, I. (2011). Water for food: the global virtual water trade network. *Water Resources Research*, 47, W05520. <https://doi.org/10.1029/2010wr010307>
- Lenzen, M. (2003). Environmentally important paths, linkages and key sectors in the Australian economy. *Structural Change and Economic Dynamics*, 14(1), 1–34. [https://doi.org/10.1016/S0954-349X\(02\)00025-5](https://doi.org/10.1016/S0954-349X(02)00025-5)
- Lenzen, M., Kanemoto, K., Moran, D., & Geschke, A. (2012a). Mapping the structure of the world economy. *Environmental Science & Technology*, 46(15), 8374–8381. <https://doi.org/10.1021/es300171x>
- Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., & Geschke, A. (2012b). International trade drives biodiversity threats in developing nations. *Nature*, 486(7401), 109–112. <https://doi.org/10.1038/nature11145>
- Lenzen, M., Moran, D., Kanemoto, K., & Geschke, A. (2013). Building Eora: A global multi-region input-output database at high country and sector resolution. *Economic Systems Research*, 25(1), 20–49. <https://doi.org/10.1080/09535314.2013.769938>
- Liang, S., Feng, Y., & Xu, M. (2015). Structure of the global virtual carbon network: Revealing important sectors and communities for emission reduction. *Journal of Industrial Ecology*, 19(2), 307–320. <https://doi.org/10.1111/jiec.12242>
- Lin, X., Dang, Q., & Konar, M. (2014). A network analysis of food flows within the United States of America. *Environmental Science & Technology*, 48(10), 5439–5447. <https://doi.org/10.1021/es500471d>
- Malik, A., Lan, J., & Lenzen, M. (2016). Trends in global greenhouse gas emissions from 1990 to 2010. *Environmental Science & Technology*, 50(9), 4722–4730. <https://doi.org/10.1021/acs.est.5b06162>
- Meng, J., Zhang, Z., Mi, Z., Anadon, L. D., Zheng, H., Zhang, B., et al. (2018). The role of intermediate trade in the change of carbon flows within China. *Energy Economics*, 76, 303–312. <https://doi.org/10.1016/j.eneco.2018.10.009>
- Moran, D., & Wood, R. (2014). Convergence between the Eora, WIOD, EXIOBASE and OpenEU's consumption-based carbon accounts. *Economic Systems Research*, 26(3), 245–261. <https://doi.org/10.1080/09535314.2014.935298>

- Nuss, P., Chen, W. Q., Ohno, H., & Graedel, T. E. (2016). Structural investigation of aluminum in the US economy using network analysis. *Environmental Science & Technology*, 50(7), 4091–4101. <https://doi.org/10.1021/acs.est.5b05094>
- Oita, A., Malik, A., Kanemoto, K., Geschke, A., Nishijima, S., & Lenzen, M. (2016). Substantial nitrogen pollution embedded in international trade. *Nature Geoscience*, 9(2), 111–115. <https://doi.org/10.1038/ngeo2635>
- Pan, C., Peters, G. P., Andrew, R. M., Korsbakken, J. L., Li, S., Zhou, D., & Zhou, P. (2017). Emissions embodied in global trade have plateaued due to structural changes in China. *Earth's Future*, 5(9), 934–946. <https://doi.org/10.1002/2017EF000625>
- Peters, G. P., Minx, J. C., Weber, C. L., & Edenhofer, O. (2011). Growth in emission transfers via international trade from 1990 to 2008. *Proceedings of the National Academy of Sciences of the USA*, 108(21), 8903–8908. <https://doi.org/10.1073/pnas.1006388108>
- Pradhan, P., Reusser, D. E., & Kropp, J. P. (2013). Embodied greenhouse gas emissions in diets. *PLoS ONE*, 8, 1–9. <https://doi.org/10.1371/journal.pone.0062228>
- Sartori, M., & Schiavo, S. (2015). Connected we stand: A network perspective on trade and global food security. *Food Policy*, 57, 114–127. <https://doi.org/10.1016/j.foodpol.2015.10.004>
- Schierhorn, F., Meyfroidt, P., Kastner, T., Kuemmerle, T., Prishchepov, A. P., & Müller, D. (2016). The dynamics of beef trade between Brazil and Russia and their environmental implications. *Global Food Security*, 11, 84–92. <https://doi.org/10.1016/j.gfs.2016.08.001>
- Schmitz, C., Biewald, A., Lotze-Campen, H., Popp, A., Dietrich, J. P., Bodirsky, B., et al. (2012). Trading more food: Implications for land use, greenhouse gas emissions, and the food system. *Global Environmental Change*, 22(1), 189–209. <https://doi.org/10.1016/j.gloenvcha.2011.09.013>
- Serrano, M. A., & Boguñá, M. (2003). Topology of the world trade web. *Physical Review E*, 68, 015101. <https://doi.org/10.1103/physreve.68.015101>
- Shutters, S. T., & Muneepeerakul, R. (2012). Agricultural trade networks and patterns of economic development. *PLoS ONE*, 7(7), e39756. <https://doi.org/10.1371/journal.pone.0039756>
- Torreggiani, S., Mangioni, G., Puma, M. J., & Fagiolo, G. (2018). Identifying the community structure of the food-trade international multi-network. *Environmental Research Letters*, 13(5), 054026. <https://doi.org/10.1088/1748-9326/aabf23>
- Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., et al. (2015). The contribution of Agriculture, Forestry and other Land Use activities to Global Warming, 1990–2012. *Global Change Biology*, 21(7), 2655–2660. <https://doi.org/10.1111/gcb.12865>
- Tubiello, F. N., Salvatore, M., Rossi, S., Ferrara, A., Fittion, N., & Smith, P. (2013). The FAOSTAT database of greenhouse gas emissions from agriculture. *Environmental Research Letters*, 8(1), 015009. <https://doi.org/10.1088/1748-9326/8/1/015009>
- UNEP (2012). Growing greenhouse gas emissions due to meat production. Retrieved from https://na.unep.net/geas/getunepagewitharticleidsript.php?article_id=92
- Valin, H., Havlik, P., Mosnier, A., Herrero, M., Schmid, E., & Obersteiner, M. (2013). Agricultural productivity and greenhouse gas emissions: Trade-offs or synergies between mitigation and food security. *Environmental Research Letters*, 8(3), 035019. <https://doi.org/10.1088/1748-9326/8/3/035019>
- Wang, X., Wei, W., Ge, J., Wu, B., Bu, W., Li, J., et al. (2017). Embodied rare earths flow between industrial sectors in China: A complex network approach. *Resources, Conservation and Recycling*, 125, 363–374. <https://doi.org/10.1016/j.resconrec.2017.07.006>
- Wiedmann, T. O., & Lenzen, M. (2018). Environmental and social footprints of international trade. *Nature Geoscience*, 11(5), 314–321. <https://doi.org/10.1038/s41561-018-0113-9>
- Wollenberg, E., Richards, M., Smith, P., Havlik, P., Obersteiner, M., Tubiello, F. N., et al. (2016). Reducing emissions from agriculture to meet the 2 °C target. *Global Change Biology*, 22(12), 3859–3864. <https://doi.org/10.1111/gcb.13340>
- Wood, R., Stadler, K., Simas, M., Bulavskaya, T., Giljum, S., Lutter, S., & Tukker, A. (2018). Growth in environmental footprints and environmental impacts embodied in trade: Resource efficiency indicators from EXIOBASE3. *Journal of Industry Ecology*, 22(3), 553–564. <https://doi.org/10.1111/jiec.12735>
- World Bank (2017). World Bank Database. Retrieved from <https://data.worldbank.org/indicator/SP.POP.TOTL>
- Wu, X. F., & Chen, G. Q. (2017). Global primary energy use associated with production, consumption and international trade. *Energy Policy*, 111, 85–94. <https://doi.org/10.1016/j.enpol.2017.09.024>
- Yu, Y., Feng, K., & Hubacek, K. (2013). Tele-connecting local consumption to global land use. *Global Environmental Change*, 23(5), 1178–1186. <https://doi.org/10.1016/j.gloenvcha.2013.04.006>
- Yue, Q., Xu, X., Hillier, J., Cheng, K., & Pan, G. (2017). Mitigating greenhouse gas emissions in agriculture: From farm production to food consumption. *Journal of Cleaner Production*, 149, 1011–1019. <https://doi.org/10.1016/j.jclepro.2017.02.172>
- Zhang, B., Zhao, X. L., Wu, X. F., Han, M. Y., Guan, C. H., & Song, S. J. (2018). Consumption-based accounting of global anthropogenic CH₄ emissions. *Earth's Future*, 6(9), 1349–1363. <https://doi.org/10.1029/2018EF000917>
- Zheng, X., Wang, R., Wood, R., Wang, C., & Hertwich, E. G. (2018). High sensitivity of metal footprint to national GDP in part explained by capital formation. *Nature Geoscience*, 11(4), 269–273. <https://doi.org/10.1038/s41561-018-0091-y>