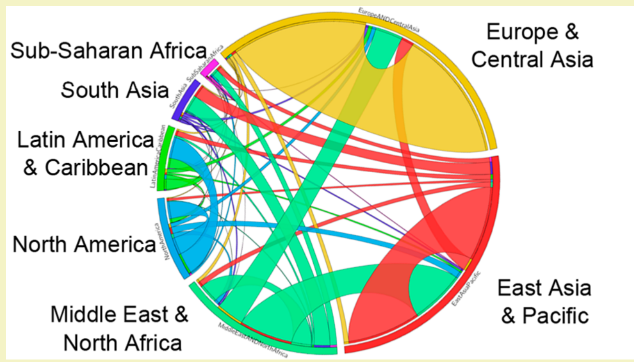
ACS Sustainable Chemistry & Engineering
pubs.acs.org/journal/ascecg
Research Article

Quantifying Energy and Greenhouse Gas Emissions Embodied in Global Primary Plastic Trade Network

Joseph Zappitelli, Elijah Smith, Kevin Padgett, Melissa M. Bilec, Callie W. Babbitt, and Vikas Khanna*

Cite This: ACS Sustainable Chem. Eng. 2021, 9, 14927−14936
Read Online



ABSTRACT: We present a model of the global primary plastic trade network (GPPTN) and report estimates of embodied impacts including greenhouse gas (GHG) emissions, cumulative fossil energy demand, and embedded carbon. The network is constructed for 11 thermoplastic resins that account for the majority of global primary plastic trade. A total of 170 million metric tonnes (Mt) of primary plastics were traded in 2018, responsible for 350 Mt of embodied GHG emissions, 8.9 exajoules (EJ) of cumulative fossil energy demand and 95 Mt of embedded carbon. In 2018, embodied GHG emissions for GPPTN were comparable to annual carbon dioxide emissions of developed nations like Italy and France. The cumulative fossil energy demand of GPPTN was equivalent to 1.5 trillion barrels of crude oil and the carbon embedded in GPPTN was equivalent to carbon in 118 Mt of natural gas or 109 Mt of petroleum. Statistical inference and network measures provide evidence that a few key trade relationships account for a majority of plastic flows and subsequent embodied impacts through the network. The significant embodied impacts and materials in GPPTN must be considered going forward as policies are developed to improve the circularity and environmental sustainability of the plastics industry.

KEYWORDS: *plastics, network analysis, life cycle assessment, circular economy, embodied energy, embodied carbon, embedded carbon*

■ INTRODUCTION

Since their commercialization in the 1950s, the use of plastics has exponentially increased. In 1950, 2 million metric tons (Mt) of plastic were produced globally, compared to 360 Mt in 2018.[1,2] Because of their low-cost, durability, and versatility, plastics are an ideal material for consumer and industrial applications. The diversity of plastic products, many of which contain more than one type of material, renders recycling plastic products difficult.[3] Only 9% of all of the plastic wastes ever generated have been recycled,[1] with the vast majority of plastic discarded to landfills and the environment where accumulation occurs because plastic polymers do not readily degrade.[4,5] At our current rate of plastic waste generation, increasing waste management capacity will not be sufficient to reach plastic pollution goals alone; there is an urgent need to take actions like limiting global virgin plastic production and designing products and packaging for recyclability.[6] Recent studies with the aim of quantifying the plastic pollution problem reported estimates of 4.8−12.1 Mt[5] and 9.5 Mt[7] of plastics entered the marine environment, largely due to waste mismanagement.

While plastic pollution of the environment poses a clear and visible risk to ecosystems, the less obvious impacts from embodied carbon emissions generated during energy-intensive production processes of plastics have not been widely studied. Plastics are derived from fossil fuels, accounting for 4% of global petroleum consumption.[3] Carbon is the predominant element, by molar mass, in fossil fuel feedstocks (e.g., ethylene or C_2H_4) that are used in the manufacturing of plastics. Upon disposal of the manufactured plastic, the embedded carbon is lost and must be reacquired from the environment through the mining and refining of more fossil fuels to produce another virgin plastic. Additional carbon impacts arise from the energy- and emission-intensive processes required to convert fossil fuel inputs to a plastic resin form that is then further transformed to a plastic product for market. Plastics are on track to account for 15% of global greenhouse gas (GHG) emissions by 2050,[8] with 61% of these GHG emissions caused by plastic resin production.[9] Converting a polyolefin resin (e.g., LLDPE, HDPE, PP) into a flexible film suitable for packaging has been estimated to cause an additional 19%−67% of embodied GHGs compared to the initial resin production, highlighting the carbon intensity of plastic manufacturing processes.[10]

Received: August 2, 2021
Revised: October 8, 2021
Published: October 28, 2021

Tracking plastics across their life cycle is key to improving the recovery and reutilization of plastic materials to achieve sustainable development goals such as reducing plastic pollution in natural environments and reducing global carbon emissions.

To meet these goals, a first step is quantifying the scale of plastic production, consumption, waste, and associated embodied impacts. A comprehensive global analysis of plastics across their life cycle between 1950 and 2015 reported aggregate estimates of global primary plastic generation and waste flows to be 8300 Mt and 5800 Mt, respectively.[1] Detailed national estimates of plastic use and waste by resin type and sector use have also been compiled for European nations[2] and the United States.[11,12] These detailed national estimates of different types of plastics across their life cycle provide important information to accurately assess production impacts and material recovery strategies, which both vary based on the type of plastic. Existing work has provided a macroscopic view of the plastics industry, with quantities typically aggregated at a global or regional level. In some cases, such as Wang et al.,[13] studies have focused on a portion of the plastics life cycle, paying particular attention to plastic products and their end-of-life treatment. However, there is still a gap in the literature exploring the resin production stage of the plastic life cycle for the global economy, while retaining specificity with regard to nation and polymer type.

International trade plays a critical role in making material goods (including plastics) available, regardless of the point of production. Network theory provides a formal mathematical framework to analyze dependent relationships within a group of interacting entities, making it an appealing framework to study international trade. Advances in network science and analysis have made it possible to evaluate material flows and their embodied impacts at regional, national, and international scales, understand network structure, and identify patterns of connection.[14−16] Recent studies[13,17,18] have utilized a network framework to study the impact of China's plastic waste import ban on the other nations participating in the global trade of plastic waste. It is estimated that 110 Mt of plastic waste will be displaced in the 10-year period following China's import ban, because of their previous role as the largest global importer of plastic waste.[17] The global plastic waste trade network was found to exhibit small world and scale-free network structure, which indicates the network is controlled by a few highly connected and active countries that are central to interacting with the rest of the less-connected countries.[13] Because of China's significant share of global plastic waste imports, followed by a sudden ban, other nations (Australia, Canada, South Korea, and Japan) were left with a significant need to improve domestic waste management capacity.[18] Potential policy responses include a ban on export of hazardous materials, clear regulations for managing plastic waste before export, and an import tax to fund improved recycling infrastructure.[17] More recently, Ren et al.[19] evaluated the structure of the international plastic resin trade network (IPRTN) and observed small world network properties, which means there is a short average path length between any two countries in the network due to "hub" nodes that have connections to many other countries. This study examined resin-specific mass flows at a national scale and presented results for various network metrics to describe behavior and trends of the primary plastic trade network. However, their mass flow model was not extended to include life cycle embodied impacts of the plastic resins. This has left a gap in the literature estimating the scale of embodied impacts associated with plastic resin production in a spatially explicit manner, which allows for tracking embodied impacts from their point of origin to point of consumption. It has been shown that international trade plays a role in environmental burden shifting, particularly carbon emission generation, because of the emission-intensive production of a good in one country that is then traded and consumed in a separate country.[20]

There exists a rich body of work on life cycle assessment of plastic resin production. Information on life cycle energy use and emissions for producing individual plastic resins is available in both published LCA studies,[21,22] as well as commercial LCA databases.[23] LCA studies focus on normalized impacts (per unit mass) across the life cycle but lack the network perspective needed to assess how plastic trade displace material and environmental impacts across spatial scales. Plastic trade networks represent conduits for not just the physical movement of plastics but also associated embodied impacts (resources and emissions). Modeling and quantifying the origin and destination of plastics flows and their embodied impacts is critical for establishing baseline information and evaluating strategies toward developing a circular economy of plastics.

The goal of this present study is to provide a quantitative understanding of energy and GHG emissions embodied in global primary plastic trade. Using publicly available UN Comtrade data,[24] we develop a network model of international plastic trade focusing on 11 key thermoplastic resins, which account for roughly half of total plastic production. We refer to this network as the Global Primary Plastic Trade Network (GPPTN). The network model, or GPPTN, is combined with life cycle assessment to quantify the total energy and GHG emissions embodied in global plastic trade. The modeling and resulting analysis presented in this work provides key insights, including (1) identification of key actors in the mobilization of plastic resins, (2) first estimates of embodied energy and GHG emissions in global primary plastic trade, (3) structure and topology of the global plastic trade network, and (4) two unique quantitative measures are presented: life cycle "embedded carbon" for plastic resins traded and "edge stability index" assessing fluctuations of trade relationships in the network over the time period of the study (1995−2018).

■ METHODS

Data Acquisition, Processing, and GPPTN Construction. Network analysis provides a computational framework to gather insights about the role of individual countries, trade relationships between countries, and structural characteristics governing the interaction within the network. For GPPTN, each country was modeled as a "node" and a trade relationship between two countries was modeled as an "edge". The trade data used for the creation of the GPPTN was sourced from UN Comtrade Database[24] for imports and exports of 11 primary thermoplastics (LDPE, HDPE, PP, PVC, PET, EPS, GGPS, PMMA, PC, PA, and LLDPE) over a 23-year time frame (1995−2018). This list of thermoplastic resins for this study was selected to be comprehensive and includes all six major plastic resins and a few of the more frequently used resins from the "other" category of the ASTM International Resin Identification Coding System,[25] which are the recycling labels on products or packaging with the number 1−7 contained within a triangle of arrows to distinguish the type of plastic resin. Thermoplastics comprised ~90% of the total plastic trade quantity by weight, thermosets comprised 9%, and bioplastics account for just under 1%. In addition, life cycle data were

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

available for all of the thermoplastic resins studied, ensuring that the modeled trade network was amenable for further analysis of embodied environmental impacts. The workflow from data collection to network construction was visualized in Figure S1 in the Supporting Information (SI) .

Trade data include the importing country, exporting country, quantity (metric tonnes), and market value ($1000 USD). The Harmonized System 92 (HS92) six-digit commodity codes[26] were used to reference annual plastic trade data from the years 1995 to 2018. Harmonized trade flow data from CEPII BACI[27] was utilized to model the GPPTN. These data originally came from the UN Comtrade database, but was modified slightly to reconcile the differences in trade quantities reported by importers and exporters. The harmonized trade flows account for the relative reliability of countries as reporters, and the different techniques used by importers and exporters to report the economic value of goods.[27] It was found that ∼5% of the reported imports and exports did not match in the raw data from UN Comtrade, so the reconciled data is a small portion of the total data utilized. Upon acquisition, data were cleaned and processed in R statistical language (for details, see section S2 in the SI) to develop adjacency matrices that were further utilized to develop both unweighted and weighted directed networks of plastic resin trade flows. The adjacency matrices formed to represent GPPTN have rows representing the exporting countries and columns representing importing countries. An element (i, j) in the matrix represents a trade relationship between exporting country i and importing country j. In the unweighted network, an element (i, j) takes on the value of 1 if there is trade between the two countries and a value of 0 otherwise. In the weighted network, an element (i, j) represents the quantity of plastic resins, embodied impacts, or embedded materials traded from country i to country j.

Quantifying Embodied Impacts in GPPTN. To evaluate embodied impacts associated with the GPPTN, life cycle inventory (LCI) estimates of embodied GHG emissions and fossil energy demand for each of the 11 resins were sourced from the Ecoinvent version 3.5[23] LCI database, accessed via SimaPro version 9.0.[28] The scope of this study and the life cycle inventory data used are taken from the extraction of primary materials, such as crude oil, up to the production of a primary plastic resin. Life cycle impacts of transforming plastic resins into plastic products and their resulting disposal are excluded from this study to present results solely focused on primary plastic resins. Life cycle GHG emissions estimates for individual resins were calculated using IPCC 100-year global warming potential characterization factors and expressed as kg CO_2-equivalent/kg resin.[29] Cumulative energy demand (CED) was used to calculate the sum of direct and indirect energy required to perform the extraction and manufacturing processes in the life cycle of a product like a primary plastic.[30,31] This measure was computed using CED 1.11 methodology, and the total life cycle energy requirements to produce each primary plastic were expressed in terms of megajoules per kilogram of resion (MJ/kg resin).[32] Fossil CED is reported for this study, which only includes energy captured from nonrenewable fossil fuels. This methodological choice was made because Fossil CED represents 90%−96% of energy demand for all primary plastics in this study, except for PVC (∼80%), and will be referred to as embodied energy for the remainder of this Article. The resulting life cycle GHG emissions intensity and Fossil CEDs for the 11 thermoplastic resins can be found in section S3 in the SI. These resin-specific LCI estimates were used to translate the network model of primary plastic mass traded into networks of embodied GHG emissions and embodied energy, which were then visualized using Circos.[33]

The embodied energy and GHG emission characterization factors and subsequent results presented in this work are subject to uncertainty. In the absence of country-specific life cycle data for the production of plastic resins, this study utilized estimates for North American and European facilities that are readily available. This limits the ability to explore variance in embodied impact intensity across nations, which may arise from different feedstocks or processing conditions.[34] Compiling national life cycle inventories for plastic resin production is key data needs that would provide insight into spatial variations in embodied impacts and allow for identification of improvement opportunities.

In addition to embodied energy and GHG emissions, we quantified elemental carbon flows embedded within the GPPTN. Carbon is the most basic building block in all plastic resins, and it is ultimately wasted if there is no form of material recovery at the end-of-life of plastics. As such, quantifying embedded carbon can provide insight into the circularity potential for plastics measured as elemental carbon. Embedded carbon flows were calculated by applying weights representing the carbon content of individual resins. For example, polyethylene resins are a chain of molecules represented by the formula $(C_2H_4)_n$ and have a carbon content of 24 g C/28 g resin, or 85.7% by molecular weight. The carbon mass percentage was multiplied by the quantity of resins traded along the edges of the baseline network model to derive total embedded carbon for GPPTN.

Network Metrics. Network analysis includes many quantitative measures, with unique reference names and formulations, to describe important characteristics and behavior of a network. Centrality measures are used to identify key actors in a network, which are the countries most active or most important in facilitating the global trade of plastic resins, in the context of GPPTN. Degree centrality[35] is simply a count of the number of edges connected to an individual node. Each node in the network has a unique score for this measure. For a directed graph or network, there can be a measure of in-degree or out-degree centrality, because each edge is assigned a direction of "incoming" or "outgoing". In the context of a trade network, in-degree is a count of relationships where the reference country is importing goods and out-degree is a count of relationships where the reference country is exporting goods. Total degree centrality refers to the sum of in-degree and out-degree centrality measures or a count of all trade partnerships. Strength centrality[36] is a sum of all edge weights for an individual node, and this measure can only be calculated for a weighted network. In-strength and out-strength can be calculated for a directed network, like in-degree and out-degree centrality. Again, in the context of a trade network, in-strength centrality is a sum of all imported goods by weight (quantity or economic value) and out-strength is a sum of all exported goods by weight. Total strength centrality is a sum of in-strength and out-strength measures or a sum of imports and exports. The detailed descriptions and mathematical formulations of basic network metrics (density, degree, strength, betweenness, and eigenvector centrality) utilized in this study can be found in section S5 in the SI.

Network Backbone. Large-scale networks such as GPPTN encode vast amounts of information about nodes, edges, and their weights that can have distributions spanning orders of magnitude, which makes the identification of relevant network actors and connections a challenge. Visualization of a network can provide quick insight into the underlying information, but large-scale networks contain too much information to be informative without undergoing a meaningful simplification process. A network representation of nodes with the highest number of connection or highest weighted connections would be an oversimplification that ignores important network interactions at smaller scales. The backbone algorithm[37] was formulated to extract edges that have the highest weights, while also retaining relevant nodes and links that are critical to the structural topology of the network. To do this, the algorithm examines one node at a time and determines which edges of that node to retain, based on local importance. Empirical edge weights of a node are compared to a null model of edge weights, which are generated from a random uniform distribution. A threshold parameter (α) is used as an indicator of statistical significance to determine whether a given edge for a node carries a statistically disproportionate weight, compared to an edge weight generated from a random null model. This is an important feature of the algorithm, because it identifies key actors and connections in the network without ignoring the significance of small-scale interactions to the overall structure and behavior of the network.

Community Detection. We utilized community detection to uncover patterns of connectedness in GPPTN, specifically identifying groups of nodes in the network that are more densely connected with each other than with other nodes in the network. The subsection of

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

countries, referred to as communities, represent subgroups that trade more with each other than countries outside of their community. While there are many different algorithms for community detection, we used Louvain grouping,[38] a popular iterative algorithm to identify communities in the present work. Other grouping algorithms were tested, but the Louvain community detection algorithm returned the highest value for modularity. Modularity is a measure of the efficacy of grouping algorithms, which is a score between −1 and 1 that indicates how dense links are within communities, compared to density of links outside of communities.

There are two iterative phases to the Louvain community detection algorithm proposed by Blondel et al.[38] The first step is to assign all nodes to a distinct community, resulting in as many communities as there are nodes. Then, node i is placed in a community with a neighboring node that leads to a maximum gain in modularity. If there is no gain in modularity, then node i remains in its own community. This first phase process runs for all nodes until a local maximum modularity is achieved. The second phase begins by constructing a network of the communities derived from the first phase. The weighted links inside a community and weighted links between communities are examined and the iterative process of the first phase is applied again, rearranging nodes between different communities until a maximum modularity score is reached.

Mixing Patterns and Assortativity. Community detection is a way to identify groups of nodes within the network that prefer to trade among themselves, which can be described as a local preferential attachment. To measure preferential attachment of the entire network, the assortativity[39,40] measure is utilized in this work. The function of this measure is to quantify an indicator of similarity and measure the preference of nodes to attach to similar nodes within the entire network. Assortativity coefficients, with respect to total degree, in-degree, out-degree, total strength, in-strength, and out-strength, are computed. The assortativity coefficient is a number between −1 and 1, where positive numbers correspond to a network wherein nodes with similar attribute values have a tendency to interact with each other. For example, an assortativity coefficient close to 1, measured using in-degree values, indicates nodes with high in-degree scores have a tendency to interact together and nodes with a low in-degree score have a tendency to interact together. Conversely, a negative assortativity coefficient value for in-degree indicates that nodes with a high score of in-degree have a tendency to interact with nodes with a low score for in-degree centrality.

Edge Stability. To measure the edge stability of a network or a node of interest, we defined a novel metric called "edge stability", which is defined as a ratio of edges that are active over a time period to the total number of times the edges could be active in the time period of interest. An active edge simply refers to an edge where there is a nonzero value, indicating there is trade along the edge between two partner countries. Trade may occur in one year between two countries, but may not occur again in the following year. This measure provides insight into the timespan that countries consistently engage in trade with their partners and the rate of change of partnerships within the network. We proposed the following procedure to calculate the edge stability score at the network level using annual plastic trade data.

The formulation of edge stability begins with defining the time period of interest. We introduced t to represent the length of time to analyze in years. The reference year, y, is the last year of the time period for computing an edge stability score. Using these variables, the time period will span from $(y - t + 1, y)$. For example, the three-year stability score for 2018 will analyze the stability of the network moving from the year 2016 to 2018. Here, $t = 3$ and y is 2018. After the time period of interest is defined, we computed the ratio of active edges to potential active edges. The number of edges where trade occurs in the network, for all years in the time period, were counted and summed for all of the nodes in the network and referred to as active edges, a. The potential active edges for the time period, a_{max}, was calculated by multiplying the total number of unique edges that were active at least once during the time period by the number of years in the time period, t. Dividing the measured number of active edges, a, by the potential unique active edges, a_{max}, yields a range of values bounded between $[1/t, 1]$ that we refer to as the *edge stability score* and is assigned the variable s:

$$s = \left(\frac{a}{a_{max}}\right) \tag{1}$$

An edge stability score of $1/t$ indicates a network that is perfectly unstable, i.e., each unique edge is only active once for the time period of interest. An edge stability score of 1 indicates a perfectly stable network where every unique edge is active in all years of the time period.

Network Topology. For topological analysis of the GPPTN, we specifically examined whether the network follows power-law behavior. Power-law behavior in real-world networks can provide evidence that a large concentration of activity in the network is taken into account by just a few nodes. In the context of the GPPTN, this would mean that a small number of countries account for a large percentage of plastic resins traded. Following the procedure outlined by Clauset et al.[41] and implementation in R,[42] we evaluated the distributions of edge weight, in-degree, out-degree, total degree, in-strength, out-strength, and total strength in the GPPTN. The distribution for GPPTN is compared to synthetic data derived from power-law, exponential, and log-normal distributions. Synthetic data are generated for each distribution type with governing parameters that best fit the original empirical datasets. To determine whether the GPPTN data fits a particular type of distribution, the empirical distribution and reference distribution type must be compared. The Kolmogorov-Smirnoff test is a two-sample nonparametric test of the null hypothesis that vectors x and y come from the same continuous distribution[43] and was used to determine which synthetic distribution has the closest fit to the empirical datasets.

After conducting KS testing, there is the possibility that an empirical dataset is a plausible fit to multiple distribution types. To provide further clarity, log-likelihood ratio testing is utilized. For this purpose, point-wise log-likelihood estimates were calculated for whether a data point is drawn from a particular distribution type. This is a helpful secondary confirmation step to conclusively determine between two likely underlying distribution types.

RESULTS AND DISCUSSION

Plastics Trade and Embodied GHG Emissions. Analysis of the GPPTN reveals that 170 million metric tonnes (Mt) of primary plastics were traded globally in 2018, with associated embodied GHG impacts of 307 Mt CO_2 equivalent. LDPE, HDPE, PP, and LLDPE accounted for ∼67% by mass of traded thermoplastics and ∼50% of embodied GHG emissions. A visual breakdown of the quantities of each resin traded and associated embodied GHGs for 2018 can be seen in Figure 1.

Figure 1 is organized in descending order, based upon quantity of the resin traded. The fifth-, sixth-, seventh-, and eighth-most traded resins (PVC, PET, PC, and Nylon-66, respectively) have greater embodied GHG emissions than the fourth most traded resin (LLDPE). The total embodied GHG emissions of traded PVC and PET are similar to HDPE and PP, with the latter resins having nearly double the trade volume, compared to PVC and PET. Most of the resins examined in this study have a similar GHG intensity value (see section S3 in the SI) of ∼2 kg CO_2 equiv/kg of resin. PVC and PET have moderately greater life cycle GHG intensity of 3.64 and 3.16 kg CO_2 eq/kg of resin, respectively. PET and PVC represent significant portions of the total embodied GHGs across GPPTN due to their greater than average GHG intensity values and moderate trade volume, relative to the other resins examined. PC has the greatest life cycle GHG intensity. Despite a relatively smaller trade volume, PC represents a significant portion of embodied GHGs across

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

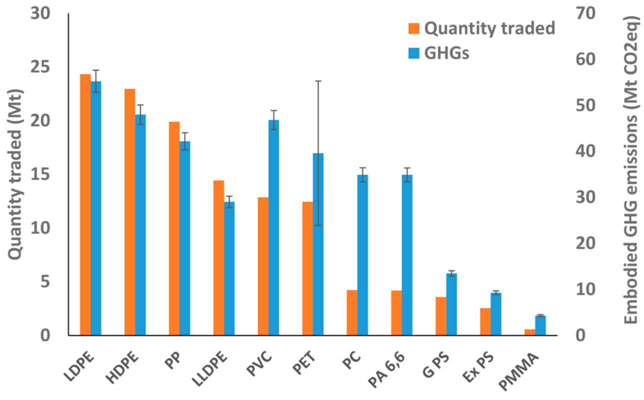


Figure 1. Quantity of resins traded and associated embodied GHG emissions for GPPTN in 2018. The resins are organized in descending order of quantity of resins traded. The error bars represent the 95% confidence interval, obtained using Monte Carlo simulations, accounting for uncertainty of life cycle GHG intensity data. Along the horizonal axis of this chart are the abbreviations of the resins included in the study. Full resin names are as follows in the same order as the horizontal axis: low-density polyethylene, high-density polyethylene, polypropylene, linear low-density polyethylene, polyvinyl chloride, polyethylene terephthalate, polycarbonate, polyamide 6,6 (Nylon), general purpose polystyrene, expandable polystyrene, and poly(methyl methacrylate).

GPPTN, because of its very high GHG intensity (8.64 kg CO_2/kg of resin).

Embodied Energy and Embedded Carbon in GPPTN. Figure 2 presents a visualization of the embodied energy (Figure 2a) and embedded carbon (Figure 2b) in a GPPTN. The visualizations in Figures 2a and 2b include the top 75 countries ranked by total strength. In total, GPPTN represents 7566 links with a total embodied fossil energy of 8.9 exajoules (EJ) and 94.5 Mt of embedded carbon. The two network visualizations in Figure 2 are quite similar, with only a few countries changing one place in rank order. A majority of the leading nodes in total strength (clockwise order in the Figure 2 visualizations starting with China) export more plastics than they import, with the few exceptions being China, India, and Italy. The top five importers of primary plastic resins and associated embodied energy for 2018 are China, Germany, the USA, Italy, and India. Saudi Arabia is the leading exporter with an almost-exclusive exporting role in the GPPTN. The next largest exporters include the USA, South Korea, Germany, and Belgium, all of whom export more resins than they import. The largest embodied energy transfer is from Canada to the USA, with a magnitude of 3.16 million GJ corresponding to the export of LLDPE.

Figure 2 shows circos visualizations with links weighted in width by embodied energy (Figure 2a) and embedded carbon (Figure 2b) for the GPPTN in 2018. Country names are abbreviated using ISO three-digit codes. Full names with their associated codes can be found in Table S1 in the SI. An export from a country is indicated by a white space between the colored semicircle segment next to each country's name and the incoming colored bands from other countries. If, instead, the space is filled with a colored segment, this represents an import. Two countries that visually illustrate the difference between importer and exporter are China, a net importer, and Saudi Arabia, a net exporter. The size of the colored semicircle segments represents the total trade of a country. The color of this segment is the same as the incoming colored bands representing flows to a country.

The life cycle estimates in this study have been presented in the context of a network, showing the mobilization of plastic resins and subsequent embodied impacts and materials along their trade routes. Net importers of plastic resins can be viewed as importing embedded carbon but exporting or offloading associated embodied impacts (e.g., GHG emissions, embodied energy) to the countries where the plastic resins were manufactured. Previous studies focusing on the transfer of embodied impacts across national boundaries have shown that developed countries have a tendency to import more embodied carbon emissions from developing nations that have a tendency to rely on carbon-intensive manufacturing.[20,46] Developing and developed countries, as categorized by United Nations Statistics Division, account for equal shares of exports in GPPTN, while developing nations import ~30% more primary plastics than developed nations.[47]

Network Density and Growth. Over the analysis period (1995−2018), the number of nodes in the network only increased from 194 to 215. The number of edges in the network increased more drastically during this time period, growing from 4538 (in 1995) to 7701 (in 2017). Network density for the GPPTN has increased for the majority of the timespan, with a peak in 2010 and a relatively steady network density score in subsequent years (see section S5 in the SI). The increase in network density indicates that countries are forming more trade relationships with countries that already participate in the GPPTN. With 200+ countries participating in the network, the GPPTN has almost-unanimous global participation. The stabilization of network density (~0.16) in the period of 2010−2018 suggests that the network has reached a saturation point. By observing total network throughput and average edge weight over the time period in this study, linear growth can be observed (see section S5 in the SI). There is not a similar stabilization of throughput or average edge weight as was the case for network density in the period from 2010 to 2018. Interpreting these analyses together indicates that the global primary plastic production and consumption continue to steadily increase, but the number of countries and trade relationships involved in the primary thermoplastic market are remaining steady.

Edge Stability. Figure 3 shows the normalized edge stability scores for the GPPTN. A steady decrease in normalized edge stability score with the length of time increment can be seen. This suggests that, generally, countries retain a majority of trade partners from year to year, but over a longer period, nodes are less likely to continue to participate in the same trade relationships. However, a normalized edge stability score of 0.47 over a 12-year time period indicates that there is a core group of trade partnerships that remain active for longer periods of time.

Network Backbone and Community Detection. The "backbone" algorithm[37] was used to simplify the GPPTN to identify the most important nodes and edges in 2018 (see Figure 4). In creating the backbone, nodes with a total strength of >1 Mt are retained, accounting for 79% of nodes, 9.6% of edges, and 78% of the quantity of trade flow in GPPTN. The percentage of edges retained is much smaller than nodes retained because a majority of plastic is traded along a few edges with high weights. The nodes in Figure 4 are colored by their community and sized by their total strength. Utilizing the Louvain community detection algorithm,[38] there were four

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

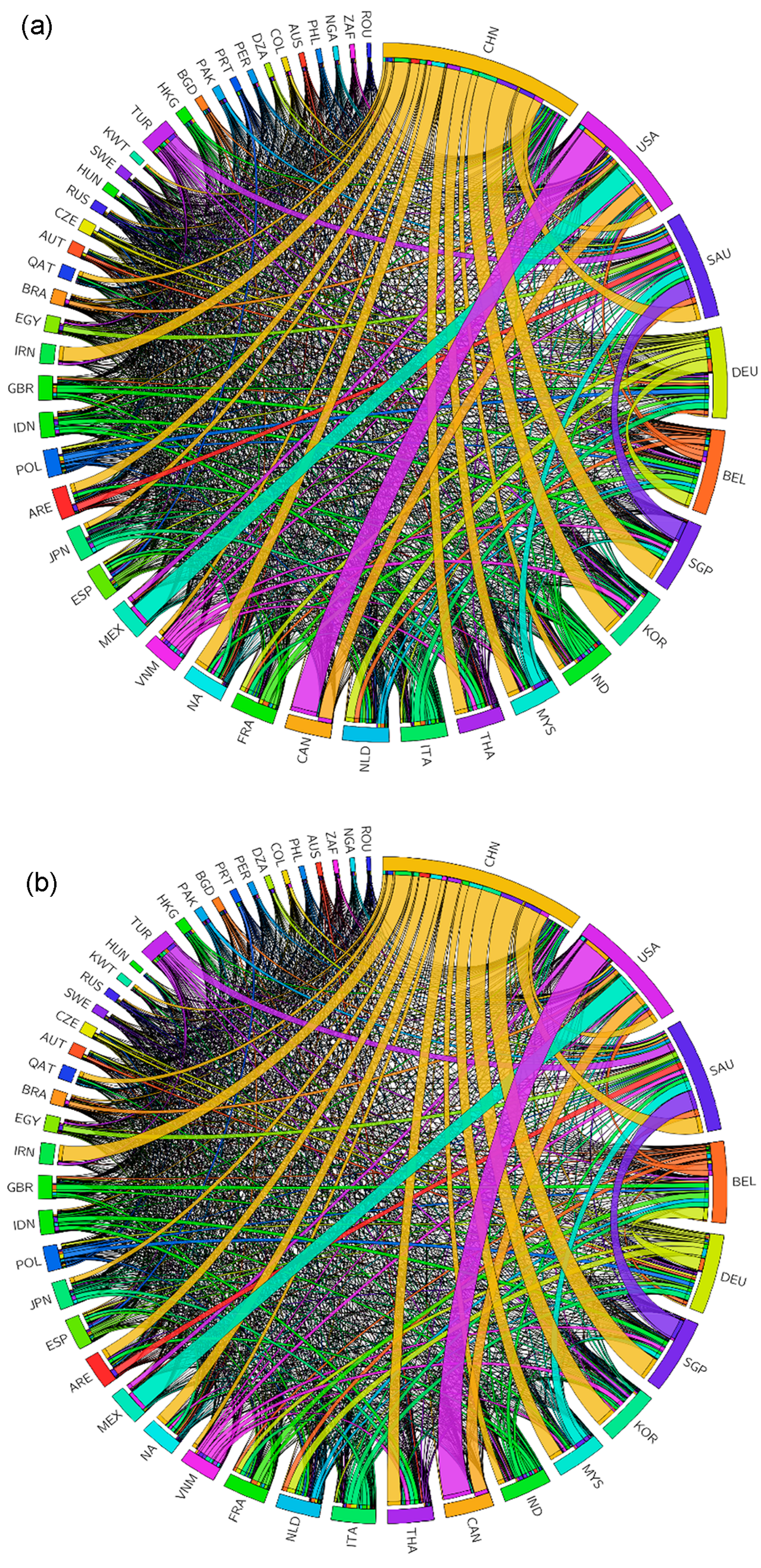


Figure 2. (a) 2018 GPPTN embodied energy and (b) 2018 GPPTN embedded carbon.

communities identified within the GPPTN in 2018. The largest community (111 countries) identified are the orange nodes, representing countries in Southeast Asia, The Middle East, and Africa. The green nodes represent a community

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

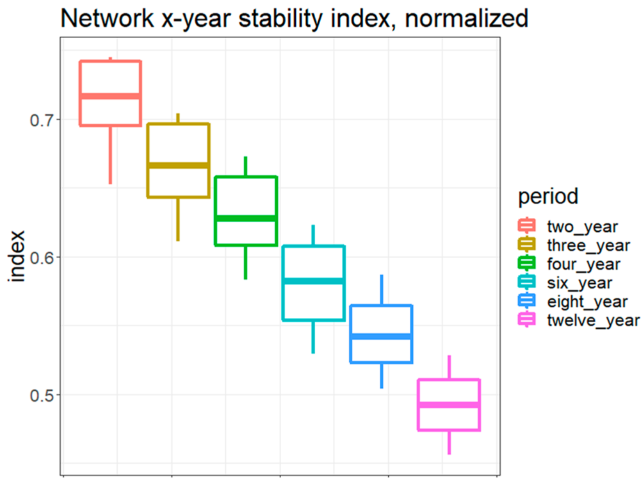


Figure 3. Normalized edge stability scores, representing the proportion of trade relationships that remain active over a time period, ranging from 2-year to 12-year measures. Edge stability scores are plotted as box and whisker ranges, because each possible iteration of n-year edge stability score were computed and plotted. For three-year edge stability measures, possible ranges include but are not limited to 1995−1997, 1996−1998, 2010−2012, and 2016−2018.

among countries from Western Europe (47 countries). The yellow nodes represent the community of countries in North America, South America, and the Caribbean Islands (49 countries). Lastly, the gray-colored community (9 countries) is the smallest and consists of countries from Eastern Europe, such as Russia and Ukraine. Identifying communities highlights countries with dense trade interactions and provides insight into the subcommunity trade patterns present in the GPPTN. China, the USA, and Germany are the largest nodes in their respective communities and standout as focal points of these communities when analyzing the backbone of the GPPTN.

Network Degree, Strength and Mixing Pattern. Investigating the degree and strength distributions for the GPPTN aids in characterizing trade patterns for the network. Histograms of degree and strength distributions are provided in section S5 in the SI. The majority of the countries do not significantly participate in exporting primary plastics, according to out-strength and out-degree analysis. The in-strength analysis provides similar results, suggesting that the majority of trade in the network is attributable to a handful of key nodes. In contrast, the in-degree shows a different behavior. Almost all countries in the network participate in importing plastics, and many of the nodes have over 50 incoming edges. This is also intuitive as plastic products are ubiquitous, so there is demand for all countries to import plastics for consumption. The limited number of countries that control the supply of

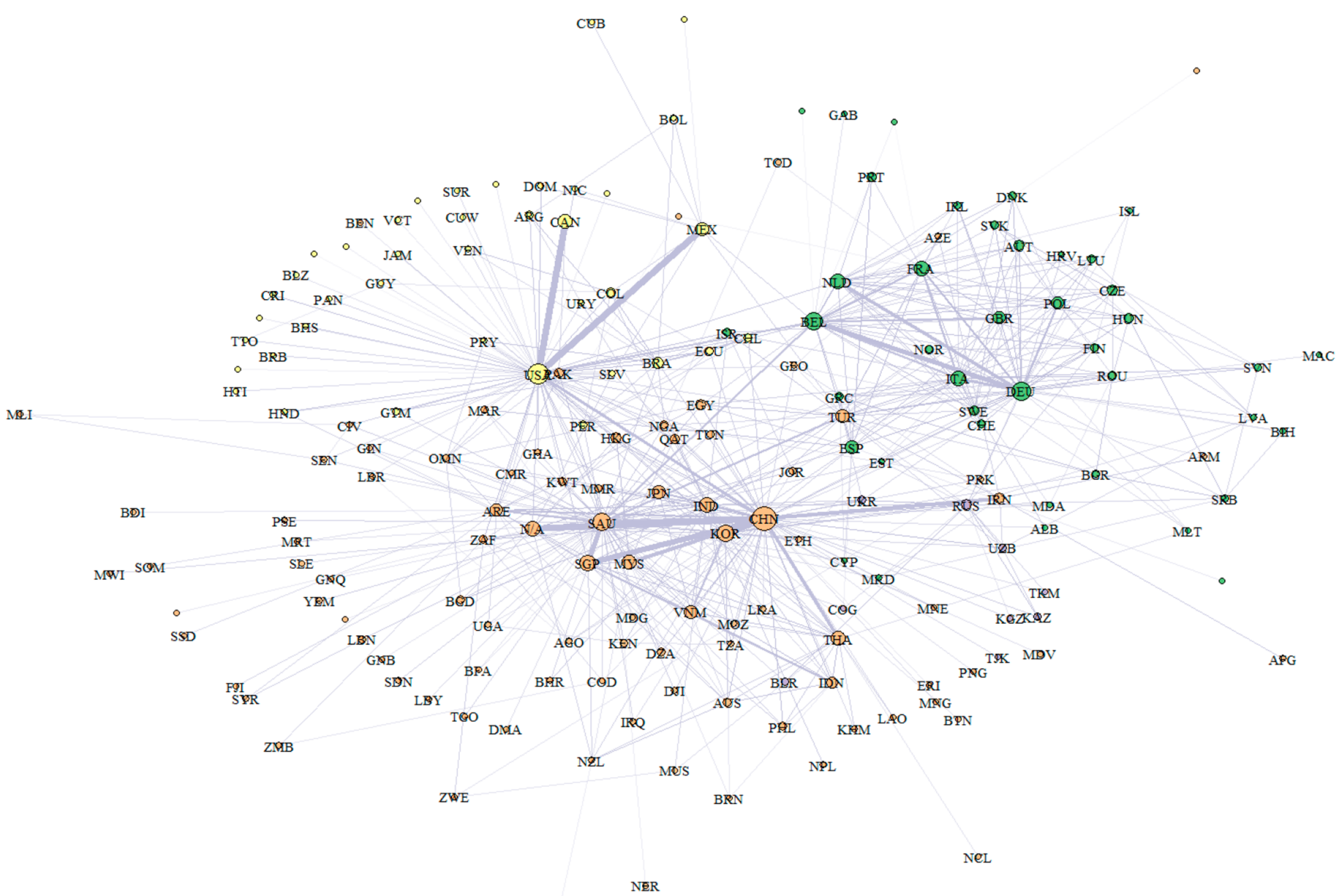


Figure 4. Backbone filter applied to the GPPTN for 2018. Nodes are sized by total strength (sum of all imports and exports, in Mt) and the thickness of each link is determined by the edge weight (aggregate quantity of plastic resins traded between the two connected nations, in Mt). Nodes with a total strength of >1 Mt of plastic resins traded are labeled. Nodes are colored according to the four Louvain communities identified.

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

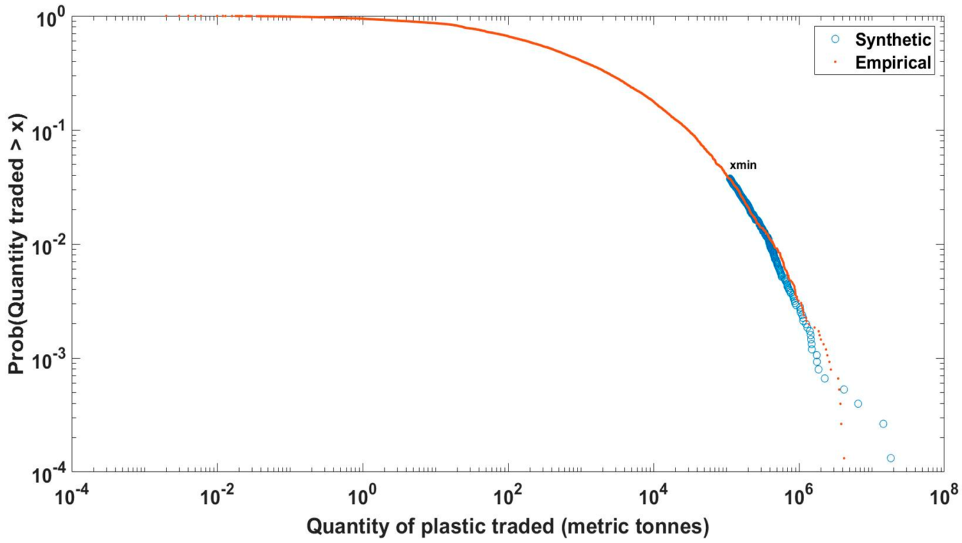


Figure 5. Complementary cumulative distribution function plot of edge weights in 2018 for the GPPTN. Edge weights represent the quantity of plastic traded between two countries, which were rank ordered from smallest to largest and are colored in orange. The blue circles are synthetic data points derived from a power-law distribution with parameters that were calculated based on empirical data. KS-tests resulted in a p-value of >0.10, indicating a good fit, because no statistically significant difference was observed between the empirical edge weight data and the synthetic edge weight data fit to a power-law distribution. A strong overlap can be seen beginning at the $x_{\min}$ value of 10^5 Mt, indicating that power-law behavior is observed for the tail of the edge weight distribution.

primary plastics can be focused on when to develop strategies to reduce primary plastic production impacts.

To assess patterns of connection in the network, assortativity coefficients were calculated with respect to in-degree, out-degree, total degree, in-strength, out-strength, and total strength. The assortativity coefficient with the greatest magnitude was −0.333 when calculating assortativity, with respect to total degree, indicating that countries that have few trade relationships have a moderate propensity to trade with countries that have more trade relationships.

Statistical Distribution Testing. Statistical distribution testing was utilized to assess edge weight, in-degree, out-degree, in-strength, and out-strength distributions for the GPPTN from 1995 to 2018. KS-testing was utilized to examine the fit of empirical data distributions to exponential, log-normal, and power-law distributions. Power-law behavior was the distribution type observed to be the best fit for all tested distributions (see section S6 in the SI). When assessing the distribution of best fit for out-strength, where power-law and exponential distributions were plausible distributions types, log-likelihood ratio tests were utilized to provide clarity. Figure 5 shows the inverse cumulative density plot of edge weights for the GPPTN. The observation of power-law behavior indicates that a small number of edges account for a majority of trade in the network. This is consistent with the vast reduction of edges using the backbone algorithm, where 9.6% of the edges in the network constituted the network backbone.

■ CONCLUSION

The analysis presented in this work fills a knowledge gap by providing estimates of life cycle environmental impacts embodied in global primary plastic trade. While the focus of our work is on embodied energy and GHG emissions, the framework can be extended to incorporate other life cycle impacts. The quantity of GHGs embodied in GPPTN (350 Mt) is on par with CO_2 emissions of developed nations such as Italy and France.[44] Embodied energy in GPPTN (8.9 exajoules (EJ)) is estimated to be equivalent to 1.5 trillion barrels of crude oil, 230 billion cubic meters of natural gas, or 407 Mt of coal.[45] The carbon embedded in GPPTN (94.5 Mt) is estimated to be the same as the carbon equivalent in 118 Mt of natural gas or 109 Mt of petroleum.

This work has also provided evidence that the majority of the GPPTN is controlled by a handful of key countries, with increasing concentration of trade activity by top countries throughout the time period of the study. Implementing circular economy strategies for plastic production and management in key countries (China, the USA, Germany, Saudi Arabia, and South Korea) would have a ripple effect throughout the rest of the network. China's plastic waste ban in 2018 provides evidence that policy changes in a large node can have cascading impacts on all other countries in the global plastic waste trade network.[13,17,18] As such, improving circularity for the majority of plastic trade may only require interventions in a few key countries that participate in the GPPTN.

Strategies to reduce embodied impacts of globally traded plastics will need to address both technological and behavioral changes, including but not limited to utilizing renewable energy, recycling and switching to biomass feedstocks, and reducing consumption.[9] Recycled plastic resins have been shown to have lower embodied energy and emissions than virgin resins.[48−51] Increasing access to the material recovery infrastructure and advancing recycling technology is a key strategy to reduce both plastic pollution[52] and embodied impacts associated with virgin plastics. New technologies capable of chemically recycling plastics to recover monomers in an economic and environmentally promising manner have been proposed and deemed technically feasible.[53−57] However, success in chemically recycling plastics requires high rates of recycling and subsequent recovery to take advantage of economies of scale and become cost-competitive with virgin plastic production. Improvements to collection and sorting infrastructure are necessary to provide sufficient quantities of clean input plastics to justify implementation of chemical

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936

recycling technologies. Future work could focus on understanding the interaction between the GPPTN and plastic waste trade network to identify opportunities to invest in infrastructure that can facilitate a circular plastics economy, wherein secondary plastics are used as production inputs in countries that are already established as dominant producers of virgin primary plastic resins.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acssuschemeng.1c05236.

Raw sourced data, further methodological details and supplementary results (PDF)

■ AUTHOR INFORMATION

Corresponding Author

Vikas Khanna − *Department of Civil and Environmental Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States; Department of Chemical and Petroleum Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States;* orcid.org/0000-0002-7211-5195; Phone: +1-412-624-9604; Email: khannav@pitt.edu

Authors

Joseph Zappitelli − *Department of Civil and Environmental Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States*

Elijah Smith − *Department of Industrial Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States*

Kevin Padgett − *Department of Chemical and Petroleum Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States*

Melissa M. Bilec − *Department of Civil and Environmental Engineering, University of Pittsburgh, Pittsburgh, Pennsylvania 15261, United States;* orcid.org/0000-0002-6101-6263

Callie W. Babbitt − *Golisano Institute for Sustainability, Rochester Institute of Technology, Rochester, New York 14623, United States;* orcid.org/0000-0001-5093-2314

Complete contact information is available at: https://pubs.acs.org/10.1021/acssuschemeng.1c05236

Notes

The authors declare no competing financial interest.

■ ACKNOWLEDGMENTS

This work is supported by the U.S. National Science Foundation, under Grant No. 1934824. Any opinion, results, conclusions, or recommendations detailed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

■ REFERENCES

(1) Geyer, R.; Jambeck, J. R.; Law, K. L. Production, use, and fate of all plastics ever made. *Science Advances* **2017**, *3* (7), e1700782.

(2) PlasticsEurope. *Plastics—The Facts 2019: An analysis of European plastics production, demand and waste data*, 2019.

(3) Hopewell, J.; Dvorak, R.; Kosior, E. Plastics recycling: challenges and opportunities. *Philos. Trans. R. Soc., B* **2009**, *364* (1526), 2115−2126.

(4) He, P.; et al. Municipal solid waste (MSW) landfill: A source of microplastics? -Evidence of microplastics in landfill leachate. *Water Res.* **2019**, *159*, 38−45.

(5) Jambeck, J. R.; et al. Plastic waste inputs from land into the ocean. *Science* **2015**, *347* (6223), 768−771.

(6) Borrelle, S. B.; et al. Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. *Science* **2020**, *369* (6510), 1515−1518.

(7) Ryberg, M. W.; et al. Global environmental losses of plastics across their value chains. *Resources, Conservation and Recycling* **2019**, *151*, 104459.

(8) WEF. *The New Plastics Economy—Rethinking the Future of Plastics*; Ellen MacArthur Foundation: World Economic Forum, 2016.

(9) Zheng, J.; Suh, S. Strategies to reduce the global carbon footprint of plastics. *Nat. Clim. Change* **2019**, *9* (5), 374−378.

(10) Poovarodom, N.; Ponnak, C.; Manatphrom, N. Impact of Production and Conversion Processes on the Carbon Footprint of Flexible Plastic Films. *Packag. Technol. Sci.* **2015**, *28* (6), 519−528.

(11) Heller, M. C.; Mazor, M. H.; Keoleian, G. A. Plastics in the US: toward a material flow characterization of production, markets and end of life. *Environ. Res. Lett.* **2020**, *15* (9), 094034.

(12) Di, J.; et al. United States plastics: Large flows, short lifetimes, and negligible recycling. *Resources, Conserv. Recycl.* **2021**, *167*, 105440.

(13) Wang, C.; et al. Structure of the global plastic waste trade network and the impact of China's import Ban. *Resources, Conserv. Recycl.* **2020**, *153*, 104591.

(14) Vora, N.; et al. Rewiring the Domestic U.S. Rice Trade for Reducing Irrigation Impacts—Implications for the Food−Energy−Water Nexus. *ACS Sustainable Chem. Eng.* **2021**, *9* (28), 9188−9198.

(15) Fan, Y.; et al. The state's role and position in international trade: A complex network perspective. *Economic Modelling* **2014**, *39*, 71−81.

(16) De Benedictis, L. et al. Network Analysis of World Trade Using the BACI-CEPII Dataset. *SSRN Electron. J.* **2014**, Banque de France Working Paper No. 471, DOI: 10.2139/ssrn.2374354.

(17) Brooks, A. L.; Wang, S.; Jambeck, J. R. The Chinese import ban and its impact on global plastic waste trade. *Sci. Adv.* **2018**, *4* (6), eaat0131.

(18) Huang, Q.; et al. Modelling the global impact of China's ban on plastic waste imports. *Resources, Conserv. Recycl.* **2020**, *154*, 104607.

(19) Ren, Y.; et al. Spatiotemporal evolution of the international plastic resin trade network. *J. Cleaner Prod.* **2020**, *276*, 124221.

(20) Zhong, Z.; Jiang, L.; Zhou, P. Transnational transfer of carbon emissions embodied in trade: Characteristics and determinants from a spatial perspective. *Energy* **2018**, *147*, 858−875.

(21) Associates, F. *Life Cycle Impacts for Postconsumer Recycled Resins: PET, HDPE, and PP*; The Association of Plastic Recyclers, 2018.

(22) Associates, F. *Cradle-to-Gate Life Cycle Analysis of High Density Polyethylene (HDPE) Resin*; American Chemistry Council, Plastics Division, 2020.

(23) Weidema, B. P. B. C.; Hischier, R.; Mutel, C.; Nemecek, T.; Reinhard, J.; Vadenbo, C.; Wernet, G. *Overview and Methodology: Data Quality Guideline for the Ecoinvent Database Version*, Vol. 3; Swiss Centre for Life Cycle Inventories, 2013.

(24) United Nations. *UN Comtrade Database*, 2019.

(25) Standard Practice for Coding Plastic Manufactured Articles for Resin Identification, ASTM Standard No. ASTM D7611/D7611M-20. In *2020 ASTM Annual Book of Standards*; ASTM International, West Conshohocken, PA, 2020, www.astm.org.

(26) *Harmonized Commodity and Coding System*; Customs Cooperation Council (CCC), 1987.

(27) Gaulier, G.; Zignago, S. *BACI: International Trade Database at the Product-Level*; CEPII Working Paper 2020-23, 2010.

(28) PRé Sustainability *SimaPro Software*, Version 9.0, 2019.

(29) Stocker, T. Q. D.; Plattner, G.; Tignor, M.; Allen, S.; Boschung, J.; Nauels, A.; Xia, Y.; Bex, B.; Midgley, B. *IPCC, 2013 Climate Change: The Physical Science Basis*; Contribution of Working Group I

to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 2013.
(30) Frischknecht, R.; et al. Cumulative energy demand in LCA: the energy harvested approach. *Int. J. Life Cycle Assess.* **2015**, *20* (7), 957−969.
(31) Huijbregts, M. A. J.; et al. Is Cumulative Fossil Energy Demand a Useful Indicator for the Environmental Performance of Products? *Environ. Sci. Technol.* **2006**, *40* (3), 641−648.
(32) Jungbluth, N. F. R. *Cumulative Energy Demand 1.11*; Swiss Centre for LCI: LCIA Implementation: Final Report Ecoinvent 2000, 2003.
(33) Krzywinski, M.; Schein, J.; Birol, I.; Connors, J.; Gascoyne, R.; Horsman, D.; Jones, S. J.; Marra, M. A. Circos: An Information Aesthetic for Comparative Genomics. *Genome Res.* **2009**, *19*, 1639.
(34) Center for International Environmental Law. *The Hidden Costs of a Plastic Planet*, 2019.
(35) Koschützki, D., et al. Centrality Indices. In *Network Analysis*; Springer: Berlin, Heidelberg, 2005; pp 16−61.
(36) Barrat, A.; et al. The architecture of complex weighted networks. *Proc. Natl. Acad. Sci. U. S. A.* **2004**, *101* (11), 3747−3752.
(37) Serrano, M. A.; Boguna, M.; Vespignani, A. Extracting the multiscale backbone of complex weighted networks. *Proc. Natl. Acad. Sci. U. S. A.* **2009**, *106* (16), 6483−6488.
(38) Blondel, V. D.; et al. Fast unfolding of communities in large networks. *J. Stat. Mech.: Theory Exp.* **2008**, *2008* (10), P10008.
(39) Newman, M. E. J. Assortative Mixing in Networks. *Phys. Rev. Lett.* **2002**, *89* (20), 208701.
(40) Newman, M. E. J. Mixing patterns in networks. *Phys. Rev. E: Stat. Phys., Plasmas, Fluids, Relat. Interdiscip. Top.* **2003**, *67* (2), 026126.
(41) Clauset, A.; Shalizi, C. R.; Newman, M. E. J. Power-Law Distributions in Empirical Data. *SIAM Rev.* **2009**, *51* (4), 661−703.
(42) Lai, W. *Fitting Power Law Distributions to Data*, 2009.
(43) Drew, J. H.; Glen, A. G.; Leemis, L. M. Computing the cumulative distribution function of the Kolmogorov−Smirnov statistic. *Comput. Stat. Data Anal.* **2000**, *34*, 1.
(44) IEA. *CO_2 Emissions from Fuel Combustion 2018*: International Energy Agency. 2018.
(45) EIA *Energy Conversion Calculators*. 2020, U.S. Energy Information Administration.
(46) Jiang, M.; et al. Factors driving global carbon emissions: A complex network perspective. *Resources, Conserv. Recycl.* **2019**, *146*, 431−440.
(47) UNCTAD *Developed/Developing Economies*; UNCTADstat, 2020.
(48) Arena, U.; Mastellone, M. L.; Perugini, F. Life Cycle Assessment of a Plastic Packaging Recycling System. *Int. J. Life Cycle Assess.* **2003**, *8*, 92.
(49) Rahim, R.; Abdul Raman, A. A. Carbon dioxide emission reduction through cleaner production strategies in a recycled plastic resins producing plant. *J. Cleaner Prod.* **2017**, *141*, 1067−1073.
(50) Benavides, P. T.; Dunn, J. B.; Han, J.; Biddy, M.; Markham, J. Exploring Comparative Energy and Environmental Benefits of Virgin, Recycled, and Bio-Derived PET Bottles. *ACS Sustainable Chem. Eng.* **2018**, *6* (8), 9725−9733.
(51) Shen, L.; Worrell, E.; Patel, M. K. Open-Loop Recycling: A LCA Case Study of PET Bottle-to-Fibre Recycling. *Resources, Conserv. Recycl.* **2010**, *55*, 34−52.
(52) Lau, W. W. Y.; et al. Evaluating scenarios toward zero plastic pollution. *Science* **2020**, *369* (6510), 1455−1461.
(53) Somoza-Tornos, A.; et al. Realizing the Potential High Benefits of Circular Economy in the Chemical Industry: Ethylene Monomer Recovery via Polyethylene Pyrolysis. *ACS Sustainable Chem. Eng.* **2020**, *8* (9), 3561−3572.
(54) Walker, T. W.; et al. Recycling of multilayer plastic packaging materials by solvent-targeted recovery and precipitation. *Sci. Adv.* **2020**, *6* (47), eaba7599.
(55) Gracida-Alvarez, U. R.; et al. System Analyses of High-Value Chemicals and Fuels from a Waste High-Density Polyethylene Refinery. Part 1: Conceptual Design and Techno-Economic Assessment. *ACS Sustainable Chem. Eng.* **2019**, *7* (22), 18254−18266.
(56) Gracida-Alvarez, U. R.; et al. System Analyses of High-Value Chemicals and Fuels from a Waste High-Density Polyethylene Refinery. Part 2: Carbon Footprint Analysis and Regional Electricity Effects. *ACS Sustainable Chem. Eng.* **2019**, *7* (22), 18267−18278.
(57) Vora, N.; et al. Leveling the cost and carbon footprint of circular polymers that are chemically recycled to monomer. *Sci. Adv.* **2021**, *7* (15), eabf0187.

https://doi.org/10.1021/acssuschemeng.1c05236
ACS Sustainable Chem. Eng. 2021, 9, 14927−14936