Toxic Chemical Pollutants in the U.S. States

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Abstract

Footprint indicators are used to evaluate chemical substance management. However, determining the impact of chemical restrictions on manufacturing processes and supply chains without a footprint analysis of the entire lifecycle is difficult. Here, we propose a new framework for estimating chemical toxicity footprints utilizing the risk-screening environmental indicators (RSEIs) published by the U.S. Environmental Protection Agency. We conducted an empirical analysis using multi-states input–output data from the U.S. in 2017 to demonstrate the usefulness of the framework, and made policy recommendations based on the obtained results. According to the production-based RSEI scores, Texas, Pennsylvania, Illinois, and Louisiana accounted for 43% of the total human health risk in the U.S. By contrast, California and New York ranked first and second in consumption-based RSEI score (i.e., health risk footprint), respectively; however, the District of Columbia and Alabama ranked first and second in per capita footprint. Three significant risk transfers, accounting for 6% of the total in the U.S. economy, were found: from California to Texas, from New York to Texas, and from Florida to Texas. In conclusion, specific states such as Texas and Louisiana were at considerable risk from major chemical substance emissions triggered by final demands in mega cities such as New York and California. Thus, the federal and state governments should select high priority sectors and states according to the production-based RSEI scores. Relevant taxes can be collected from states based on the consumer's responsibility. Footprint-based inter-state financial cooperation is crucial in mitigating chemical pollutions in the U.S.

Data availability statement: The environmentally-extended MRIO data of the U.S. states is available upon request.

Competing Interest Statement: The authors declare no competing interest.

Keywords: Chemical toxicity footprint; multi-regional input–output dataset; RSEI

1. Introduction

Toxic chemical management is being promoted worldwide to realize a healthy and prosperous society (1). The use of chemicals dramatically increases our convenience (2); however, toxic chemicals generated during manufacturing, utilization, and disposal of products have adverse effects on human health and ecosystems (3). To address these challenges, target 12.4 from the Sustainable Development Goals states the following: "By 2020, achieve the environmentally sound management of chemicals and all wastes throughout their life cycle, in accordance with agreed international frameworks, and significantly reduce their release to air, water and soil in order to minimize their adverse impacts on human health and the environment." However, this target is difficult to achieve, and a global action plan (i.e. post strategic approach to international chemicals management) has been proposed for implementation even after 2020 (4).

In response to this situation, efforts to manage toxic chemicals are increasing mainly in developed countries. In 2016, the toxic substances control act (TSCA), the basic federal law for handling general industrial chemicals in the U.S., was amended for the first time in 40 years to establish priorities for risk assessment of chemicals, and to establish proposed rules regarding risk reduction of individual substances (5). Moreover, to protect workers who handle hazardous chemicals, a hazard communication standard was established under the Occupational Safety and Health act in 2012, which imposes obligations such as communication of chemical hazard information and employee training (6). These chemical toxicity assessment and on-site information communication efforts are expected to promote appropriate chemical management and mitigate toxic effects on human health and ecosystems (7).

In Europe, the "chemicals strategy for sustainability" was announced in October 2020, and efforts are underway to achieve zero pollution for a toxic-free environment (8). In this context, the revision of the Registration, Evaluation, Authorization, and Restriction of Chemicals (REACH) regulation, which guides the management of toxic chemicals, is also under consideration (9). It should be noted that the EU is considering to expand the information requirements of REACH to include information on the overall environmental footprint of chemicals (8).

Footprint indicators can evaluate not only the direct toxicity impact of chemical substances but also the indirect toxicity impact through intermediate goods inputs, allowing the evaluation of chemical substance management throughout their entire life cycle (10). Since the transition of the economic system to a circular economy is underway, especially in the EU, the method whereby the toxic effects of chemical substances are assessed over their entire life cycle plays an important role in building the circular chemistry system (11).

Various studies have been conducted on the management of toxic chemicals using data from pollutant release and transfer register (PRTR) systems [e.g., U.S. (12-14)]. Many of these studies have focused on the effects of toxic chemical exposure on human health and appropriate chemical management methods at business sites. However, there have been limited studies on footprint coverage of the entire supply chain (10, 15–17).

One of the reasons for the lack of progress in footprint research on chemical substances is their characteristics; unlike, for example, CO_2 emissions, which are the subject of much footprint research (18), chemical substances have diverse characteristics (7). Specifically, toxic effects on human health and ecosystems vary widely among chemicals, and an analytical framework that explicitly takes these differences into account is needed (19). Since the EU has proposed a management method that uses integrated chemical substance risk as an indicator, there is a growing social demand for using footprint information in integrated risk minimization (11).

Footprint indicators can be used to monitor the effects of chemical substance regulations. Chemical restrictions can lead to shifts in manufacturing processes and supply chains; however, these impacts are difficult to determine without an analysis of the entire lifecycle. In addition, the EU aims to "develop a framework of indicators to monitor the causes and effects of chemical pollution and to assess the effectiveness of chemical legislation," and footprint analysis with integrated risk indicators for chemical substances is consistent with these objectives (8).

The objective of this study was to propose a new framework for estimating chemical toxicity footprints utilizing the risk-screening environmental indicators (RSEIs) published by the U.S. Environmental Protection Agency (EPA). In addition, to demonstrate the usefulness of the estimation framework, we conducted an empirical analysis using U.S. multi-regional input–

output data from 2017 and made policy recommendations based on the footprint estimation results.

RSEI uses three indicators to assess toxic chemical emissions (19). The first is the simple sum of chemical emissions, expressed in pounds. The second one is “hazard,” which is the toxicity-weighted emissions and is measured in toxicity-weighted pounds. The third one is the “score,” which is an indicator that reflects the size of the chemical release as well as the size of the exposed population and ecosystem and indicates the potential risk due to toxicity effects. The relationship between these three indicators is summarized in Figure 1. The RSEI scores are designed to be comparable to each other (19), with a 10-fold higher number indicating a 10-fold higher likelihood of risk. Even relatively small/large releases of chemicals tend to have higher/lower RSEI scores when the toxicity weight is high/low or when the modeled exposed population is large/small.

A high RSEI score identifies areas that require further investigation, but does not indicate the health risk itself (19). Therefore, while the analysis results from the RSEI score are useful for gaining new insights through relative comparisons of potential risk across regions and industries, it is difficult to identify causal factors affecting human health based on these results alone. In other words, the RSEI score reflects the relative degree of risk and can be used as useful information when considering priorities for pollution control measures.

In this study, we used the U.S. multi-regional input–output table fed by the RSEI data to identify the production-based and consumption-based toxicity footprints for each state and sector, while considering the limitations in data availability. Then, we used the results of the RSEI model to develop a policy recommendation framework.

[Insert Figure 1 here]

2. Methodology

2.1 MRIO model

We formulated the U.S. production-based and consumption-based toxicity emissions and risk indicators using an MRIO analysis. The production- and consumption-based environmental accounting method using the MRIO framework has been widely adopted (20, 21).

An intermediate input from industry i in state r to industry j in state s is defined as Z_{ij}^{rs} $(i, j = 1,2, \dots, M; r, s = 1,2, \dots, N)$. The final demand from industry i in state r to final consumers in state s is defined as F_i^{rs} $(i = 1,2, \dots, M; r, s = 1,2, \dots, N)$. As a result, the total output of industry i in state r is defined as $x_i^r = \sum_{s=1}^{N} \sum_{j=1}^{M} Z_{ij}^{rs} + \sum_{s=1}^{N} F_i^{rs}$. If the intermediate input coefficient $a_{ij}^{rs} = Z_{ij}^{rs} / x_j^s$ is defined, the total output can be formulated as $\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$ in matrix notation, where $\mathbf{x} = (x_i^r)$, $\mathbf{A} = \left(a_{ij}^{rs}\right)$, and $\mathbf{f} = (\sum_{s=1}^{N} F_i^{rs})$. The MRIO model, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f}$, can show the extension of the final demand that directly and indirectly generates the industrial output. Here, $\mathbf{I}$ is the identity matrix; $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1} = \left(l_{ij}^{rs}\right)$ is the Leontief inverse, which is a direct and indirect requirement matrix that represents how many units of a product of industry i in state r are needed to produce one unit of a product of industry j in state s. In addition, we defined the row vector $\mathbf{e}^r$, whose element of industry i is 1 in state r and 0 in others, and the final demand column vector $\mathbf{f}^s$ for the state s, which is the s^{th} column vector of the final demand matrix; then, the production of industry i in state r directly- and indirectly-induced by final demand in state s can be represented with $\mathbf{e}^r\mathbf{L}\mathbf{f}^s$.

2.2 Production- and consumption-based accounting

Production-based accounting for a state represents the pollution by industry in the state. Production-based RSEI hazard and RSEI score of state r is the local pollution by industry in state r and the local exposure dose, respectively. Production-based RSEI hazard PH^r and RSEI score PS^r of state r can be obtained as

$$PH^r = \mathbf{h}^r\mathbf{L}\mathbf{f} \tag{1}$$

$$PS^r = \mathbf{s}^r\mathbf{L}\mathbf{f} \tag{2}$$

where $\mathbf{h}^r$ and $\mathbf{s}^r$ are the row vectors whose elements of industry i in state r are the RSEI hazard and RSEI score per unit of output of industry i in state r, respectively, and 0 in the others.

Consumption-based accounting for a state represents the total pollution induced by final consumption in the state. Consumption-based RSEI hazard and RSEI score are the total pollution exposure dose in U.S. allocated to the states in the U.S. finally consumed through the import of industries, government, and residents. The consumption-based RSEI hazard CH^r and RSEI score CS^r of state r can be obtained as:

$$CH^r = \mathbf{hLf}^r \quad (3)$$

$$CS^r = \mathbf{sLf}^r \quad (4)$$

where **h** and **s** are the RSEI coefficient row vectors whose elements are the RSEI hazard and RSEI score per unit of industrial outputs, respectively. The superscript T indicates the transposition.

As above, total pollution can be allocated to each state based on where the state produced or finally consumed. This accounting can be decomposed as follows:

$$\mathbf{hLf} = \sum_{r=1}^{N} PH^r = \sum_{s=1}^{N} CH^s$$

$$= \sum_{r=1}^{N}\sum_{s=1}^{N} \mathbf{h}^r\mathbf{Lf}^s = \sum_{r=1}^{N}\sum_{s=1}^{N} TH^{rs}$$

$$(5)$$

Here, $TH^{rs} = \mathbf{h}^r\mathbf{Lf}^s$ is called the gross emission transfer from state *s* to state *r*, that is, pollution emitted in state *r* induced by final consumption in state *s* (22). The same applies to that of the RSEI score ($TS^{rs} = \mathbf{s}^r\mathbf{Lf}^s$). In addition, the balance of pollution across state transfer [“net” emission transfer NH^{rs} and NS^{rs}] can be obtained as follows (23, 24):

$$NH^{rs} = TH^{rs} - TH^{sr} \quad (6)$$

$$NS^{rs} = TS^{rs} - TS^{sr} \tag{7}$$

3. Data sources

We used the U.S. multi-regional input–output (U.S.-MRIO) table for 2017 constructed using the US Industrial Ecology Laboratory by Faturay *et al*. (25), which includes data on 20 industries (Table S1) and 52 regions (50 states, the District of Columbia, and Puerto Rico; Table S2).

For analysis of industrial toxicity emission, we used the RSEI, which is publicly available at the Toxic Release Inventory database in the EPA website (https://www.epa.gov/rsei). The RSEI is constructed from the amount of toxic chemicals released, the chemical's fate and transport through the environment, each chemical's relative toxicity, and potential human exposure. This allows RSEI scores for different substances to be added together. In this study, we used the RSEI score and RSEI hazard among the RSEI parameters.

The RSEI hazard considers the size of the release and the chemical's toxicity. The RSEI hazard does not consider environmental fate and transport modeling or adjustments for population exposure. Therefore, the potential risk of exposure to humans may not be high even if the RSEI hazard is high. The RSEI score is a unitless value because it considers the size and location of the exposed population, and is only meaningful in comparison with other sectors and states. Even if the chemical release is relatively small, the RSEI score will be high if the toxicity weight is particularly high or if the exposed population is large. The relationship between the three indicators is illustrated in Figure 1.

We particularly focused on five chemical substances, chromium, ethylene oxide, cobalt, nickel, and asbestos, which are the top five chemical substances for the RSEI score. Note that the compounds are integrated for chemical substance category.

4. Results

4.1 Production-based RSEI hazard and score of the U.S.

Based on the Toxic Release Inventory program provided by the EPA, the total amount of the RSEI hazard in the U.S. was 9.5 trillion toxicity-weighted pounds in 2017. Toxicity-weighted pounds reflect the size of the release and the chemical's toxicity from industrial production. Importantly, there existed a large difference in the production-based RSEI hazard among the various states in the U.S. Figure 2 depicts the spatial distributions of the RSEI hazard in the U.S. It shows that Texas and Louisiana had the highest shares among the states, occupying 20% and 16% of the total U.S. RSEI hazard, respectively.

We next examined the reason for the significant contribution of Texas and Louisiana to the RSEI hazard. We found that not only the ethylene oxide hazard was spatially concentrated in Texas and Louisiana (Figure 3) but also that ethylene oxide was a major chemical substance greatly contributing to the higher RSEI hazard in Texas and Louisiana, accounting for 48% and 35% of the total hazard in each state, respectively. Ethylene oxide is a human-made chemical intermediate used mainly in the manufacture of ethylene glycol, textiles, detergents, polyurethane foam, and other products (26, 27); however, chemical manufacturing was a major source of ethylene oxide emissions in Texas and Louisiana (Tables S3 and S4).

In Pennsylvania, which was the third largest emitter, cobalt emitted from primary metal manufacturing was a major chemical substance (Figure 3 and Table S5). Cobalt is used to produce alloys used in the manufacture of aircraft engines (28). Alabama was ranked fourth in the production-based RSEI hazard (Figure 3), with more than 80% of the asbestos hazard being caused by industrial activities (Figure 2). The detailed RSEI database of 2017 (29) shows that U.S. military facilities in Alabama remarkably contributed to a considerable asbestos hazard of 178 toxicity-weighted billion pounds, accounting for 100% of the total asbestos hazard in the U.S.

It is important to note that the RSEI hazard does not describe potential human health risks that are comparable between the states of the U.S. The RSEI "score" estimated using the RSEI "hazard" (i.e., toxicity-weighted pound), exposed population, and estimated dose (29) describes a potential human health risk indicator. For example, a larger exposed population leads to a higher RSEI score.

[Insert Figure 2 here]

[Insert Figure 3 here]

Figure 4 depicts the spatial distributions of the RSEI score in the U.S. Texas was the largest emitter (Figure 2), accounting for 20% of the total RSEI hazard, and ranked first in the RSEI score. Louisiana was the second largest emitter and ranked fourth in the RSEI score. Pennsylvania and Illinois ranked second and third in the RSEI score, respectively (Figure 4). The sub-total of the RSEI scores in the four states of Texas, Pennsylvania, Illinois, and Louisiana accounted for 43% of the total human health risk in the U.S. Thus, the U.S. economy imposed considerable health risks on people in these four states in 2017.

Figure 5 shows the major chemical substances involved in the production-based RSEI scores (i.e., production-based health risk) in the U.S. Texas and Pennsylvania had higher potential health risks due to the emission of different major chemical substances of ethylene oxide and chromium, which together accounted for 71% and 85% of the RSEI score in Texas and Pennsylvania, respectively (Figure 5). Therefore, the state governments should identify the higher priority sectors listed in Table S2 and major chemical substances listed in Figure 5, and aid the important stakeholders under limited resource constraint.

[Insert Figure 4 here]

[Insert Figure 5 here]

4.2 Consumption-based RSEI hazard and score of the U.S.

To aid relevant stakeholders through inter-state cooperation, we further need to evaluate the consumption-based RSEI scores (i.e., health risk footprint) of a particular state (10). The footprint indicator of a state can help policy makers understand how the final demand of goods and services in that state can have potential health risks in other U.S. through supply chains.

We found that there was a large gap between the production- and consumption-based RSEI scores in the U.S. (Figures 4 and 6). Among the considered regions (the 50 states, the District of Columbia, and Puerto Rico), Texas and Pennsylvania ranked first and second in the rankings of production-based RSEI score, respectively (Figure 4). By contrast, California and New York ranked first and second in the rankings of consumption-based RSEI score (Figure 6). California and New York accounted for 9% and 7% of the total consumption-based RSEI in the U.S. (Figure 6), implying that consumers in California and New York had a significant responsibility on health risks in other states of the U.S.

When noting that mass consumption in an urban area with high population density induces a large health risk footprint, it is important to observe the per capita footprint of that specific state. Figure 7 illustrates the health risk footprint in the bar plot and the per capita health risk footprint is indicated by the x mark. The District of Columbia (Washington, D. C.) and Alabama had low health risk footprints; however, they were ranked first and second in the rankings of per capita footprint, respectively (Figure 7). In other words, final consumers in the District of

Columbia (Washington, D. C.) and Alabama had a high "personal" responsibility for the potential health risks in their own state as well as those in other states.

[Insert Figure 6 here]

[Insert Figure 7 here]

4.3 Health risk transfer in the U.S.

Consumptions in California induced a considerable potential health risk in Texas in 2017 and vice versa (Figure 6). Therefore, the net health risk transfers (i.e., difference between the consumption-based RSEI scores of the states) can quantify the environmental responsibility of a particular state through supply chains. Thicker flows in Figure 8 show higher net health risk transfers between the U.S. We found three significant risk transfers: from California to Texas, from New York to Texas, and from Florida to Texas (Figure 8). Specifically, Texas was the epicenter for chemical pollution in the U.S. supply chains in 2017. Importantly, the total of those three significant risk transfers accounted for 6% of the total in the U.S. economy. Figure 8 can help policy makers quickly identify higher priority states that indirectly contributed to regional human health risks.

Figure 9 depicts a net transfer coefficient matrix whose elements are percentages of the net health risk transfers from a particular demand state (a row sector in the matrix) to a particular emission state (a column sector in the matrix) to the total of whole net health risk transfers in the U.S. economy. In Figure 9, the net transfer coefficients are calculated by dividing the net transfers between states by the total of the net transfers. The sum of all the matrix elements in

Figure 9 coincides with unity (i.e., 100%). The column sum shows the net potential health risk in a particular state induced by the final demand of the U.S., while the row sum shows the net potential health risk in the U.S. induced by the final demand of goods and services in a particular state. In other words, a state with a higher row sum should have a greater responsibility for toxic chemical-induced health risk in the other states. In the following section, we show how to use the information in Figure 9 in policy strengthening.

[Insert Figure 8 here]

[Insert Figure 9 here]

5. Policy implications

The TSCA, administered by the U.S., authorizes the EPA to provide grants to states for the establishment and operation of programs aimed at preventing or eliminating unreasonable risks to health or the environment associated with chemical substances or mixtures (see p. 4 of (30)). This is a general grant guidance for many toxic chemical substances identified by the EPA; however, the government can provide a special grant guidance with a focus on the five major chemical substances that caused the highest potential health risk—chromium, ethylene oxide, cobalt, nickel, and asbestos.

In doing so, the above-mentioned four states of Texas, Pennsylvania, Illinois, and Louisiana showed higher potential health risks resulting from the five chemical substances that exceeded the average production-based RSEI scores of the U.S. Therefore, the federal and state governments should focus on preventing or eliminating the five major chemicals in the four states identified in this study. It will be important to determine who will pay the total prevention program costs in the specific exposed state.

In covering the total program costs, we suggest that the federal government should collect relevant taxes from states based on the previous year's net risk transfers of the potential health risk (i.e., RSEI scores) formulated in this study. When the federal government focuses on the above-mentioned four states with the highest potential health risks in 2017 (Texas, Pennsylvania, Illinois, and Louisiana), Figure 8 can help plan the collection of taxes from states based on the consumers' responsibility.

For example, Figure 9 shows that 2.8% and 3.2% of the potential health risk in Texas was attributable to consumptions in New York and California, respectively. Therefore, the prevention program costs in Texas should be covered by tax collections based on the respective responsibility shares of 2.8% by New York and 3.2% by California. Thus, we propose a policy framework for sharing total program costs to prevent or eliminate health risks associated with toxic chemical substances.

Subsequently, the state governments with higher potential health risks can receive reasonable grants from the federal government and then allocate the grants to green companies with higher production-based RSEI scores. The grantee should not only set reduction targets on major toxic chemical substances, but also publish regular reports on how to reduce and/or eliminate the toxic chemical substances, and submit them to the federal and state governments.

Finally, this combined policy framework based on production- and consumption-based accounting approaches is summarized in Figure 10.

[Insert Figure 10 here]

6. Conclusion

This study contributes to the existing chemical footprint research. A previous study developed environmentally extended input–output tables with a focus on toxic chemical substances in the U.S. economy (10); however, an environmentally extended multi-regional input–output dataset with a focus on the toxic chemical substances in the U.S. was missing. To the best of our knowledge, this is the first study attempting to develop such a multi-regional input–output (MRIO) dataset of the U.S. in 2017.

We found that specific states such as Texas and Louisiana were at considerable risk from major chemical substance emissions triggered by final demands of goods and services in mega cities such as New York and California. Figure 8 can help policy makers or stakeholders easily understand how consumption activities in a particular state were linked with potential health risks resulting from chemical substance emissions by industrial activities in a particular state through supply chains.

Stakeholders in states need financial support to prevent or eliminate toxic substances. Nevertheless, we did not find any concrete policy frameworks for targeted states with higher potential health risks. We suggest that the TSCA should be prioritized following the production-based RSEI scores of sectors in the U.S., followed by the selection of high priority sectors and states. Once the high priority states are selected by policy makers (i.e., federal government), the Figure 9 obtained in this chemical footprint approach provides a guidance on how much a specific state (e.g., New York) needs to share the prevention costs incurred to prevent or eliminate toxic chemical substances from industrial activities in the high priority states (e.g., Texas). Footprint-based inter-state financial cooperation is crucial in mitigating chemical pollutions in the U.S.

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Figures

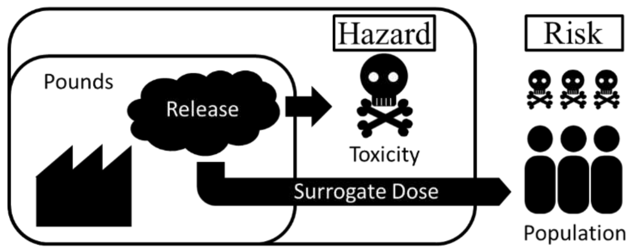

Figure 1. Relationship between the three risk-screening environmental indicators (RSEIs).

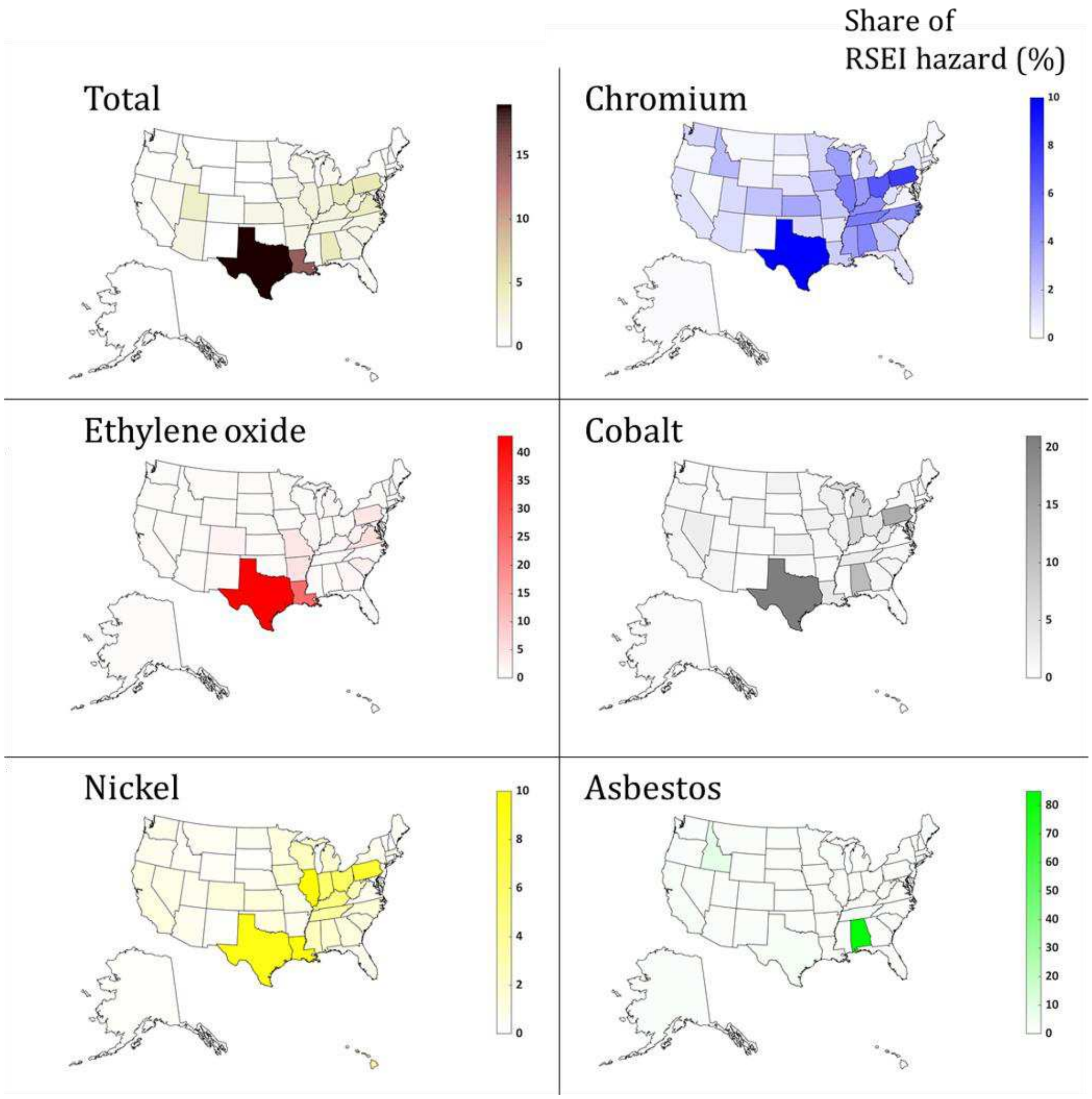

Figure 2. Spatial distribution of the production-based risk-screening environmental indicator (RSEI) hazards in 2017 in the U.S.

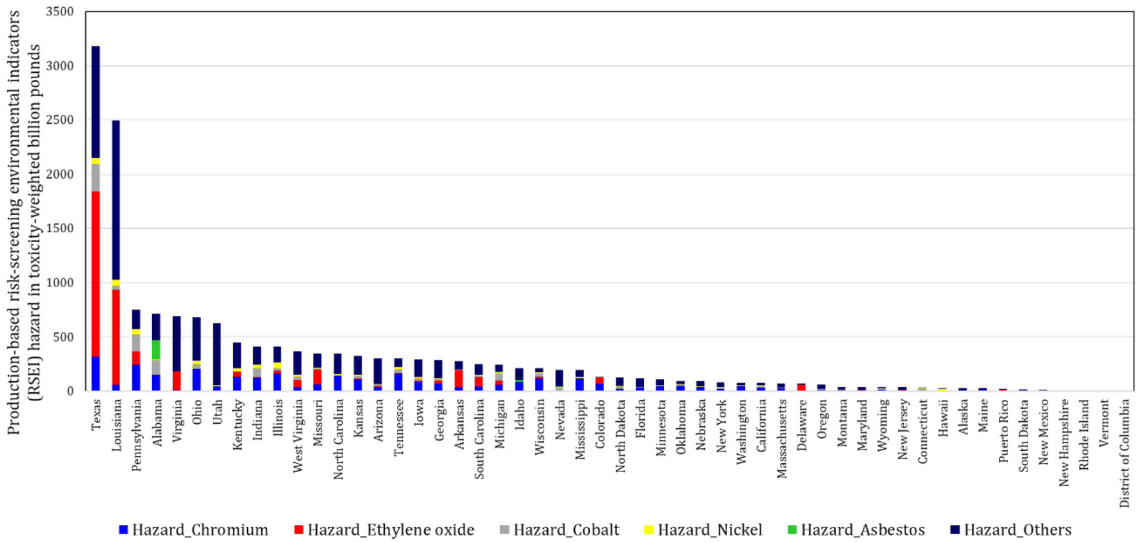

Figure 3. Major chemical substances for the production-based risk-screening environmental indicator (RSEI) hazards in 2017 in the high priority U.S.

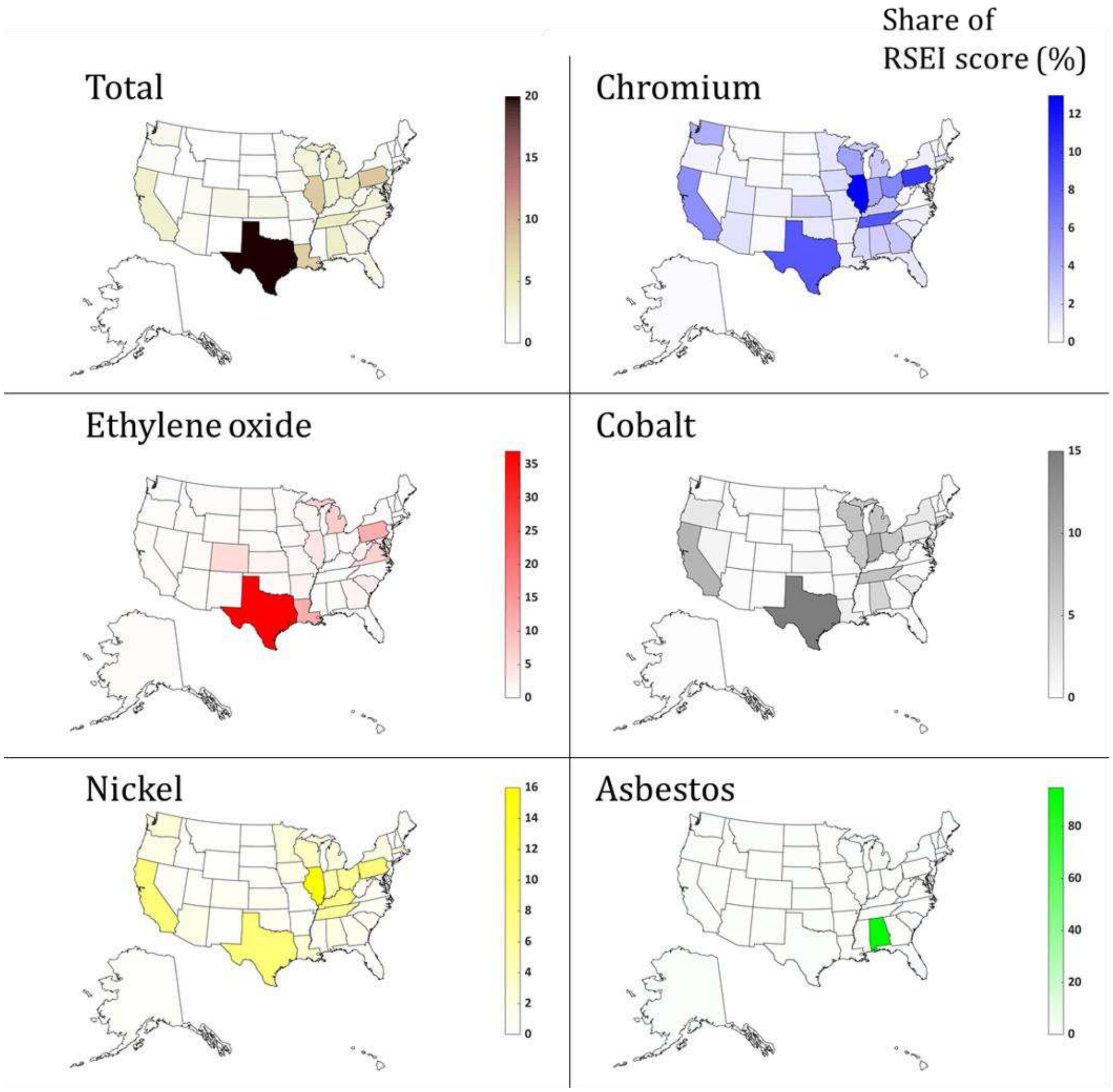

Figure 4. Spatial distribution of the production-based risk-screening environmental indicator (RSEI) scores (i.e., production-based health risk) in 2017 in the U.S.

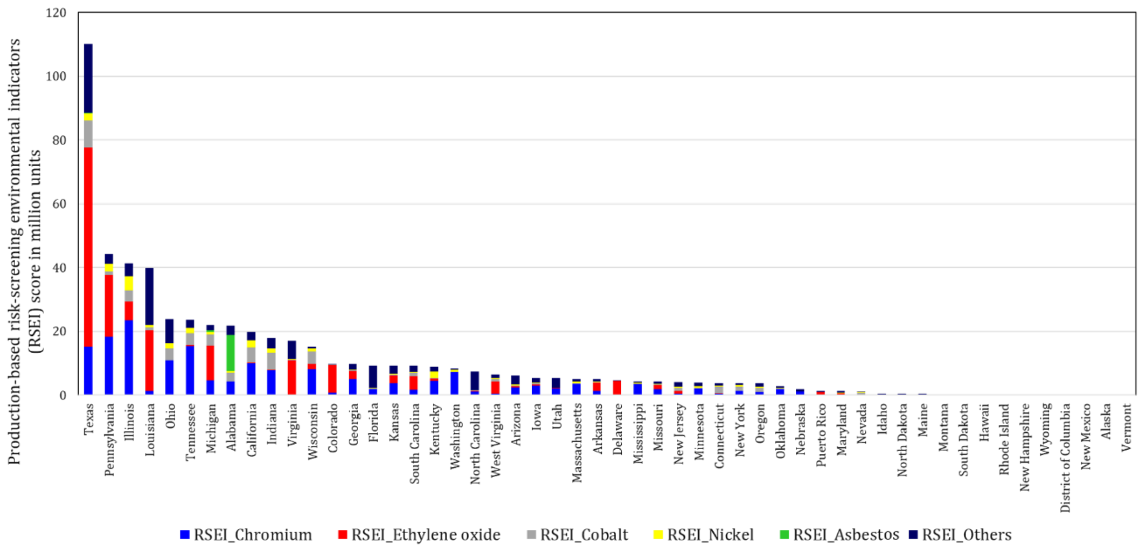

Figure 5. Major chemical substances for the production-based risk-screening environmental indicator (RSEI) scores (i.e., production-based health risk) in 2017 in the U.S.

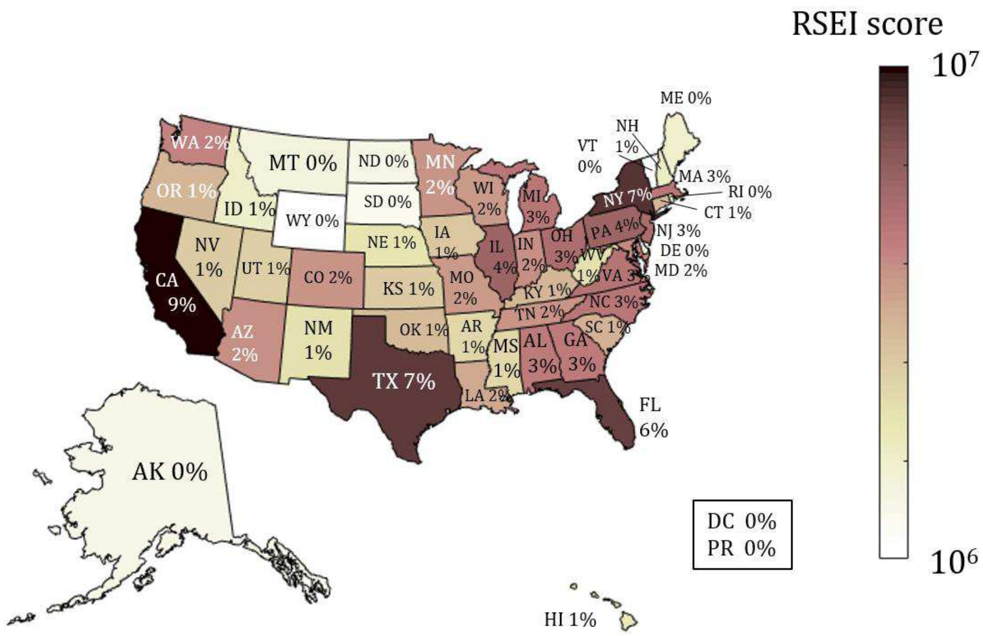

Figure 6. Spatial distribution of the consumption-based risk-screening environmental indicator (RSEI) scores (i.e., health risk footprint) in 2017 in the U.S.

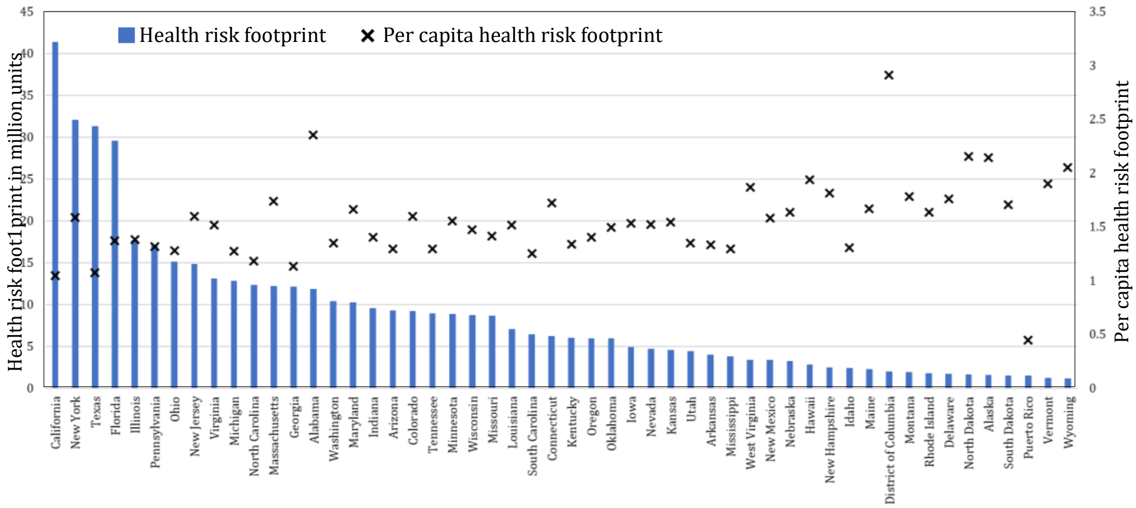

Figure 7. Consumption-based risk-screening environmental indicator (RSEI) scores (i.e., health risk footprint) in 2017 in the U.S.

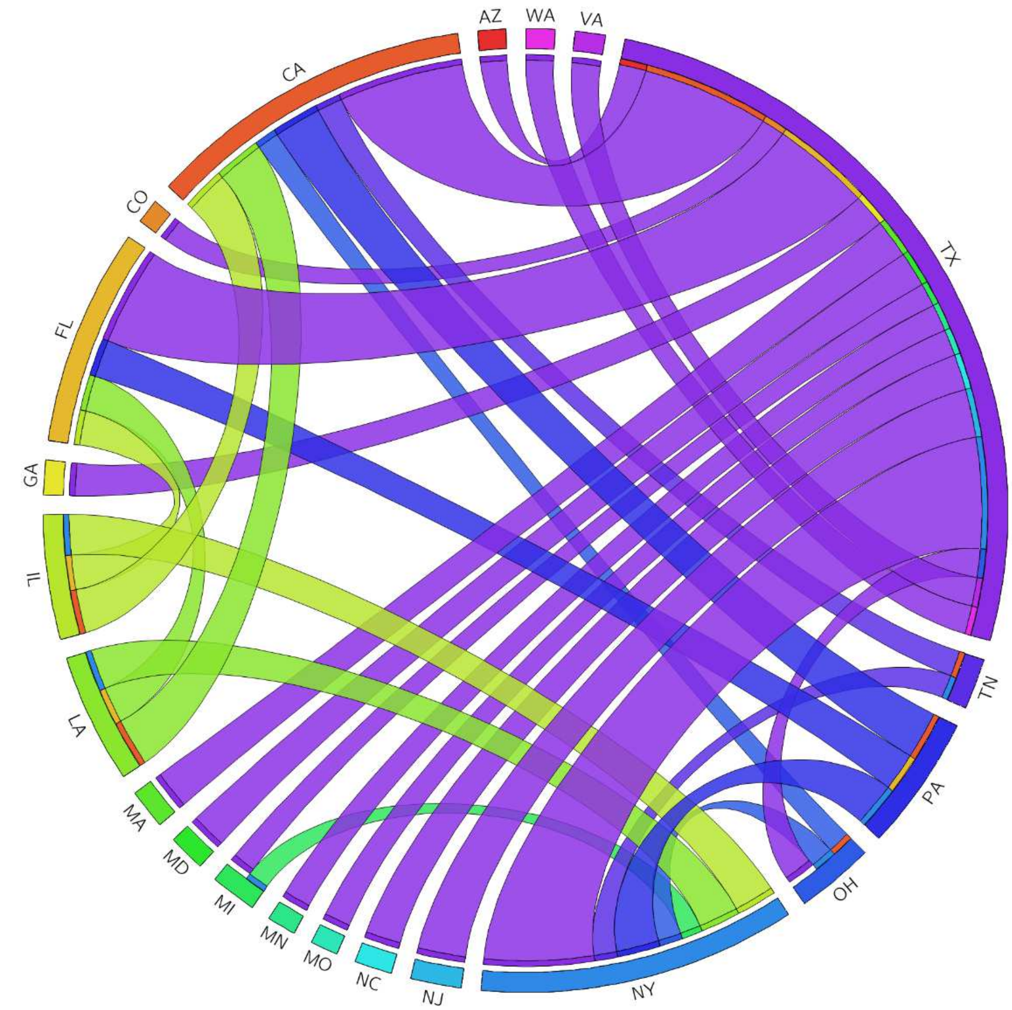

Figure 8. Net health risk transfers between the states of the U.S.in 2017.

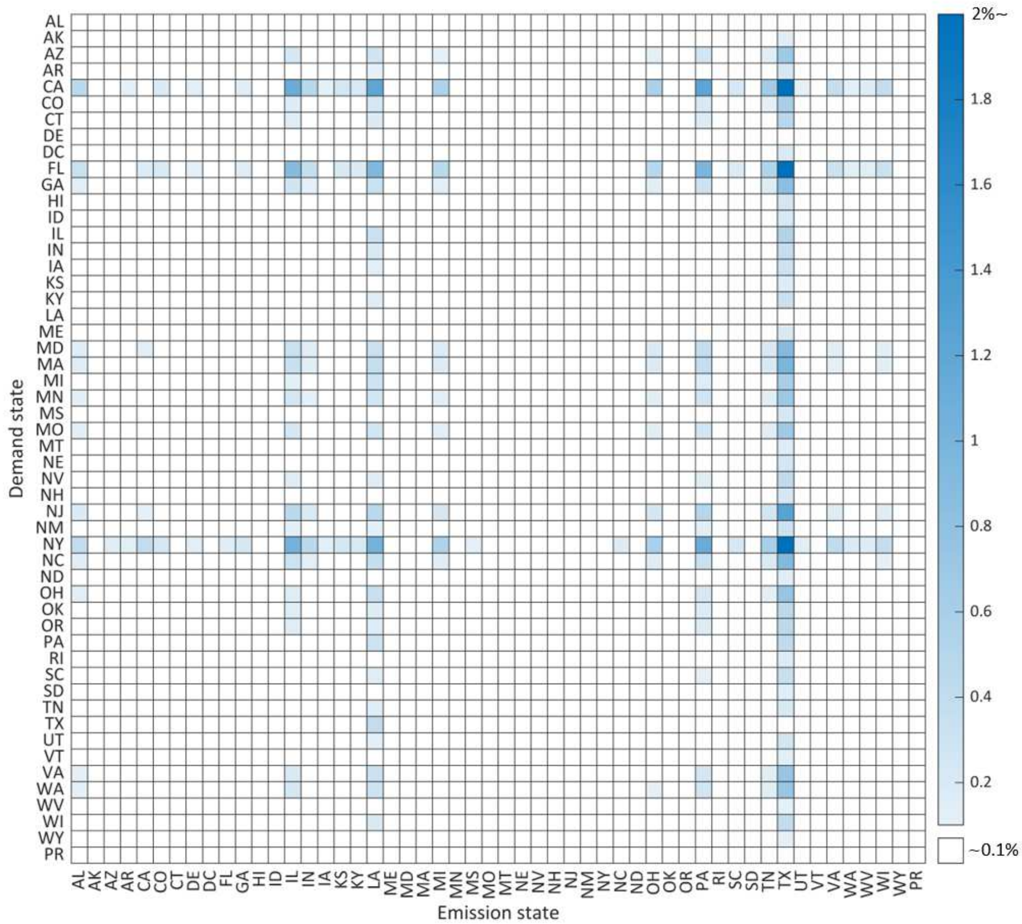

Figure 9. Net transfer coefficient matrix whose elements are percentages of the net health risk transfers from a particular demand state (a row sector in the matrix) to a particular emission state (a column sector in the matrix) to the total of whole net health risk transfers in the U.S. economy.

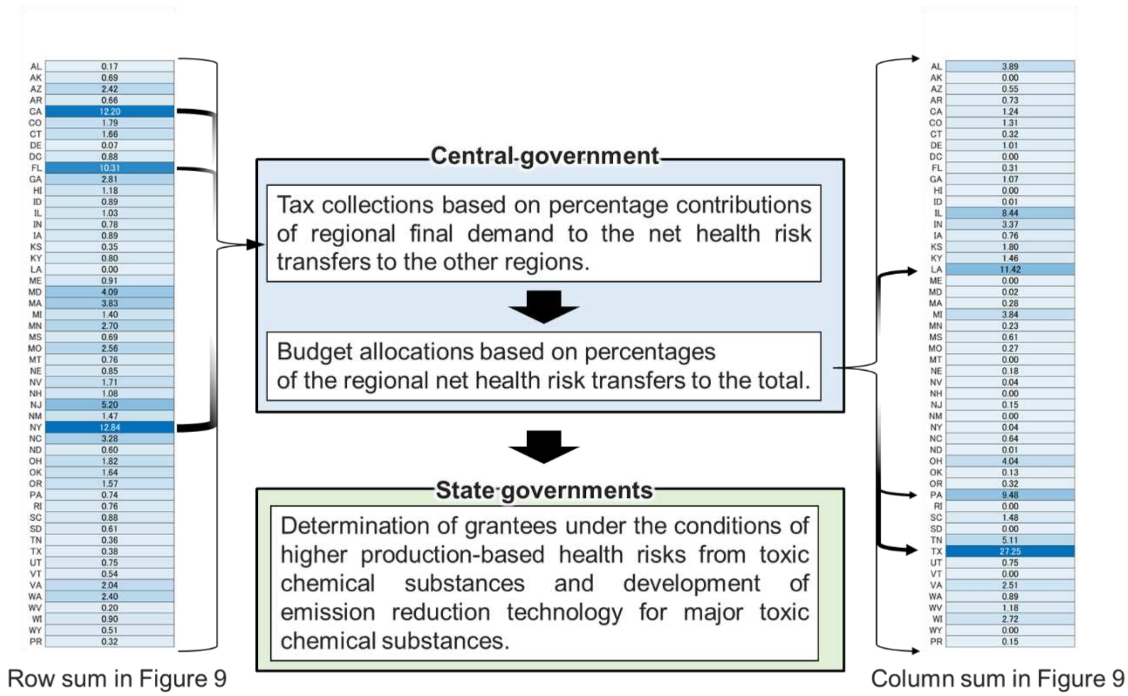

Figure 10. A combined policy framework for the mitigation of chemical pollutions based on production- and consumption-based accounting approaches.

Supplementary Files

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