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Trade-offs between social and environmental Sustainable Development Goals

Laura Scherer[a,*], Paul Behrens[a,b], Arjan de Koning[a], Reinout Heijungs[a,c], Benjamin Sprecher[a], Arnold Tukker[a]

[a] Institute of Environmental Sciences (CML), Leiden University, Leiden, the Netherlands
[b] Leiden University College The Hague, 2595 DG, The Hague, the Netherlands
[c] Department of Econometrics and Operations Research, Vrije Universiteit, Amsterdam, the Netherlands

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ABSTRACT

The UN's 17 Sustainable Development Goals (SDGs) aim to improve the lives of people, increase prosperity, and protect the planet. Given the large number of goals, interactions are inevitable. We analyse the interaction between two social goals (related to SDG1 Poverty and SDG10 Inequality) and three environmental goals (related to SDG13 Carbon, SDG15 Land, and SDG6 Water). We use a trade-linked, consumption-based approach to assess interactions in 166 nations, each subdivided into four income groups. We find that pursuing social goals is, generally, associated with higher environmental impacts. However, interactions differ greatly among countries and depend on the specific goals. In both interactions, carbon experiences smaller changes than land and water. Although efforts by high- and low-income groups are needed, the rich have a greater leverage to reduce humanity's footprints. Given the importance of both social and environmental sustainability, it is crucial that quantitative interactions between SDGs be well understood so that, where needed, integrative policies can be developed.

1. Introduction

In response to increasing concern about the long-term sustainability of human societies, the United Nations developed the Sustainable Development Goals (SDGs), a 2030 agenda including 17 goals and 169 targets (United Nations, 2016). Despite criticisms of the framework (Kopnina, 2015), these goals currently dominate the sustainability and policy discussions surrounding development. Some initial progress towards the SDGs was achieved, but our understanding of interactions between SDGs remains limited (Allen et al., 2018). With such a plethora of goals and targets, interaction is inevitable. Possible interactions range from cancellation (achievement of an SDG makes progress on another impossible) to indivisibility (success in an SDG is contingent on success of another) (Nilsson et al., 2016). Correlations between SDGs mostly point towards synergies, but also indicate trade-offs (Pradhan et al., 2017). For some SDGs these interactions are clear, while others are opaque. For example, the environmental impact of increasing equality across income groups could be positive or negative (Rao and Min, 2018). The magnitude of interaction effects is also critical. Although one can assume that increasing incomes above extreme poverty will increase environmental pressures, the magnitude and location of these impacts caused by the global economy are rarely investigated (Hubacek et al., 2017). Given the importance of these goals and their short time horizon, it is critical that policy makers receive relevant and timely information to facilitate potential mitigation or adaptation policies on SDG trade-offs.

Here we quantitatively assess the environmental impacts of ending poverty (related to SDG 1: no poverty), and reducing inequality (related to SDG 10: reduced inequalities). Our choice of social SDGs is motivated by previous findings that individual consumption is the most significant driver of environmental pressures, rather than population (Bradshaw et al., 2010). Furthermore, since poverty and inequality are reflected in consumption volumes (Aguiar and Bils, 2015), any developments suggest concomitant changes in environmental impacts among income groups.

The majority of environmental impacts can be attributed both directly and indirectly (through supply chains) to the consumption by households (Ivanova et al., 2016). Household consumption is a key indicator of wealth and poverty within the SDG framework. Previous work on the environmental impact of household consumption has generally focused solely on a single country or region and a single footprint (López et al., 2017; Sommer and Kratena, 2017; Wiedenhofer

* Corresponding author at: Institute of Environmental Sciences (CML), Leiden University, P.O. Box 9518, 2300 RA, Leiden, the Netherlands.
E-mail address: l.a.scherer@cml.leidenuniv.nl (L. Scherer).

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et al., 2017). Cross-country analyses rarely distinguish income levels (Ivanova et al., 2016), or are limited to one interaction with the environment (Hubacek et al., 2017). In this work, we quantify the effect of reducing extreme poverty and inequality on environmental impacts. We estimate country-specific effects for 166 nations of the world (Fig. A1), covering 6.84 billion people (99% of the total population; UN, 2017). We choose three environmental footprint categories corresponding to carbon (CO_2-equivalents, related to SDG 13: climate action), land (land stress, related to SDG 15: life on land), and water (freshwater scarcity, related to SDG 6: clean water and sanitation). Water and land, as our most vital resources, are scarce (Lambin and Meyfroidt, 2011; Scherer and Pfister, 2016a), and global temperature rise is still accelerating (Smith et al., 2015), which highlights the importance of these three environmental categories.

To perform the analysis, we link the Global Consumption Database of the World Bank (World Bank, 2017c) to EXIOBASE (Stadler et al., 2018). In EXIOBASE, international trade links the production and consumption of countries. This approach is essential, as 20–37% of environmental impacts are related to production for exports (Lenzen et al., 2012; Wiedmann, 2016). Our year of reference is 2010. As the magnitude and pattern of expenditure differs among income groups (see Figs. A2 and A3), we investigate trends within four different income groups.

2. Methods

2.1. Household expenditures

Fig. A4 shows the conceptual framework of the main analysis. The World Bank distinguishes four income groups for household expenditures of 106 products and services in 91 countries in 2010 (World Bank, 2017c). The income groups use international dollars, considering the purchasing power parity, and are split by absolute monetary boundaries: lowest ≤ \$2.97, low = \$2.97–8.44, middle = \$8.44–23.03, and higher ≥ \$23.03 per capita per day. Per-capita expenditures are multiplied with the population of each income group to obtain total expenditures per income group. To link the World Bank database to EXIOBASE, the expenditures are reclassified to the 200 products and services of EXIOBASE. First, a concordance matrix (C) is built, which indicates if a class from the World Bank is (partially) contained in a class of EXIOBASE (1) or not (0). Second, a bridge matrix (B) is estimated that translates the classes from one system to the other:

$$f_2 \approx f_{2,100} = B_{100}{}^T \bullet f_1$$

where f_1 is the total expenditures or final demand vector from the World Bank and f_2 is the total final demand vector in the classification of EXIOBASE. The index of 100 indicates the maximum number of iterations during which B is estimated. A first guess of B (B_1) is derived from C with the additional information about the distribution of total expenditures among the EXIOBASE classes (d_2), a vector whose sum equals 1:

$$B_i = (C \hat{\cdot} d_2)^{-1} \bullet C \bullet \hat{d}_2$$

where the hat (ˆ) denotes a diagonal matrix of a vector. Subsequently, B is iteratively updated to further harmonise the two classification systems using a variant of the RAS algorithm (Stone, 1961):

$$B_{i+1} = \hat{r}_i \bullet A_i \bullet \hat{s}_i$$

where

$$A_i = \hat{f}_1 \bullet B_i$$

$$s_i = d_2 \oslash d_{2,i} = d_2 \oslash (f_{2,i} / (\vec{1}^T \bullet A_i \bullet \vec{1}))$$

$$r_i = f_1 \oslash f_{1,i} = f_1 \oslash (A_i \bullet \hat{s}_i \bullet \vec{1})$$

where ⊘ is Hadamard (element-wise) division and $\vec{1}$ is a column vector of 1′s. B is calibrated without distinguishing income groups in either classification, and then applied to reclassify the World Bank's detailed expenditures to EXIOBASE's product system.

We estimate expenditures per income group for additional 74 countries (24% of the analysed population but 82% of the expenditures) by assuming a lognormal distribution of incomes (Bílková and Malá, 2012; Easterly, 2009). The income Gini index (Central Intelligence Agency, 2017; World Bank, 2017b) (G) allows to calculate the standard deviation (σ) of that distribution (Bílková and Malá, 2012):

$$\sigma = 2 \bullet erf^{-1}(G)$$

where erf^{-1} is the inverse error function. The Lorenz curve with the resulting standard deviation, calculated with the function "Lc.lognorm" in R package "ineq" (Zeileis, 2014), provides the cumulative income shares. Income shares are then multiplied with the mean per-capita expenditures (World Bank, 2017d) and a sample population of 10,000 to get individual incomes, which are subsequently split into income groups at a precision of 2 decimal percentages. Since the income boundaries are expressed in international dollars, but expenditures in US dollars, we multiply the thresholds with the country's price level ratio (World Bank, 2017e). Gaps in expenditures are first filled with estimates from a linear regression with the country's GDP (World Bank, 2017a) (adjusted $R^2 = 0.89$). Remaining gaps in income Gini indices and expenditures are filled with values from nearby countries. Population data is obtained from the United Nations (UN, 2017). EXIOBASE provides expenditure patterns for 32 of the additional countries without differentiating incomes (Tukker et al., 2013; Wood et al., 2015). In contrast to countries covered by the Global Consumption Database, expenditure patterns of countries covered by EXIOBASE are assumed not to differ among income groups. For the remaining 43 countries (9% of the analysed population), the expenditure patterns are assumed to be equal to nearby countries. Which countries follow which approach is listed in Appendix B.

To validate our approach of using the Gini index to derive income contributions of EXIOBASE countries, we compare our estimates of income quintiles with the income quintiles given in the World Bank's Development Indicator Database. The estimates and reference values are provided in Appendix C, along with the Pearson correlation coefficients for a total of 40 countries for which the required data is available in the year 2010. The correlation coefficient ranges from 0.9965 to 0.9999, demonstrating the robustness of our method.

For visualization and interpretation, products are aggregated to seven consumption categories. 1) Food includes plant-based and animal products as well as restaurant services. 2) Housing includes real estate services, forestry and wood products, construction materials, water, and waste. 3) Energy includes electricity, housing fuels, and hot water. 4) Transport includes vehicles, transport services, and transportation fuels. 5) Clothing includes wearing apparel, furs, and products from wool, textile, and leather. 6) Manufactured goods include machinery, equipment, and other manufactured goods. 7) Services include education, health, recreational, and other services.

2.2. Environmentally extended multi-regional input-output analysis

We use the product-by-product version 3.4 of EXIOBASE (Stadler et al., 2018) based on the industry technology assumption for environmentally extended multi-regional input-output analyses (EE-MRIO). It allows to connect national consumption to production anywhere in the world, and covers 200 product groups per country and 49 countries or regions. The impacts of a country's consumption sourcing products from different locations are then evaluated by:

$$H = Q \bullet B \bullet (I - A)^{-1} \bullet F + D$$

where H is the impact matrix with income groups as columns. Q is the characterization matrix that describes the impacts per unit of emission

or resource. B is the satellite matrix that describes the emissions and resources per product unit. $(I-A)^{-1}$ is the Leontief inverse that expresses the total requirements per product unit for each product and A is the structural matrix of the economy, which is essential for input-output analyses (Tukker et al., 2013; Wood et al., 2015). F is the final demand disaggregated into income groups and consumption categories. Finally, D represents the direct household impacts disaggregated into income groups.

Direct emissions and resource uses are allocated to the income groups based on the final demand of associated products. Greenhouse gas emissions are allocated based on expenditure shares of 44 fuels, the total energy use (TJ) of each fuel (from EXIOBASE v3.3, as the energy extension is aggregated in v3.4), and the CO_2 emission intensity of those fuels (from IPCC's emission factor database; IPCC, 2018). Land use is allocated based on "real estate services", and water consumption based on "collected and purified water, distribution services of water" and "steam and hot water supply services". When these products amount to zero in the final demand, the total expenditure is used for allocation instead. This concerns Tajikistan for land use, and Honduras, Iceland, India, Ireland, and Papua New Guinea for water consumption.

We characterize the environmental impacts of three impact categories – climate change, land use, and water consumption – using a linearized model through matrix Q above. Climate change impacts are assessed by greenhouse gas emissions (GHG) and their global warming potentials (GWP) at a 100-year time horizon (IPCC; Myhre et al., 2013) to characterize the impacts of those emissions. Considered gases include CO_2, CH_4, N_2O, SF_6, HFCs, and PFCs. The impacts are aggregated to a carbon footprint (CF) expressed in kg CO_2-equivalents.

$$CF = GHG \bullet GWP$$

Land use and water consumption are also weighted, as non-weighted resource use does not always align with the consequences of that use (Font Vivanco et al., 2017). Land use (LU) includes agricultural and forest land, which is converted to a land footprint (LF) in km^2-equivalents using land stress indices (LSI; Pfister et al., 2011). These stress indices are the ratio of the site-specific net primary productivity of the natural reference vegetation (NPP_0; Haberl et al., 2007) to the global maximum ($NPP_{0,max}$). It implies that using land with a higher NPP_0 causes more damage, as NPP_0 positively influences biodiversity and the provision of ecosystem services (Haberl et al., 2007).

$$LF = LU \bullet LSI = LU \bullet \frac{NPP_0}{NPP_{0,max}}$$

Water consumption (WC) focuses on surface and groundwater (blue water). We do not take into account soil moisture (green water), as the two types of water are not directly comparable. Green water can only be consumed by the vegetation that occupies land and cannot be used for other purposes, which might lead to double counting with land use impacts. In addition, natural vegetation would also have consumed green water, and the net change might even be positive (Pfister et al., 2017). Blue water consumption is translated to water scarcity footprints (WF) in million m^3-equivalents using the average of two water scarcity index (WSI) estimates (Pfister and Bayer, 2014; Scherer and Pfister, 2016a). Water scarcity indices are derived from the water consumption-to-availability ratio (CTA) and scaled to a 0-to-1 range using a logistic function.

$$WF = WC \bullet WSI = WC \bullet f(CTA)$$

Both land stress and water scarcity indices are available as global rasters and aggregated to country averages by overlaying the rasters with country boundaries (Hijmans et al., 2014). Since the weighted land use and water consumption metrics are not as familiar as the carbon footprint, we perform a sensitivity analysis (Appendix A, Fig. A5).

2.3. Inequality in footprints

We have used Gini indices (G) above to split the population of some countries into income groups. Like in previous studies where Gini indices have already been applied to environmental inequality, especially carbon footprints (Steinberger et al., 2010; Teixidó-Figueras et al., 2016; Teng et al., 2011; Wiedenhofer et al., 2017), we follow Teng and colleagues (Teng et al., 2011) to derive environmental Gini indices from the Lorenz curve. The Lorenz curve displays the cumulative impact shares against the cumulative population shares, sorted so that the impact per capita is ascending. The 45-degree line marks perfect equality. The Gini index is defined as the ratio of the area between the equality line and the Lorenz curve to the total area below the equality line. Since the total area below the line is 0.5, the equation can be reformulated based on the area below the Lorenz curve (A_L):

$$G = 1-2 \bullet A_L$$

A value of 0 represents perfect equality with all people having the same footprint and a value of 1 represents the highest inequality with one person among many being responsible for the total footprint of all. A_L is approximated by the sum of the trapezoidal areas. Since trapezoids overestimate A_L, especially with small sample sizes ($n = 4$), and, as such, underestimate G, we reduce the bias by calculating an adjusted Gini index (G_{adj}; Deltas, 2003):

$$G_{adj} = \frac{n}{n-1} \bullet G$$

As an alternative measure of inequality, we also calculate the coefficient of variation, i.e. the ratio of the standard deviation to the mean. The measure does not have an upper limit, i.e. it can exceed 1. While the Gini index is more sensitive to the centre of the distribution than its extremes, the coefficient of variation is neutral in terms of the distribution (Duro, 2012).

2.4. Scenario analysis

We explore two scenarios related to the social SDGs 1 (no poverty) and 10 (reduced inequality) of the United Nations (2016). In the first scenario, extreme poverty is eliminated and we allow expenditure of those concerned to increase to 1.25 international dollars per capita and day. While a previous study considered average incomes of the lowest income group for a similar scenario (Hubacek et al., 2017), we explicitly analyse how many people of the lowest income group live in extreme poverty. The population of each country that lives in extreme poverty and their average expenditure is estimated in the same way as the income groups have been split, by using the Gini index of income. The price levels of the countries contained in the World Bank's database are derived from expenditures given in both US and international dollars. Subsequently, country-specific impacts of the lowest income group are increased by the same factor as the expenditure increases.

In the second scenario, inequality is reduced by limiting the Gini index of income or expenditure to a maximum of 0.3, slightly less than the median or half the maximum. The original Gini indices of countries contained in the World Bank's database are estimated in the same way as the Gini indices of footprints have been estimated. After modifying the Gini indices of income or expenditure, new population and expenditure distributions are estimated for all countries, while total expenditures are maintained at the original level. Similar to the previous scenario, country-specific impacts of all income groups are changed by the same factor as the expenditure changes.

We apply these scenarios to the year of analysis, 2010, and do not project into the future. On the one hand, some argue for a delay in environmental impact mitigation due to inequalities among present and future generations. They discount future generations and because future generations are on average richer they can easier afford mitigation costs (Budolfson et al., 2017). On the other hand, others argue for fast

environmental impact mitigation due to high inequalities within our present generation. The poor disproportionately suffer from environmental damages and if the rich assume a greater responsibility in bearing the costs, the poor of today, the ones most in need, will benefit (Budolfson et al., 2017). We follow the latter argumentation that we need to act now or should already have started acting back in 2010 and, therefore, keep our scenarios in that year. This also avoids increasing the uncertainties from extrapolation into the future.

As a sensitivity analysis, we also explore modified versions of the above scenarios. First, we assume a higher international poverty line of $1.90 per capita and day, according to an update by the World Bank (Ferreira et al., 2016). Second, we halve the Gini index of income of all countries.

We further explore mitigation efforts. To meet the 2°C climate target, the carbon footprint must be halved from 1990 to 2050 (Meinshausen et al., 2009). For water, a similarly ambitious target was suggested, which implies halving the water footprint (Scherer and Pfister, 2016a), while for land, the Aichi target 15 of the Convention on Biological Diversity (2010) demands to restore at least 15% of degraded ecosystems. Based on these global targets, we aim to reduce the water, land, and carbon footprints of households by 50, 15, and 50%. We identify universal footprint caps without increasing the footprints of those still below the thresholds after eliminating extreme poverty. The required reduction of each income group is then derived from the ratio of the footprint cap to the current footprint without extreme poverty.

2.5. Limitations of the study

While EXIOBASE relies on top-down estimates of the national consumption, the detailed Global Consumption Database is based on surveys of a sample of the total population. Therefore, the total consumption and the consumption patterns in EXIOBASE and the World Bank's Global Consumption Database do not always match well. For this work, we assumed that the survey data is more accurate than the top-down estimates.

Extreme incomes of the extremely poor and the super-rich might be associated with extreme lifestyles such as illegal deforestation (Tollefson, 2015) and the use of private jets (Datta, 2013), and severe environmental impacts. Those extremes are not well represented by the homogeneous product categories available in EXIOBASE.

While the impact inequalities are large, it should be noted that we might even underestimate them. Investments made by households are not included in the household expenditures (Ivanova et al., 2016). These are expected to be proportionally higher in higher income groups. Besides, infrastructure capital, such as roads enabling transport, are not considered in household expenditures (Ivanova et al., 2016) and are also expected to be proportionally more used by higher income groups. In contrast, the analysis assumes that members from all income groups buy products with the same impacts per unit expenditure, while higher expenditures within a product category might be due to higher prices for the same physical amount, and this same amount might even be more sustainable, e.g. due to higher efficiencies. Therefore, an overestimation of the impact inequality is also possible. These uncertainties in impact inequality similarly affect the scenarios of poverty alleviation and income redistribution for an income inequality reduction.

We measure inequality by two indices to increase robustness; however, only the Gini index is used in the scenario related to SDG 10 and the reduction of inequality. We have already mentioned that the Gini index is more sensitive to the centre of the distribution than its extremes. Alternative measures, such as the Theil and Atkinson family of indices, are more sensitive to the bottom of the distribution, and are also valuable or even preferable in inequality studies (Duro, 2012). Still, the Gini index is the most commonly used measure and, therefore, allows for greater comparability across studies.

While each SDG is subdivided into several targets, we represent each goal with only one indicator. We believe that our quantitative study of these key indicators at a global, economy-wide scale is very valuable.

Another limitation of our study is the unchanged structure of the economy and associated environmental intensities. In reality, these might change after successful implementation of the SDGs. For an example of scenario-based analyses within the input-output framework, see de Koning et al. (2015) who considered such changes.

3. Results and discussion

3.1. Global inequality and environmental impacts

The food sector dominates footprints of all income groups. Globally, it comprises 28% of households' carbon footprint. Within the food category, the major contributions to the carbon footprint come from cattle and rice. The second largest sector is energy use (19%), especially electricity from coal, followed by direct household emissions (16%). Food also dominates the land footprint (43%), followed by direct land use (32%). In the lowest income group, the shares differ significantly from those across income groups (55% for food and 20% for direct land use). Food alone is responsible for 73–92% of the water footprint.

The lowest income group represents 45% of the population (three billion people), but is associated with an estimated 10, 14, and 30% of household's carbon, land, and water footprints (Fig. 1, Table A1). In contrast, the higher income group (17% of the population) cause an estimated 57, 42, and 32% of household's carbon, land, and water footprints (Fig. 1, Table A1). Differences in footprints between income groups are higher for carbon than they are for land and water. This is driven by the increase in high-carbon, low-water, and low-land intensive activities (such as transportation) as people move to higher incomes; and further accentuated by low increases of food spending (which dominate water and land use) from low to high incomes. Hence, high-income groups shift their consumption from necessities to luxuries (Aguiar and Bils, 2015).

We examine these differences further using the Gini index (Teng et al., 2011). Globally, we find Gini indices of 0.71, 0.57, and 0.28 for carbon, land, and water footprints (Fig. 2). The coefficient of variation, an alternative measure of inequality, shows a similar trend with values of 0.75, 0.41, and 0.27 (Table A2). Teixidó-Figueras et al. (2016) also find that carbon footprints show a higher inequality than other environmental impacts. When moving to higher income groups, the consumption of high-impact products generally increases at a slower rate than lower-impact products (e.g. services). Generally, as incomes increase, the impacts per dollar decrease (Sommer and Kratena, 2017). Consequently, income redistribution increases footprints on average (López et al., 2017).

When distinguishing nations and income groups, footprint inequalities can change significantly. The water footprint shows the biggest change, with the Gini index increasing from 0.28 to 0.45 and the coefficient of variation from 0.27 to 5.52 (Table A2, Fig. A6). This

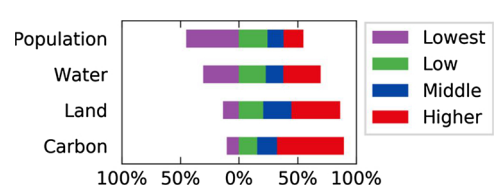

Fig. 1. Share of population and environmental footprints for consumers of different income groups. The left and right sides of zero contrast the lowest with the other income groups. The carbon footprint measures greenhouse gas emissions, the land footprint measures land stress, and the water footprint measures freshwater scarcity. The income groups are split by absolute monetary boundaries in international dollars: lowest ≤ $2.97, low = $2.97–8.44, middle = $8.44–23.03, and higher ≥ $23.03 per capita per day.

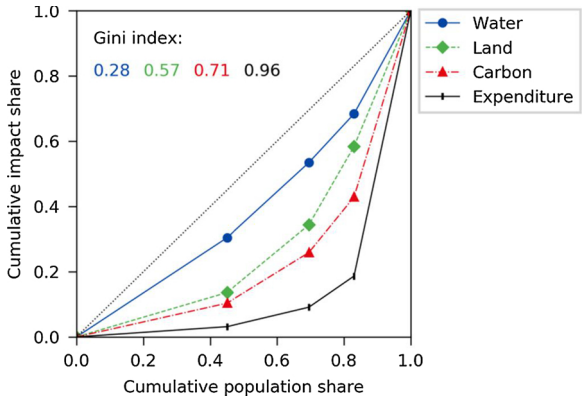

Fig. 2. Lorenz curves and Gini indices for carbon, land, and water footprints of household consumption. The carbon footprint measures greenhouse gas emissions, the land footprint measures land stress, and the water footprint measures freshwater scarcity. The dotted line marks the equality line at which the Gini index would be 0. The dot-shaped markers on the solid lines indicate the position of the four income groups (the last being at coordinates (1,1)).

emphasises the significance of location, and the need for spatially explicit water scarcity assessments (Behrens et al., 2017; Scherer and Pfister, 2016a). Environmental Gini indices within countries are especially high in Brazil (0.47-0.57) and Botswana (0.59-0.73), whereas they are low in higher-income countries, such as the United States (< 0.1) (Fig. A7, Appendix D). This further highlights the importance of spatially explicit analyses for examining the trade-offs and synergies between SDGs.

Environmentally intensive international trade exacerbates these trends among income groups. Most rich countries are net importers, and often source their products from poorer countries, thereby benefiting from the environmental burdens felt elsewhere (Scherer and Pfister, 2016b). In addition, environmentally intensive trade limits the potential of rich countries, where most of the rich people are living, to reduce their footprints through technological advances (Ivanova et al., 2016).

3.2. Interactions of Sustainable Development Goals

The detailed, global dataset allows to investigate the country-specific environmental impacts of changes in the minimum income level and national inequality by either increasing the expenditure of the lowest income group or by redistributing income across income groups. The imposition of a minimum income level of $1.25 per capita per day (SDG 1) for the extremely poor (Fig. A8) leads to a limited increase in environmental impacts (Fig. 3). Carbon footprints show the lowest increase, 0.8% on average (0.21 Gt CO_2-equivalents globally), while land and water footprints increase by 1.4 and 2.1% (420,000 km^2-equivalents and 10 billion m^3-equivalents). These increases are higher than the increase in average expenditure by 0.3%. As may be expected, increases are greater in nations with a low human development index (HDI) (13%), with several extreme outliers, including Burundi (52–54%), Madagascar (73–77%), and the Democratic Republic of the Congo (83–85%) (Fig. A9, Appendix E). This is driven by the exceptionally low level of income in these nations. Raising the international poverty line to $1.90 a day, as recently suggested (Ferreira et al., 2016), increases carbon, land, and water footprints by 1.9, 3.3, and 5.6% (Fig. A10). This compares to a carbon footprint increase of 2.8% found in other work (Hubacek et al., 2017). The effects might even be larger today, as the population of low-income countries grows faster than that of high-income countries (World Bank, 2018).

The environmental impacts of reducing intra-national inequality (SDG 10) by limiting the Gini index of income to a maximum of 0.3 show significantly more heterogeneity than those for the elimination of extreme poverty (Fig. 4). As before, carbon footprints show the lowest increase in impacts on average (0.8% at the global level), followed by land and water (0.9 and 1.3%). Previous findings confirm that reduced intra-national inequality may increase greenhouse gas emissions, while they also suggest possible improvements when reducing international inequality (Rao and Min, 2018). We find diverging relationships across development stages and impact categories. For example, the environmental impacts in South Africa increase by 7–11%, while in Saudi Arabia they reduce by 2–8% (Fig. A11). In a country with a relatively small number of rich persons like South Africa, redistribution of income to poorer groups results in a significant reduction of wealth in the richer groups. This results in a net increase in environmental impacts, since lower income groups have higher impacts per dollar as income increases. In contrast, in a rich country like Saudi Arabia, income redistribution means that the smaller number of poorer individuals climb to higher expenditure groups with lower impacts per dollar. This has a limited impact on the status of the upper expenditure groups.

There are also diverging relationships in footprint impacts within nations (Appendix E). For instance, in Niger the carbon footprint decreases (-1%), but the land and water footprints increase (1 and 9%). Likewise, in India the land footprint decreases (-1%), but the carbon and water footprint increase (3 and 5%). Reducing intra-national inequality more by halving the Gini index of all countries increases carbon, land, and water footprints globally by 1.7, 1.8, and 5.7% (Fig. A12).

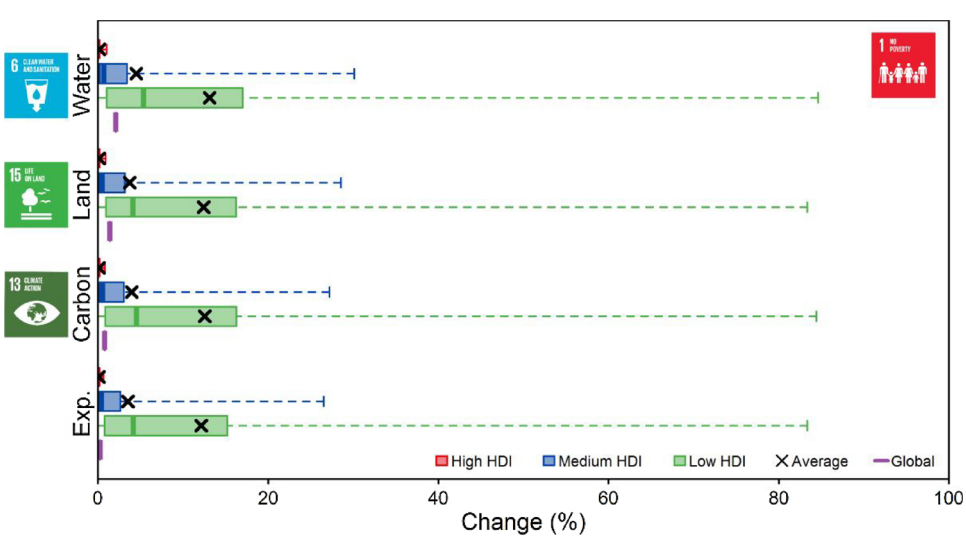

Fig. 3. Environmental impacts of meeting a minimum income of $1.25 a day (SDG 1). Countries are grouped by the human development index (HDI, low: < 0.55, medium: 0.55–0.7, high: > 0.7). Exp. stands for expenditure. The boxes range from the first to the third quartile, with the band inside indicating the median. Its whiskers extend to the extreme values. The crosses mark the population-weighted average.

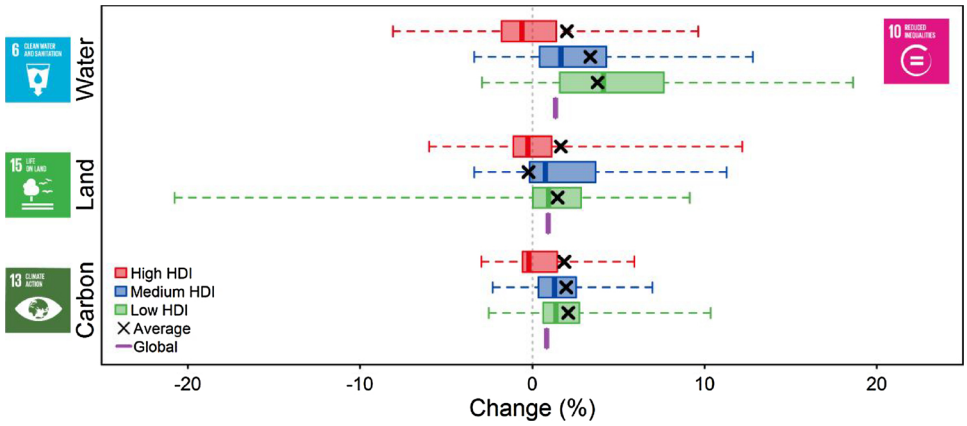

Fig. 4. Environmental impacts of reducing inequality (SDG 10, here: limiting the income Gini index to a maximum of 0.3). Countries are grouped by the human development index (HDI). The boxes range from the first to the third quartile, with the band inside indicating the median. Its whiskers extend to the extreme values. The crosses mark the population-weighted average. Countries with assumed constant expenditure patterns are excluded in this figure.

3.3. Efforts needed

Today's challenge to reduce humanity's environmental footprint is set to become harder, with increasing population and economic growth in many regions of the world. Since many countries, including India and China as the most populous countries, are still in early and middle stages of development, their growth is expected to continue accelerating for decades (Modis, 2013). The development of poorer countries is desired to alleviate poverty and achieve social equity, but it increases their environmental impacts. There is a clear role for high-income households and countries to take the lead to reduce humanity's footprint (Chakravarty et al., 2009; Mont and Plepys, 2008).

We explore which efforts the different income groups need to put into reaching universal footprint caps. In line with international targets (Convention on Biological Diversity, 2010; Meinshausen et al., 2009; Scherer and Pfister, 2016a), we reduce the water, land, and carbon footprints of households at the global level by 50, 15, and 50%, respectively, while eliminating extreme poverty. Consequently, the footprints of the lowest income group rise, while high-income groups have to put even more effort into reducing their footprints (Fig. 5). Even if low footprints are not increased beyond the elimination of extreme poverty, a uniform footprint cap requires an estimated reduction of up to 77% for the carbon footprint of the higher income group. However, even the lowest income group would have to reduce its water footprint by about a quarter due to the higher equality for water among income groups. Efforts by both high- and low-income groups are needed, but the rich have a greater leverage to reduce humanity's footprints.

3.4. Policy implications

The interactions between social and environmental SDGs point to the importance of designing policies across sectors and actors (Stafford-Smith et al., 2017). Such integrative policies can help converting trade-offs into synergies. The results from this study show where trade-offs are high, and where therefore additional efforts as well as multi-sectoral and multi-actor collaboration are required.

Since SDG interactions vary by country, it is essential to consider the specific context of a country when designing policies for sustainable development (Pradhan et al., 2017; Yonehara et al., 2017). The trade-offs presented in this study provide first insights into this context.

Implementing the SDGs also requires collaboration across countries (Stafford-Smith et al., 2017). The results showed that, while low-income nations require more attention to social goals, high-income nations play a key role to improve environmental sustainability. The United Nations can take on a mediating role between those countries.

4. Conclusions

The increased impacts per unit of expenditure at lower incomes point to the challenge to achieve both social and environmental sustainability. Poverty alleviation (SDG 1) allows low-income countries and groups to approach the development stage of those with higher incomes. Likewise, a reduction in inequality (SDG 10) reduces the gap between the poor and the rich. At the same time, environmental footprints must be reduced in line with other SDGs. However, countries' strategies are often imbalanced between social and environmental priorities (Schmidt-Traub et al., 2017). O'Neill et al. (2018) show that meeting basic human needs is likely to transgress planetary boundaries of resource use. All this highlights the size of the challenge to find an environmentally safe and socially just operating space for humanity (O'Neill et al., 2018).

The mapping of trade-offs and synergies between different development goals will become increasingly important as policy implementation accelerates. According to previous categorisations of SDG interactions (Nilsson et al., 2016), the interactions investigated here would be overall mostly counteracting. As such, the interactions weaken the effectiveness of their implementation (Allen et al., 2018). However, interactions are highly heterogeneous in both location and impact type, highlighting the importance of quantitative assessments and specific locational responses (Pradhan et al., 2017; Yonehara et al., 2017). This work provides important information to policy makers on the location and magnitude of necessary, additional efforts for environmental SDGs, if progress towards social SDGs are to be achieved. Further quantitative mapping of other interactions will be necessary to explicitly reveal the implicit trade-offs, synergies, and challenges posed by making progress towards multiple SDGs.

Data statement

The major underlying data sources are all publicly available:

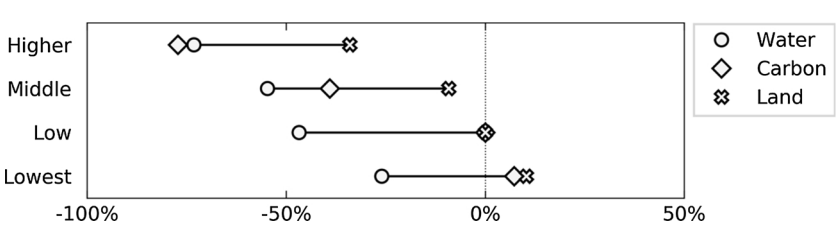

Fig. 5. Estimated reduction requirements in water, land, and carbon footprints (displayed as negative numbers) to meet environmental targets, while allowing the lowest income group to get out of extreme poverty and to increase expenditures and associated impacts (displayed as positive numbers).

EXIOBASE v3.4 (https://www.exiobase.eu/index.php/data-download/exiobase3), the World Bank's Global Consumption Database (http://datatopics.worldbank.org/consumption/detail), and the World Bank's Development Indicator Database (https://data.worldbank.org/). Data that support the findings of this study – including population, expenditure, footprints, and Gini indices of all countries and income groups – are available within the paper and its supporting information files.

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Appendix. Supplementary material

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.envsci.2018.10.002.

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