Multiregional accounting of corporate carbon emissions

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Supplementary Information:
Figure S1

Corporations routinely use environmentally-extended input-output models to estimate and report greenhouse gas emissions upstream in their supply chain. However, the most widely used of such models assume that the structure of supply chains and the emissions intensity of industries match those of a single region—usually the U.S. or the U.K. Here, we use a high-resolution multiregional input-output model to demonstrate the scale and pattern of emissions that may be missed when using these single-region models. We find that the upstream emissions of all the companies who report to CDP are in the aggregate 2.0 GtCO_2e greater when estimated by a multiregional model instead of a U.S.-based single-region model, with especially substantial differences related to manufacturing sectors of moderate emissions intensity (i.e., 0.4-0.8 kgCO_2e/\$). Although the magnitude of emissions embodied in international trade is well-recognized in the context of national inventories, our results underscore the importance of international differences in emissions for corporate carbon accounting. High-resolution, multiregional models can both improve the accuracy of corporate emissions inventories and help companies to prioritize both primary data collection and emissions reduction efforts. ***[180 words]***

Corporations began voluntarily estimating greenhouse gas (GHG) emissions related to their operations and business in the 1990s[1], supported since 2001 by the GHG Protocol Corporate Standard (a joint effort of the World Resources Institute and the World Business Council for Sustainable Development)[2]. But interest in corporate-level GHG accounting has surged in recent years, as companies increasingly prioritized sustainability and new regulations require emissions disclosures[3-5]. At the same time, companies are also increasingly making commitments to drastically reduce GHG emissions related to their business in support of international climate targets[6,7].

Corporate-level emissions inventories, or "footprints", commonly separate emissions related to a company's own activities (scope 1), emissions related to electricity or heat purchased by the company (scope 2), and emissions upstream or downstream in the value chain of the company's products or services (scope 3)[2]. Whereas companies typically have good records of their own GHG-emitting activities and purchases of electricity (scopes 1 and 2), they initially lack detailed data about the emissions related to goods and services they purchase (scope 3.1) —which in many cases dominate the total corporate footprint. Although such lack of data may contribute to companies underreporting their scope 3 emissions[7-11], it is also the main reason that companies routinely estimate their scope 3.1 emissions using secondary data such as the average emissions per unit of monetary value of products or services produced by the relevant industry sector (i.e. a sector-specific emissions factor or emissions intensity)[12]. Although primary data specific to companies' supply chains are preferable when and where it can be obtained[2,13], such industry average intensities are often instrumental to companies prioritizing subsequent data-gathering and decarbonization efforts.

However, the fidelity of such sector-specific emissions factors depends on the data and methods on which they are based, including whether and how finely industry sectors and source regions are differentiated[14]. Of the 624 companies that specified the source of their scope 3.1 emissions in corporate carbon footprints disclosed to CDP in 2023[15], 75% obtained such sector-specific emissions factors from a single-region environmentally-extended input-output (EEIO) model such as the USEEIO modeled developed by the Environmental Protection Agency (EPA). The USEEIO model is based on U.S. economic and GHG emissions data, and the emissions factors produced reflect the activities and interactions of 411 different industry sectors. Although the USEEIO model's sectoral resolution (411 sectors) is quite high relative to other EEIO models in common use by governments and academics, it does not distinguish products and services produced in the U.S. from those produced in other countries or regions of the world. That is, USEEIO models business activities in the U.S. as if the U.S. were a closed economy, with no imports or exports (known as the "domestic technology assumption"). Yet it has long been recognized that the emissions intensity of aggregated imports to the U.S., Japan, and European countries is substantially higher than that of goods and services produced domestically[16-18], and that national and city-level inventories thus need to account for the effects of international trade[19,20]. Here, we demonstrate and quantify the large effects of multiregional resolution on individual companies' emissions inventories, and further explore the implications for those companies' reduction priorities and exposure to new and contemplated carbon border adjustment mechanisms, as well as climate mitigation efforts more broadly.

Details of our analytic approach are included in the *Methods*. In summary, we use multiregional and single-region versions of the Comprehensive Environmental Data Archive (CEDA) EEIO model[21], which was first published in year 2000 and has been regularly updated since, to evaluate differences in sector-specific emissions factors, and then assess the aggregate effect on both the emissions inventories and reduction priorities of various types of companies. Based on publicly available input-output tables and macroeconomic statistics, the CEDA model we use here maintains similar sectoral resolution to the USEEIO model (400 sectors), but adds multiregional resolution of 65 countries and a "rest of world" region (n.b. a condensed version of the full 148 country model). The emissions intensities estimated by the multiregional model are much more consistent with published country- and industry-specific values than a single-region (U.S.) model (Supplementary Fig. 1).

Among the 10 industries that most commonly disclose their emissions to the CDP[15], we find substantial differences in average upstream emissions related to goods and services they purchase (i.e. scope 3.1) between the single-region (U.S.) and multiregional models, with multiregional inventories consistently larger (Fig. 1). In each case, the observed differences represent the scale by which a single-region model based on the U.S. economy may underestimate companies' scope 3.1 emissions. The largest differences are in manufacturing of structural products (+71.3%), construction machinery (+69.7%), fabricated metal (+50.6%), and electronic components (+39.3%), with more modest differences in chemical product and plastic manufacturing (+2.2% and 1.2%, respectively), business support services (+10.1%), financial investments (+6.8%), truck transportation (+10.5%), and software publishing (13.3%). These differences reflect reliance on imports to the U.S. that are more emissions-intensive than their domestic counterparts. Indeed, where differences are large we find that much of the additional emissions often track to energy-intensive sectors in regions with carbon-intensive energy systems such as iron and steel or resin production in China and Russia.

For example, examining the key upstream sectors of the same commonly-disclosing industries, we find that emissions intensities vary enormously across regions, with standard deviations in each case >180 gCO_2e/$ (Fig. 2a). In some cases, such as electronics manufacturing, we find that the single-region (U.S.) model suggests very low emissions intensity relative to the multiregional distribution. This may be because large U.S. companies in this category such as Apple Inc. are primarily engaged in design and branding and not actual manufacturing. However, the U.S. value is not consistently higher or lower than the central tendency of these regional distributions (vertical lines in Fig. 2a). Sectoral resolution (i.e. the level of granularity in sector classification) also remains important: Figure 2b shows the similarly wide distributions of emissions intensity when aggregating from 400 to 71 sector categories (in each case 1σ>150g CO_2e/$; multiregional median of the specific sector of interest indicated by vertical lines).

Comprehensively assessing differences in sectors' emissions intensities as estimated by single-region (U.S.) and multiregional models, we find that the multiregional model intensities are generally higher, but there are 29 sectors (7%) in which the single-region model intensities are higher, including plastic bottle manufacturing, pesticide and agricultural chemical manufacturing, and fats and oils refining and blending; Fig. 3a). In particular, the emissions intensities of manufacturing sectors are often >20% higher according to the multiregional model (light orange circles in Figs. 3a and 3b). Relatedly, the greatest differences in the multiregional results are concentrated in sectors with midrange emissions intensities (between 0.4 and 0.8 kgCO2e/$; Fig. 3c).

Multiregional and single-region model estimates of corporate footprints in many cases differ with respect to the location and magnitude of hotspots in upstream emissions. Figure 3d highlights how the ranking of the emissions sources across all 400 industry sectors changes when using the multiregional model: darker shaded cells indicate cases in which the multiregional model ranks the emissions of a contributing (row) sector higher than the single-region model for a sector of interest (column). In particular (and consistent with the sectoral comparison in Figure 3a), the multiregional results reveal emissions hotspots in the manufacturing sector (as well as the sectors related to equipment repair which often also entail manufactured parts).

As with sectors, the differences in emissions estimated by multiregional and single-region models are also unevenly distributed by region. Colors on the map in Figure 4 indicate the scale of differences in country-level emissions when using the multiregional rather than single-region (U.S.) model to estimate upstream emissions of all the companies that report their emissions to CDP (a total difference of 2.0 $GtCO_2e$ globally). The dark red of China thus reflects both that country's outsized role in international supply chains as well as often greater emissions per unit of Chinese production: in the aggregate, CDP-reporting companies using a U.S.-based single-region may miss >900 $MtCO_2e$ of related emissions occurring in China (Fig. 4). On the other hand, emissions in other countries may be overestimated by single-region models for example where low-carbon energy sources are a larger share of energy used than in the U.S., as with nuclear in France or hydroelectricity and bioenergy in some South American countries (blue shading in Fig. 4). The arrows shown in Figure 4 highlight the largest international transfers of emissions embodied in CDP-reporting companies' upstream supply chains according to the multiregional model. The prevalence of arrows out of China thus reflects the importance of Chinese production in these companies' supply chains while arrows into the U.S. reflect the disproportionate size and proportion of U.S. companies among CDP-reporters.

Discussion and Conclusions

Our analysis demonstrates that there may be substantial and consequential differences in corporate carbon accounts when resolving multiregional sources of upstream emissions. These differences reflect the large regional differences in production technologies and energy sources not captured by single-region models. In the common situation of U.S. companies that have been using the U.S. EEIO model to estimate upstream emissions, switching to a multiregional model will almost inevitably lead to increases in their corporate footprint. Where such multiregional resolution is still not required by standards or regulations, many companies may therefore continue to use single-region models, which may ultimately lead to underestimation of their footprints and misallocation of mitigation efforts. For example, insofar as U.S. climate policies are more ambitious than those in other regions, corporations may not only underestimate their footprints but neglect otherwise cost-effective reduction opportunities that might be realized by engagement with international suppliers. Aggregated across voluntary corporate efforts, such missed opportunities could conceivably undermine the efficacy of corporate climate action. For example, assuming all the companies reporting their emissions to the CDP in 2023 were to estimate their upstream emissions using one or the other type of model, the multiregional model captures 2.0 Gt CO_2e more emissions in the aggregate than the single region model (~14% of global CO_2 emissions in the same year[22,23]). In contrast, where governments plan to regulate emissions embodied in imports (e.g., the E.U.'s Carbon Border Adjustment Mechanism[24,25]), single-region model results may be missing substantial emissions liabilities. Future work might productively explore the underlying sources of regional differences in emissions to reveal, for example, the extent to which they can be explained by regional differences in energy sources as opposed to the type and efficiency of industrial processes.

Several limitations and caveats apply to our results. First and foremost, the emissions intensities derived from EEIO models represent industry averages. Regardless of whether the model is multiregional or single-region, primary activity data from a company's suppliers is generally preferred. However, footprint uncertainty may be minimized by hybrid approaches that use supplier-specific activity data to adjust industry averages within a multiregional input-output model, especially if data collection efforts target upstream hotspots[26]. Secondly, the version of the CEDA model used in this study does not include emissions related to land-use change, which are a substantial and somewhat uncertain global emissions source that is extremely heterogenous across regions[27]. Third, as demonstrated in Figure 1b, sectoral detail is approximately as important as regional resolution: using a multiregional EEIO model with much more aggregated sectors (e.g., EXIOBASE[28]) risks increasing overall uncertainty. Fourth, companies might use multiregional resolution to seek out and switch to suppliers in less emissions-intensive regions rather than engaging to improve energy systems and processes in their existing supply chains. Although such a strategy might reduce these companies' upstream emissions footprint, it could undermine the overall climate benefits of corporate climate action insofar as the suppliers in more emissions-intensive regions can find new corporate buyers not concerned with their GHG emissions (perhaps due to a lack of multiregional emissions accounting). Finally, because the quality and availability of data on GHG emissions, economic structure, and international trade are geographically uneven and rapidly evolving, the CEDA model uses various methods and assumptions to fill gaps for those countries where such data are either not available or available at a lower resolution or quality than elsewhere (see Methods).

Nonetheless, our results show that GHG emissions embodied in international trade—long-recognized as a substantial share of many nation's emissions inventories—are similarly important for the individual corporations which are increasingly estimating their own footprints. The geography and magnitude of upstream emissions thus support targeted collection of supplier-specific activity data—data that may become critical as companies increasingly commit to reducing their emissions and work to prioritize reduction efforts. Especially in the context of voluntary efforts, the shift in such priorities afforded by multiregional resolution could fundamentally alter the actionability and efficacy of corporate efforts by unblinding companies to upstream emissions that are amenable to mitigation.

Methods

Our analysis and results are based on CEDA v5.0, a multiregional, environmentally extended input-output (EEIO) model. CEDA was first released in 2000 and has been regularly updated since. To ensure consistency between the multiregional and single-region results, we create a single-region CEDA model for the United States (US) by endogenizing imports to domestic production, which is common practice among single-region EEIO models. This treatment of imports is equivalent to assuming that all goods and services worldwide are produced in the US with U.S. technologies.

The method and data sources used for the compilation of CEDA was published in 2005[21]. In the years since, the model has undergone regular updates and improvements, with the latest version (v5.0) encompassing 400 sectors across 148 countries and regions which are classified into three tiers (see Model Construction below). For simplicity, in the current study we focus on 65 countries that belong to the first and second tiers.

Sectors in the CEDA model are defined according to industry and commodity classifications of the US Bureau of Economic Analysis (BEA), which in turn follows the United Nations' standard accounting framework, the System of National Accounts (SNA)[29]. The same sector classification is used in all 148 countries and regions covered by CEDA.

CEDA data sources. CEDA is constructed by using and reviewing over 100 data sources of three main types: (1) national input-output tables, (2) international trade statistics and (3) GHG emissions inventories. Table 1 summarizes the main sources and their corresponding base years.

Table 1 | CEDA Data Sources.

Data type	Source and Reference	Base year
Input-Output tables	U.S. Bureau of Economic Analysis (BEA)[30] U.K. Office for National Statistics (ONS)[31] National Bureau of Statistics of China (NBS)[32] Bank of Korea[33] Statistics of Japan[34] Organisation for Economic Co-operation and Development (OECD)[35]	2012, 2018 2018 2015 2018 2018 2018
International trade statistics	U.N. Comtrade[36] Organisation for Economic Co-operation and Development (OECD)[35]	2018 2018
GHG emissions inventories	U.S. Environmental Protection Agency (EPA)[37] U.K. Office for National Statistics (ONS)[38] National Bureau of Statistics of China (BNS)[32] Greenhouse Gas Invenotry & Research Center of Korea[39] National Institute for Environmental Studies of Japan[40] United Nations Framework Convention on Climate Change (UNFCCC)[41]	2018 2018 2014 2018 2018 2018

In addition to these data sources, the CEDA model is validated against multiple, independent statistics and data sources including the European Union's Emissions Database for Global Atmospheric Research (EDGAR)[42], the Global Carbon Project database[22], and numerous statistics and reports[43-47].

CEDA compilation follows the key principle of identifying and using the best available data as well as using assumptions, models, and proxies in the event that suitable data is not available. Our methods are described in more detail in the following section.

CEDA Model Construction. Here, we adopt common notations and matrix algebra used in EEIO models[28,48] and LCA[49,50]. The overall balancing equation for the flows of goods and services in monetary terms is shown as:

$$x = Ax + y \qquad \textbf{(eq. 1)}$$

where x is a vector of total commodity output by region, y is a vector of final demand of commodity by region combination), A shows the ratio of commodity input per unit of output, which is commonly referred to as technology coefficient[49,50]. The equation can be solved for x: $x = (I - A)^{-1}y$, where $(I - A)^{-1}$ is the Leontief inverse matrix, or L, and I is an identity matrix. In a multiregional input-output model, A is constructed in such a way that domestic intermediate economies are shown in the block diagonal matrices, e.g. $A_{1,1}$, while imports and exports are shown in off-diagonal matrices, e.g. $A_{1,r}$ (eq. 2).

$$\begin{bmatrix} A_{1,1} & \cdots & A_{r,1} \\ \vdots & \ddots & \vdots \\ A_{1,r} & \cdots & A_{r,r} \end{bmatrix} \qquad \textbf{(eq. 2)}$$

Next, the emissions intensity matrix, B, is calculated as:

$$B = Ex^{-1} \qquad \textbf{(eq. 3)}$$

where B is direct emission intensity of each sector in all regions, and E is national total emissions from each production activity and region combination.

Finally, the direct and indirect emission intensity of each sector in all regions is represented by:

$$M = BL \qquad \textbf{(eq. 4)}$$

In practice, construction of CEDA is a more complicated approach than simple matrix multiplication because of different data granularity and availability for different countries included in CEDA. To solve this, we develop a Tiered Approach framework (Tiers 1, 2, and 3), described below.

We categorize Tier 1 countries as the U.S., the U.K., Japan, South Korea, and China. This categorization is based not only on their significant roles in global trade and GHG emissions but also on the availability of the highest quality data sourced from each country's statistical reports on national input-output (IO) tables, energy flow, and GHG emission inventories. Tier 1 countries have relatively more granular and up-to-date IO tables and emissions data, which sets the foundation for CEDA's canonical sectoral classification.

Tier 2 countries encompass 60 countries featured in the OECD dataset, derived from excluding the 5 Tier 1 countries from a total of 65 OECD countries. National IO tables and GHG emissions data of Tier

2 countries are obtained from the OECD dataset where economic sectors are much more aggregated compared to those in Tier 1 countries[35]. Therefore, we develop a Structural Reflection technique to disaggregate national data of Tier 2 countries from OECD classification to CEDA's canonical 400 sector/product classification using the most closely related economy's highly detailed data. First, the country-level tables are disaggregated using Structural Reflection approach, and the resulting IO and GHG emissions data are cross-examined among themselves and across alternative data sources for manual adjustments. The resulting tables are used to calculate the GHG emissions embodied in each product by all 60 countries. These results are again cross-examined among themselves and across alternative data sources to identify outliers and anomalies.

Tier 3 countries do not have coherent IO statistics and are excluded from our analysis in this study.

CDP Data. Of the 10,867 companies from 112 unique countries that reported their emissions to CDP in 2023, 4,446 companies (40.9%) reported their scope 3.1 emissions, and 2,800 (25.8% of the total) disclosed that they used a spend-based approach to estimate those upstream emissions. Among those 2,800, 624 companies (i.e. 14% of those reporting scope 3.1) further specified the type of EEIO model used: 75% used a single-region EEIO model, and 25% a multiregional model. Here, we model emissions of all 5,450 companies that reported their revenues to CDP in 2023. Using a single-region (U.S.) EEIO model, we estimate these companies' aggregate upstream emissions were 12.2 GtCO2 in 2022. If we instead use a multiregional model, we estimate their upstream emissions were 14.1 GtCO2—a difference of 2.0 Gt of emissions worldwide.

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Figure 1 | Sector-specific differences in upstream emissions due to multiregional resolution. Paired bars show differences in the industry average upstream emissions related to purchased goods (i.e. scope 3.1) per unit revenue among the top 10 industry sectors of companies reporting their emissions to CDP 2021-2023 calculated by single-region (U.S.-specific) and multiregional input-output models. The differences are further decomposed as they relate to specific sectors (**a**) and regions (**b**). In all these cases, the single-region model underestimates upstream emissions.

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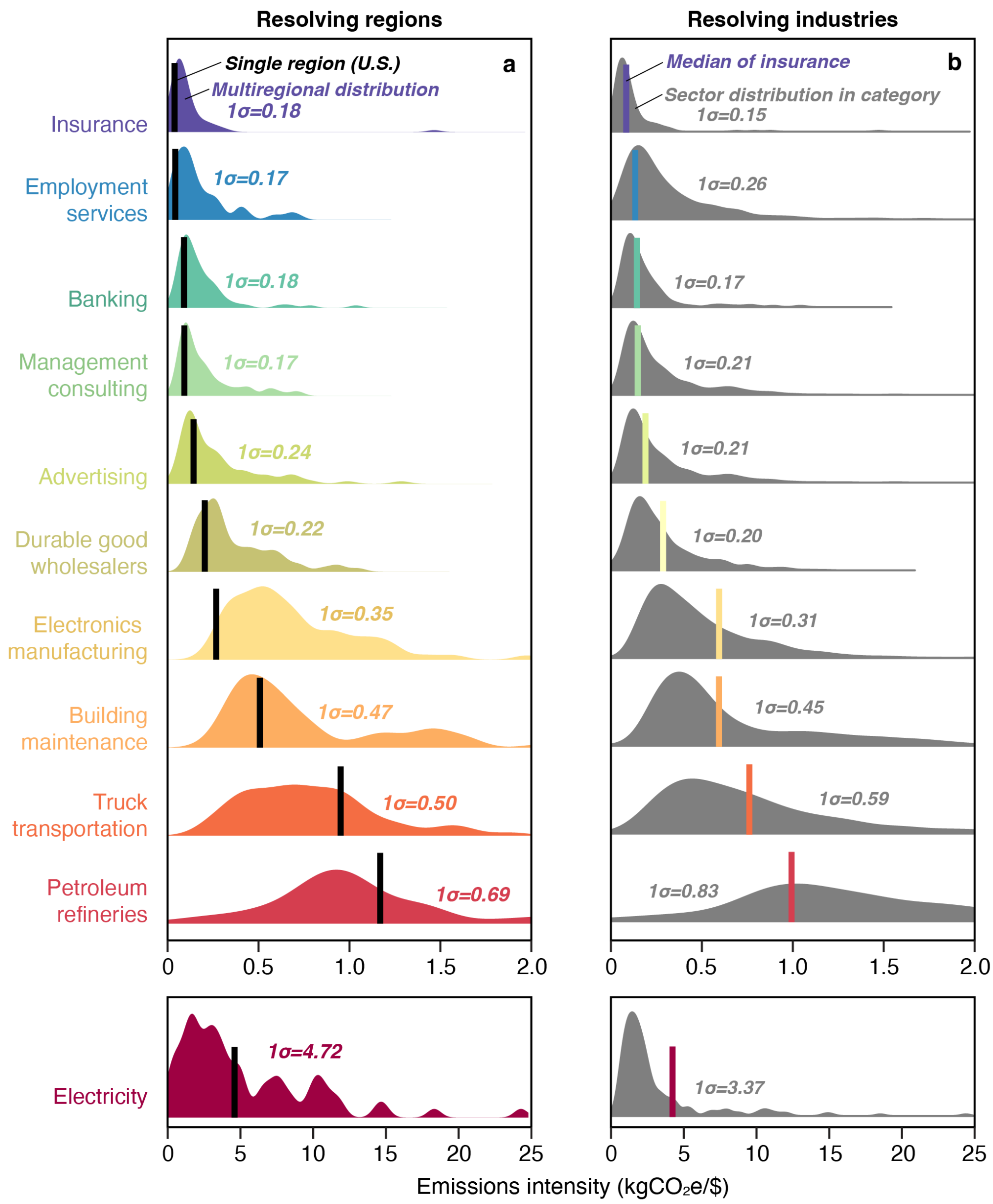

Figure 2 | Distributions of emissions intensity in key supplier sectors. Industry average emissions per unit of revenue in the 10 sectors that contribute most to the upstream emissions of the types of companies commonly reporting their emissions to the CDP 2021-2023 (the types shown in Fig. 1). A single-region (U.S.-based) model may substantially over- or underestimate the emissions intensities of these key supplier sectors because such intensities vary across regions (**a**). However, the emissions intensities of industry sectors within broader industry categories also vary considerably so that multi-regional models with fewer (more aggregate) industry sectors may also over- or -underestimate emissions intensities by a similar margin (**b**).

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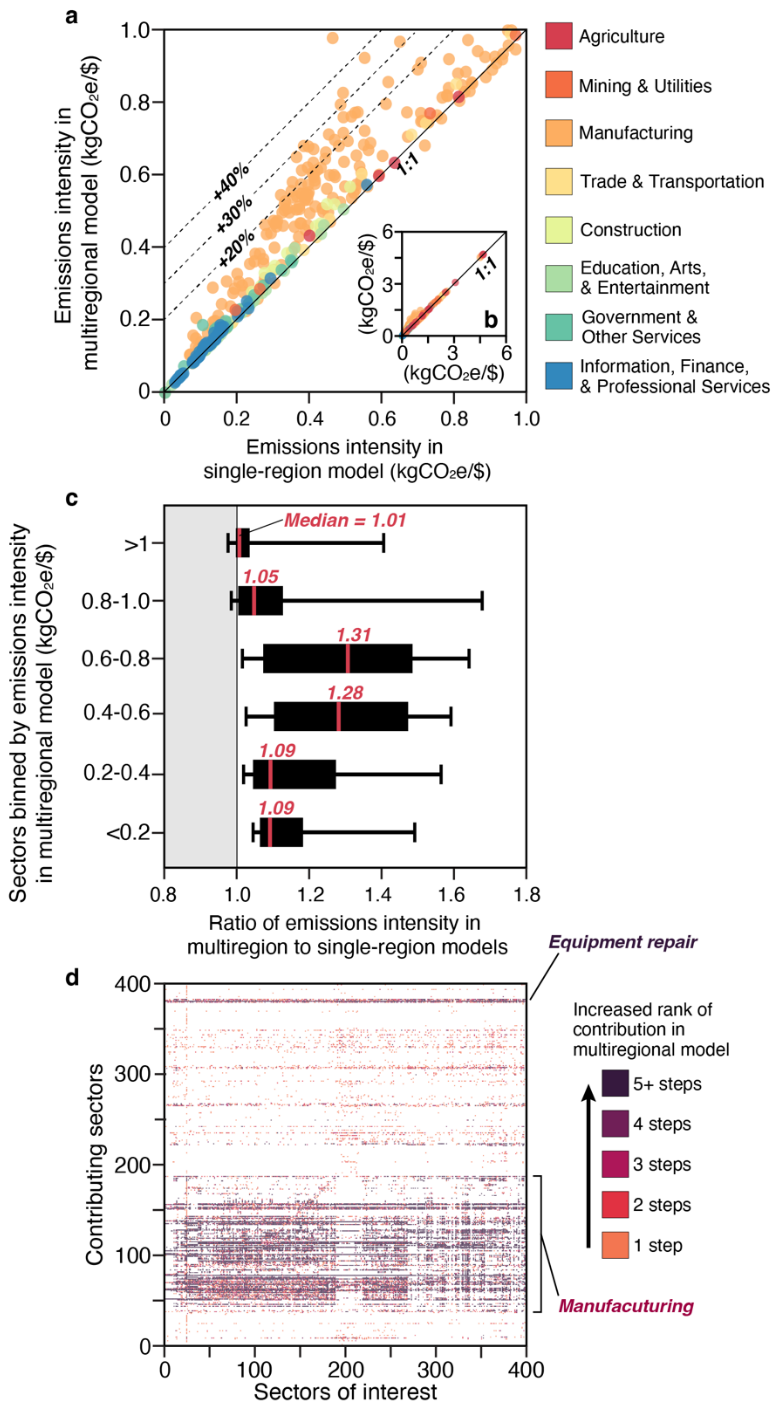

Figure 3 | Comprehensive comparison of sector-level differences between single-region (U.S.-based) and multiregional models. Across all 400 industry sectors, emissions intensities estimated by the multiregional model are generally greater than those estimated by the single-region model, particularly among manufacturing sectors (orange points, **a** and **b**). Grouped by the emissions intensity as estimated by the multiregional model, the greatest differences tend to be in those sectors with average emissions of 0.4-0.8 kgCO_2e/$, and the rare cases in which the single-region model estimates greater emissions intensity than the multiregional model are mostly in sectors which very high emissions intensities (>0.8 kgCO_2e/$; **c**). In many cases, the multiregional model further suggests substantially different hotspots in the upstream emissions (**d**).

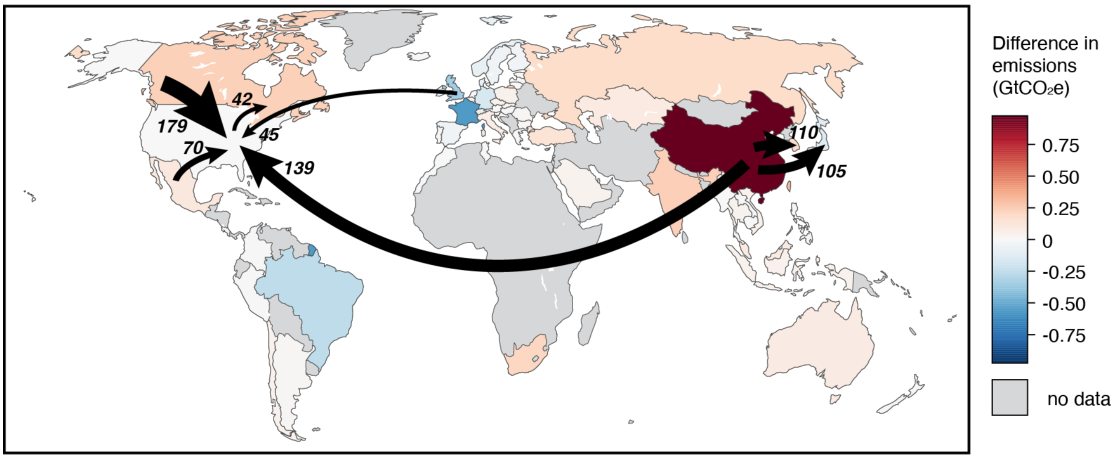

Figure 4 | Map of differences between single-region (U.S.-based) and multiregional EEIO models. Shaded colors indicate country-level differences in emissions when estimating upstream emissions of CDP-reporting companies using the multiregional model instead of a single-region (U.S.) model. In total, the multiregional model estimates 2.0 $GtCO_2e$ more emissions worldwide than the single-region model, but international supply chains and higher emissions-intensities of production in China lead to much greater emissions in China (+973 $MtCO_2e$), and somewhat lower emissions in areas which rely more heavily on low-carbon sources of energy (e.g., France, Brazil, and the U.K.). Arrows highlight the largest international transfers of emissions embodied in these companies' upstream supply chains that are missed by a single-region model.

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Supplementary Information

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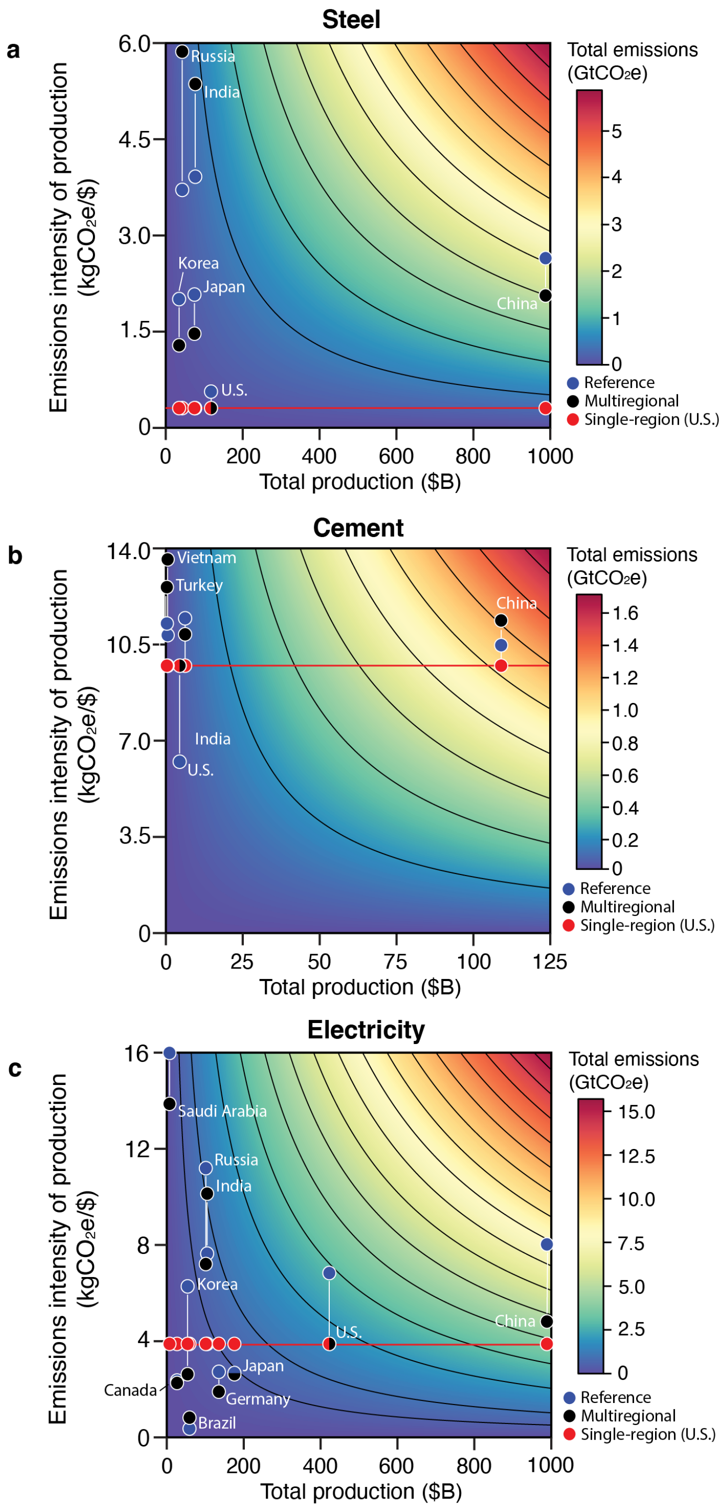

Supplementary Figure 1 | Comparison of key commodities' emissions intensity. Colored contours indicate country-level emissions related to steel (**a**), cement (**b**), and electricity (**c**) as the product of emissions per monetary unit produced (y-axis) and total production (x-axis). Points in each panel then show relevant values from our single-region (U.S.-based) input-output model (red circles), our multiregional model (CEDAv5.0, black circles), and reference values from published sources (blue circles, refs. *34-39*). To facilitate comparisons, reference and multiregional values are connected by vertical white lines, and a horizontal red line emphasizes the static single-region intensity. In many cases, the multiregional model estimates are closer to the reference values, which is particularly important in cases like China where total production of these commodities is very large.