Periodica Polytechnica Social and Management Sciences, 31(2), pp. 91–99, 2023

Multi-region Input-Output-based Carbon and Energy Footprint Analysis of U.S. Manufacturing

Kadhim Abbood[1], Gokhan Egilmez[2], Ferenc Meszaros[1*]

[1] Department of Transport Technology and Economics, Faculty of Transportation Engineering and Vehicle Engineering, Budapest University of Technology and Economics, Műegyetem rkp. 3., H-1111 Budapest, Hungary
[2] Mechanical and Industrial Engineering Department, Tagliatela College of Engineering, University of New Haven, 300 Boston Post Rd, CT 06516 West Haven, United States of America
[*] Corresponding author, e-mail: meszaros.ferenc@kjk.bme.hu

Received: 17 November 2021, Accepted: 19 April 2022, Published online: 28 June 2022

Abstract

In this research, U.S. manufacturing activities' life cycle-based carbon and energy footprint impacts have been quantified, taking international trade linkages with the rest of the world into account. The U.S economy has been integrated into a multi-region input-output (MRIO) life cycle assessment framework where total of 40 major economies, including the USA, China, Russia, and others, plus the rest of the world (ROW) were modelled to assess global energy and carbon footprint impacts. Each country's economy is assumed to compromise 35 major industries based on the WIOD database classification. A total of 1435 (41 × 35 = 1435) industries has therefore been taken to represent the global structure of the world economy. The novelty of the approach is that the MRIO model has been developed in a stochastic fashion, plus global trade-linked uncertainties have also been taken into consideration. Top carbon emitting and energy consumer industries and countries have been analysed using data analytics and statistical modelling methods. The results show that the USA is the largest contributor to the total carbon footprint (CFP) and the total energy footprint (EFP) with 81.73% and 84%, respectively. Moreover, the agriculture/hunting forestry/fishing sector and the electricity/gas/water supply sectors dominate the overall U.S. carbon footprint, contributing 22% and 21.28%, respectively. The coke/refined petroleum/nuclear fuel sector has the largest share of the total energy footprint, with 47.9% of the total impacts.

Keywords

carbon and energy footprint, life cycle assessment, multi-region input-output (MRIO), sustainability, uncertainty, statistics

1 Introduction

The concept of tracing the impact of a change in the regional or national economy on the entire interdependent industry matrix, known today as supply chains, has long been the focus of academic interest, especially in the field of economics. In the 1930s, Professor Wassily Leontief developed a function which is considered today to be the foundation for input-output analysis. The essential objective of input-output analysis is to identify the interdependence of sectors in a particular economy. Many types of economic analysis continue to regard Leontief's input-output analysis as a key concept (Miller and Blair, 2009). In this context, an input-output model is made up of system linear equations that individually explain how a product is distributed across the economy (Miller and Blair, 2009).

1.1 Sustainability and life cycle assessment

Sustainability has been a critical topic of interest worldwide ever since it was defined and its importance signified in the 1987 Brundtland Commission's Our Common Future report. Since then, governments, various political, profit, and non-profit organisations have placed significant emphasis on developing analytical frameworks to support the decision-making processes from an environmental sustainability perspective. Life cycle assessment is a very basic, widely accepted, and analytical sustainability assessment method that is used to quantify primarily the environmental effects of a product considering the entire life cycle (Amadei et al., 2021). Nowadays, the concept of life cycle sustainability includes the social and economic dimensions as well as the environmental perspective (Purvis et al., 2019). The raw material extraction,

Cite this article as: Abbood, K., Egilmez, G., Meszaros, F. (2023) "Multi-region Input-Output-based Carbon and Energy Footprint Analysis of U.S. Manufacturing", Periodica Polytechnica Social and Management Sciences, 31(2), pp. 91–99. https://doi.org/10.3311/PPso.19554

manufacturing/production, distribution/routing, usage, and end of life stages are all included in the term Entire Life Cycle Assessment (LCA) (Egilmez et al., 2013; Herczeg and Baranyi, 2005; Koltai and Lozano, 1996). Recently the links between blockchain technology, the circular economy, sustainability, and corporate social responsibility have become a new research path (Upadhyay et al., 2021). The overall purpose of conducting an LCA study is discussed in numerous studies, ranging from earlier general studies (Hendrickson et al., 1998) to more recent specific multi-region input-output approaches (Cabernard et al., 2019), with a view to assisting with the following goals:

- minimising the magnitude of pollution, especially the greenhouse gases,
- preserving resources which are non-renewable, including energy, water, biodiversity,
- maintaining environmental system, minimising climate change impacts,
- improving and employing clean technology, minimising health impacts
- ensuring that the environmental system is maintained, especially when it is critical to preserve balance in the supply chain,
- increasing recycling and reuse by developing alternative renewable materials.

1.2 Manufacturing in the United States

In the US, serious environmental impacts and resources depletions have resulted in as carbon, energy, and land footprint are highly attributed to manufacturing sectors (Egilmez et al., 2015b). The goods and raw materials used every day are produced by various industries in the U.S. economic supply chains. Two types of emissions are produced, direct emissions manufactured at the facility and indirect emissions which occur off-site. The atmosphere receives different amounts of heat-trapping gases from the world's major countries. China, the United States, Russia, India, and Japan are viewed as the largest contributors of total carbon dioxide emissions from the energy consumption (Million Metric Tons) with 10773, 5144, 1848, 2315, and 1103, respectively (U.S. Energy Information Administration, 2019). The Environmental Protection Agency (EPA) has indicated that manufacturing sectors contribute 21% of GHG emissions and energy depletion in the US. Manufacturing sectors were considered the third largest contributor to U.S. GHG emissions after the electricity and transportation sectors. The U.S. Manfacturing contribution of GHG emission is 24 % (U.S. Environmental Protection Agency (EPA, 2020). While GHG emissions released from industry sectors since 1990 have fallen by approximately 12%, GHG emissions from other sectors had increased in 2011. According to the US Energy Information Administration (EIA), industrial sectors in the US consumed 88% non-renewable energy (11% coal, 32% natural gas, 9% nuclear electric power and 36% petroleum) and just 19% renewable energy (such as hydroelectric power, geothermal, solar, wind, and biomass) (U.S. Energy Information Administration, 2021). Moreover, the U.S. industrial sectors exhaust 355,000 million gallons of water per day. 45% of total water consumption are exhausted by irrigation and livestock. Thermo-electric power, irrigation, and public supply are the largest consumption sectors which exhaust 90% of the national total. Other industries, such as industrial, aquaculture, mining, household, and livestock, consume 10% of the total water withdrawal. 17% of global greenhouse gasses emissions are released from deforestation, peat soil, and land clearing for agriculture. Industrial sectors that use land such as forest and crop lands have essential impacts on carbon sequestration (Egilmez et al., 2015a).

1.3 Sustainability and manufacturing

Sustainable manufacturing is the economic process whereby products are created while environmental effects are eliminated or reduced. Sustainable manufacturing also boosts employee, community, and product safety. To grow and be competitive globally, companies have to improve their strategy and operations, with sustainability viewed as a crucial objective. Consequently, companies pursue sustainability for a variety of reasons. For example, they may:

- increase operational efficiency by reducing costs and waste;
- become more competitive and gain new customers;
- build public trust, establish a good reputation and protect and strengthen their brand;
- build long-term business viability and success,
- react to constraints and opportunities.

Several industrial and government projects have depended on sustainable manufacturing in their decision-making process due to rising environmental concern (Egilmez et al., 2013) or the requirements of energy management (Fűr and Csete, 2010). The U.S. Department of Commerce defines sustainable manufacturing as "manufactured products that are initiated using processes which preserve energy and natural resources, minimise pollution, and are economically appropriate and safe for employees, communities, and consumers" (Egilmez et al., 2013:p.93).

The life cycle effects have to be measured consistently in order to achieve sustainable manufacturing aims which are natural resources and energy conserving, and eliminate waste and pollution (Egilmez et al., 2013).

We live in a world in which products are mostly available for sale anywhere, especially with the help of online sales and marketing. The supply chains have become more complex and longer for a product unless local products are specifically wanted. The impacts of the supply chain can be more than 50% of the total impacts in both economic and environmental terms. Therefore, it is crucial for a sustainability assessment study to consider both direct and indirect impacts.

2 Literature review

Zhao et al. (2016) analysed the environmental effects of battery-electric trucks and compared them to the impacts of diesel-electric hybrid, diesel, and compressed natural gas trucks. It was concluded that electric trucks do not have less of an environmental impact than other truck types. In addition, electric trucks were found at that time to have energy consumption and greenhouse emissions that were greater than those of other truck types.

Another study used a MRIO to investigate the embodied energy and the energy-intensive industry policy in China's foreign trade (Cui et al., 2015). The results showed that embodied exported energy in China increased almost three times between 2001 and 2007. In addition, it was revealed that the energy-intensive industry policy decreased the consumption of energy.

Meanwhile, 27 American and Canadian major cities were evaluated in terms of their environmental sustainability performance (Egilmez et al., 2015a). On a scale between zero and one, the highest ranking was achieved by New York with 0.703 while the lowest score of 0.394 was obtained in Cleveland. It is important to note that public transport and CO_2 emissions had the most influence on cities' sustainability performance scores.

A quasi-MRIO model was used to study CO_2 emissions attributable to UK household energy use (Druckman and Jackson, 2009). The study has shown that the CO_2 emissions of households in 2004 were 15% greater than in 1990. Besides, different segments of the UK population have diverse carbon footprints. The most affluent segment emits 64% more CO_2 than the lowest segment.

In 2004, over one-quarter of UK households' CO_2 emissions were due to recreation and relaxation purposes. To address the uncertainty in the outcomes of input-output-based LCA methods, fuzzy data envelopment analysis was proposed (Druckman and Jackson, 2009). This approach could be used to evaluate life cycle models of sustainability benchmarking such as food manufacturing.

In Kucukvar et al. (2014), the Triple Bottom Line (TBL) of the United States' final demand categories were analysed. According to the analysis results, household consumption has the biggest TBL effect, and consumption reduction would be accomplished by an efficient, green resource-based economy.

It has been shown that the fragmentation of international manufacturing produces worldwide carbon emissions during the analysis of the pollution haven hypothesis (Zhang et al., 2017). In addition, every country exhibits different environmental effects due to trade.

Another study aimed to analyse and study the environmentally sustainable supply chains for 15 years using a MRIO modelling framework (Acquaye et al., 2017). It was observed that both China and India were the biggest water consumer and sulphur oxide emissions originators in the electricity sector in 2004.

To evaluate inter-city economic consumption, pollutant emission, and concentration among 13 cities in the Beijing–Tianjin–Hebei (BTH) urban agglomeration, this study combines an inter-city multi-regional input-output (MRIO) model with an air quality dispersion model consisting of a weather research and forecasting (WRF) model and the CALPUFF model (WRF/CALPUFF) (Wang et al., 2020). As an example, NOx is used. Due to the combined impacts of economic connection and atmospheric transfer, the results of this article highlight that consumption outside of a city might have a higher impact on the city's air quality.

The US multi-region input-output (US-MRIO) is used in this article to estimate regional and sectoral spillover impacts from the integration of wind energy farms in ten US states (Faturay et al., 2020). The overall economic gain was estimated to be $26 billion, with $3 billion allocated to areas where no new wind energy capacity was developed. Using the US-MRIO model and the energy intensity of industrial sectors, the overall change in economic throughput resulting from the addition of wind farms was calculated to be around 6952 trillion Btu. Among other manufacturing sectors, the primary metal production and machinery manufacturing sectors stood out with significant increases in energy consumption of 3074 trillion Btu and 1537 trillion Btu, respectively.

The purpose of this research is to assess the substitution effects of four bioeconomic innovations in terms of the European Commission's policy objectives (Asada et al., 2020). Point estimates and uncertainty intervals were calculated using a multi-regional input-output (MRIO) method. The sustainability characteristics of a future bioeconomy will be heavily influenced by decisions on future biomass use paths. To promote the development of an effective bioeconomy capable of delivering "sustainable growth", just encouraging increased biomass usage as a policy strategy is insufficient.

In Shepard (2020) a new hybrid input-output database of energy flows within and among the world's 136 major economies was created and used to compare and contrast indirect energy security indicators with direct energy security metrics. From the data, it can be observed that indirect energy trade links between primary energy-producing countries and countries with whom they have no direct trade relations account for 23% of the world's embodied energy network. Moreover, indirect energy imports are 90 percent more significant than direct energy imports, and countries have many more trade partners in indirect energy than they do indirect energy.

3 Methodology

3.1 Structure of the assessment

In this paper, a four-step methodology is followed. In the first step, the Input-Output data of the 40 main economies in the world (Russia, Japan, India, USA, and others) and the Rest of the World were collected. The second step was the building of a deterministic MRIO model for those data for each country which consists of 35 main industries. Then, as the third step a stochastic MRIO model was built. In the fourth step a Monte-Carlo Simulation method was utilised to create thirty replications for the total output for each country and industry.

The focus of analysis includes the onsite and supply chain carbon and energy footprint impacts of U.S. industrial economic transactions. Indirect impacts consist of the supply chain industries in the U.S. economy that supports the U.S. manufacturing and the supply chain industries in the other countries that exports to U.S. market.

3.2 Data collection

Most of our data has been collected from World Input-Output Database (WIOD). The World Input-Output Database (WIOD) is one of the up-to-date multi-region input-output databases. The dataset consists of a time series of symmetric input-output (I-O) table between the duration of 2000 and 2009, which covers world economy with 40 major countries (based on gross domestic production) and the Rest of World (RoW). The WIOD table provides detailed information about commodity productions in dollars by industry and commodity consumptions per industry. A fixed product sales structure has been assumed. Therefore, each sector has its own sale structure, which accounts for a product output that is sold to intermediate and final users (Kucukvar et al., 2015).

3.3 Mathematical background of deterministic MRIO

In this MRIO model, the $\left(\boldsymbol{A}_{ij}^{rs}\right)_t$ matrix is the direct requirement matrix, and each row of the $\left(\boldsymbol{A}_{ij}^{rs}\right)_t$ matrix represents the inputs from other sectors (local and foreign inputs) to create a unit of output. The $\boldsymbol{i}$ refers to the input from country $\boldsymbol{r}$ into industry $\boldsymbol{j}$ in countrys. However, in our MRIO model $\boldsymbol{i}$ and $\boldsymbol{j}$ are the same and equal to 35 which is the total number of industries in a certain country. Also, 41 is the total number of countries, including the Rest-of-the-World (RoW), and it is represented by $\boldsymbol{r}$ and $\boldsymbol{s}$, which are equal. The total output vector for the given economic output can be estimated using the MRIO framework's basic linearity assumption, which is:

$$\boldsymbol{x}_t^r = \left(\boldsymbol{I} - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1} \left(\boldsymbol{f}_i^r\right)_t, \tag{1}$$

where $\left(\boldsymbol{f}_i^r\right)_t$ is a vector consisting of a dollar production from the manufacturing sector $\boldsymbol{i}$ in region $\boldsymbol{r}$ and zero everywhere else. Moreover, $\boldsymbol{I}$ is the identity matrix in which all entries are zero except for the diagonal entries which are equal to 1, and $\boldsymbol{x}_t^r$ represents the total output vector based on a final-output change in country $\boldsymbol{r}$. The term $\left(\boldsymbol{I} - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}$ is also known as the Leontief's Inverse. After estimating the total output vector, total carbon footprints can be determined by multiplying each sector's output by its carbon impact per dollar of output (Kucukvar et al., 2015):

$$\boldsymbol{C}_t = \boldsymbol{B}_t \left(\boldsymbol{I} - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1} \left(\boldsymbol{f}_i^r\right)_t, \tag{2}$$

where $\boldsymbol{C}_t$ is the vector of total environmental impact (e.g. GHG emissions) and the environmental impact multiplier is represented by $\boldsymbol{B}$, which is a matrix of diagonal elements (e.g. Global Warming Potential (GWP) per $M economic output). The Global Warming Potential (GWP) is determined by multiplying each sector's total GHG emissions by conversion factors provided from the U.S. Environmental Protect Agency (US EPA) (Kucukvar et al., 2015).

3.4 Mathematical background of deterministic MRIO

In the stochastic MRIO model, both the total requirement matrix $\left(\left(\boldsymbol{I} - \left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'$ and the final demand $\left(\boldsymbol{f}_i^r\right)_t'$

variables are assumed to be a random variable, with mean and standard deviation. Mean values are assumed to be equal to the data points, obtained from WIOD database. Moreover, standard deviation values are then derived from the means based on multiplying the mean value with a factor, *k*, which was assumed to be 10%. In fact, a 10% variation is initially assumed (Lenzen et al., 2010). Considering total requirement matrix $\left(\left(\boldsymbol{I}-\left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'$ and final demand (in this study economic output of each manufacturing industry is considered as final demand) $\left(\boldsymbol{f}_i^r\right)_t'$ are notated as follows, where $\boldsymbol{x}_t^{r'}$ is derived as the stochastic total economic output (direct + global supply chains).

$$\boldsymbol{x}_t^{r'}=\left(\left(\boldsymbol{I}-\left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'\left(\boldsymbol{f}_i^r\right)_t' \quad (3)$$

The total carbon footprint and the total energy footprint of all sectors in 41 countries can be easily obtained after the calculating of the stochastic total economic output $\left(\boldsymbol{x}_t^{r'}\right)$. In the deterministic MRIO model, the total CFP and EFP were calculated by multiplying the total economic output with (a matrix with diagonal elements representing the Global Warming Potential (GWP) per million dollar economic activity) (Kucukvar et al., 2015). In the stochastic case, since both variables are random, Monte Carlo simulation is used to find out the mean and standard deviation of resulting total mean GWP and standard deviation of GWP impacts.

$$\boldsymbol{C}_t'=\boldsymbol{B}_t\left(\left(\boldsymbol{I}-\left(\boldsymbol{A}_{ij}^{rs}\right)_t\right)^{-1}\right)'\left(\boldsymbol{f}_i^r\right)_t' \quad (4)$$

3.5 Monte Carlo simulation

Monte Carlo Simulation is a process that uses repeated random sampling and statistical analysis to calculate outcomes (Raychaudhuri, 2008). This method of simulation is linked with random experiments about specific outcomes which are not known (Raychaudhuri, 2008). In our case, the Monte Carlo experiments were used to calculate of the total impact of CFP and EFP of the USA manufacturing sectors confidence intervals. Thirty replications of the stochastic MRIO model, for each year from 2000 to 2009 for both EFP and CFP, were created by using the Monte Carlo Simulation Method. Moreover, we obtained 600 experiments after running all twenty years, 10 years for CFP and 10 years of EFP, altogether 30 times (Hogg and Tanis, 1997). Then, we calculated the mean and the standard deviation of the 30 samples for each year for both EFP and CFP. The steps of the Monte Carlo simulation are the following:

1. Calculation the Total Impact of EFP and CFP for each year from 2000 to 2009.
2. Creating thirty replications also for each year.
3. Thirty replications for each year from 2000 to 2009 for the EFP and CFP.
4. Calculating the expected value and the standard deviation from 30 samples.

4 Results

4.1 Carbon footprint impacts

4.1.1 Total mean impacts (onsite + supply chain)

In terms of the total impact (onsite + supply chain) of countries, Fig. 1 shows that the U.S.A is the greatest contributor of the carbon footprint with 81.73% share of the total impact. The remaining countries' carbon footprint ranged from 6.64% to 0.02%. Moreover, the top ten countries account for 97.57% of the total carbon footprint.

In terms of sectors, agriculture, hunting forestry and fishing is the dominant sector, contributing 22% of the total impact of the carbon footprint. In addition, electricity, gas, and water supply sectors contributed greatly to the carbon footprint: 21.28%, as shown in Fig. 2. The top ten industries account for 92.12% of the total carbon footprint. The remaining industries shared a carbon footprint ranging from 16.35% to 0.12%.

4.1.2 Analysis by Industry without U.S. manufacturing

Among the industries examined for their contribution to the CFP, the electricity, gas and water supply sectors make the biggest contribution, 23.943% of the total impact. The mining and quarrying sector also makes a high contribution to the carbon footprint of 18.160%, as shown in Fig. 3. The top ten industries account for 90.308% of the total carbon footprint. The remaining industries' carbon footprint ranged from 13.261% to 0.057%.

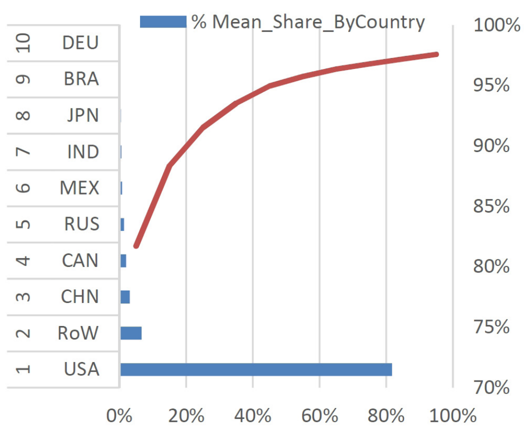

Fig. 1 The total carbon footprint impacts of all countries including the U.S.A.

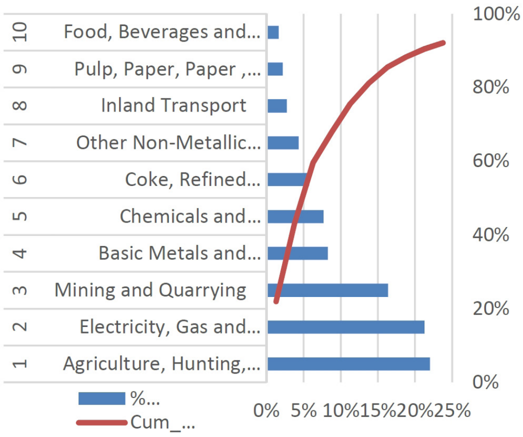

Fig. 2 The total impacts of the top ten industries

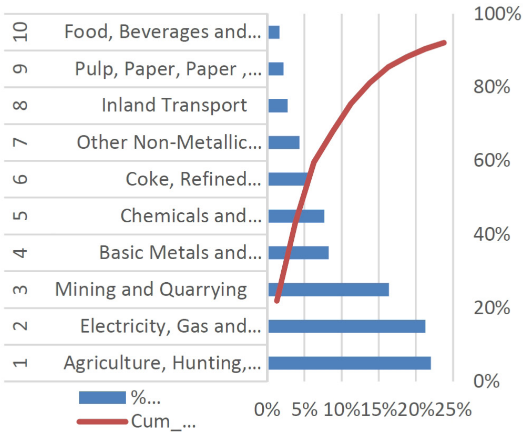

Fig. 3 The supply chain impacts of the carbon footprint of the industries

4.1.3 Confidence intervals of carbon footprint impacts

Fig. 4 explains the total impact of the CFP for the top ten sectors with 95% confidence intervals. Agriculture/ hunting/ forestry and fishing had the highest value of the total impact with large confidence intervals. Among the investigated countries, the U.S.A. has the highest value of the total impact of CFP with large values of the confidence intervals (see Fig. 5).

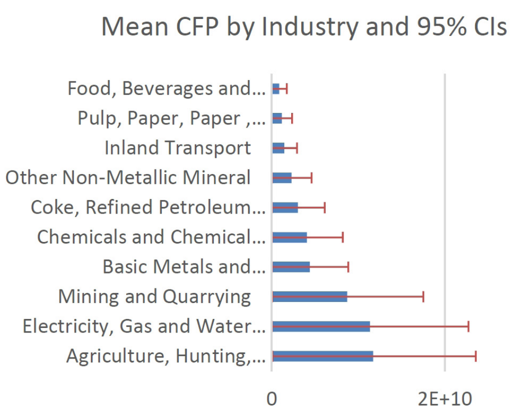

Fig. 4 The total effect of CFP by industry and 95% confidence intervals

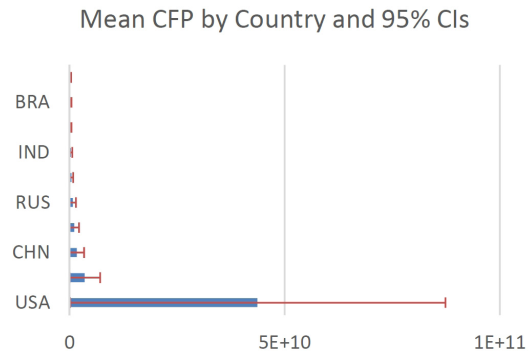

Fig. 5 The total impact of CFP by country and 95% confidence intervals

4.2 Energy footprint impacts

4.2.1 Total impacts (onsite + supply chain)

In terms of the total mean share of the energy footprint (EFP) of countries in the Fig. 6 the U.S.A is the largest contributor of the EFP with 84% share of the total impact. The remaining countries' carbon footprint ranges from 0.57% to 0.012%. The top ten countries account for 97.5% of the total energy footprint.

In the energy sector, coke/refined petroleum/nuclear fuel proves to be the dominant industry with 47.9% share of the total impact of the energy footprint. Also, the electricity/gas/water supply sector contributes greatly to the energy footprint with 14.9%, as shown in Fig. 7. The top

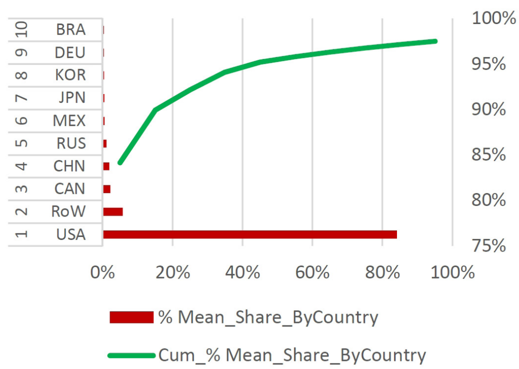

Fig. 6 The energy footprint of all countries including the U.S.A.

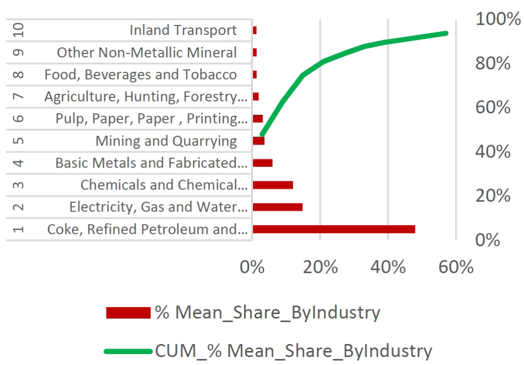

Fig. 7 The total impacts of the ten industries

ten industries account for 93.7% of the total energy footprint. The remaining industries shares an energy footprint ranging from 12.03% to 0.094%.

4.2.2 Analysis by industry

The energy footprint of the coke/ refined petroleum/ nuclear fuel sector dominates with 30.56% share on the total impact of the carbon footprint. Electricity/gas/water supply sector contributes to a high share of the energy footprint with 20.06%, as shown in Fig. 8. The top ten industries account for 92.5% of the total energy footprint. The remaining industries' share of the energy footprint ranges from 15.08% to 0.0641%.

4.2.3 Confidence intervals of energy footprint impacts

Fig. 9 shows that coke, refined petroleum, and nuclear fuel has the highest value of the total impact of EFP with largest values of the confidence intervals. Fig. 10 shows another indicator that the U.S.A. had the highest value of the total impact of EFP with largest confidence intervals.

5 Conclusion

The U.S.A. had the most contribution of the total of both carbon footprint (CFP) and energy footprint (EFP). The

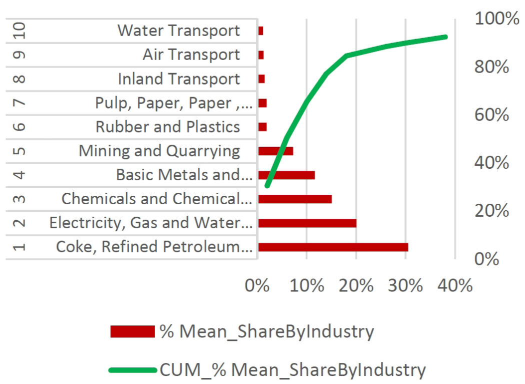

Fig. 8 The supply chain energy FP impacts

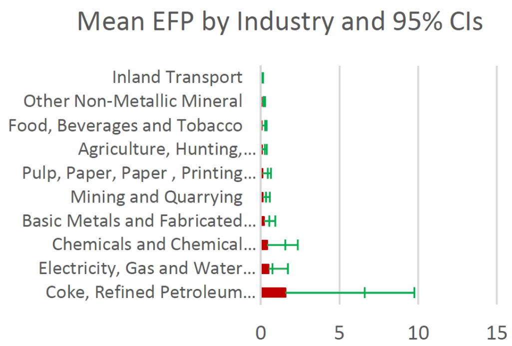

Fig. 9 The total impact of EFP by industry and 95% confidence intervals

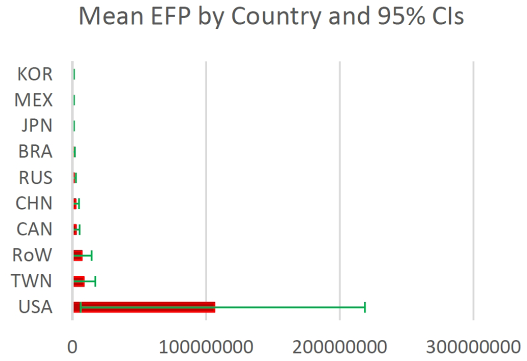

Fig. 10 The total impact of EFP by country and 95% confidence intervals

Rest of the World (RoW) is considered the second largest contributor of the total of CFP and EFP after the USA. China and Canada also have high values of the total share of CFP and EFP.

Among the thirty-five industries, agriculture/hunting forestry/ fishing sector is the biggest contributor of the total carbon footprint. Moreover, both electricity/gas/ water supply sector and mining/quarrying industry contribute heavily to the CFP. This also underlines the importance of switching to clean energy across the world and creating a more environmentally friendly pattern of consumption behaviour across the U.S., which may also highlight the ultimate responsibility of U.S.A. to take part in worldwide environmental related conventions.

Coke/refined petroleum/ nuclear fuel sector dominate the total impacts, while the electricity/ gas/water supply sector and chemical/chemical products sector were found to be the second and the third large contributor, respectively.

For future research, similar assessment can be performed for the entire U.S. economy, in addition to manufacturing industries. Besides ecological impacts, endpoint impact could be also modelled along with the newly developed stochastic MRIO framework. In terms of other environmental impact categories factors, water withdrawals (WW), hazardous waste generation (HWG), and toxic releases (TR) could also be the focus of further research (see Cabernard et al., 2019). Moreover, social impacts including child labour, income inequality, poverty, safety, work-related injuries, etc. could be also be focused on in future studies.

In addition, a more complete sustainability assessment methodology that takes not only the environmental and economic aspects of sustainability into account, but also the social aspect (Bulle et al., 2019), could be a useful future endeavour. The eco-efficiency analysis can be utilised in combination with the integration of social impacts into a newly developed economic-input output (EIO-) LCA approach (Hendrickson et al., 1998; Matthews and Small, 2000). Finally, because EIO-LCA does not consider environmental interventions of manufactured products linked to use and end-of-life phases, which might have significant impacts, the environmental impacts of each manufacturing sector are studied from cradle to grave (Song et al., 2018). Notwithstanding that a cradle-to-grave environmental LCA is an essential method for quantifying sustainability impacts, the existing EIO-LCA tool might nonetheless be improved by taking utilisation and end-of-life phases into account.

References

Acquaye, A., Feng, K., Oppon, E., Salhi, S., Ibn-Mohammed, T., Genovese, A., Hubacek, K. (2017) "Measuring the environmental sustainability performance of global supply chains: A multi-regional input-output analysis for carbon, sulphur oxide and water footprints", Journal of Environmental Management, 187, pp. 571–585.
https://doi.org/10.1016/j.jenvman.2016.10.059

Amadei, A. M., De Laurentiis, V., Sala, S. (2021) "A review of monetary valuation in life cycle assessment: State of the art and future needs", Journal of Cleaner Production, 329, 129668.
https://doi.org/10.1016/j.jclepro.2021.129668

Asada, R., Cardellini, G., Mair-Bauernfeind, C., Wenger, J., Haas, V., Holzer, D., Stern, T. (2020) "Effective bioeconomy? A MRIO-based socioeconomic and environmental impact assessment of generic sectoral innovations", Technological Forecasting and Social Change, 153, 119946.
https://doi.org/10.1016/j.techfore.2020.119946

Bulle, C., Margni, M., Patouillard, L., Boulay, A. M., Bourgault, G., … Jolliet, O. (2019) "IMPACT World+: a globally regionalized life cycle impact assessment method", The International Journal of Life Cycle Assessment, 24(9), pp. 1653–1674.
https://doi.org/10.1007/s11367-019-01583-0

Cabernard, L., Pfister, S., Hellweg, S. (2019) "A new method for analyzing sustainability performance of global supply chains and its application to material resources", Science of The Total Environment, 684, pp. 164–177.
https://doi.org/10.1016/j.scitotenv.2019.04.434

Cui, L. B., Peng, P., Zhu, L. (2015) "Embodied energy, export policy adjustment and China's sustainable development: A multi-regional input-output analysis", Energy, 82, pp. 457–467.
https://doi.org/10.1016/j.energy.2015.01.056

Druckman, A., Jackson, T. (2009) "The carbon footprint of UK households 1990-2004: A socio-economically disaggregated, quasi-multi-regional input-output model", Ecological Economics, 68(7), pp. 2066–2077.
https://doi.org/10.1016/j.ecolecon.2009.01.013

Egilmez, G., Kucukvar, M., Tatari, O. (2013) "Sustainability assessment of U.S. manufacturing sectors: An economic input output-based frontier approach", Journal of Cleaner Production, 53, pp. 91–102.
https://doi.org/10.1016/j.jclepro.2013.03.037

Egilmez, G., Gumus, S., Kucukvar, M. (2015a) "Environmental sustainability benchmarking of the U.S. and Canada metropoles: An expert judgment-based multi-criteria decision making approach", Cities, 42(A), pp. 31–41.
https://doi.org/10.1016/j.cities.2014.08.006

Egilmez, G., Kucukvar, M., Park, Y. S. (2015b) "Supply chain-linked sustainability assessment of the U.S. manufacturing: An ecosystem perspective", Sustainable Production and Consumption, 5, pp. 65–81.
https://doi.org/10.1016/j.spc.2015.10.001

Faturay, F., Vunnava, V. S. G., Lenzen, M., Singh, S. (2020) "Using a new USA multi-region input output (MRIO) model for assessing economic and energy impacts of wind energy expansion in USA", Applied Energy, 261, 114141.
https://doi.org/10.1016/j.apenergy.2019.114141

Fűr, A., Csete, M. (2010) "Modeling methodologies of synergic effects related to climate change and sustainable energy management", Periodica Polytechnica Social and Management Sciences, 18(1), pp. 11–19.
https://doi.org/10.3311/pp.so.2010-1.02

Hendrickson, C., Horvath, A., Joshi, S., Lave. L. (1998) "Peer Reviewed: Economic Input–Output Models for Environmental Life-Cycle Assessment", Environmental Science & Technology, 32(7), pp. 184A–191A.
https://doi.org/10.1021/es983471i

Herczeg, M., Baranyi, R. (2005) "Tracing Substances in the Technosphere and Products", Periodica Polytechnica Social and Management Sciences, 13(2), pp. 151–167.

Koltai, T., Lozano, S. (1996) "The Illustration of the Routing Sensitivity Calculation of Flexible Manufacturing Systems with Perturbation Analysis", Periodica Polytechnica Social and Management Sciences, 4(1), pp. 5–28.

Kucukvar, M., Egilmez, G., Tatari, O. (2014) "Sustainability assessment of U.S. final consumption and investments: triple-bottom-line input–output analysis", Journal of Cleaner Production, 81, pp. 234–243.
https://doi.org/10.1016/j.jclepro.2014.06.033

Kucukvar, M., Egilmez, G., Onat, N. C., Samadi, H. (2015) "A global, scope-based carbon footprint modeling for effective carbon reduction policies: Lessons from the Turkish manufacturing", Sustainable Production and Consumption, 1, pp. 47–66.
https://doi.org/10.1016/j.spc.2015.05.005

Lenzen, M., Wood, R., Wiedmann, T. (2010) "Uncertainty Analysis For Multi-Region Input-Output Models - A Case Study Of The UK's Carbon Footprint", Economic Systems Research, 22(1), pp. 43–63.
https://doi.org/10.1080/09535311003661226

Matthews, H. S., Small, M. J. (2000) "Extending the Boundaries of Life-Cycle Assessment Through Environmental Economic Input-Output Models", Journal of Industrial Ecology, 4(3), pp. 7–10.
https://doi.org/10.1162/108819800300106357

Miller, R. E., Blair, P. D. (2009) "Input-Output Analysis", Cambridge University Press. ISBN 9780511626982
https://doi.org/10.1017/CBO9780511626982

Purvis, B., Mao, Y., Robinson, D. (2019) "Three pillars of sustainability: in search of conceptual origins", Sustainability Science, 14(3), pp. 681–695.
https://doi.org/10.1007/s11625-018-0627-5

Raychaudhuri, S. (2008) "Introduction to Monte Carlo simulation", In: 2008 Winter Simulation Conference, Miami, FL, USA, pp. 91–100.
https://doi.org/10.1109/WSC.2008.4736059

Hogg, R. V., Tanis, E. A. (1997) "Probability And Statistical Inference", Prentice Hall. ISBN 9780132546089

Shepard, J. U., Pratson, L. F. (2020) "Hybrid input-output analysis of embodied energy security", Applied Energy, 279, 115806.
https://doi.org/10.1016/j.apenergy.2020.115806

Song, C., Gardner, K. H., Klein, S. J. W., Souza, S. P., Mo, W. (2018) "Cradle-to-grave greenhouse gas emissions from dams in the United States of America", Renewable and Sustainable Energy Reviews, 90, pp. 945–956.
https://doi.org/10.1016/j.rser.2018.04.014

Upadhyay, A., Mukhuty, S., Kumar, V., Kazancoglu, Y. (2021) "Blockchain technology and the circular economy: Implications for sustainability and social responsibility", Journal of Cleaner Production, 293, 126130.
https://doi.org/10.1016/j.jclepro.2021.126130

U.S. Energy Information Administration (2019) "International", [online] Available at: http://www.eia.gov/emeu/international/carbondioxide.html [Accessed: 16 November 2021]

U.S. Energy Information Administration (2021) "U.S. energy facts explained", [online] Available at: https://www.eia.gov/energyexplained/us-energy-facts/ [Accessed: 16 November 2021]

U.S. Environmental Protection Agency (EPA) (2020) "Inventory of U.S. Greenhouse Gas Emissions and Sinks" [online[Available at: https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks [Accessed: 16 November 2021]

Wang, Y., Li, X., Sun, Y., Zhang, L., Qiao, Z., Zhang, Z., Zheng, H., Meng, J., Lu, Y., Li, Y. (2020) "Linkage analysis of economic consumption, pollutant emissions and concentrations based on a city-level multi-regional input–output (MRIO) model and atmospheric transport", Journal of Environmental Management, 270, 110819.
https://doi.org/10.1016/j.jenvman.2020.110819

Zhang, Z., Zhu, K., Hewings, G. J. D. (2017) "A multi-regional input–output analysis of the pollution haven hypothesis from the perspective of global production fragmentation", Energy Economics, 64, pp. 13–23.
https://doi.org/10.1016/j.eneco.2017.03.007

Zhao, Y., Onat, C. N., Kucukvar, M., Tatari, O. (2016) "Carbon and energy footprints of electric delivery trucks: A hybrid multi-regional input-output life cycle assessment", Transportation Research Part D: Transport and Environment, 47, pp. 195–207.
https://doi.org/10.1016/j.trd.2016.05.014