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Mapping the Structure of the World Economy

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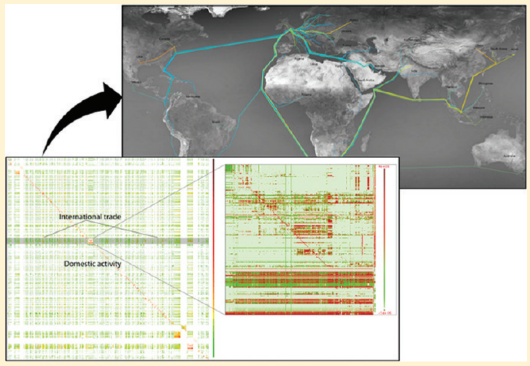
Ⓢ *Supporting Information*

ABSTRACT: We have developed a new series of environmentally extended multiregion input−output (MRIO) tables with applications in carbon, water, and ecological footprinting, and Life-Cycle Assessment, as well as trend and key driver analyses. Such applications have recently been at the forefront of global policy debates, such as about assigning responsibility for emissions embodied in internationally traded products. The new time series was constructed using advanced parallelized supercomputing resources, and significantly advances the previous state of art because of four innovations. First, it is available as a continuous 20-year time series of MRIO tables. Second, it distinguishes 187 individual countries comprising more than 15,000 industry sectors, and hence offers unsurpassed detail. Third, it provides information just 1−3 years delayed therefore significantly improving timeliness. Fourth, it presents MRIO elements with accompanying standard deviations in order to allow users to understand the reliability of data. These advances will lead to material improvements in the capability of applications that rely on input−output tables. The timeliness of information means that analyses are more relevant to current policy questions. The continuity of the time series enables the robust identification of key trends and drivers of global environmental change. The high country and sector detail drastically improves the resolution of Life-Cycle Assessments. Finally, the availability of information on uncertainty allows policy-makers to quantitatively judge the level of confidence that can be placed in the results of analyses.



1. INTRODUCTION

In 2009, China's chief climate negotiator Li Gao argued that carbon emissions due to the production of export goods should be the responsibility of the consuming country.[1] Multiregion input−output (MRIO) tables are acknowledged to be an appropriate tool to underpin this consumer-responsibility accounting.[2−4] MRIO tables document thousands of relationships between industry sectors (so-called "production recipes") and are thus able to trace carbon emissions through complex international trade and supply chains networks. We present a new MRIO database called Eora that substantially advances the state of the art and contains the world's largest and most detailed map of the global economy.

Wiedmann et al.[5] provide a comprehensive account of the policy relevance of MRIO applications in a world where consumption and production are increasingly spatially separated. MRIO tables are used to establish the carbon footprints of nations,[6] a concept that complements the conventional territorial allocation of emissions as reported to the UNFCCC with a consumer-responsibility perspective of global CO_2 emissions.[7,8] Carbon footprint results obtained from such MRIO tables have demonstrated the marked growth of emissions facilitated by international trade.[9−11] MRIO tables also have applications in advanced techniques for Life-Cycle Assessment (LCA), where product- and process-specific data are combined with overarching input−output data.[12]

The widespread adoption of MRIO models has so far been hampered by a number of factors. First, constructing an MRIO database has been labor-intensive. Second, currently available MRIO tables either do not cover the entire world, group a large number of individual countries into regions, and/or aggregate detailed industries into broad sectors. Third, MRIO tables are often not available as a long, continuous time series, and at the time of their release, the most recent tables are already many years outdated. Finally, MRIO databases currently provide only results without accompanying estimates of reliability and uncertainty. Of course, existing MRIO databases are designed with different purposes in mind, however limited resolution and untimeliness are impediments for any MRIO application, no matter its purpose.[5] All these shortcomings are mainly due to problems in handling of incomplete, conflicting, and misaligned data, but also due to previous limitations in computational capacity.

The research needs listed above are now addressed by the new Eora MRIO database. Measured in terms of detail, coverage, size, continuity, timeliness, and comprehensiveness, Eora has considerably extended current limits (Table 1).

2. METHODS

2.1. Input−Output Analysis. Leontief's input−output analysis (IOA) framework is at the heart of many models

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Table 1. Performance Comparison of the Eora MRIO Database with the Previous State of the Art

	previous state of the art[5]	Eora
country coverage	43–57 individual countries plus 129 regions	187 individual countries
sector coverage	3760–7353 sectors[a,b]	15909 sectors[a,c]
environmental indicator coverage	30 emission types, 80 resource types	35 indicator categories >1700 single indicators[d]
continuity	1995–2007[e]	annual tables 1990–2009
timeliness	publication delayed by at least 5 years	1–2 years prior to current year
reliability and uncertainty information	none	standard deviations for every MRIO element

[a]A "sector" can be an industry or a product. The values listed include the number of both industries and products, since some countries feature asymmetrical Supply–Use Tables (SUTs) in which these numbers are different. [b]GTAP 8: 57 sectors and 129 regions for 2004 and 2007, in total 7353 transactions; EXIOPOL: EU27 and 16 non-EU countries, and about 129 sectors for 2000, in total 5547 sectors; WIOD: 27 EU countries and 13 other major countries in the world, more than 35 industries and at least 59 products for 12 years, in total 3760 sectors. [c]187 single countries at 25–500 sectors totalling 15909 sectors, 5 valuation sheets, 20 years, makes in total more than 20 billion transactions. [d]Energy, CO_2, CH_4, N_2O, HFC-125, HFC-134a, HFC-143a, HFC-152a, HFC-227ea, HFC-23, HFC-236fa, HFC-245fa, HFC-32, HFC-365mfc, HFC-43-10-mee, C_2F_6, C_3F_8, C_4F_{10}, C_5F_{12}, C_6F_{14}, C_7F_{16}, CF_4, c-C_4F_8, SF_6, HANPP, CO, NO_x, NMVOC, NH_3, SO_2, HC, HCFC-141b HCFC-142b, Ecological Footprint, and Water Footprint. [e]GTAP: 1992, 1995, 1997, 2001, 2004, 2007; EXIOPOL: 2000; WIOD: 1995–2006.

informing national economic policy. Input–output tables that map the production recipes and trade structures in national economies are published regularly by more than 100 national statistical agencies around the world, as well as supranational institutions such as the OECD or Eurostat. Leontief envisaged input–output analysis to be applied to environmental issues,[13] and since then his design of an environmentally extended input–output table has been employed in thousands of empirical and theoretical studies [14] (Supporting Information (SI), Text S1).

In the 1970s and 1980s, Leontief already had a vision of an information system for the world economy.[15,16] However, only during the past two decades, possibly driven by the increasingly complex interdependence of national economies through international trade, and contemporary global problems such as climate change and resource depletion, has research veered more toward multiregional input–output (MRIO) databases.[3]

In contrast to national IO tables, global MRIO databases are not compiled by statistical agencies, but by a handful of research groups around the world.

2.2. Construction of the MRIO Tables and Satellite Accounts. There exist serial and parallel approaches to estimating a time series of input–output tables.[17] A serial, iterative approach was chosen for constructing the Eora tables because it has advantages over parallel approaches in situations where the data required for setting up annual initial estimates are unaligned or incomplete.[18] We first generate an initial estimate in accordance with United Nations guidelines[19] from a selected set of raw data for the base year 2000 (SI, Text S3), because data availability is best for this year (SI, Table S3). In the case of countries for which an input–output table is unavailable we construct a proxy input–output table combining other macro-economic data for these countries with a template input–output structure based on an average of the Australia, Japan, and United States tables (SI, Table S3.1). We then determine a year-2000 MRIO table by reconciling all raw data available for 2000. This year-2000 MRIO table is taken as the initial estimate for the subsequent year 2001. A 2001 MRIO table is then calculated on the basis of all raw data available for 2001, and the entire time series is completed in the same stepwise manner.

The solution of the reconciliation process for each year is hence obtained from two ingredients: an initial estimate, and a set of raw data. The entire MRIO table construction procedure can be summarized in five steps:

1 All raw data (assume M points) available for the year in question are collated into a vector $\mathbf{c}$ (all data sources are listed in SI, Text S6). Since the Eora tables distinguish 5 valuations, including basic prices, margins, taxes, and subsidies, no transformation of raw data expressed in purchasers' prices into basic prices is necessary.

2 An $M \times N$ matrix $\mathbf{G}$ is set up that contains constraints coefficients describing the relationship $\mathbf{Ga} = \mathbf{c}$ between M raw data points in $\mathbf{c}$, and N MRIO table elements (vectorized as a $N \times 1$ vector $\mathbf{a}$). In addition, $N \times 1$ vectors $\mathbf{l}$ and $\mathbf{u}$ are constructed that contain lower and upper bounds on all MRIO elements in $\mathbf{a}$. These lower and upper bounds result from definitions of accounting variables. For example, the bounds for changes in inventories are $[-\infty,+\infty]$, those for subsidies are $[-\infty,0]$, and those for remaining MRIO elements are $[0,+\infty]$.

3 Constraints based on raw data stemming from different sources often conflict, so that $\mathbf{Ga} = \mathbf{c}$ can usually not be fulfilled exactly. We therefore follow van der Ploeg[20] by extending the vector $\mathbf{a}$ with slack variables $\boldsymbol{\varepsilon} = \mathbf{Ga} - \mathbf{c}$, effectively allowing the MRIO realizations $\mathbf{Ga}$ to deviate from their prescribed values $\mathbf{c}$. $\mathbf{a}$ and $\boldsymbol{\varepsilon}$ are collated into one vector $\mathbf{p} = [\mathbf{a}|\boldsymbol{\varepsilon}]'$.

4 A constrained optimization algorithm is invoked for finding a reconciled solution for $\mathbf{p}$ that best fulfills the constraints $\mathbf{Gp} = \mathbf{c}$ and $\mathbf{l} \leq \mathbf{p} \leq \mathbf{u}$, while minimizing the departure of $\mathbf{p}$ from its initial estimate $\mathbf{p}_0 = [\mathbf{a}_0|\mathbf{0}]'$. The optimization step is necessary because the number of MRIO elements by far exceeds the number of constraints and there is not enough information to analytically solve the system for $\mathbf{p}$. The objectives "best fulfills" and "minimizes departure" can be specified mathematically. For example, in the approach by van der Ploeg,[20] "best" means minimizing the slack variables $\boldsymbol{\varepsilon}$.

5 The time series is constructed iteratively, by starting with the 2000 initial estimate, reconciling this with all 2000 constraints, and taking the solution as the initial estimate for 2001, and so on. Back-casting to 1990 proceeds similarly. A balanced table for one year will be an inappropriate initial estimate for the next year under strong economic growth. Therefore, we have constructed initial estimates by scaling all prior solutions with interyear ratios specific to transactions (use, trade), final demand, value added, and supply tables. These ratios were derived from country time series data on GDP, exports, imports, and value added.[21]

A simple example is provided in the SI, Text S5.

While there exists a plethora of optimization approaches, the literature on input−output table estimation favors variants of the RAS iterative scaling method,[22] and Quadratic Programming algorithms.[20] These methods differ by the quantitative specification for penalties that are imposed for any departure from the constraints $\mathbf{Gp} = \mathbf{c}$ and $\mathbf{l} \leq \mathbf{p} \leq \mathbf{u}$ (Figure 1). Balancing and time series iteration are discussed further in the SI, Text S2.

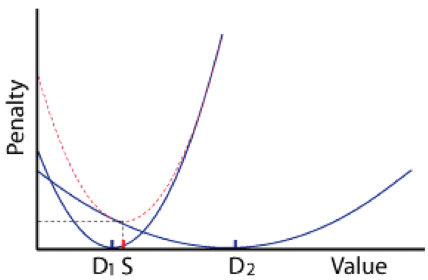

Figure 1. Schematic representation of a compromise solution between two conflicting data points. Points D_1 and D_2 represent two conflicting reported values of the same data point. D_1 has high confidence (a small standard deviation) and D_2 has low confidence (large standard deviation). The solution point S lies closer to D_1. This schematic shows a quadratic penalty function. Using linear, entropy, or another objective function will result in the solution S representing a different compromise between the two constraints.

A key feature of the optimizers used for constructing Eora MRIO tables is their ability to deal with conflicting constraints. A prime example for such data conflict are exports and imports data contained in the United Nations' Comtrade database.[23] One would expect that bilateral trade volumes, reported by the exporting country exclusive of international trade margins and import duties, are slightly smaller but comparable in magnitude to the corresponding volumes reported by the importing country.[24] However, a surprisingly large proportion of the data violate this basic requirement (Figure 2).

This circumstance imposes restrictions on the choice of optimizer, in the sense that conflicting equations in the linear system $\mathbf{Gp} = \mathbf{c}$ render the balancing and reconciling of the Eora MRIO tables an infeasible problem for the most widely used RAS method. The problem of conflicting raw data can only be solved through the introduction of quantitative information on data reliability and uncertainty, slack variables $\boldsymbol{\varepsilon}$, and through combining this information with advanced optimization methods such as Quadratic Programming and KRAS.[25] Variants of these methods have been implemented in the Eora optimizer suite.

Note that the constraints coefficients matrix $\mathbf{G}$ is sparse, but very large. Since for an average time series year, we were able to locate about 70 million raw data points, and our MRIO has more than one billion elements for each year, $\mathbf{G}$ has about 70 million rows, and more than 1 billion columns. The timely construction of $\mathbf{G}$ was achieved by automating data mining, processing, and reclassification procedures as much as possible[26,27] (see SI, Text S4). The design and implementation of constrained optimizers on such a large scale is an achievement in itself, since variable spaces sized in excess of 1 billion are beyond the capability of commercially available software (see Section 3.1). We constructed, balanced, and reconciled Eora's large MRIOs on a purpose-built scientific computing cluster. Tables currently deployed online have been

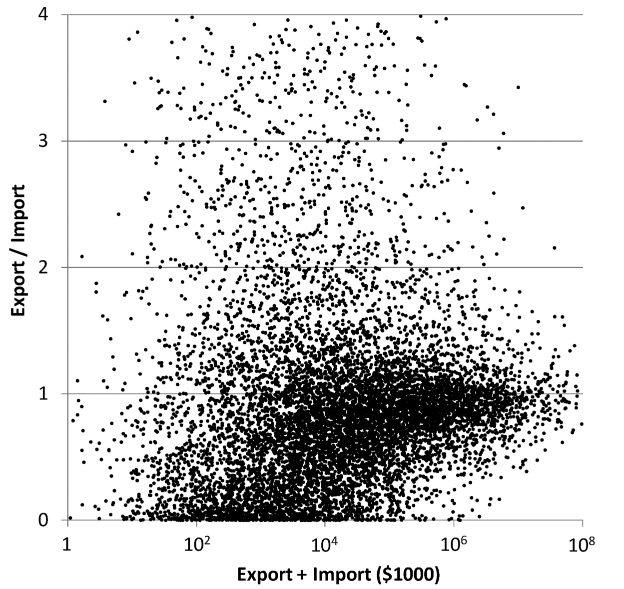

Figure 2. Data conflict in the United Nations Comtrade database.[23] The scatter plot contains 187^2 bilateral national trade volumes. The horizontal line crossing the vertical axis at 1 means country A's reported exports to country B equal country B's reported imports from A. Reported imports should be slightly larger, so that in theory there should be no values above the said horizontal line. This principle is clearly violated, though integrity does improve slightly with larger trade values. Resolving fundamental disagreement in the original data such as this is a major challenge Eora attempts to solve.

generated using a parallelized version of KRAS.[25] We provide further details on the implementation of steps 1−5 in Section 3.1.

2.3. Construction of the Standard Deviations Table.

The standard deviations σ_{p_j} accompanying MRIO elements $\mathbf{p}_j$ are estimated in two steps. First, assuming normally distributed observations, standard deviations σ_{c_i} of raw data points c_i are partly estimated based on published data or expert interviews, but mostly set according to certain world views on the uncertainty of various sets of raw data. For example, our interviews revealed that input−output data issued by national statistical offices are widely viewed as accurate representations of "true" input−output transactions, whereas for example United Nations statistical officers acknowledged limitations in their ability to interrogate and correct data supplied to them from various sources. Hence, the version of Eora available at the time of writing was constructed with national data being set "tight" (i.e., small standard deviations), and UN data "loose" (large standard deviations). Different specifications based on different world views are possible, and if rerun, would result in a different version of Eora. There is hence no unique, "true" set of MRIO tables.[28] Nevertheless, it can generally be found that smaller raw data values are associated with higher relative standard deviations, and vice versa.

Second, a modified RAS optimization algorithm is employed in order to fit standard deviations σ_{p_j} to an error propagation formula $\sigma_{c_i} = (\sum_j (G_{ij}\, \sigma_{p_j})^2)^{1/2}$ This procedure is consistent with the estimation of the MRIO elements $\mathbf{p}$, based on raw data $\mathbf{c}$. In fact, the error propagation formula can be derived from the optimization condition $\mathbf{Gp} = \mathbf{c}$. The $\boldsymbol{\sigma}_p$ are influenced by two factors. The first is an uncertainty characteristic: the smaller the uncertainty $\boldsymbol{\sigma}_c$ of a raw data item c, the smaller the uncertainty

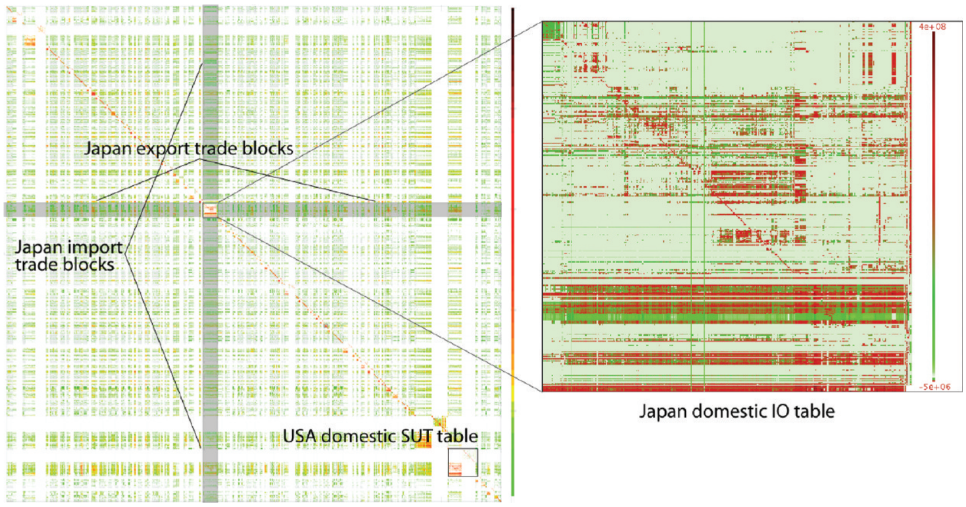

Figure 3. Heat map of the Eora MRIO 2009 basic price table, with call-out of the Japan domestic IO table. Each pixel encodes the total value of transactions from one sector to another. As seen in the colormap legend at right, darker red pixels represent larger values. The Eora MRIO time series (1990−2009) represents 187 countries with total of more than 15,000 sectors and has five valuation layers.

$\boldsymbol{\sigma}_p$ of MRIO elements addressed by this raw data item. The second is a data conflict characteristic: the premodified-RAS initial estimate $\boldsymbol{\sigma}_{p_0}$ of the $\boldsymbol{\sigma}_p$ is set to the difference between the MRIO initial estimate $\mathbf{p}_0$ and the MRIO final solution $\mathbf{p}$. This difference is influenced by the conflict in the raw data, because conflicting raw data lead to movements in elements during optimizer runs. For further details see ref 29.

3. THE EORA GLOBAL MRIO INFORMATION SYSTEM

3.1. Structure and Innovations. The Eora MRIO database is deployed online (www.worldmrio.com). Its main feature is a continuous series of environmentally extended global MRIO tables. Each MRIO table is a representation of the structure of the global economy; it contains a complete account of monetary transactions between the industry sectors of 187 countries (SI, Table S2). Because each country has a different economic structure, most of Eora's countries are represented by different table formats (SI, Text S1), and at a different level of sector detail, ranging from 26 to 500 sectors per country (SI, Table S2).

The strategy of heterogeneous sector classification and table type was chosen so that the Eora MRIO could incorporate maximum sector detail overall. For example, the economies of Brazil, China, and Singapore are heavily based on agriculture, manufacturing, and trade/services, respectively. To represent these economies in a homogeneous sector classification as in existing MRIOs requires substantial aggregation and reclassification steps,[24] and causes loss of information and transparency. In addition, Eora's heterogeneous sector classification ensures flexibility, because a homogeneous MRIO time series where all countries' transactions are expressed in the same sector classification can always be calculated from the original heterogeneous MRIO tables. Complementing the full table, a 26-sector homogeneously classified version is available for download from the Eora Web site.

Each monetary MRIO table identifies 15909 sectors, both supplying and receiving, and hence in excess of 250 million transactions. Basic prices of transactions are valued separately to trade margins, transport margins, taxes, and subsidies, in five valuation sheets, expressed in units of current U.S. dollars; (see Figure 3 for a heat map of the 2009 basic price table). The tables exist in a constant format and sector/indicator classification for a 20-year period 1990−2009. The total number of transactions data exceeds 1 billion per year, or 20 billion in total, and including the constraint matrices, satellite accounts, and ancillary result files and reports, that complete result time series occupies more than 3 Terabytes.

Environmentally extended MRIOs append so-called satellite accounts in physical units, which complement the monetary table with nonmonetary inputs to production. Thus the production recipes contained in an environmentally extended MRIO include the conventional economic inputs (steel, machinery, labor, capital) as well as resources (land, energy, water) and environmental impacts (emissions, biodiversity loss). The strength of this setup is that both the monetary MRIO and the satellite accounts adhere to the same sector classification. This data integration enables the straightforward translation of economic activity in one country into biophysical impacts in another. Hence, environmentally extended MRIOs provide a powerful tool and data set to a wide range of footprinting and LCA applications.

Eora's satellite accounts provide details on 35 broad indicator groups. At the finest level of detail (fuel types, gas types, individual threatened species), these indicator groups break down into 20,832 indicator line items.

To assemble and balance MRIO tables at such a large scale, a host of obstacles had to be overcome by developing a number of innovative features: (1) a streamlined, automated workflow management including a custom-built programming language, (2) a novel constrained optimization algorithm that can solve large-scale quadratic programming problems, and (3) a tailored hardware configuration for parallelized handling of the Eora build-pipeline (see SI, Text S2.4).

3.2. Uncertainty Information. A unique and innovative feature of the Eora MRIO tables is that every MRIO and satellite account element is accompanied by corresponding standard deviations. Transparent information on uncertainty is important in any application of input−output analysis, because it helps decision-makers in understanding assumptions and limitations underlying the data, and thus enables them to engage in informed and transparent decision-making.

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One example for applications of IO tables is increasingly widespread hybrid approaches to life-cycle assessment (LCA) that combine detailed bottom-up process information with comprehensive top-down input−output information.[12] LCA is often used in comparative assessments, for example of technology options. To decide whether one option is preferable over others, it is not sufficient to simply consider final LCA results. Depending on the standard deviations associated with these results, decisions may well be different after uncertainty information is taken into account.

Similarly, comparative carbon footprint studies that utilize carbon multipliers derived from global MRIO models should always be accompanied by transparent and comprehensible uncertainty estimates. Only then can decisions be supported by measures of statistical significance, for example using hypothesis testing.

In Eora, MRIO standard deviations are calculated by fitting an error propagation formula to standard deviations of the raw data points. This method is described in detail elsewhere.[29] Standard deviations of multipliers can be derived from MRIO standard deviations using Monte Carlo techniques.[30] Standard deviations are essential for determining the uncertainty of any quantitative measure derived from MRIO tables. Moreover, error propagation theory yields that relative standard deviations decrease with aggregation, so that Eora's quantitative estimates of standard deviations of MRIO elements enable analysts to aggregate the Eora tables according to their own uncertainty requirements.

The Eora Web site offers tabular and graphic information on the reliability of MRIO blocks, separately for every country and year. Tabular information includes two ranked lists of raw data points that are best/least represented by the MRIO table. An example for a visualization of MRIO table reliability is what we call a *rocket plot* (Figure 4).

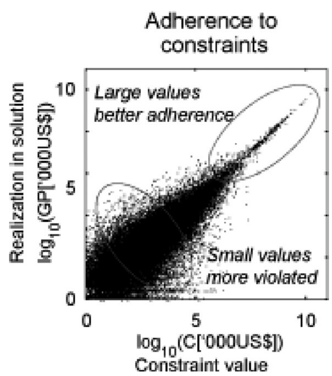

Figure 4. Rocket plot of constraints and their adherence in the MRIO solution, shown here for the United States. Large constraint values (increasing along the logarithmic horizontal axis) are more reliable and thus the MRIO elements addressed by these constraints are better preserved in the final MRIO (logarithmic vertical axis). Small constraint values are less reliable and thus less adhered to in the final realized MRIO.

In agreement with previous studies, and in turn with our uncertainty specifications of raw data items, we find that large transactions are better represented than small ones. This is because the optimization of any large MRIO table is an underdetermined optimization problem: The number of raw data items that can serve as support points for the MRIO table is much smaller than the number of MRIO table elements. Those elements that are supported by only a few raw data points, and hence restricted by only a few constraints, can be subject to large adjustments during an optimization run, and hence their reliability is low. On the other hand, for virtually all large and important MRIO table elements, there exist supporting raw data, so that the adjustment of these elements is minimal, and hence their reliability is high (Figure 4).

Even though many MRIO elements are supported by only few raw data points, one can show using Monte Carlo techniques that it is always beneficial for MRIO table construction to exploit as much information as possible.[31] This principle also refers to the inclusion in the Eora MRIO table of countries for which input−output tables must be estimated as no official tables are available. For all Eora countries there exists at least some sectoral breakdown of final demand[32] and value added,[33] plus detailed data on international commodity trade,[23] which can be used to infer their input−output structure. Such estimates, however coarse, provide more information than the regional country aggregates in existing global MRIO databases.

Despite their abundance, small and unreliable MRIO elements are unlikely to significantly distort input−output multipliers,[34,35] and therefore do not compromise the quality of footprints, LCA results, and other policy-relevant measures.

3.3. Validation. We validated our results by comparison with footprint studies by Peters et al.,[9] GFN,[36] and the Water Footprint Network.[37] As seen in Figure 5 the Eora-based results are in line with the national carbon footprint (CF), water footprint (WF), and Ecological Footprint (EF) results calculated in these other studies.

4. POTENTIAL APPLICATIONS

In addition to MRIO table elements and their standard deviation the Eora database supports a range of analytical concepts. The most overarching of these are national accounts balances. Such balances are known from economic statistics where they reflect, in monetary units, that for each nation, production plus imports must equal consumption plus exports. Being an environmentally extended MRIO framework, Eora also shows national account balances in terms of the environmental indicators quantified in the satellite accounts, in physical units of tonnes of emissions, liters of water, etc. The production column of each balance table contains the territorial use of resources or emission of pollutants. The exports and imports columns can be interpreted as resources and pollutants embodied in international trade. The consumption column reflects the country's footprint in terms of the respective indicator. Footprints are calculated from environmental multipliers in the standard manner using the Leontief inverse.

In policy contexts the production account is also interpreted as the producer-responsibility perspective while the footprint account represents the consumer-responsibility perspective.[38,39] While most national and global data compendia portray environmental variables as characteristics by territory, recent thinking emphasizes the view that resource use and emissions are ultimately driven by consumers who, through their demand, require production, and as a consequence, drive environmental pressure. For example, Eora data confirm earlier findings of a carbon footprint study of the UK[10] showing that the UK was outsourcing its emissions-intensive production by importing from overseas, and that—counter to UK government claims—the UK's actual carbon footprint had been increasing. This finding prompted the British Minister for the Environment to

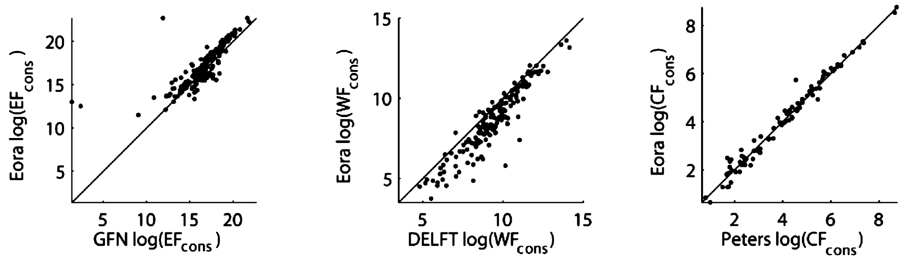

Figure 5. Comparison of final national Ecological Footprint (EF) of consumption in 2007, water footprint (WF) in 2000, and CO_2 footprint (CF) in 2008 as calculated by Eora and other authors. The Eora-based results are in line with the results reached by other studies.

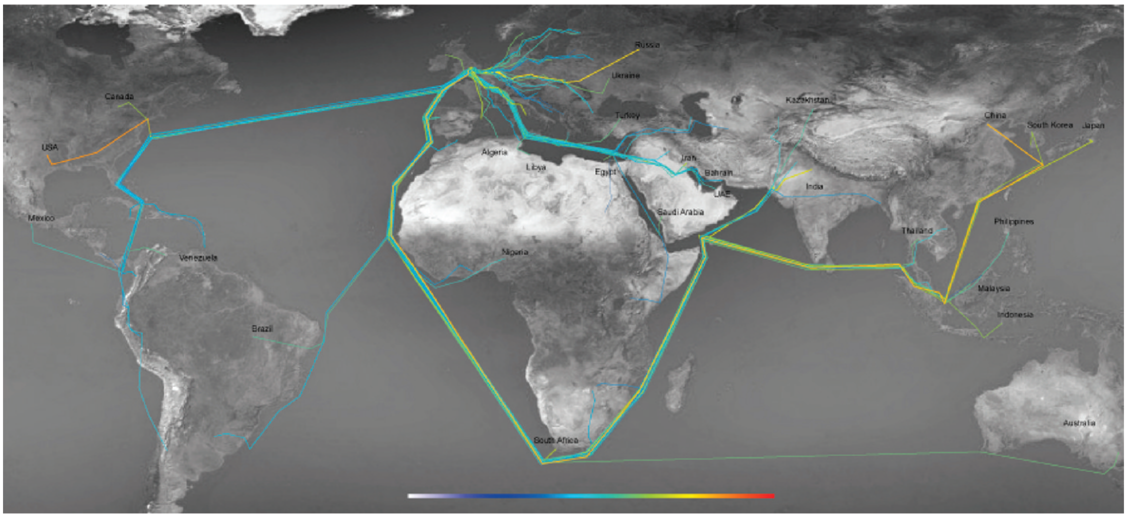

Figure 6. Global flow map of embodied energy consumed in the UK. Energy used in the United States to produce goods finally used by UK consumers is illustrated by a line between the U.S. and UK. Red, yellow, and green lines encode larger values. Line width encodes flow magnitude.

address the public on BBC Radio,[40] and led to a public inquiry by the UK Government Select Committee on Climate Change.[41,42] A flow map visualization showing embodied CO_2 imports into the UK is shown in Figure 6.

The Eora database contains annual national accounts balances for the entire period 1990–2009, for every country, in monetary terms as well as for every satellite indicator. Such balances reveal which countries are net exporters or net importers of environmental pressure.

While there exist several carbon, water, and ecological footprint studies based on global MRIOs, these have not yet been widely utilized in LCA studies. Nevertheless, the potential for future MRIO-assisted LCA applications is large, especially when MRIO databases feature sufficiently high country and sector detail to be able to integrate with detailed bottom-up, process-specific data. The global coverage of MRIOs is particularly important given that manufacturing processes increasingly draw on raw and semifabricated intermediate inputs sourced from global locations with comparative cost advantages. It is not uncommon for consumer products to be underpinned by global supply chain networks involving dozens of countries.[5]

Individual supply chains can be isolated from the MRIO using a technique called Structural Path Analysis (SPA).[43] SPA uses tree-scanning algorithms to trace and extract the most important paths from the network, and to rank paths according to their financial magnitude or according to their content of CO_2, embodied air pollution, or any other satellite indicator. The Eora database provides ranked SPAs for all satellite indicators. SPA can be used to investigate supply chains originating, or ending, in a certain country and/or sector (Figure 5), or to identify supply chains passing through a sector of interest. SPAs provide a versatile microscopic sectoral and geographic view of the aggregates in the macroscopic national account, footprint, and LCA measures.

A widely used technique for identifying drivers of change is *Structural Decomposition Analysis* (SDA).[44] SDA has been used for unravelling the roles of technological change, production structures, demand structures, affluence (per-capita consumption), and population growth, in driving up CO_2 emissions. Understanding of such key drivers is essential for designing policies for mitigating climate change, because such policies are potentially most effective when aimed at the most important structural determinants of emissions. This time series must feature tables in a constant sector classification, and should ideally include a long, continuous sequence of annual tables. The lack of MRIO tables meeting this requirement has so far prevented a comprehensive assessment of global environmental trends.

A key requirement for SDA is the availability of a time series of IO tables expressed in constant prices. The literature on the topic of converting national currency to constant-price U.S. dollars appears to recommend the approaches of "convert-first then deflate" and double deflation, i.e. the residual adjustment of value added to achieve the table balance. The literature also recommends the usage of Purchasing Power Parity (PPP) exchange rates[45,46]. The conversion and deflation of the transaction tables of Eora's 187 countries can be achieved by using PPP exchange rates published by the OECD[47] and deflators published by U.S. Bureau of Labor Statistics.[48] For those countries where PPP exchange rates are not available, market exchange rates published by the International Monetary Fund (IMF) can be used (comparing with WIOD practice[49]). The construction of constant-price Eora tables is part of ongoing work.

In conclusion, the Eora tables represent a major advance in the resolution, timeliness of multiregion input−output (MRIO) tables, and therefore also in the relevance of a wide range of applications such as carbon, water, and ecological footprinting, and Life-Cycle Assessment. This advance was possible through the development of a number of innovations such as a data processing language, new optimization algorithms, advanced computational solutions, and the simultaneous construction of uncertainty estimates.

The free availability of Eora was intended to enable MRIO databases to be accessible to a wider audience of analysts, translating into more frequent usage of MRIO techniques in applications to real-world problems.

The timeliness of Eora means that a host of MRIO time series applications such as Structural Decomposition Analysis will be able to generate more current and relevant results than has been achievable so far. The multiyear delay of publication of input−output tables is one of the most frequently cited reasons for impediments to the uptake of input−output techniques. Timely annual MRIO updates are now significantly more feasible given the high degree of automation in Eora's construction procedures.

The high sector resolution in Eora is especially important if carbon and water footprinting, consumer product labeling, global-corporate emissions reporting, environmental life-cycle assessment (LCA), and similar frameworks underpinning decisions with a demand-side perspective are to attain widespread and high-level policy relevance.[50] This is because input−output analysis is increasingly being recognized as an indispensable component of hybrid footprinting and LCA techniques combining the specificity of detailed product and process data with the completeness of comprehensive input−output data.[12] One of the main perceived weaknesses of existing IO components in footprinting and LCA methods is the apparent lack of sector detail,[5] and hence the development of the Eora tables was guided by the goal of including the largest possible number of sectors. For example, the production of aluminum and copper entails significantly different levels of electricity use, and therefore emissions. However, if those metal industries were aggregated into a single "nonferrous metals" sector then any copper products, such as motors, would be assigned too high a carbon footprint because it would appear that aluminum was part of the input into motors. Similarly, if aquaculture and open ocean fishing are not distinguished it is impossible to tell whether fish exports from a country come from farms, with fewer sustainability implications, or from open ocean fishing, with potentially serious overfishing and bycatch concerns.

Eora's country resolution is particularly important in applications dealing with biodiversity and poverty indicators, since these are particularly important for developing countries that are not distinguished in existing MRIO databases. Examples of such countries are Madagascar, a global hot spot of endemic species threatened by habitat loss to agriculture,[51] and Uzbekistan, where foreign demand of cotton places the Aral Lake water metabolism under severe pressure.[52] Any MRIO analysis aimed at identifying the global driving forces of threats to species in Madagascar, and of water use in Uzbekistan, must distinguish these as separate countries.

Finally, it is essential that MRIO information is presented as values along with their standard deviations. Only then can users understand the assumptions and limitations underlying MRIO tables, engage in rational and informed debate, and facilitate transparent decision-making.

■ ASSOCIATED CONTENT

Supporting Information

Additional text, figures, and tables. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

The authors declare no competing financial interest.

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