We present a model that integrates the economic input-output approach of life cycle assessment with environmental fate, exposure, and risk assessment to estimate the spatial distribution of air toxic health risks due to sector-specific economic activity in the U.S. The model is used to relate the economic activity and exposure potential (population density and meteorology) associated with point source emissions of the heavy metal and carcinogen, hexavalent chromium, or Cr(VI), on a county basis. Total direct annual airborne emissions of Cr(VI) in the U.S. were 44 tonnes in 2002, with 97% from facilities in four major sectors: power generation, wood, plastics, and chemicals, metals, and scientific services. These include 6 tonnes of Cr(VI) emitted in the supply chains of these sectors. A highly variable national distribution of lifetime cancer risk is predicted, with a population-weighted mean of $2.7 \times 10^{-7}$, but with hot-spot counties with lifetime risks as high as $6 \times 10^{-4}$. Furthermore, high exposures and risks tend to occur in more highly populated counties. In particular, the population of Los Angeles County is exposed to the highest level of risk in the country and almost three-quarters of the total predicted cancer incidence due to inhalation of airborne Cr(VI) emissions.

Introduction

In recent years significant efforts have been made to link insights from the fields of life cycle assessment and environmental health risk assessment (1, 2). Life cycle assessment (LCA) has traditionally been used to evaluate the environmental impacts of industrial products from production to consumption, including air pollutant emissions. Separately, health risk assessment has been used to evaluate the exposure and health risk associated with emissions. In particular, human health exposure and risk estimates are often a critical component of life cycle impact assessment (LCIA) (3–6). However, few studies have assessed the impact of economic inputs and environmental discharges on human health and the environment in a geographically disaggregated manner (9). Such studies are important since they allow control strategies to focus in areas where they are needed most, and many decisions by local or regional policy makers would be better informed by data and model results that are local or regional in context.

We develop an economic-spatial risk model for the U.S. to predict how changes in economic activity for various sectors will impact county level health risks due to point source emissions of air toxics. We estimate the relative contributions of industrial point source emissions of air pollutants from different sectors and model the fate, human exposure, and associated health risks of these emissions. We gauge the effect of supply chain economic activity on total emissions by using economic input-output life cycle assessment (EIO-LCA) to estimate emissions. This study advances existing environmental impact models by disaggregating health risks by economic sector and by source and receptor locations, to allow for the creation of better-targeted air quality and economic policies.

In the LCA field, material flow analysis (MFA) and EIO-LCA have been used to estimate the impacts of alternative industrial products and processes. MFA has been used to track the movement of materials, such as heavy metals, through industrial processes, use, disposal, and release to the environment, but it does not typically model the fate and associated risk of these releases (10, 11). Johnson et al. (2006) assessed material flows of chromium at the national and global aggregate level including environmental releases but did not model their fate and subsequent exposure and risk. EIO-LCA has been used to estimate changes in emissions due to changes in economic demand, in most cases using national aggregate data, and does not translate emissions into localized health risk (12). Hawkins et al. (2006 and 2007) and Higgins et al. (2007) combine a national input-output model with a model based on physical flows of cadmium and lead to forecast the effect of changes in economic activity, but do not estimate health risks.

In the health risk assessment field, the U.S. EPA has done significant research into modeling and assessing the fate, transport, and associated risk of toxic air pollutants at a locally disaggregated level. One of these assessments is the National-Scale Air Toxics Assessment (NATA) produced in 1996, 1999, and 2002 (released in June 2009) (13–15). The EPA conducts the NATA every three years to produce nationwide estimates of toxic air pollutant emissions from various sources and resulting ambient concentrations, human exposures, and cancer and noncancer risks for use as a screening tool for prioritization of air toxics and locations with the highest risks. A limitation of the NATA is that it does not include disaggregated exposure and health risks by economic sector or by emissions source locations. However, the most recent Human Exposure Model (HEM III) produced by EPA, which is used by the Agency, local agencies, and industry to estimate health risks that may result from air pollutant emissions from an industrial facility or a cluster of facilities located near one another, does allow for modeling of exposure and health risks of pollutants by economic sector (16, 17). HEM III incorporates the atmospheric dispersion model, AERMOD, to produce ambient air toxics concentrations and an exposure model, HAPEM, to provide estimates of population exposure.
to air toxics from outdoor emission sources by accounting for population time-activity budgets, such as the time spent outside, indoors, and commuting to and from work. A limitation of HEM III is that it is typically not intended for nationwide assessments (17).

A recent development among LCA and health risk assessment practitioners has been to use the concept of intake fraction, or the ratio of the mass of pollutant intake to the mass of pollutant emitted, to express and interpret emissions source and exposure relationships in place of the dispersion/mass of pollutant emitted, to express and interpret emissions fraction, or the ratio of the mass of pollutant intake to the assessment practitioners has been to use the concept of intake nationwide assessments (outside, indoors, and commuting to and from work). A recent initiative, typically measured as disability adjusted life-years (DALYs) (21).

Our economic-spatial risk model uses AERMOD to estimate ambient concentrations and a unit risk factor to estimate exposure and resulting cancer risk, which is used as the end point for human health characterization because we are trying to capture spatial variation in both sources and receptors and also for its regulatory significance (13). In our case, from an LCA perspective, it would follow that the average lifetime risk of cancer increases incrementally by economic activity ($) in a sector. As such, our model can be generally applied to air toxics or criteria pollutants using appropriate cancer and noncancer end points.

Thus, our model builds on MFA, EIO-LCA, the NATA and HEMIII to support a nationwide assessment of the economic sources and distribution of health impacts due to air pollutants in the U.S. There are advantages to assessments and models that locally disaggregate environmental impacts like NATA and HEM instead of using national averages like MFA and EIO-LCA. For example, by estimating localized disaggregated risks across the U.S. our model can be used to avoid policy responses that lower overall average risk but create isolated areas of high risks. Likewise, there are advantages to models like MFA and EIO-LCA that disaggregate environmental impacts by economic sector and direct vs supply chain sources, including the ability to evaluate the impacts of a product over its entire life cycle. Additionally, there are advantages to a model that disaggregates environmental impacts by emissions source locations, such as the ability to regulate production in the areas that contribute the most to health risks. We discuss uncertainties in the model we have developed (due to limited ground truth data and other factors) in the Results section.

Here we use the model to explore spatial variation in health risk and how it relates to variations in economic activity and exposure potential around associated toxic air emissions of hexavalent chromium, or Cr(VI). Cr(VI) is a good candidate for this analysis because it is a prevalent industrial heavy metal and a human carcinogen in air causing lung cancer (22, 23). Additionally, Cr(VI) emissions are not ubiquitous but instead tend to be concentrated at a small number of facilities across the country, and they also have a relatively short transport range, which results in most observed levels being locally generated, so Cr(VI) as a hot-spot pollutant should tend to show significant spatial resolution in both emissions and impacts. An earlier assessment in 1999 (results for Cr(VI) for the most recent NATA in 2002 were not available) showed that Cr(VI) emissions from facility, area, and mobile sources contributed 4% to an EPA-estimated average lifetime cancer risk of $4.2 \times 10^{-5}$ from all air toxics in the U.S. or approximately seven annual cancer cases (See the Supporting Information for a breakdown of the predicted contribution from all toxic air pollutants.) (24). The current assessment for 2002 is expected to produce a similarly small number; however, targeted reductions of Cr(VI) emissions may still be warranted if hot-spot communities are identified. Additionally, because Cr(VI) emissions are produced primarily as a result of industrial activity (22, 24), there is an opportunity to improve human health by reducing emissions due to direct economic and supply chain activity. Reducing emissions of Cr(VI) will also likely lead to reductions in the risks due to coemitted pollutants, since these are often affected by the same control measures.

**Method and Data Sources**

Our economic-spatial risk model calculates the change in cancer risk in each county in the U.S. that would result from a change in output for an economic sector or sectors (Figure 1). First an economic component allows a change in demand to be input into an economic sector. The change in demand in a sector is equal to the change in producer value (in $) of a product or fraction of the total industry output based on the most recent data for economic sectors from the U.S. Economic Census for the year 2002 (25). The change in demand is translated into a proportional change in output and subsequently of emissions (emissions per unit demand) and risk resulting from facilities in that sector. This assumes a linear relationship between outputs, emissions, ambient concentrations, exposures, and risks in a sector.
To model annual average ambient concentrations resulting from point sources, several parameters are input into EPA’s AERMOD atmospheric dispersion model (26) (See the Supporting Information for a full description of the dispersion model.). These include annual emissions per unit demand and pollutant parameters from specific stacks at facility locations based on the most recent data (2002) from the EPA National Emissions Inventory (27). EPA-processed hourly weather station data from the National Weather Service for the year 1991 including default specified values for surface characteristics (28); and pollutant specifications from the literature, which are discussed in more detail below. Each source is assigned to the nearest weather station. Time-averaging of resulting hourly ambient concentrations is handled internally by AERMOD. Annual average ambient air concentrations are then estimated at affected county centroids using interpolation. Next for each county the model then estimates human exposure, lifetime individual risk, and cancer incidence resulting from the simulated ambient air concentrations using EPA unit risk factors based on default exposure factors and cancer slope factors (29, 30) and county population data from the U.S. Census Bureau for the year 2002 (31). The resulting risk and cancer cases are disaggregated by NAICS (North American Industry Classification System) sector codes and the emissions source counties and risk receptor counties.

We also estimate the degree to which changes in economic activity lead to changes in supply chain activity and corresponding nationwide facility emissions using EIO-LCA (32). We multiply supply chain economic activity for each of the major Cr(VI)-emitting sectors (the sum of supply chain activity due to related Cr(VI)-emitting subsectors) by an emissions factor based on the corresponding sector’s facility emissions and total annual economic output in that sector. However, we cannot model supply chain impacts with any spatial resolution because the data are at the industry level and, thus, do not show specific product locations.

For example, to estimate the effect of raising national electrical output by 10% (corresponding to $30 billion demand into NAICS 2211), the model 1) increases economic output in this sector by 10%; 2) increases emissions released from each of the facilities in this sector by 10% (and increases corresponding emissions produced due to purchases by this sector and its chain of suppliers from other sectors); 3) estimates the resulting ambient concentrations due to point source emissions based on AERMOD; 4) finds the ambient concentration at the centroid of affected counties using interpolation; 5) calculates human exposure and cancer risk due to the ambient concentration in each county keeping track of the contributing economic sectors and emissions source locations; and 6) displays the impacts of emissions in terms of the distribution of risk of cancer or number of cancer cases among populations, for example on a map showing risk by county or with a cumulative distribution function (cdf) showing population-weighted risk by county.

Modeling Cr(VI) Point Source and Supply Chain Emissions. Cr(VI) is one of three valence states of the heavy metal, chromium. The others are chromium metal, Cr(0), and trivalent chromium, Cr(III), an essential nutrient. Cr(VI), however, is a human carcinogen in air causing lung cancer (22, 23). Cr(VI) air emissions are produced primarily as a result of industrial activity (22, 24). Cr(VI) air emissions can be particle-bound or dissolved in droplets (due to its extremely high boiling point, chromium is rarely found in the gas phase). Cr(VI) stack particles from heating processes such as smelting, combustion systems and electroplating are found to have diameters less than 10 µm with most particles in the fine mass range (0 to 2.5 µm) (22). Fine particulate matter containing Cr(VI) can travel distances over 100 km from their sources. Its transport range is limited due to major sinks, such as dry and wet deposition, and its reduction to Cr(III) in the atmosphere according to a half-life ranging from 16 h to 5 days due to the presence of reducing agents such as vanadium and acidity (22). However, Cr(VI) can be introduced or reintroduced into the atmosphere by wind resuspension.

Pollutant specifications input into AERMOD for Cr(VI) include deposition and half-life. Both wet and dry deposition are accounted for assuming 100% of airborne particles are fine mass (less than 2.5 µm diameter) and have an average diameter of 2 µm. This assumption is based on the literature for Cr(VI) particle emissions (22) as well as characteristics of lead particle emissions from stacks, because stack particles of different pollutant types are generally similar (33). The model can take into account the atmospheric half-life of the pollutant to address chemical transformations other than deposition. The upper bound estimate of half-life for reduction from Cr(VI) to Cr(III) of 5 days is used. Exposure and cancer risk is modeled using an inhalation unit risk factor for Cr(VI) of 1.2 × 10^{-2} (µg/m^{3})^{-1}, which is based on an inhalation cancer slope factor of 41 mg/kg-day, assuming exposure 24 h per day over a 70-year lifetime (34). For this analysis of Cr(VI) we focused on four major economic sectors that produced the bulk (97%) of emissions in 2002: electric power generation (70%), metal manufacturing (14%), and wood product manufacturing, plastics and rubber manufacturing, chemical manufacturing, and printing (12%), and professional, scientific, and technical services (1%).

NEI point source emissions data for Cr(VI) for the U.S. for 2002 are from nearly 9200 stacks at 970 facilities. Of these emissions sources approximately 1500 are electric power utility stacks that emit a total of 30 t (tonnes) of Cr(VI), 1250 are metal manufacturing stacks that emit a total of 6 tonnes of Cr(VI), about 2750 are wood and other manufacturing stacks that emit a total of 5 tonnes of Cr(VI), about 350 are utility stacks that emit a total of 30 t (tonnes) of Cr(VI), and about 3300 are stacks from 15 other sectors that emit a total of 1.5 tonnes of Cr(VI) (See Table S1 in the Supporting Information for a breakdown of all Cr(VI) data by sector.) (27) (Figure 2). Figure 3 shows facility locations and their relative emissions overlaid on a map of population by county.

Electric power utilities emit Cr(VI) during combustion of chromium-containing fossil fuels, such as coal and oil (22). In this situation the chromium is not originally hexavalent, but the high temperatures involved in the process result in oxidation that converts the chromium to its Cr(VI) state. Metals manufacturing plants emit Cr(VI) when metals, including chromium, are combined and heated, such as in stainless steel, or when Cr(VI)-containing acid is electroplated onto metal parts in a bath to provide a decorative or protective...
coating, such as in chrome plating. The scientific services sector emits Cr(VI) during chrome plating for research and development of defense vehicles, landing gear, etc. NEI point source emissions of Cr(VI) from chrome plating are typically measured directly (35). Wood, plastics and rubber, and chemical manufacturing emit Cr(VI) during the processes of adding Cr(VI)-containing compounds to wood to provide pest resistance, to dyes, paints, inks, and plastics to provide pigmentation, and to paints and primers to provide corrosion resistance.

For the four major Cr(VI)-emitting sectors, Cr(VI) emissions may also be associated with the other sectors in their upstream supply chain production. For example, to make stainless steel, the metal manufacturing sector purchases energy from power utilities and materials, such as metal and wood, from manufacturers to create the final product, and in the process these different sources generate waste and Cr(VI) emissions.

Results

Distribution of Chromium Risks by County and Economic Sector. We predict a highly variable national distribution of lifetime individual cancer risk (LIR) due to emitted ambient Cr(VI), with a population-weighted mean of $2.7 \times 10^{-7}$, but with hot-spot counties with lifetime risks as high as $6 \times 10^{-6}$. Figure 5 shows the combined estimated LIR on a map for the sectors evaluated (See the Supporting Information for maps of estimated lifetime individual risk by sector.). Cumulative distribution functions of risk by county (ranked and population-weighted, respectively) are shown in Figure 4. These indicate that 37% of the counties and 20% of the population have minimal LIR (less than $10^{-11}$), with high exposures and risks tending to occur in more highly populated areas. The top 10% or 30 million people face an average risk of $8 \times 10^{-7}$, and the top 5% or 15 million people face an average risk of $2 \times 10^{-6}$.

As with many single-compound air toxics risk estimates, the total predicted U.S. annual cancer incidence associated with this lifetime average risk is small, 1.1 (expected cases over a lifetime due to annual exposure), just slightly higher than the NATA estimate for 1999 of about 0.7 (See the Supporting Information.). However, this number will be larger when area and mobile sources are added, and it will add to other risk factors in hot-spot communities. Table S4 in the Supporting Information shows the top ten receptor counties, or hot-spot communities, with regard to cancer incidence, the associated risk exposure and population, and the economic sectors and emissions source counties contributing to them. The scientific services and the metals manufacturing sectors were responsible for the bulk of incidence (0.8 and 0.2 cases, respectively) (Figure 6). Three of the counties were predominantly responsible for their own risk, while seven of the counties had computed risks predominantly associated with emissions from one or more neighboring counties. Six of the counties had predicted risk due to only one sector, while the others had significant risk contributions from two or more sectors.

Los Angeles County was exposed to and was also responsible for the highest risk level and almost three-quarters of cancer incidence due to Cr(VI). This can be attributed largely (99%) to emissions from its scientific services facilities. Responsible facilities include various aeronautical, defense, and space vehicle contractors including Northrop Grumman, Lockheed, Vought Aircraft, Boeing,
McDonnell Douglas, and their associated suppliers who use Cr(VI) to plate various airplane, missile, or rocket parts for corrosion resistance. Other hot-spot counties include Middlesex County, Massachusetts, which is impacted by another defense contractor, Lawrence Ripak, located about 350 km away in Suffolk County, New York; Calhoun, IL, which is impacted by metals manufacturing and electric power utilities from other counties; and Denton County, Texas, which is impacted by metal manufacturing and other facilities in neighboring Dallas County, Texas.

The relative risk of emissions from different economic sectors can be gauged using a risk-emissions ratio, or population-weighted average risk to kilograms of Cr(VI) emissions (See Table S3 in the Supporting Information.). The risk-emissions ratio for power generation and wood and chemical manufacturing sectors was lower than the overall average, for metals manufacturing it was the same as the overall average, and for scientific services it was 49 times higher than the overall average, another indicator that this sector’s emissions occur in locations where they do the most harm. Cr(VI) emissions in the supply chains from each of these sectors were computed, totaling 6 tonnes, or approximately 14% of facility emissions (See the Supporting Information.). However, since these emissions cannot be localized, their risk implications are not pursued further.

Discussion of Uncertainties. There are uncertainties and limitations concerning model data and methods, including those in the NEI Cr(VI) emissions, the atmospheric transport model (AERMOD) assumptions (such as linearity), the processed meteorological data, pollutant specifications, using the county centroid to represent risk across a county, exposure assumptions, including the unit risk factor, and Census Bureau economic output data and EIO-LCA modeling. These concerns are addressed in the Supporting Information in a discussion for the scientific services sector in Los Angeles County, since it emerges as a major driver of risk. We also compare model results with external data sets. Our findings are summarized as follows:

- Emissions inventories are likely to underestimate total emissions due to omitted sources (36); however, emissions estimates for included sources can be either high or low (27).
- For the scientific services sector in Los Angeles County, where chromium emissions result primarily from plating applications, NEI point source emissions estimates of Cr(VI) are typically measured directly by facilities through stack tests, according to the local pollution control agency, California Air Resources Board (CARB) (35, 37).
- The assumption that emissions respond directly to economic sector output most likely overestimates the elasticity of emissions, due to capacity and regulatory constraints on source facilities.
- The AERMOD atmospheric dispersion model is applied with a number of simplifications, though overall errors are likely to be only moderate given the annual averaging period employed (See the Supporting Information.).
- Significant errors can occur in selected counties as a result of the use of county vs average of census track centroids for exposure calculations (in Los Angeles County exposures were underestimated by nearly a factor of 10 using the coarser vs the finer spatial resolution) (See the Supporting Information.).
- Simulated annual average concentrations for chromium compounds compare favorably to reported values in the 2002 NATa (results for Cr(VI) were not available) (See the Supporting Information.); the NATa tends to underestimate measured values by a factor of 2–3 (38).
- In many areas ambient concentrations of Cr(VI) will likely be dominated by other factors, such as mobile sources.

FIGURE 5. Predicted lifetime individual cancer risk of Cr(VI) due to point source emissions from current production of NAICS 2211 power generation, NAICS 32 wood product manufacturing, chemical manufacturing, plastics and rubber manufacturing, and printing, NAICS 33 combined metal manufacturing sectors, and NAICS 54 professional, scientific, and technical services.

McDonnell Douglas, and their associated suppliers who use Cr(VI) to plate various airplane, missile, or rocket parts for corrosion resistance. Other hot-spot counties include Middlesex County, Massachusetts, which is impacted by another defense contractor, Lawrence Ripak, located about 350 km away in Suffolk County, New York; Calhoun, IL, which is impacted by metals manufacturing and electric power utilities from other counties; and Denton County, Texas, which is impacted by metal manufacturing and other facilities in neighboring Dallas County, Texas.

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- The assumption that emissions respond directly to economic sector output most likely overestimates the elasticity of emissions, due to capacity and regulatory constraints on source facilities.
- The AERMOD atmospheric dispersion model is applied with a number of simplifications, though overall errors are likely to be only moderate given the annual averaging period employed (See the Supporting Information.).
- Significant errors can occur in selected counties as a result of the use of county vs average of census track centroids for exposure calculations (in Los Angeles County exposures were underestimated by nearly a factor of 10 using the coarser vs the finer spatial resolution) (See the Supporting Information.).
- Simulated annual average concentrations for chromium compounds compare favorably to reported values in the 2002 NATa (results for Cr(VI) were not available) (See the Supporting Information.); the NATa tends to underestimate measured values by a factor of 2–3 (38).
- In many areas ambient concentrations of Cr(VI) will likely be dominated by other factors, such as mobile sources.

FIGURE 6. Breakdown of cancer incidence by economic sector associated with a lifetime average risk of $2.7 \times 10^{-7}$ due to Cr(VI) point source air emissions in 2002.
or highways and soil and dust resuspension from naturally occurring sources, or from historic chromium emissions deposited to the land surface, roadways, and buildings (total exposure and risk are thus underestimated, recognizing that our estimates are limited to the exposures and risks associated with current emissions to the air) (36).

- Moderate errors in exposure estimates occur due to the use of ambient (vs both outdoor and indoor) concentrations and due to the assumption that individuals spend their entire life in a single county (proper consideration of the latter would lessen the variance of the national population distribution of exposure and risk) (39).
- The cancer unit risk factor Cr(VI) is derived from conservative assumptions based on an upper confidence limit (23).

While we believe that errors associated with these uncertainties could result in a net shift in the absolute risk associated with current ambient emissions of Cr(VI) either upward or downward, most apply in a similar manner across all locations. As such, the relative magnitudes of the Cr(VI) risks predicted for different counties (i.e., those shown in Figure 4) are likely more robust. Furthermore, we are not aware of any estimates at this time that are more accurate or precise.

Discussion

The results of this analysis suggest that the use of economic activity as an input into fate and transport models and the level of spatial variation in emissions sources and impacts produced offer important lessons for LCA and health risk comparative assessments. First, inhalation exposure and cancer risk are not proportional to emissions from different economic sectors due to differing plant locations (e.g., relative to population and populations), characteristics (e.g., stack heights), and meteorology (e.g., wind speed and direction). In 2002, the scientific services sector produced a fifth of the estimated point source emissions of Cr(VI) in Los Angeles County but were responsible for over ninety percent of the predicted cancer risk there due to the use of lower stacks (averaged 7 m tall compared to 35 m for other stacks) and meteorology that concentrates exposure in the metropolitan area. Other studies have found that various factors not considered here also tend to increase exposure to Cr(VI) emissions in the Los Angeles area (39). Additionally, the scientific services sector did not produce any emissions in Middlesex County, Massachusetts, but due to meteorology that carries pollution northeast from Suffolk, New York to the populated area, the County is predicted to be a hot-spot location for Cr(VI) exposure.

Second, location relative to large population centers is clearly important. In 2002, electric power generation produced 70% of U.S. point source emissions of Cr(VI) but was responsible for only 5% of predicted cancer incidence due to the use of higher stacks, which disperses particles further, and siting generally far away from population areas; whereas the scientific services sector produces only 1% of point source emissions of Cr(VI) but is estimated to be responsible for 75% of cancer incidence due to the use of lower stacks and siting in higher population areas. Consideration of these lessons in LCA and comparative health risk assessments can allow for better targeted reductions of emissions in areas that are hot-spots for exposure and risk.

Future work includes the following: 1) investigating the contribution to air pollutant exposure from other heavy metals (e.g., mercury, lead, and PCBs) and due to other exposure pathways (e.g., ingestion) and considering how they act in combination for use in evaluating multipollutant trade-offs and policy decisions; 2) implementing the model as a Web site for use by consumers, companies and local governments; and 3) disaggregating supply chain emissions by locality to account for spatial variation in risk due to impacts over the full life cycle of a toxic material.

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Supporting Information Available

Additional information on 1) the parameters used in model calculations; 2) the emissions data used in the analysis; 3) the economic sectors and source counties contributing to the top 10 receptor counties by predicted cancer risk; 4) maps of risk by sector; 5) supply chain emissions; 6) the full dispersion, exposure and risk models; and 7) the full discussion of uncertainties. This material is available free of charge via the Internet at http://pubs.acs.org.

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