CIRCLE ECONOMY

The GLOBAL CIRCULARITY GAP Report

2021

Methodology Document

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Summary

This methodology document is meant to provide the technical information behind our assessment of the global greenhouse gas (GHG) mitigation potential of Circular Economy strategies. Because of the new focus of this year's edition - the link between the climate change and circular economy agendas - the data, methods and structure differ from those of the 2020 global CGR and instead come much closer to the latest work done on nations (e.g. Norway). Similarly to National CGRs, the Global CGR 2021 revolves around 3 key analytical elements (deliverables), namely:

1. Scenario modelling through Input/Output Analysis (IOA)
2. Global Circularity and Emissions Gap/Indicator (GCI)
3. Visualizations - Sankey Diagram (SD)

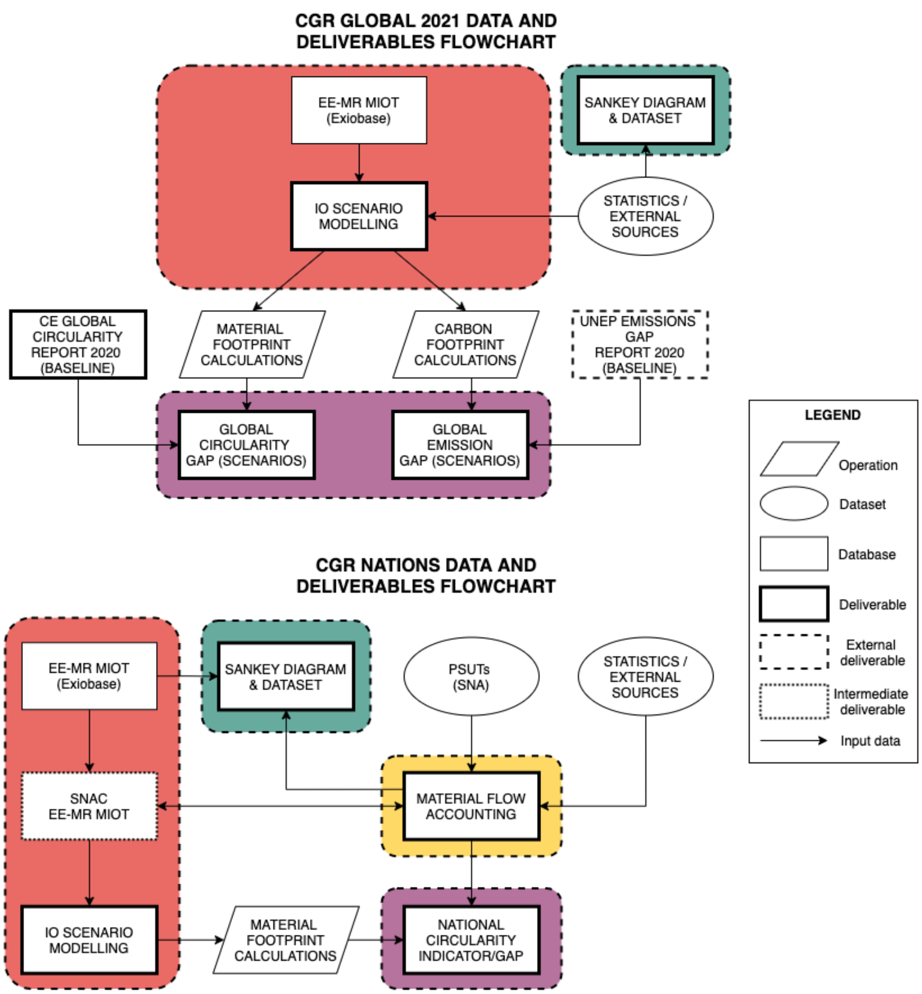


Figure 1. *Comparison of data and deliverables flowcharts for the nations and global 2021 CGRs*

Figure 1 compares the data source and deliverables flowcharts of the reports, pinpointing the high level differences and similarities of the two. With the focus of this year's report being on carbon and scenario analysis rather than on an update of the GCI, the Material Flow Accounting (MFA) was not included as a deliverable. Additionally, a new approach relying solely on external statistics was implemented to create a carbon equivalent of the global material Sankey, linking carbon footprints of resource groups to societal needs. Finally, because of the global scope of the report, no Single-country National Account Consistent (SNAC) version of EXIOBASE had to be developed.

Taking stock of these differences, the analytical scope of the Global CGR 2021 report is to provide a quantified understanding of how circular economy strategies can help mitigate global warming. As mentioned above, the ***accounting*** step (yellow quadrant) represented by the MFA deliverable is not present in this year's report. Consequently, the ***mapping*** (blue step) represented by the Sankey Diagram relies uniquely from the data gathered by external sources such as peer reviewed studies, Systems of National Accounts (SNAs) or grey literature and thus acts as a standalone deliverable. The central element of the CGR 2021 is the ***modelling*** step, in which the Environmentally-Extended Monetary Input Output Tables (EE-MIOT) and external data are used to characterize and parametrise scenarios to calculate economy-wide indicators of environmental pressure. The ***measuring*** step (purple quadrant) is expressed by two headline indicators termed "Global Circularity Gap/Indicator" (GCI) and "Emission Gap" for materials and emissions, respectively. While the CGI - developed by Circle Economy - measures the share of secondary materials in the total material consumption of an economy, the emission gap - introduced by UNEP[1] - gauges how much of the global GHG footprint still needs to be reduced in order to stay within the 1.5- and 2-degrees emissions pathways set by the IPCC. Because for nation reports the baseline circularity indicator needs to be quantified, there is always a first link between the accounting and measuring steps, followed by a second one between modelling and measuring. In the global CGR 2021 the baseline indicators are instead already known and thus the only link that occurs is between the modelling and measuring steps.

[1] United Nations Environment Programme (2020). Emissions Gap Report 2020. Nairobi (https://www.unep.org/emissions-gap-report-2020)

1. Data and system set-up

Our study draws upon an increasingly broad research stream that makes use of Environmentally-extended Multi-regional Input-Output Analysis (EE-MRIOA) to model and assess the potential environmental impacts and benefits of the circular economy from a macroeconomic perspective. Relying on the EE-MRIO database EXIOBASE, our model and underlying methodology builds upon three other studies, namely Wood et al. (2017), Vita et al. (2019) and Donati et al. (2020). While we refer to the aforementioned articles for an explanation of the EE-IOA basics; hereafter a description of the data, modelling methods and system set-up is provided.

Our modelling is based on EXIOBASE v3.7, the latest available version at the time of writing (doi: 10.5281/zenodo.3583071). EXIOBASE represents the production and consumption of 164 industries and/or 200 economic goods for 43 countries and 5 resort- of the-world regions for the year 2016. Satellite accounts for resources and emissions are available for each sector and country. As of v3.7, the end year for the accounts is: 2015 energy, 2016 all GHG (non fuel, non-CO2 are nowcasted from 2015, CO2 fuel combustion is based on data points), 2013 material and 2011 most others, (e.g. land and water). As reported in the methodology document of the CGR Norway, the material extractions are updated to the year 2017 on a country-by-country basis based on the Global Material Flow Database (GMFD) provided by the IRP[2]. For the purpose of this study, we further updated the GHG accounts based on 2018 data from the EDGAR database[3]. In both the case of material and emissions, the update was implemented based on total figures for the materials/GHGs while the allocation to the extracting/emitting industries was based on the EXIOBASE shares for the baseline year (i.e. 2013 for materials and 2016 for GHGs). For each footprint, we consider the resources and pollutants in **Table 1**. Where the input-output database fell short, additional data sources were used to provide further detail, particularly in concerning:

- *Emissions from households*, namely the IEA[4], CAIT[5] and the International Council on Clean Transport (ICCT) for passenger transport-related emissions

[2] https://www.resourcepanel.org/global-material-flows-database

[3] Olivier, J. G., Schure, K. M., & Peters, J. A. H. W. (2020 revision). Trends in global CO2 and total greenhouse gas emissions. *PBL Netherlands Environmental Assessment Agency*, *5*.

[4] https://www.iea.org/data-and-statistics?country=WORLD&fuel=CO2%20emissions&indicator=TotCO2

[5] The World Resource Institute's Climate Data Explorer provides data from CAIT

and the World Green Building Council (WGBC) and Urge-Vorsatz et al. (2015)[6] for domestic heating and cooking data;

- *Land Use and Land Use Change and Forestry* (LULUCF) emissions data from FAO.

Footprint	**Coverage**	**Unit**
Carbon	Global Warming Potential of CO_2, CH_4, NO_2 (combustion and non-combustion) and SF_6. Includes direct households emissions (GWP 100, IPCC 2007)	Gt CO_2 equivalent
Material	Used Extraction of all biotic and abiotic resources	Gt

Table 1. *Comparison of data and deliverables flowcharts for the nations and global 2021 CGRs*

Furthermore, the original 48 regions EXIOBASE IOT was aggregated to only 3 country typologies named: Shift, Grow and Build countries. The classification, already introduced in last year's CGR[7], is based on the ratio between a country's ecological footprint[8] (EF, expressed in Global Hectares) and its Human Development Index[9] (HDI). Shift countries have the highest HDI (>0.8), but also the largest EF per capita (>1). Conversely, Build countries have a very low impact on the planet (EF<1) but they are also falling short from meeting human development targets (HDI<0.8). In between, Grow countries have mixed profiles generally consisting of a moderate EF per capita (>1) but also dwindling levels of human development (<0.8). Clearly, there are outliers to these archetypes, for instance Uruguay is one of the few Shift countries with high HDI to live below the 2 planets threshold. The table matching EXIOBASE regions to their country topology is presented in the **Annex** ("Regions" tab) (Note that for the five Rest-of-the-World regions a population-weighted average was used).

An important dataset used in the calculation of the GCI is the volume of secondary materials used in an economy. Comprehensive datasets around waste and secondary resources are knowingly scarce, uncertain and not up-to-date. For this reason, we relied on one of the few comprehensive sources of waste data, the hybrid

[6] Ürge-Vorsatz, D., Cabeza, L. F., Serrano, S., Barreneche, C., & Petrichenko, K. (2015). Heating and cooling energy trends and drivers in buildings. Renewable and Sustainable Energy Reviews, 41, 85-98.

[7] CGR 2020

[8] https://data.footprintnetwork.org/?_ga=2.168892257.1315424895.1611590891-2708315.1580139050#/

[9] http://hdr.undp.org/en/indicators/137506

version of EXIOBASE v 3.3.18 Supply-and-Use (MR-HSUT) and Input-Output Tables (https://www.exiobase.eu/index.php/data-download/exiobase3hyb). The tables include 43 countries plus five rest-of- the-world regions and are built for the period 2000–2011. MR-HSUTs are compiled in mixed units, that is, tangible goods in mass units, intangible energy flows in terajoules, and, finally, services in euros. In order to bring the waste data in line with the other, we have estimated global industrial waste generation intensities for each sector (tons of waste per M€ of sector output) and municipal waste generation intensities for services and households (tons of waste per capita). For industrial waste, this was done by overlaying the physical and monetary EXIOBASE tables for the baseline year 2011 (v.3.4 and previous) and using 2016 sector outputs (v.3.7) to estimate 2016 waste generation data under the assumption of linear correlation between sector output and waste generation. For municipal solid waste instead, population data from UNEP was used. A summary of the waste data used in this study can be found in the **Annex** ("Waste" tab).

Finally, the information and data to select and build scenarios was gathered from a selected number of studies; among the others and in order of importance: Ivanova et al. (2020)[10], Vita et al. (2019)[11], Moran et al. (2020)[12], Donati et al. (2020)[13], Hertwich et al (2019)[14] and the Drawdown project[15]. As a first step, we extended the harmonised list of interventions built by Ivanova and colleagues (2020), adding more interventions from peer reviewed studies and the drawdown project. A set of 800 non-unique interventions were classified into aggregated interventions archetypes and their results harmonised in CO2eq. per capita. The outcome of this operation was a shortlist of about 70 aggregated interventions archetypes with an average CO2eq. mitigation potential calculated as the mean of all the individual interventions within

[10] Ivanova, D., Barrett, J., Wiedenhofer, D., Macura, B., Callaghan, M., & Creutzig, F. (2020). Quantifying the potential for climate change mitigation of consumption options. Environmental Research Letters, 15(9), 093001.

[11] Vita, G., Lundström, J. R., Hertwich, E. G., Quist, J., Ivanova, D., Stadler, K., & Wood, R. (2019). The environmental impact of green consumption and sufficiency lifestyles scenarios in Europe: connecting local sustainability visions to global consequences. Ecological economics, 164, 106322.

[12] Moran, D., Wood, R., Hertwich, E., Mattson, K., Rodriguez, J. F., Schanes, K., & Barrett, J. (2020). Quantifying the potential for consumer-oriented policy to reduce European and foreign carbon emissions. Climate Policy, 20(sup1), S28-S38.

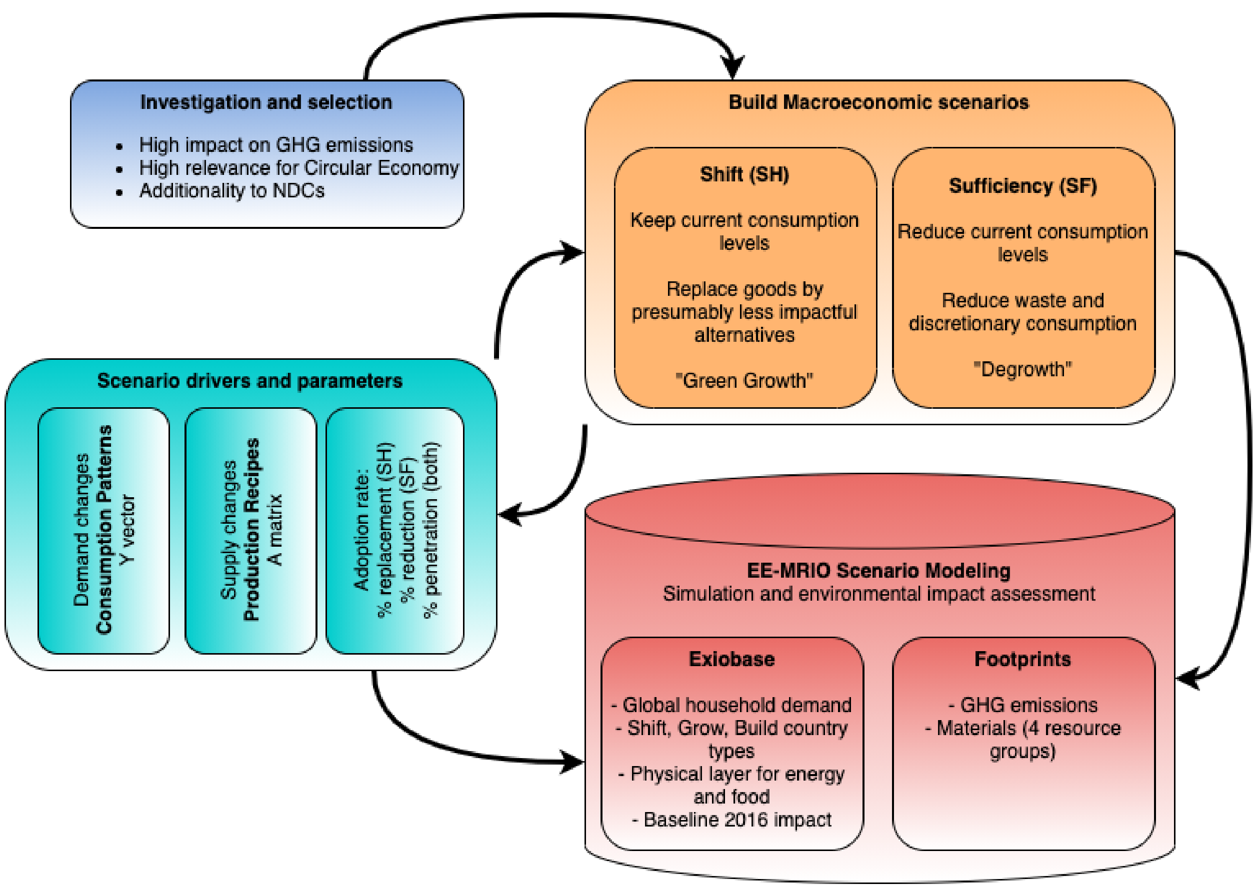
[13] Donati, F., Aguilar-Hernandez, G. A., Sigüenza-Sánchez, C. P., de Koning, A., Rodrigues, J. F., & Tukker, A. (2020). Modeling the circular economy in environmentally extended input-output tables: Methods, software and case study. Resources, Conservation and Recycling, 152, 104508.

[14] Hertwich, E. G., Ali, S., Ciacci, L., Fishman, T., Heeren, N., Masanet, E., ... & Wolfram, P. (2019). Material efficiency strategies to reducing greenhouse gas emissions associated with buildings, vehicles, and electronics—a review. Environmental Research Letters, 14(4), 043004.

[15] https://drawdown.org/

the category. The use of the mean mitigation potential was two-fold: as a criteria to select the most effective archetypes in terms of CO2eq. mitigation potential and as a benchmark to compare the results of our model against.

Two additional criteria were used to further slim down the list and prioritise interventions archetypes: relevance to material footprint and circularity and additionality to National Defined Contributions (NDCs). Each criterion is related to a salient feature of the analysis, namely the link between the circular economy and the climate mitigation agendas and the additionality of circular strategies to the current commitments related to the Paris Agreement. Finally, the selected interventions archetypes were grouped further to form the final 21 scenarios presented in the report. More information about the interventions, their aggregation into scenarios and the underlying modelling parameters can be found in **Chapter 3** and summarised in the **Annex** ("Param" tab).



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2. Global Circularity Indicator

The **Global Circularity Indicator (GCI)** and **National CIrcularity Indicator (NCI)** are CIrcle Economy's flagship metrics to measure circularity. There are two sides to each metric: The "Indicator", which measures the degree of circularity of an economy, and its inverse – the "Gap" – which measures the share of non-circular inputs to an economy. Building upon the work by Haas and colleagues[16] and the indicators framework for an economy-wide Circular Economy (CE) assessment put forward by Mayer and colleagues[17], in its most generalized way the formula for calculating the Circularity Indicator is the following:

$$GCI_i = \left(\frac{w_{rec_i} + sm_{ntb_i} + wu_i}{RMC_i + w_{rec_i} + sm_{ntb_i} + wu_i}\right) * 100$$

Where w_{rec} is the amount of recycled and recovered materials, sm_{ntb} represents the *Net Trade Balance of secondary (or cycled) materials* while $RMC$is the *Raw Material Consumption*. From a global perspective imports, exports and thus also the trade balance are null, therefore:

$$imp_i - exp_i = 0 \Leftrightarrow ntb_i = 0$$

$$sm_{imp_i} - sm_{exp_i} = 0 \Leftrightarrow sm_{ntb_i} = 0$$

$$DE_i + imp_i - exp_i = RMC_i \Leftrightarrow DE_i = RMC_i$$

$$sm_{dom_i} + sm_{imp_i} - sm_{exp_i} = smc_i \Leftrightarrow sm_{dom_i} = smc_i$$

$$GCI_i = \left(\frac{sm_{dom_i} + wu_i}{DE_i + sm_{dom_i} + wu_i}\right) * 100$$

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[16] Haas, Willi, et al. "How circular is the global economy?: An assessment of material flows, waste production, and recycling in the European Union and the world in 2005." *Journal of industrial ecology* 19.5 (2015): 765-777.

[17] Mayer, Andreas, et al. "Measuring progress towards a circular economy: a monitoring framework for economy-wide material loop closing in the EU28." *Journal of industrial ecology* 23.1 (2019): 62-76.

$$GCG = 100 - GCI$$

Therefore, the GCI measures the share of secondary materials in the total material consumption of an economy which, from a global perspective, corresponds to the global virgin material extraction plus the secondary materials input. As such, according to the distinction introduced by Mayer et al. (2019) and Haas et al.[18] (2020), the CGI can be classified as an input-side rate indicator and it is equivalent to what they termed "*socio-economic cycling*"[19]. **Table 2** lists all the variables involved in the estimation of the GCI together with a short description.

Table 2. *GCI-related variable definitions*

Variable	Definition
sm_{dom_i}	Secondary materials of resource group *i* deployed domestically
sm_{imp_i}	Secondary materials of resource group *i* deployed domestically and imported (the latter include imported waste for recycling and share of secondary materials in imported products)
sm_{exp_i}	Secondary materials of resource group *i* consumed domestically
sm_{ntb_i}	Secondary materials trade balance of resource group *i*
wu_i	Waste of resource group *i* reused domestically without (or with minimal) pre-processing
imp_i	Net direct imports of physical products of resource group *i*
exp_i	Net direct exports of physical products of resource group *i*
ntb_i	Trade balance of physical products of resource group *i*
DE_i	Domestic extraction of resource group *i*
RMC_i	Raw Material Consumption of resource group *i*

Table 3 shows the latest estimated GCI figures for the year 2016 used in the CGR 2021. For more details on the data and methods behind the GCI please refer to the Measuring & Mapping Circularity - methodology document.

[18] Haas, W., Krausmann, F., Wiedenhofer, D., Lauk, C., & Mayer, A. (2020). Spaceship earth's odyssey to a circular economy-a century long perspective. Resources, Conservation and Recycling, 163, 105076.

[19] As presented by the authors, the socio-economic cycling is just one of the input-side indicators of the frameworks, which includes among the other the ecological cycling potential and the stock additions. Circle Economy has already started to implement the full indicator set in its upcoming national reports

Table 3. *Global Circularity rates per resource groups as per CGR 2020 (2016 - partial update)*

Biomass	**Fossil Fuels**	**Metal Ores**	**Minerals**	**Average**
8.9%	0.8%	9.0%	13.8%	**8.6%**

3. I-O Scenario Modelling

Building upon the original work of Wood et al (2017)[20], we use an environmentally-extended input-output framework to calculate the current environmental pressures of global consumption as a baseline (year 2016), and then compare it with the resulting footprints from the modelled scenarios. We employ a counterfactual method and operational tool for scoping the potential impact of such actions, focusing on economy-wide impact. This "quickscan" tool can model shifts and reductions in demand, changes in domestic and international production recipes, and reductions in the environmental intensity of production. However, conversely from the one by Wood and colleagues, it does not allow to model rebound effects using marginal expenditure.

Environmental pressures or footprints, fp, represents the total consumption impacts from global households (divided into Build, Grow, Shift regions). We calculate fp as a function of household demand, y, as follows:

$$\mathbf{fp} = \mathbf{s}\,(\mathbf{I} - \mathbf{A})^{-1}\,\mathbf{y} + \boldsymbol{dhe}$$

where s is the intensity coefficient vector resulting from dividing the total resource or emission required for the production of a given good by its economic output (e.g. CO_2/EUR), I is the identity matrix and A is the technical coefficient matrix, representing the inter-industry requirements. The dhe vector represents direct household emissions from the combustion of fuels for transport, cooking and heating.

The global EE-MRIO described so far accounts for different production recipes, trade supply chains and household consumption patterns across nations. The parameters that ultimately drive the scenarios are changes in consumption, production recipes

[20] Wood, R., Moran, D., Stadler, K., Ivanova, D., Steen-Olsen, K., Tisserant, A., & Hertwich, E. G. (2018). Prioritizing consumption-based carbon policy based on the evaluation of mitigation potential using input-output methods. Journal of Industrial Ecology, 22(3), 540-552.

and uptake rates. The basis of the model to simulate backcasting scenarios is to perturb the EE-MRIO by modifying the consumption patterns in the y vector or production recipes in the A industry matrix (Wood et al. 2017, Vita et al. 2019, Donati et al. 2020). The magnitude of the perturbations is determined by the technical change coefficients (0 to 1) and penetration coefficients (0 to 1) presented in the **Annex** (Tab “Param”) which together determine the uptake rates of an intervention. For a description of the full mathematical model refer to Wood et al. (2017) and Donati et al. (2020).

In this report, we model visions of alternative consumption patterns in households (y vector of final demand per product), and/or changes in industrial recipes (A matrix of technical coefficients). We assume a regular functioning of welfare institutions (health, education, pensions etc.) by holding all services provided by governments and social institutions (NPISH) constant.

After Wood, Vita, Donati and colleagues we model three types of scenarios:

1. Change in households’ demand (Change in y): Either a reduction in consumption or consuming different goods. In both cases, the scenario modelling consists of simulating a demand change in the relevant goods.
2. Change in industries’ demand (Change in A): When the envisioned scenario depends on changes in inter-industries production recipes and inputs. For example, to produce Natural Fibres implies reducing the inputs of synthetic textiles to the apparel sectors.
3. Change at both households’ and industries’ demand (Change in A and y): Some scenarios entail simultaneous changes in household demand and industrial practices.

For example, adopting vegetarian diets would imply that households reduce their purchase of meat directly (y) but also that restaurants have less demand for meat products (A). While *sufficiency* scenarios imply a *net reduction* in the consumption of specific goods, *shift* scenarios imply that the reduced *consumption of one product* (i) *is substituted by increasing the demand of another product* (g) (**Figure 2**). Substitute products may differ in price or energy content per functional unit, the extent of replacement is affected by the relative differences (p) between the products, with no differences having a unitary value.

Expenditure was kept as the monetary functional unit for most services and aggregated product categories, as no physical layer could be derived. The original model allowed for price differences in product substitutes but did not explicitly consider the physical utility delivered by goods (e.g., energy use, calories provided) (Wood et al. 2017). Following the improvements by Vita et al. (2019), we enhanced the model by introducing a physical layer to balance food and energy goods to ensure food and energy sufficiency in our scenarios. For food and energy, which make up nearly half of the EXIOBASE 3 goods, prices underlying the EXIOBASE 3 model (Wood et al. 2015)[21] were used to convert to mass or volume. Further, data on energy content was applied in order to convert to physical functional units i.e. kcal or TJ by weight in kilograms (or by volume in m3). For more information over the data sources and assumptions behind the physical layers please refer to the SI of Vita et al. (2019). For the physical layer data and calculations refer to the **Annex** (tab "Layers"). Deriving physical functional units allows us to introduce the current living standards as a constraint by keeping the same level of nutrition (kcal) or energy use (kWh) while shifting the means of provision. This allows us to model reductions in food and shelter without falling in a situation of food scarcity or energy poverty. The differences in prices or energy content per kilogram of fuels and food that modulate product substitution are modelled as follows:

$$p_{ig} = \frac{p_g}{p_i}$$

Where p_{ig} determines the proportion of expenditure shifted in a given scenario. For example, a value of 0.5 would mean 50% of the expenditure of reduced products, i is shifted to increased products, g. This would be the case if a substitute energy carrier delivered twice as dense as the current i.e. double energy per weight. For monetary layers, an example would be buying textiles for do-it-yourself clothes is five times cheaper than in-store apparel i.e. $p \approx 0.2$. Differences in price and energy densities modulate the substitution share in products demanded by households and industries alike (Wood et al. 2017, Vita et al. 2019). While differences in energy densities are modelled for all food and energy, price differences between substitute goods modelled in monetary terms were rarely assumed, reported in the "price deflator" row in the **Annex** (tab "Param"). Differentiating price and quality between comparable goods is limited by the product aggregation in EE-MRIO analysis[22].

As highlighted by Moran et al (2019), this model considers the impact of actions at the margin, if taken tomorrow. Modelling the efficacy of the options if they are adopted at different points in time becomes far more complex, as the sequencing creates many different path-dependent trajectories (e.g. the carbon footprint of electric vehicles depends strongly on the carbon intensity of the electricity used to fuel them). Some of the behaviour changes considered affect the volume of a particular stock while other affect yearly flows. We considered the impact of a

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[21] Wood, R., K. Stadler, T. Bulavskaya, S. Lutter, S. Giljum, A. de Koning, J. Kuenen, et al. 2015. Global Sustainability Accounting—Developing EXIOBASE for Multi-Regional Footprint Analysis. Sustainability 7(1): 138–163. http://www.mdpi.com/2071-1050/7/1/138/.

[22] Girod, B. and P. de Haan. 2010. More or better? A model for changes in household greenhouse gas emissions due to higher income. Journal of Industrial Ecology 14(1): 31–49.

particular behaviour change as the yearly impact in a future year in which the relevant stock has been fully replaced. For example, the impact of improving building insulation is the comparison between the baseline scenario against a future steady-state situation in which the relevant stock has been replaced following the change.

All the input-output and counterfactual scenario calculations are performed using a custom-made software that integrates the open source tool for analysing global EE-MRIOTs **pymrio**[23] and the Python package for modeling circular economy policy and technological interventions in EE-MRIOs named **pycirk**[24]. A comprehensive overview of the scenario results is provided in the **Annex** (Tab “results’).

[23] https://pymrio.readthedocs.io/en/latest/index.html

[24] https://pycirk.readthedocs.io/en/latest/readme.html

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4. Visualizations

4.1 Sankey Diagram

For the first time in a CGR, the topic of the Sankey diagram changed from displaying the global material flows of the 4 resource groups to the emissions embodied in such flows. The goal this year was to link emissions at the point of their release by industrial processes - upstream to the amounts in which they are embodied in resource groups - and downstream to the amounts in which they are embodied in final demand for industries/goods as they contribute to the 7 key societal needs.

The change in subject was followed by a change in the method used to assemble the Sankey as well. Instead of relying on the EXIOBASE hybrid input-output tables, this version was based on a collection of statistics and data points gathered from a variety of sources and put together to generate the flow diagram. The process followed the method outlined by Allwood and colleagues (2013)[25] in which each stage of the chain (resource groups, take, process, produce and provide) defines a complete inventory of emissions (e.g., Va) for sectors and activities belonging to that stage. Adjacent inventories (e.g., Vb) must therefore be connected by transformations (Vb = [A]·Va) which fully reallocate the same total emissions, so the rows of A sum to unity. Because existing data do not always match the inventories required in each stage, the exercise is to produce such transformation matrices by gathering, interpreting and harmonising data form different sources.

Because of the inherent uncertainty of such a process, the majority of the efforts were focused on a few stages for which robust references could be found. For other transformation matrices (or parts thereof), instead, the data was either scarce or difficult to interpret, in which case the chosen values were based on expert judgment and are to be considered more as ballpark estimates rather than accurate representations of reality. The tables with allocation factors are presented in the **Annex** ("Allocations" tab).

[25] Bajželj, B., Allwood, J. M., & Cullen, J. M. (2013). Designing climate change mitigation plans that add up. Environmental science & technology, 47(14), 8062-8069.

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4.2 Material Footprint of Consumption Categories

This section explains how EXIOBASE was used to estimate the carbon footprint of consumption categories (or societal needs) for the Sankey diagram

Building upon the work by Ivanova et al. (2017)[26], we applied a similar classification to final demand items belonging to 9 consumption groups: Nutrition, Housing, Energy, Capital Equipment, Consumables, Communication, Services, Mobility and Healthcare. Differently from Ivanova et al. (2017), we assigned a classification to all products and not only those for which there was a final demand. We then calculated the consumption-based footprint for the 4 resource groups and performed a contribution analysis to reveal how the key consumption groups contributed the resource footprint. Finally, we narrowed down the number of the groups to 7 keys societal needs by re-allocating Energy and Capital Equipment to the other groups. This step was carried out by using the structure of the total requirement matrix to find out how much of Capital Equipment and Energy (the total input requirement per unit of total output) would feed into every other consumption group. We used these shares calculated from the total requirement matrix to re-distribute the Energy and Capital Equipment footprint to the other 7 consumption categories and disregarded the rest of their footprint (i.e. Energy to Energy and Capital Equipment to Capital Equipment). We applied the same principle to split the housing footprint into the actual housing part (total input requirement per unit of output of housing to housing) and the infrastructure and non-residential part (total input requirement per unit of output of housing to other consumption groups) and re-allocated it to the other consumption groups. All the operations were done using EXIOBASE v3.7 and the open source tool for analysing global EE-MRIOTs, **pymrio**.

[26] Ivanova, D., Vita, G., Steen-Olsen, K., Stadler, K., Melo, P. C., Wood, R., & Hertwich, E. G. (2017). Mapping the carbon footprint of EU regions. Environmental Research Letters, 12(5), 054013.