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Teixidó-Figueras, J, Steinberger, JK, Krausmann, F et al. (5 more authors) (2016) International inequality of environmental pressures: decomposition and comparative analysis. Ecological Indicators, 62. 163 - 173. ISSN 1470-160X

https://doi.org/10.1016/j.ecolind.2015.11.041

International inequality of environmental pressures: decomposition and comparative analysis

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ABSTRACT
Natural resource scarcity is no longer merely a remote possibility and governments increasingly seek information about the global distribution of resource use and related environmental pressures. This paper presents an international distributional analysis of natural resource use indicators. These encompass both territorial (national production) and footprint (national consumption) indicators for land-related pressures (human appropriation of net primary production, HANPP, and embodied HANPP), for material use (domestic material extraction and consumption and material footprint), and for carbon emissions (territorial carbon emissions and carbon footprints). Our main question is "What, both from a territorial and a footprint perspective, are the main driving factors of international environmental inequality?". We show that, for the environmental indicators we studied, inequality tends to be higher for footprint indicators than for territorial ones. The exception is land use intensity (as measured by HANPP), for which geographical drivers mainly determine the distribution pattern. The international distribution of material consumption is mainly a result of economic drivers whereas, for domestic extraction, demographic drivers can explain almost half of the distribution pattern. Finally, carbon emissions are the environmental pressure that shows the highest international inequality because of the larger contribution of economic drivers.

1. INTRODUCTION

Natural resource scarcity is no longer a remote, hypothetical possibility. Today, global human economic activities require more natural resources than ever before: globalization connects distant regions of the world through trade flows, and emerging economies claim their part of the natural resource pie in order to support their economic growth (UNEP, 2011; Wiedmann et al, 2015). International competition for the control of more or less scarce natural resources use has sharply increased (Schaffartzik et al, 2014, Giljum et al, 2014b). The ongoing combination of resource depletion and increased international competition brings distributional issues of natural resources to the top of the agenda.

Recent decades have seen a flourishing of research interest, both in the development of new environmental indicators and in the improvement of traditional ones. In particular, some environmental indicators can be approached both on a territorial basis (environmental pressures within national boundaries) and on a footprint basis (pressures anywhere on earth related to national consumption) (Peters 2008). This is the case for CO_2 emissions (territorial vs. consumption-based emissions), material flow indicators (domestic extraction vs. domestic material consumption vs. material footprint), and land use intensity indicators (HANPP, vs. embodied HANPP)[1]. Many studies suggest that reductions of territorial environmental pressures in developed countries are at least partially related to increasing imports from developing and emerging economies (Peters et al 2011). The availability of robust trade-adjusted environmental indicators allows a more comprehensive analysis of resource use distribution and consequently provides additional insights for global environmental governance. The first aim of this article is to compare the international inequality of territorial-based indicators with that of footprint-based indicators. The results shed light on the role of international trade in environmental equity issues, as well as giving greater insight into the environmental indicators themselves.

There have been many studies that consider distributional issues related to resource use and related ecological pressures. The topics and indicators investigated range from the distribution of CO_2 emissions (Strazicich and List, 2003; Nguyen Van, 2005; Aldy, 2006; Padilla and Serrano, 2006; Duro and Padilla, 2006; Ezcurra, 2007; Duro and Padilla, 2008; Criado and Grether, 2011; Cantore, 2011; Steinberger et al. 2012), to energy efficiency distribution (Alcantara and Duro, 2004; Miketa and Mulder, 2005; Duro et al. 2014), of the ecological footprint (Dongjing et al. 2010, White, 2007; Wu and Xu, 2010, Duro and Teixidó-Figueras 2013; Teixidó-Figueras and Duro 2014, 2015a, 2015b), material flow indicators (Steinberger et al., 2010, Bruckner et al., 2012; Giljum et al., 2014a; Wiedmann et al., 2015), water (Chen and Chen, 2013; Hoekstra and Mekonnen, 2012) and land (Bruckner et al., 2015; Weinzettel et al., 2013; Yu et al., 2013). These analyses provide information on how resource use is currently shared among nations. They discuss equity issues involved in sustainability concepts or policy implications where resource inequality might play a critical role. These include climate change negotiations for CO_2 studies or political economy involved in trade relationships for material flows indicators or Ecological Footprint (Moran et al. 2013). But, why do these international inequalities in resource use among countries exist? And why are some environmental pressures more unequally distributed than others? The second aim

[1] There are other environmental indicators that also consider the territorial versus footprint dichotomy whose inclusion to the analysis would certainly be of interest. This is the case of virtual water (Chen and Chen, 2013; Hoekstra and Mekonnen, 2012) or other land area indicators (Bruckner et al., 2015; Weinzettel et al., 2013; Yu et al., 2013). However, the set of indicators used was chosen reflecting the availability of data and their accessibility to the authors.

of this article is to answer these two questions by analysing the drivers of environmental pressures.

We use the term "drivers" to describe the range of factors that may influence the distribution of environmental pressure indicators across countries: drivers can be socio-economic (income, trade), geographical or historical (climate, population density), demographic (urbanization), or biophysical (resource endowment) (Rosa and Dietz, 2012). The study of drivers of environmental pressures has been of widespread interest to researchers and policy makers. Typically, by the use of multiple linear regressions (York et al., 2003), these analyses reveal a driver's elasticity (β coefficients in the regressions), and the amount of variability in their indicator captured by all drivers taken together (R^2 statistic). Consider the case where an environmental pressure can be explained by selected drivers, such as income and climate, for example. It then stands to reason that we can expect the inequality in its distribution to be related not only to the inequality of these drivers, but also to the strength (elasticity) with which these drivers are coupled to the environmental pressure. In this analysis, we apply a method which allows us to perform this decomposition (Fields 2003, Teixidó-Figueras and Duro, 2015b): it explains international inequality in environmental pressures in terms of the inequality and strength in the driving components of these pressures.

Hence, the objective of this study is firstly to analyse the international inequalities of a set of environmental indicators, with special emphasis on comparing the distribution of territorial and footprint indicators and, secondly to decompose the inequality of the indicators in terms of their drivers. The analysis is applied to three families of environmental indicators, each family consisting of a territorial indicator and a footprint indicator. The first family covers land use intensity: Human appropriation of net primary production; HANPP, (Krausmann et al 2009), and embodied HANPP; eHANPP (Erb et al 2009, Haberl et al 2012). The second family covers three indicators related to material use: domestic extraction; DE, domestic material consumption; DMC (Krausmann et al 2008), and the material footprint; MF (Wiedmann et al 2015). The third family refers to carbon emissions with territorial CO_2 emissions and consumption-based CO_2 emissions (Peters and Hertwich 2008, Boden et al 2013).

2. MATERIALS AND METHODS

Our comparative analysis proceeds in three stages: first, we calculate the distribution dispersion through inequality indices to determine unambiguously the distribution pattern of environmental indicators and determine which of those are the most unequally distributed. In a second stage, we estimate linear regressions in order to determine the relationship between proposed drivers and the environmental indicators considered. In a third stage, we decompose the inequality measured in stage one in terms of the drivers estimated in stage two. Such information might be critical for policy making, since it could indicate where the source of the total inequality lies and at the same time which drivers are more important in determining the variability of environmental indicators.

Territorial (or production-based) indicators refer to the environmental pressures taking place within national (including administered) territories and offshore areas over which the country has jurisdiction, whereas footprint indicators (or consumption-based) add imports to, and subtract exports from, territorial indicators (see Peters, 2008). All data refers to the year 2000, the only year for which all indicators were available and accessible. This analysis is entirely novel, since very few studies have done comparative analysis across different resources/indicators and even fewer have considered both territorial and footprint indicators. The research question of our analysis is not particularly time-specific, but focuses on a comparative view of a broad set of environmental indicators revealing fundamental differences. The basic findings of this analysis, therefore, are of current significance, despite the focus on the year 2000. It is also clear, however, that given the major changes in the global economy since 2000, in particular the rising significance of emerging economies in global resource use, the observed patterns in global inequalities may have changed since 2000 (Wiedmann et al. 2015; Schaffartzik et al. 2013; Giljum et al. 2014). This may encourage future research in this issue when further data is available. The countries sampled comprise between 88%–97% of the world population, depending on the availability of data for each indicator considered (see Table 1). As in Steinberger and Roberts (2010), countries are weighted by their population, so that global population is better represented in both inequality measurement and regressions.

Table 1. Environmental indicators database

Territ. / Footp.	Indicator	Unit(s)	Source	Countries sampled	% world pop
T	CO_2 emissions (*)	metric tonnes CO_2/cap	Peters et al. (2011)	86	88%
F	CO_2 consumption based	metric tonnes CO_2/cap	Peters et al. (2011)	86	88%
T	Domestic extraction	tonnes/cap	Steinberger et al. (2010)	152	97%
(T)	Domestic material consumption	tonnes/cap	Steinberger et al. (2010)	152	97%
F	Material footprint	tonnes/cap	Wiedmann et al. (2015)	148	97%
T	HANPP	tonnes of dry matter/cap	Kastner et al. (2015)	150	97%
F	Embodied HANPP	tonnes of dry matter/cap	Kastner et al. (2015)	152	97%

(*) We used two data sources to analyse territorial CO_2 emissions for robustness issues: one from World Bank data (141 countries) and the other from the Peters et al. (2011) database (86 countries). However, the results obtained are not sufficiently different to merit inclusion of both datasets in the main text of this article. Despite it being a smaller sample, we decided to include the sample of Peters et al. (2011) in the main text with a view to keeping inequality comparisons with consumption-based emissions more consistent.

2.1 Environmental indicators

In this section, in order to allow the reader a proper interpretation of their international distribution, we briefly describe the environmental indicators used. Further details on the indicators, and how they are calculated, can be found in the literature cited.

Notice, however, that some methodological issues need to be considered here in the way footprint indicators are calculated (CO_2 consumption-based, MF and eHANPP). Whereas CO_2 consumption-based and MF are derived using a EE-MRIO approach, eHANPP was calculated based on physical accounting methods. This might involve different logics among footprint indicators on how to allocate environmental factors along supply-chains (see Kastner et al. 2014; Hubacek and Feng, 2016). Also, the EE-MRIO approach uses different databases; the CO_2 consumption-based uses GTAP datasets whereas MF uses Eora. Owen et al (2014), for example, found that variations in carbon footprint calculations between Eora and GTAP can be attributed to differences in the IO table structure and emissions data, whereas variations between Eora and WIOD are mainly due to differences in final demand and the IO structure. Research into understanding differences between MRIO databases continues (Inomata & Owen 2014).

2.1.1 Emissions: Territorial and consumption-based CO_2 emissions

CO_2 is the primary emission of human economies. CO_2 emissions from the combustion of fossil fuels and other activities increase the concentration of CO_2 in the atmosphere and contribute to human induced climate change. Nearly all national and global climate policies, such as the Kyoto protocol, focus on CO_2 emissions that occur within national territories (Peters 2008; Peters et al 2009). Territorial-based emissions (also referred to as production-based emissions) are reported by most nations and by several international organisations (Andres et al 2012).

In the last few decades, territorial-based emissions in developed countries (the so-called Annex B countries in the Kyoto protocol) have stabilized, while emissions have grown rapidly in developing countries. This called for methods to quantify consumption-based CO_2 emissions which correct standard territorial emissions for emissions embodied in international trade (Peters and Hertwich 2008). This enables the allocation of emissions to the goods and services consumed, rather than those produced (Hertwich and Peters 2009).

2.1.2 Material use: domestic extraction, domestic material consumption and material footprint

Material flow accounts (MFA) provide comprehensive information about the material inputs and outputs of national economies (i.e. their metabolism) (Fischer-Kowalski et al. 2011). Material flow indicators measure the annual tonnage of aggregate material flows (biomass, fossil energy carriers, metals and non-metallic minerals) through national economies, and are considered comprehensive macro-indicators for the overall environmental pressure exerted by the economy (OECD 2008).

We use three MFA-derived pressure indicators, two of which can be considered territorial indicators: the first, domestic extraction (DE), measures all materials extracted within an economy's boundaries for further socio-economic use. The second, domestic material consumption (DMC), measures apparent consumption (the total amount of materials directly used in an economy) and is defined as the annual quantity of materials extracted from the domestic territory (DE), plus all physical imports, minus all physical exports (Eurostat, 2012). DMC does not measure the materials used upstream (embodied) in traded goods and services. DMC is not only a measure for apparent consumption of resources but it can also be understood as the domestic waste potential of an economy (as argued by Weisz et al. 2006). DMC indicates the amount of material that ultimately turns into end of life waste within the country, i.e. the amount of waste material the country has to handle and in that sense is indeed equivalent to e.g., territorial carbon emissions. Its inclusion to the analysis is in further justified as it is indeed the most widely used MFA derived headline indicator, e.g. in the context of EU's Resource Efficiency Roadmap (European Commission, 2011). In contrast, the third indicator, the material footprint, is purely consumption-based. It includes all upstream raw materials related to imports and exports into account and quantifies the materials embodied in a country's final demand (Wiedmann et al. 2015).

2.1.3 Land use intensity: HANPP and eHANPP.

The human appropriation of net primary production (HANPP) is a socio-ecological indicator that measures the intensity with which human society uses terrestrial ecosystems (Haberl et al., 2012; Haberl et al., 2014). Net Primary Production (NPP) is the amount of CO_2 fixed by autotrophs such as green plants through photosynthesis net of the plant’s own metabolic needs (i.e. plant respiration). NPP provides the trophic energy supply of all food chains in an ecosystem. HANPP measures the amount of NPP appropriated by humans through both land change and harvest (Haberl et al., 2014). Hence, HANPP (measured in tons of dry matter or carbon) carries information on the intensity of land use in the territory of a country: The higher the average HANPP per unit of land in a country, the higher the pressures on the land systems in its own territory. Recent research has shown that HANPP varies strongly across countries and is influenced by both bio-geographic (e.g. climate) and socio-economic factors (e.g. agricultural technology, population density) (Krausmann et al. 2009). Our aim here is to quantify to what extend such factors (drivers) determine the international differences in HANPP.

HANPP is a territorial indicator and measures the effect of domestic land use on domestic NPP, but not the pressures related to its consumption level—countries that import a high proportion of biomass-based products might register a lower HANPP than countries that produce and export large amounts of biomass products. This can be captured by the embodied HANPP (eHANPP) indicator which considers the HANPP associated with imported goods and subtracts the HANPP of exported goods. For details on this indicator and its operationalization, see Haberl et al. (2012, 2014), Kastner et al. (2015) and Krausmann et al. (2013). Data were taken from the study by Kastner et al. (2015).

2.2 Drivers

Regarding the socio-economic and geophysical drivers of the environmental indicators above, we apply the same empirical model for all environmental pressures. The model should capture the common drivers shared by all the environmental indicators considered, hence permitting a clear comparative analysis. In order to find such a common model,[2] we refer to the main literature focused on the estimation of such drivers (York et al 2003, Dietz et al 2007, Rosa and Dietz, 2012; Lamb et al. 2014). As in Lamb et al (2014), our drivers can be divided into three broad and overlapping categories: economic (income and active population share), demographic (urbanization and population density) and geographic (climate and bioproductivity of land). Table 2 describes drivers and also provides international inequality as measured by the Gini index: this is useful in understanding that the distributional pattern of drivers will play a central role in the decomposition analysis.

Table 2. Common drivers of environmental pressures

	Variables	Unit(s)	Mean	Gini (rank.)	Source
ECO	Income (GDP/ capita)	1000 constant 2000 US$ /cap	5.322	0.75 (1)	World Bank Group
	Active Population (% Pop. Ages 15-64)	% of total population	62.872	0.05 (6)	World Bank Group
DEM	Population density (Pop./ Km^2)	people per sq. km of land area	186.045	0.50 (3)	World Bank Group
	Urbanization rate (Urban pop/total Pop)	% of total population	46.587	0.25 (5)	World Bank Group
GEO	Ecosystem Productivity (NPP_{pot})	1000 tonnes of dry matter/cap	11.089	0.66 (2)	Haberl et al. (2012)
	Climate (Daily min. temperature)	Celsius. Average 1961-1990	10.686	0.45 (4)	World Bank Group

We should note here that population is well known to be a key driver of overall resource use and environmental pressures: however, since we are interested here in international differences, we use per capita measures throughout to remove the effects of population size.

Economic: Income, as measured by GDP per capita, accounts for the economic activity of nations and is one of the most widely used indicators for affluence[3]. It is considered the main macro-driver of environmental pressure (Rosa and Dietz, 2012). Higher GDP

[2] The authors have estimated several models by trying different sets of independent variables and the results obtained are always virtually equivalent. The chosen model is the one that yields the highest overall significance.

[3] GDP per capita is a measure of national income that measures economic performance. It must not be confused with either measures of actual household income in an economy or measures of a society's welfare.

per capita entails, on the one hand, higher consumption and hence higher resource use and, on the other, higher economic activity which also increases resource use. Additionally, it is the most unequally distributed driver. This link between income and resource might drive resource use inequality (Weinzettel et al 2013). Active Population: Age structure is also widely used in the environmental pressure driver literature (O'Neill et al 2010, Rosa and Dietz, 2012); in particular, the fraction of the population aged 15 to 65, considered economically active, might affect environmental pressure through (income-independent) lifestyle patterns: populations with larger fraction of working age population will consume more than populations with larger proportions of children or elderly (Zagheni, 2011, Lugauer et al., 2014). On the other hand, a higher share of active population affects labour supply through higher labour productivity and, ceteris paribus, higher environmental pressure (O'Neill et al 2010).

Demographic: Population density has been argued to have a significant impact on countries resource use patterns: countries with low population densities tend to have a high level of resource use per capita, while countries with high population density will use fewer resources per capita (Krausmann et al 2008). Population density (or its inverse, the land area availability per person) is considered a proxy of per capita resource endowment (as a higher population density decreases the probability of per capita resource availability in a country) and thus may have an impact on the resource intensity of the economies' mode of production (Haberl et al 2012, Steinberger et al 2010, Wiedmann et al 2015, Krausmann et al 2009, Lamb et al 2014). Urbanization; development is related to the migration of rural population to urban areas in search of jobs and subsequent urban growth. The sprawl of growing cities with large suburbs is associated with construction activities, expansion of supply, discharge and communication infrastructures, commuter travel, freight transport to connect urban centres with the hinterland and so forth. This all drives increases in resource consumption (Liddle and Lung 2010). Nonetheless, cities might also provide economies of scale and more efficient use of resources and also contribute to reductions in environmental pressure (Weisz and Steinberger, 2010). Urbanization is measured through the percentage of a country's population living in urban areas.

Biogeography and climate; as a proxy for climate, we use the national average minimum temperature. The climate driver consists of a climatic normal (minimum temperature averaged over 30 years). Climate has an impact on resource use and environmental pressures (e.g. through higher heating necessities; Lamb et al 2014). We further use potential net primary production (NPP_{pot}) per capita (i.e. the NPP that would prevail in the absence of land use) as a proxy for natural ecosystem productivity. NPP_{pot} per capita is probably the exogenous regressor that best captures land qualitative characteristics available per capita.

2.3 Inequality measurement

The analytic approaches employed are derived from methods commonly used in economics. Inequality is traditionally measured by the use of the Lorenz curve, a graph which plots the cumulative proportion of total available resource (usually income or wealth, but in our case environmental pressure) against the corresponding cumulative population using this resource, ranked from poorest to richest (Cowell, 2011). Lorenz curves are used to rank distributions: when one distribution curve lies completely above a second (closer to equality line), the first is unambiguously more equal than the second. However, Lorenz curves might intersect, what would indicate that a distribution is more equalitarian than the other (closer to equality line) according to which part of the distribution we focus on. Only inequality indices allow for consistent comparisons among different distributions. We propose using a set of different inequality indices with different underlying assumption (see equations in the Annexes): Theil index T(0) and Theil index T(1) give more importance to the observations in the lower percentiles of the distribution, whereas the Gini index gives symmetrical weight to both distribution extremes, but gives more importance to those observations closer to the distributional mode. The Theil index T(2) is argued to be neutral index since it does not weight any part of the distribution differently (Duro 2012).

Inequality indices are a widely used tool to compare the dispersion exhibited by a distribution. To do so, however, some basic axioms are indispensable, namely: anonymity, population principle, scale independence, and Pigou-Dalton principle of transfers (see the Annexes for technical details). The decomposability axiom allows us to account for the underlying structure of the observed inequality. Decomposing an index consists of determining which part of the total inequality observed is attributable to each of its components. Regression-based decomposition (Fields, 2003) informs us about the contribution of those drivers to international environmental inequality.

2.4 STIRPAT model and regression-based decomposition

The value added by regression-based decomposition (RBD) of inequality is easy to see if we compare its research question with those asked by other regressions, such as the Stochastic IPAT (STIRPAT) model. The results of a STIRPAT model are the regression coefficients, their value, sign and statistical significance[4]: the primary question asked in STIRPAT models is "What is the effect of one unit change in GDP per capita (or any other driver) on CO_2 emissions, holding all other drivers constant?". A secondary question in the same regressions is "How much of the variance in the CO_2 emissions is accounted for by the drivers taken together (the R^2 statistic)?". However, the regression-based decomposition applied here answers a third question: "How much of the variation in the distribution of CO_2 emissions is accounted for by each driver?". Hence, decomposing international inequality of environmental pressures in terms of its drivers is not only useful for studying international equity issues, but also enables the determination of which drivers contain more information in explaining each environmental pressure and which ones can be safely ignored.

Firstly, a multiple least squares regression is applied to the drivers described. In this RBD approach, the model is restricted to a semi-log linear function[5] for country i:

$$\ln Y_i = \beta_0 + \sum_k^K \beta_k X_{ik} + \varepsilon_i \tag{1}$$

where Y_i is its environmental indicator and X_i represents the different k drivers considered. β_k is the estimated semi-elasticity of driver k while ε_i stands for the error term with typical assumptions involved, $\varepsilon|X \sim N(0, \sigma^2)$.

Once the semi-log model is estimated, variances on both sides of the equation must be taken:

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[4] See York et al., 2003

[5] The semi-log model $\ln(Y) = \beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i$ is equivalent to: $Y = \exp(\beta_0 + \beta_1 F_1 + \beta_2 F_2 + ... + \beta_k F_k + \varepsilon_i) = \exp(\beta_0) \cdot \prod_{k=1}^{k} \exp(\beta_k F_k) \cdot \exp(\varepsilon_i)$. Then, the contribution β_0 is null since it is a constant of each observation.

$$\operatorname{var}(\ln Y) = \operatorname{var}\left(\sum_{k}^{K+2} \beta_k X_k\right) \quad (2)$$

On the right hand side, we obtain the variance of logarithms, an inequality measure. Since the variance is already a measure of inequality, this equation decomposes the inequality into components describing the STIRPAT model's drivers. Rearranging Expression (2), we obtain:

$$\operatorname{var}(\ln Y) = \sum_{k}^{K+2} \operatorname{cov}(\beta_k X_k, \ln Y) \quad (3)$$

which is an analogue of the expression of the natural decomposition rule of the variance (Shorrocks 1982, 1983). Therefore, the relative contribution of Y's drivers, X_k, to total environmental indicator inequality is defined by:

$$s_k(\ln Y) = \frac{\operatorname{cov}[\beta_k X_k, \ln Y]}{\operatorname{var}(\ln Y)} \quad (4)$$

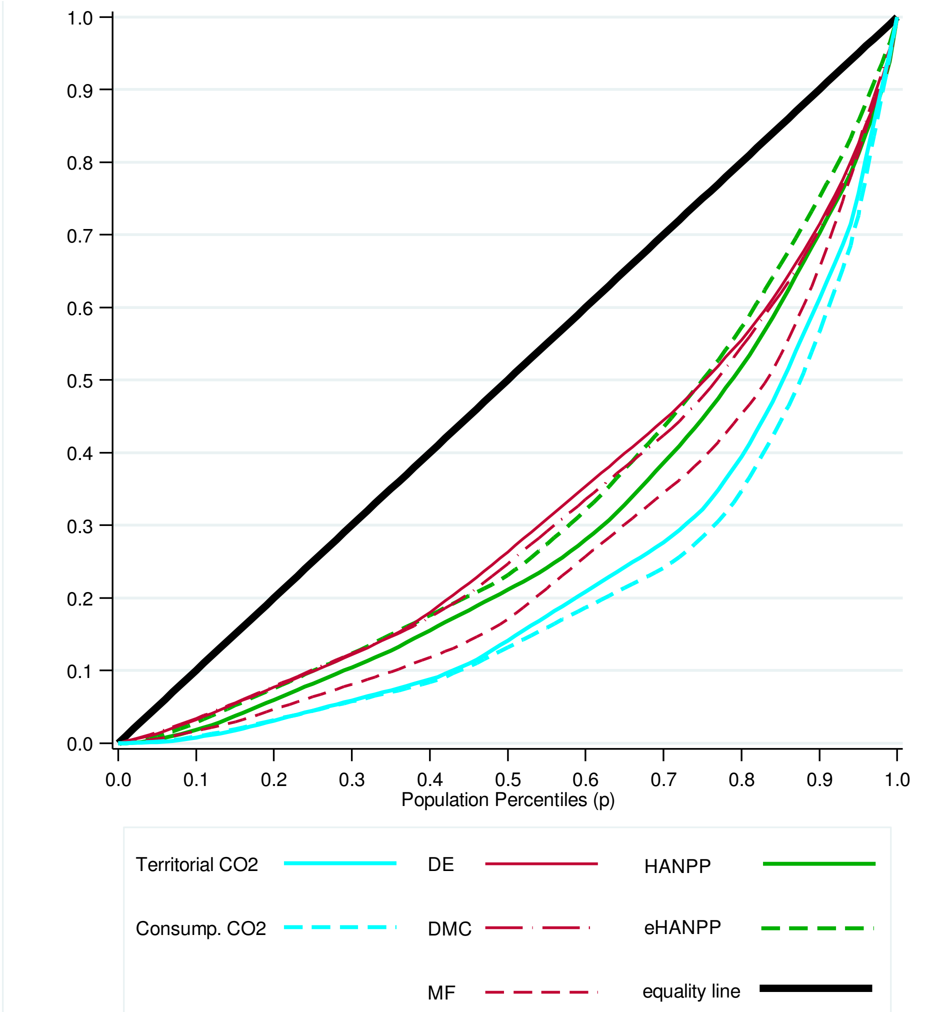
Under this decomposition rule, the contribution of each component corresponds to $\operatorname{cov}(\beta_k X_k, Y)$ and its relative contribution is defined as $\operatorname{cov}(\beta_k X_k, Y)$ / $\operatorname{var}(Y)$. Note that $\sum_{k=1}^{K+2} s_k(\ln Y) = 100\%$, so that s_k answers the question of how much of each environmental indicator total inequality is accounted for by the driver k. If we removed the residual term, then what we would get is the R^2 of the regression $\sum_{k=1}^{K+1} s_k(\ln e) = R^2$ (ln Y).

Then, since we have that corr(x, y)=cov(x, y)/(sd(x)sd(y)), it can be shown that:

$$s_k(\ln Y) = \frac{\operatorname{cov}[\beta_k X_k, \ln Y]}{\operatorname{var}(\ln Y)} = \frac{\boldsymbol{\beta_k} \cdot \sigma(X_k) \cdot \operatorname{corr}(X_k, \ln Y)}{\sigma(\ln Y)} \quad (5)$$

Hence, the contribution of each driver k to the international inequality of Y is based on considering the product of the estimated coefficients (β), the dispersion in the driver $\sigma(X_k)$, and the existing correlation between dependent variable and driver.

Figure 1. Lorenz Curves of Environmental indicators



3. RESULTS

3.1 International Inequality in Environmental Pressure

Figure 1 shows Lorenz curves for all the environmental pressures considered and reveals a first insight concerning differences in inequality: carbon indicators are the most unequally distributed. However, the rest of Lorenz curves intersect, which prevents an unambiguous ranking. We thus complement this analysis with a set of inequality indices to allow a consistent ranking of distribution inequalities (see Table 3).

Table 3 shows a set of inequality indices for each indicator: the family of carbon emission indicators are the least equally distributed; the consumption-based CO_2 emission showing the highest level of international inequality according to most indices. Notice however that var(ln) from Table 3 reverses this relation and assigns higher inequality to the territorial emissions indicator. This is because this index gives more weight to the low part of the distribution (see Figure 1), i.e. the carbon transfers between low carbon emitters and low carbon consumers have greater weight than similar transfers in other parts of the distribution. These greater weights are enough to change the ranking in comparison to the other inequality indices. Material consumption also registers a higher inequality in its footprint indicator (MF), whereas the apparent consumption (DMC), and domestic extraction (DE), exhibit a similar and more egalitarian distributional pattern. In contrast, the HANPP and eHANPP distributions behave differently: eHANPP, a footprint type indicator, shows a lower inequality than territorial HANPP. Hence, while international trade tends to increase resource use inequality for carbon and material (Wiebe et al., 2012), it seems to play an equalizing role for land use intensity, as it makes HANPP more equitable. In contrast, NPP, which measures ecosystem productivity (Krausmann et al 2009), appears to be rather unequally distributed with a Gini of 0.659 (see Table 2). This remarkable progressive redistribution must be related to the fact that basic human needs are more connected to this indicator than to any other one, as already suggested by previous studies (Krausmann et al 2009, Hertwich and Peters 2009, Steinberger et al 2010): trade will thus by necessity be used to supply NPP-deficient countries from countries with NPP surpluses.

Table 3. Environmental indicators considered ranked by inequality indices.

T/F	Variable	T(2)	ranking	Gini	ranking	T(0)	ranking	T(1)	ranking	var(ln)	ranking
F	Consum. CO2	0.87	1	0.579	1	0.655	1	0.613	1	1.298	2
T	Territ. CO2	0.698	2	0.546	2	0.61	2	0.528	2	1.369	1
F	MF	0.533	3	0.479	3	0.421	3	0.4	3	0.820	3
T	HANPP	0.41	4	0.423	4	0.316	4	0.306	4	0.667	4
T	DE	0.343	5	0.359	7	0.215	7	0.237	6	0.386	7
F	DMC	0.31	6	0.373	5	0.226	5	0.242	5	0.409	6
F	eHANPP	0.239	7	0.362	6	0.218	6	0.209	7	0.442	5

Note: all indicators are referred to in per-capita terms.

In the next section, we decompose the observed patterns of international inequality in terms of the proposed drivers.

3.2 Decomposition Results

First, the regression results show the estimated semi-elasticities that allow, in a second stage, the relative contribution of the drivers of global distributions of environmental pressures to be obtained.

3.2.1 The regression results

Our empirical model[6] is in a semi-logarithmic form. Hence, coefficients should be interpreted as semi-elasticities (the increase in one unit of X, imply an increase of $100\cdot\beta\%$ in y); e.g. an increase of one unit in GDP per capita (1000$) or an additional 1% of active population involves a cross sectional increase of 2.47% and 3.98% of DMC per capita, respectively (Table 4). Multi-collinearity is not a substantial problem in any of the models: the highest Variation Inflation Factor (VIF) for any of the drivers considered is safely below accepted standards.

Table 4. Regression results (OLS)

	Land Use Intensity		Material Use			Carbon Emissions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	HANPP	eHANPP	DE	DMC	MF	CO_2 Territ.	CO_2 Consump.
Income	0.007	0.015***	0.008***	0.025***	0.038***	0.028***	0.038***
	(0.007)	(0.005)	(0.003)	(0.002)	(0.005)	(0.006)	(0.005)
Active Population	0.007	0.005	0.038***	0.040***	0.066***	0.117***	0.090***
	(0.014)	(0.010)	(0.005)	(0.005)	(0.010)	(0.014)	(0.012)
Pop. density	-0.0012***	-0.0009***	-0.0011***	-0.0008***	-0.0004	-0.0004	-0.0002
	(0.0004)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0003)
Urbanization	0.002	0.008***	0.011***	0.008***	0.011***	0.019***	0.021***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.003)	(0.004)	(0.003)
Ecosystem Productivity	0.021***	0.014***	0.005***	0.004***	-0.001	-0.003	-0.004
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Climate	0.021**	0.023***	-0.005	-0.007**	-0.004	-0.016**	-0.017**
	(0.008)	(0.006)	(0.003)	(0.003)	(0.006)	(0.008)	(0.007)
Constant	0.270	0.247	-0.900**	-0.890***	-2.991***	-21.243***	-19.716***
	(0.865)	(0.607)	(0.345)	(0.298)	(0.652)	(0.930)	(0.785)
R-squared	0.471	0.607	0.853	0.896	0.759	0.874	0.906
Mean VIF	1.93	1.93	1.93	1.93	1.94	2.04	2.04
Observations	150	150	152	152	148	86	86

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[6] It is important to keep in mind that we do not attempt to provide any evidence of causality, but we use the estimated coefficients to weight the drivers' contribution to environmental indicators international inequality

For HANPP and eHANPP indicators, the drivers showing strongest explanatory power are those related to geographical factors; NPP_{pot} and minimum temperature. Consistent with previous analyses (Krausmann et al 2009, Haberl et al 2012), population density has a negative effect on HANPP. The main difference between HANPP and eHANPP is due to the contrasting drivers GDP per capita and NPP_{pot} (purely economic and purely biophysical, respectively). GDP per capita is non-significant for HANPP, but positive and strongly significant for eHANPP. On the contrary, NPP_{pot} has a higher semi-elasticity for HANPP than for eHANPP. Also remarkable is the urbanization driver, which is significant for eHANPP but not for HANPP; per capita HANPP tends to be low in countries with high urbanization rates, however, the increase of global urban population delinks local patterns of production from patterns of consumption (Krausmann et al 2009).

For the material flow indicators, the first result to highlight is the increasing role of economic variables from DE to DMC and MF. That is, with indicators becoming more consumption-based, the always significant income coefficient increases its semi-elasticity as we shift to footprint accounting. We can thus expect that the income contribution indicator's inequality will also increase—the same pattern is observed for active population. On the other hand, population density exhibits an inverse pattern, presenting a lower semi-elasticity as the indicator shifts to consumption-based. Hence, when other factors are held constant, land availability per person explains less material pressure once trade is taken into account. Urbanization presents a significant and more strongly positive coefficient for DE and MF than for DMC.

Finally, some stylized facts can also be observed for the carbon family. Results obtained show that the shift from territorial to footprint measures involves an increase of income's explanatory power (as in Steinberger et al 2012). However, the other socio-economic variable, active population, changes its coefficient in the opposite direction, being lower for the consumption-based emissions. The three carbon models show a similar relationship between urbanization and emissions (an additional 1% of urban population involves a cross-country variation of 2% in CO_2 emissions per capita, either territorial or footprint). Finally, the last significant driver is climate, approximated by the mean minimum temperature of a country; as temperature gets colder, emissions increase due to higher heating energy demand. Differences in the empirical model aside, our results are in the same direction as those found by Lamb et al (2014) who also compared territorial and footprint carbon emissions.

In the next section, we use the estimated coefficients as weighting factors to decompose the international inequality of the environmental indicators in terms of their drivers.

3.2.2 RBD decomposition results

In this section, we decompose international inequality of indicators into driver contributions, which in turn consist of the product of several elements (Equation 5). Table 5 shows the results obtained (only significant contributions are shown).

Table 5. Regression-based decomposition. Contributions (%) to environmental indicators distribution for the year 2000

		Land Use Intensity		Material Use			Carbon Emissions	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Distributional contributors	HANPP	eHANPP	DE	DMC	MF	CO_2 Territ.	CO_2 Consum.
ECO	Income	-	8.2	7.6	**28.3**	**30.3**	**16.9**	**26.3**
	Active Population	-	-	**18.9**	**20.9**	**24.9**	**36.2**	**26.7**
DEM	Population density	**10.8**	**10.7**	**17.9**	9.7	-	-	-
	Urbanization rate	-	**13.8**	**30.3**	**20.4**	**17.2**	**25.4**	**29.9**
GEO	Ecosystem Productivity	**32.5**	**27.1**	7.1	4.9	-	-	-
	Climate	1.2	0.9	-	5.4	-	7.6	8.1
	Residual	*52.9*	*39.3*	*14.7*	*10.4*	*24.1*	*12.6*	*9.4*
	Total	100	100	100	100	100	100	100
	Inequality – GINI	0.423	0.362	0.359	0.373	0.479	0.546	0.579

3.2.2.1 Land use intensity distribution

Geographical drivers, in particular NPP_{pot} per capita, determine most of the international differences in land use intensity. This driver alone explains 32.5% of the total observed HANPP inequality and 27% of eHANPP. This high contribution is mostly explained by the high inequality of per capita NPP_{pot} (see Table 2) rather than by the coefficient estimated (which weights the driver inequality contribution). To see this, we can compare NPP_{pot} with the other significant geographical factor, minimum temperature. Despite both drivers being statistically significant, their importance in the variation of land use intensity differs considerably. Population density has the same influence in both territorial and footprint indicator's distribution. This suggests that land use intensity distribution is more a matter of land quality availability (NPP_0 per capita) rather than just land availability (inverse of population density). However, the main difference between territorial and footprint inequality drivers is the significant contribution of income and urbanization rate for eHANPP. Once trade is taken into account, income and urbanization rate have an influence on land use intensity distribution.

As mentioned earlier, and in contrast to the other environmental indicators considered, the footprint indicator (eHANPP) shows a lower inequality than the territorial indicator (HANPP). This contrasting result might be explained by the geographical importance of its distribution. The statistically significant contribution to eHANPP of the most unequal driver, GDP per capita, is not sufficient to compensate the higher contribution of NPP_0 per capita. In other words, the footprint of land use intensity is more equally distributed because land use intensity is much more determined by geographic factors (e.g. resource endowment) than economically based (a result that cannot solely be inferred from the regression).

3.2.2.2 Material use distribution

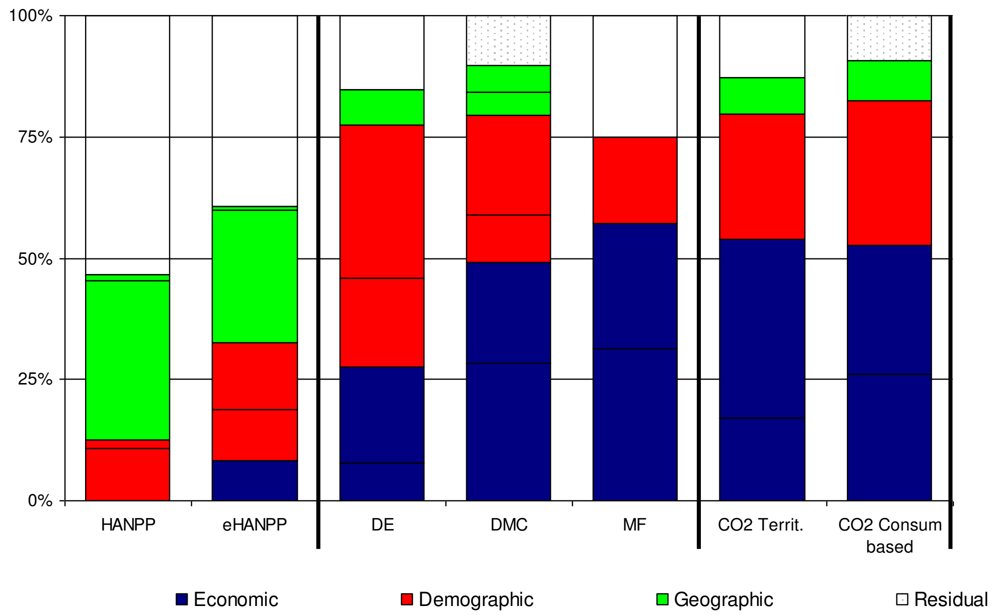
The distribution of material use indicators is strongly determined by the two economic drivers: income and active population. The total contribution of both economic drivers accounts for 26% of the DE distribution, 49% of DMC and 55% of MF. Both income and active population contributions increase as the indicator is more consumption-based. The inverse behaviour is found for inequality contributions of demographic drivers (population density and urbanization) whose contribution shrinks since the indicator is more consumption-based: the most important drivers of DE distribution are the demographic ones (48.3% in total): population density contributes 17.9% to DE's inequality and reduces its contribution until not differing from zero for MF's inequality. The more land is available, the more territorial extraction of minerals, crops, etc., occurs (as the regression results show). Consequently, the DE distribution is noticeably influenced by the land availability distribution, whereas consumption indicators' distributions are rather delinked from this initial endowment. Urbanization rate is the major contributor to DE distribution and despite being lower for DMC and MF remains important. Following from this, we note that geographical drivers become less important as trade allows further disconnection from a country's own geographical characteristics. For DE, NPP_{pot} is responsible for part of its distribution pattern (7%); however, for DMC such contribution shrinks (4.9%) and becomes not significantly different from zero for MF, where the indicator captures physical quantities that actually have not even been directly imported/exported by the country: this makes this last indicator even more delinked from its own geographical characteristics.

3.2.2.3 Emissions distribution

Finally, economic drivers are again the main contributors to the international inequality of carbon emissions: both income and active population explain more than 50% of the total carbon inequality for both production and consumption emissions. As in material indicators, income contribution to the CO_2 inequality increases as the indicator shifts from production-based to consumption-based, reaching 26.3% for the distribution of consumption-based CO_2 emissions. The active population driver contributes to territorial emissions' distribution at a level of 36.2% and reduces its contribution to a similar level as income for the consumption-based emissions. According to this result, the distribution of active population is more than twice as important as that of income in determining the distribution of territorial emissions. This high contribution is the result of the high strength (large regression coefficient) with which this driver is coupled to carbon emissions, which makes its relative low inequality of the distribution of active population more important in determining carbon distribution. Regarding demographic variables, the urbanization driver shows a significant contribution which is rather stable across both carbon indicators, at the 25–30% level. Population density and geographic characteristics account for little in carbon distributional terms; only climate accounts for 7.6% of the territorial CO_2 emissions and 8.1% of the consumption-based emissions. Hence, our results show that the carbon emissions distribution follows an opposite direction than the land use intensity distribution: carbon distribution is more unequally distributed because it is more linked to a country's economy than to its geography.

The differences in the contributions made by the residual to all indicators should also be noted (Table 5 and Figure 2). This residual can be interpreted as the drivers not captured by the proposed model, which is in particular of importance for the family of land use intensity indicators, whereas for material and carbon indicators it is much lower. This phenomenon indicates the part of international distribution of the resource use that is not identified by our proposed model, for instance international differences in technology. In the case of HANPP, the applied model can only explain the 47.1% of the distribution (R^2). This residual component is higher in the inequality decomposition for HANPP than eHANPP, again reflecting the higher contribution of socio-economic factors in explaining eHANPP.

Figure 2. Inequality contributions grouped by economic, demographic and geographic factors



4. DISCUSSION

From this analysis, we gain new insights regarding the international distributional patterns of the different environmental indicators considered, and the factors contributing to their inequality. This is particularly interesting in the context of the strong prevailing international competition for natural resources. Firstly, the results show that footprint indicators for material use and carbon emissions tend to be more unequally distributed than territorial indicators. This suggests that international trade exacerbates the inequality of material and carbon rather than contributing to its reduction. This is evident in the decomposition analysis: this higher inequality for footprint indicators is accompanied with a higher contribution of economic drivers (and lower contribution of geographic drivers) in explaining the indicator's distributional pattern (see Figure 2). Hence, regardless of other endowments, income distribution is the main contributor to the distribution of materials and fossil energy. Insofar as global governance is to be framed within a resource-constrained world, international trade does no favours to environmental equity goals.

In contrast, land use intensity distribution behaves differently; eHANPP, the footprint indicator, is more equally distributed than is territorial HANPP. This is the only one of the indicators considered for which trade does not increase environmental inequality, but rather alleviates it. In future research (depending on availability of data), it would interesting to contrast this result with area-based indicators (actual land use and land footprint). Since HANPP and eHANPP considers both land-use intensity and area, a comparison with pure area-based indicators would allow to better understand of the underlying processes of this particular result. The distribution of both land use intensity indicators is highly linked to the distribution of countries' ecosystem productivity (NPP_{pot}); this geographic endowment is rather unequally distributed, however much less than income, and for HANPP economic factors have no influence on its international distribution. From this we infer that the difference between HANPP and NPP_{pot} distributions is a consequence of the international differences in countries' land use technologies, i.e. how intensively the productive potential of land is used. This technological driver is captured in the residual contribution of both land use indicators. Nonetheless, the most interesting aspect of this family of indicators is that international trade makes human appropriation (eHANPP) more equally distributed. This can be explained by the stronger connection that land use has with basic human needs, as already suggested elsewhere (Krausmann et al 2009, Hertwich and Peters 2009, Steinberger et al 2010): income has a significant semi-elasticity in explaining eHANPP, however, this driver only contributes some 8.2% of its international distribution, as our results show. This lower contribution is in part due to its low semi-elasticity (regression result): An additional income of 1000$ increases eHANPP by only 1.5%, but increases MF or consumption-based CO_2 emissions by 3.8%. This is consistent with Hertwich and Peters (2009) who showed lower elasticity for food than for other consumables. We learn here that income distribution is only responsible for a small part of international eHANPP distribution (decomposition result). Also remarkable is that urbanization rates contribute to eHANPP inequality, but not to HANPP (although significant). This indicates that, for the eHANPP distribution, the fraction of the population which is actually separated from land (living in cities), although their basic needs (food supply) are still connected to the land, is of high relevance. Countries with higher urbanization rates will tend to have a greater necessity to import such basic resources.

The analysis shows that environmental indicators become more unequally distributed as they are more economically based and less dependent on geographical and demographical drivers[7]. However, for carbon emissions indicators, the distribution appears to be highly determined by economic factors, suggesting that carbon emissions' higher inequality is in fact a consequence of it being a sink resource: the sink (the atmosphere) is equally distributed across the planet, all countries have the same access to it, but it is the distribution of income, active population and urbanization rate that drives the actual distribution of emissions. In this regard, since active population approximates the labour supply of an economy, an indispensable factor of production, results point out this driver as the main contributor of territorial (production-based) emissions. Indeed, active population's distribution is more than two times more important than income's distribution in determining territorial emissions. On the other hand, since income approximates consumption, it is a main contributor of consumption-based emissions. Finally, urbanization rates appear virtually equivalent between both indicators, indicating that this variable contribution to emissions distribution is beyond the footprint-territorial basis for the carbon family.

The three MFA indicators reflect a gradual shift from territorial to footprint (consumption-based) type indicators, which enables a simple interpretation of the results described: the more consumption-based the indicator, the larger its international inequality, the larger the contribution of economic drivers, and the lower that of

[7] As indicated in section 2.1, footprint indicators are derived using different methodologies. CO_2 consump. based and MF are calculated with MRIO models whereas eHANPP is calculated with physical accounting. This methodological difference has an influence on the results: MRIO approaches follow a monetary allocation and product homogeneity is assumed (i.e. the same price and quality for all countries). This may lead to a higher allocation of footprints to wealthy countries compared to physical approaches, reflecting the value that is placed on satisfying the countries' final demand. This is consistent with the dichotomy of economic versus physical allocation in Life Cycle Assessment. The lower link of eHANPP to income compared to other footprint indicators might be in part explained by its underlying physical accounting. However, although we acknowledge that the underlying methodologies of footprint indicators might play a role in the findings of this analysis, we do not consider them to be distorting the results obtained.

demographic and geographic drivers. Trade not only tends to increase environmental inequality, but also delinks resource use from its territorial characteristics. The MF international distribution is mainly determined by economic drivers (income and active population); 55.2% in total. Economic factor contribution accounts for 49.2% for DMC distribution and only 26.5% for DE. Income captures consumption scale distribution whereas active population can be interpreted as consumerist behaviour of different age structures once income is controlled for (in line with Zagueni (2011) and Lugauer et al. (2014)); i.e. two countries with the same income level, and different age structures will consume differently.

On the contrary, whereas the DE distribution lies also on active population, the main contributors are demographic ones (population density and urbanization) plus active population: Active population accounts for 18.9% and can be interpreted as countries' labour supply contribution (in line with O'Neill et al (2010)). In fact, the importance of this particular driver can be explained by the concentration of the labour force in agriculture (one important extractive sector) in least developed countries, where DE tends to be higher. This also explains why, in part, income only explains 7.6% of DE distribution. All together makes an important part of international DE distribution to be dragged by active population. The contribution of population density is also remarkable and it can be seen as the importance that land availability distribution has on per capita DE extraction distribution: a sizeable 17.9%. Finally, urbanization is the most important driver for DE's international distribution (30.33%) and is still important for DMC (20.42%) and MF (17.16). Urban areas contain massive stocks of materials in buildings and infrastructure such as bricks, aggregates or cement, which usually come from national mineral production (Douglas and Lawson, 2000, Steinberger et al 2010). Besides, material flows from the agricultural biomass support life in urban areas. Hence, urbanization rate appears as an important contributor of inequality in international DE. This driver, however, loses importance as the material indicator is adjusted for international trade, and hence economic drivers become dominant in explaining their international distribution.

5. CONCLUSIONS

Environmental indicators provide critical information for managing the environmental pressure caused by modes of production and consumption. This article has focused on comparing the international distribution of three families of physical environmental indicators: land use intensity, material use, and carbon emissions. Special attention has been given to the different distributional patterns between territorial-based indicators, which measure pressure within national boundaries, and footprint-based indicators, which measure pressures related to consumption, i.e. corrected for international trade.

Between the three families of environmental pressures considered, carbon emissions are unambiguously more unequally distributed across countries. As it is not tied to any geographic endowment, nothing prevents this distribution from being influenced by economic factors: this makes these indicators especially unequal.

The main conclusion of this article can be framed in the ongoing debate on whether or not international trade harms or preserves the environment. Our analysis shows unequivocally that international trade worsens environmental equity in terms of energy and material use. When resource use is measured on a territorial basis, environmental inequality tends to be lower and more tied to geographic endowments and demographic characteristics. However, once the resource use indicator is trade-corrected, i.e. measured as a footprint including elements embodied in goods and services, then its international inequality tends to be higher and more linked to economic factors. This is true for material and fossil energy (carbon emissions) indicators.

In contrast, land use intensity indicators exhibit a higher inequality for the territorial-based indicator than for its trade-corrected indicator: land use intensity indicators remain tied to differences in countries' geographic endowments and in technologies of land productivity. Income driver contributes to a part of the trade-adjusted eHANPP distribution, but not enough as to dominate its distribution pattern; this is because of the indicator's connection with basic needs and food supply.

Acknowledgement

The authors would like to acknowledge the financial support received from the Spanish research project ECO2013-45380-P. Establishment of the HANPP dataset was funded by the Austrian National Science Fund FWF (project number P20812-G11) and by the FP7 project VOLANTE, no. 265104. Establishment of the material flow dataset was funded by the Austrian National Science Fund FWF (project P21012-G11)

References

Alcántara, V., Duro, J. A. 2004. Inequality of energy intensities across OECD countries: A note. Energy Policy 32(11), 1257–1260.

Aldy, J. 2006. Per capita carbon dioxide emissions: Convergence or divergence? Environmental and Resource Economics 33(4), 533–555.

Andres, R. J., Boden, T. A., Bréon, F.-M., Ciais, P., Davis, S., Erickson, D., Gregg, J. S., Jacobson, A., Marland, G., Miller, J., Oda, T., Olivier, J. G. J., Raupach, M. R., Rayner, P., and Treanton, K. 2012. A synthesis of carbon dioxide emissions from fossil-fuel combustion, Biogeosciences 9, 1845-1871.

Arto, I., Genty, A., Rueda-Cantuche, J. M., Villanueva, A. and Andreoni, V. 2012. Global Resources Use and Pollution: Volume 1 - Production, Consumption and Trade (1995-2008). Joint Research Centre Technical Reports. Publications Office of the European Union, Luxembourg.

Boden, T. A., Marland, G. and Andres, R. J. 2013. Global, Regional, and National Fossil-Fuel CO_2 Emissions in Trends. (Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, http://cdiac.ornl.gov/, Oak Ridge, Tenn., U.S.A.

Bruckner, M., Giljum, S., Lutz, C., Wiebe, K., 2012. Materials embodied in international trade - Global material extraction and consumption between 1995 and 2005. Global Environmental Change 22, 568-576.

Bruckner, M., Tramberend, S., Fischer, G., Giljum, S., 2015. Measuring telecouplings in the global land system: a review and comparative evaluation of land flow footprint accounting methods. Ecological Economics 114, 11-21.

Cantore, N. 2011. Distributional aspects of emissions in climate change integrated assessment models, Energy Policy 39(5), 2919–2924

Chen, Z.-M., Chen, G.Q., 2013. Virtual water accounting for the globalized world economy: National water footprint and international virtual water trade. Ecological Indicators 28, 142-149.

Cowell, F. 2011. Measuring Inequality, Oxford University Press.

Criado, C. O., and Grether, J. 2011. Convergence in per capita CO2 emissions: A robust distributional approach, Resource and Energy Economics 33(3), 637-665

Dietz, T., Rosa, E. A., and York, R. 2007. Driving the human ecological footprint. Frontiers in Ecology and the Environment 5(1), 13-18.

Dongjing, C., Xiaoyan, M., Hairong, M., and Peiying, L. 2010. The inequality of natural resources consumption and its relationship with the social development level based on the ecological footprint and the HDI. Journal of Environmental Assessment Policy and Management 12(1), 69-85

Douglas I. and Lawson N. 2002. Material flows due to mining and urbanization, in A Handbook of Industrial Ecology edited by Ayres, R. and Ayres, L. Pub. Edward Elgar

Duro J.A., Teixidó-Figueras J. 2013 Ecological Footprint Inequality across countries: the role of environment intensity, income and interaction effects. Ecological Economics 93, 34–41

Duro, J.A. 2012, On the automatic application of inequality indexes in the analysis of the international distribution of environmental indicators, Ecological Economics 76(0), 1-7

Duro, J.A., Padilla, E. 2006. International inequalities in per capita CO_2 emissions: A decomposition methodology by kaya factors. Energy Economics, 28(2), 170–187.

Duro, J.A., Teixidó-Figueras, J.,Padilla, E. 2014. Empirics of the International Inequality in CO_2 Emissions Intensity: Explanatory Factors According to Complementary Decomposition Methodologies. Environmental and Resource Economics, in press

Erb, Karl-Heinz, Fridolin Krausmann, Wolfgang Lucht, Helmut Haberl, 2009. Embodied HANPP: Mapping the spatial disconnect between global biomass production and consumption. Ecological Economics 69(2), 328-334

European Commission, 2011. Roadmap to a Resource Efficient Europe. European Commission, Brussels.

Eurostat, 2012. Economy-wide Material Flow Accounts (EW-MFA). Compilation Guide 2012

Feng, K., Chapagain, A., Suh, S., Pfister, S., Hubacek, K., 2011. Comparison of bottom-up and top-down approaches to calculating the water footprints of nations. Economic Systems Research 23, 371-385.

Fields, G. S. 2003. Accounting for income inequality and its change: A new method, with application to the distribution of earnings in the united states, in Solomon W. Polachek (ed.) Worker Well-Being and Public Policy (Research in Labour Economics, Volume 22), Emerald Group Publishing Limited, 1-38.

Fischer-Kowalski, M., Krausmann, F., Giljum, S., Lutter, S., Mayer, A., Bringezu, S., Moriguchi, Y., Schütz, H., Schandl, H., Weisz, H., 2011. Methodology and Indicators of Economy-wide Material Flow Accounting. Journal of Industrial Ecology 15, 855–876

Foster, J.B. York, R., Clark, B. 2010. The Ecological Rift: Capitalism's War on the Earth. Monthly Review Press. New York.

Giljum, S., Bruckner, M., Martinez, A., 2014a. Material Footprint Assessment in a Global Input‐Output Framework. Journal of Industrial Ecology 19, 792–804

Giljum, S., Dittrich, M., Lieber, M., Lutter, S., 2014b. Global patterns of material flows and their socio-economic and environmental implications: a MFA study on all countries world-wide from 1980 to 2009. Resources 3, 319-339.

Haberl H., Wackernagel M., Krausmann F., Erb K, Monfreda C. 2004. Ecological footprints and human appropriation of net primary production: a comparison. Land Use Policy 21, 279–288

Haberl, H., Erb, K.-H., Krausmann, F., 2014. Human Appropriation of Net Primary Production: Patterns, Trends, and Planetary Boundaries. Annual Review of Environment and Resources 39, 363–391

Haberl, H., J. K. Steinberger, C. Plutzar, K.-H. Erb, V. Gaube, S. Gingrich and F. Krausmann. 2012. Natural and socioeconomic determinants of the embodied human appropriation of net primary production and its relation to other resource use indicators. Ecological Indicators 23, 222–231

Hertwich, E. G. and Peters, G. P. 2009. Carbon Footprint of Nations: A Global, Trade-Linked Analysis. Environmental Science and Technology 43, 6414-6420.

Hoekstra, A.Y., Mekonnen, M.M., 2012. The water footprint of humanity. Proceedings of the National Academy of Sciences 109, 3232-3237.

Hubacek, K., Feng, K., 2016. Comparing apples and oranges: Some confusion about using and interpreting physical trade matrices versus multi-regional input–output analysis. Land Use Policy 50, 194–201.

Inomata, S. and Owen, A. 2014. Comparative Evaluation of MRIO Databases. Economic Systems Research, 26(3), 239-244.

Kastner, T., Erb, K-H., Haberl, H. 2015. Global human appropriation of net primary production for biomass consumption in the European Union, 1986 – 2007. Journal of Industrial Ecology 19, 825–836.

Kharrazi A., Kraines S., Hoang L., Yarime M. 2014 Advancing quantification methods of sustainability: A critical examination emergy, exergy, ecological footprint, and ecological information-based approaches, Ecological Indicators 37, 81-89

Krausmann F, Fischer Kowalski M, Schandl H and Eisenmenger N. 2008 The global sociometabolic transition: past and present metabolic profiles and their future trajectories. Journal of Industrial Ecology 12, 637–56

Krausmann F, Haberl, H. Erb, K-H, Wiesinger, M, Gaube, V.,Gingrich, S. 2009. What determines geographical patterns of the global human appropriation of net primaty production? Journal of Land Science 4 (1-2), 15-33

Le Quéré, C., Peters, G. P., Andres, R. J., Andrew, R. M., Boden, T. A., Ciais, P., Friedlingstein, P., Houghton, R. A., Marland, G., Moriarty, R., Sitch, S., Tans, P., Arneth, A., Arvanitis, A., Bakker, D. C. E., Bopp, L., Canadell, J. G., Chini, L. P., Doney, S. C., Harper, A., Harris, I., House, J. I., Jain, A. K., Jones, S. D., Kato, E., Keeling, R. F., Klein Goldewijk, K., Körtzinger, A., Koven, C., Lefèvre, N., Maignan, F., Omar, A., Ono, T., Park, G.-H., Pfeil, B., Poulter, B., Raupach, M. R., Regnier, P., Rödenbeck, C., Saito, S., Schwinger, J., Segschneider, J., Stocker, B. D., Takahashi, T., Tilbrook, B., van Heuven, S., Viovy, N., Wanninkhof, R., Wiltshire, A., and Zaehle, S. 2014 : Global carbon budget 2013, Earth Syst. Sci. Data 6, 235-263

Liddle B and Lung S 2010 Age structure, urbanization, and climate change in developed countries: revisiting STIRPAT for disaggregated population and consumption related environmental impacts. Popul. Environ. 31, 317–43

Lugauer, S., Jensen, R., Sadler, C. An estimate of the Age Distribution's Effect On Carbon Dioxide Emissions. Economic Inquiry 52(2), 914-929

Miketa, A., and Mulder, P. 2005. Energy productivity across developed and developing countries in 10 manufacturing sectors: Patterns of growth and convergence. Energy Economics 27(3), 429-453.

Nguyen Van, P. 2005. Distribution dynamics of CO_2 emissions. Environmental and Resource Economics 32(4), 495–508.

OECD, 2008. Measuring Material Flows and Resource Productivity. Volume II. The Accounting Framework. OECD, Paris

O'Neill B., Dalton M., Fuchs R., Jiang L., Pachauri S., Zigova K. 2010. Global demographic trends and future carbon emissions.. Proc. Natl. Acad. Sci 107(41), 17521-6.

Owen, A., Steen-Olsen, K., Barrett, J., Wiedmann, T., Lenzen, M., 2014. A Structural Decomposition Approach to Comparing MRIO Databases. Economic Systems Research 26, 262-283.

Padilla, E., Serrano, A. 2006. Inequality in CO2 emissions across countries and its relationship with income inequality: A distributive approach. Energy Policy 34(14), 1762–1772.

Peters, G, Minx, J., Weber, C.L., Edenhofer, O. 2011. Growth in emission transfers via international trade from 1990 to 2008. Proc. Natl. Acad. Sci. 108, 8903-8

Peters, G. 2008 From Production-Based to Consumption-Based National Emission Inventories. Ecological Economics 65(1), 13-23

Peters, G. P. and Hertwich, E. G. 2008. CO_2 Embodied in International Trade with Implications for Global Climate Policy. Environmental Science and Technology 42, 1401-1407.

Peters, G. P. Marland, G., Hertwich, E. G., Saikku, L., Rautiainen, A., Kauppi P. E. 2009. Trade, Transport, and Sinks Extend the Carbon Dioxide Responsibility of Countries. Climatic Change 97, 379-388,

Rosa, E. A. and T. Dietz 2012. "Human drivers of national greenhouse-gas emissions." Nature Clim. Change 2(8), 581-586.

Rosa, E. A., York, R., and Dietz, T. 2004. Tracking the anthropogenic drivers of ecological impacts. AMBIO: A Journal of the Human Environment 33(8), 509-512

Schaffartzik, A., Mayer, A., Eisenmenger, N., Krausmann, F., Gierlinger, S., Gingrich, S., 2013. The Global Metabolic Transition Regional Patterns and Trends of Global Material Use, 1950 – 2010. Global Environmental Change 26, 87-97

Schoer, K., Wood, R., Arto, I., Weinzettel, J., 2013. Estimating Raw Material Equivalents on a macro-level: Comparison of multi-regional input output analysis and hybrid LCA-IOA. Environmental Science & Technology 47, 14282−9.

Shorrocks, A. F. 1982. Inequality decomposition by factor components. Econometrica 50(1), 193-211.

Shorrocks, A. F. 1983. The impact of income components on the distribution of family incomes. The Quarterly Journal of Economics 98(2), 311-326.

Steinberger, J.K., Krausmann, F. and Eisenmenger, N. 2010, Global patterns of materials use: A socioeconomic and geophysical analysis. Ecological Economics 69(5), 1148-1158.

Steinberger, J.K., Krausmann, F., Getzner, M., Schandl, H., West, J., 2013. Development and Dematerialization: An International Study. PloS ONE 8(10), e70385.

Steinberger, J.K., Roberts, J.T., Peters, G.P. Baiocchi, G. 2012. Pathways of human development and carbon emissions embodied in trade. Nature Clim. Change 2(2), 81-85

Steinberger,J., Roberts,T., 2010. From constraint to sufficiency: the decoupling of energy and carbon from human needs,1975–2005.Ecological Economics 70, 425–433.

Strazicich, M. C., List, J. A. 2003. Are CO_2 emission levels converging among industrial countries? Environmental and Resource Economics 24(3), 263–271.

Teixidó-Figueras, J., Duro, JA. 2014. Spatial Polarization of the Ecological Footprint Distribution. Ecological Economics 104, 93-106.

Teixidó-Figueras, J., Duro, JA. 2015a. International Ecological Footprint Inequality: A Methodological Review and Some Results. Environmental and Resource Economics 60(4), 607-631.

Teixidó-Figueras, J., Duro, JA. 2015b. The building blocks of International Ecological Footprint inequality: A Regression-Based Decomposition. Ecological Economics 118, 30-39.

UNEP, 2011. Decoupling Natural Resource Use And Environmental Impacts From Economic Growth. United Nations Environment Programme. A Report of the Working Group on Decoupling to the International Resource Panel., Nairobi, Kenya.

Weinzettel, J., Hertwich, E.G., Peters, G.P., Steen-Olsen, K., Galli, A., 2013. Affluence drives the global displacement of land use. Global Environmental Change 23, 433-438.

Weisz, H. and Steinberger, J.K. 2010, Reducing energy and material flows in cities, Current Opinion in Environmental Sustainability 2 (3), 185-192.

Weisz, H., Krausmann, F., Amann, C., Eisenmenger, N., Erb, K.H., Hubacek, K., Fischer-Kowalski, M., 2006. The physical economy of the European Union: Cross-country comparison and determinants of material consumption. Ecological Economics 58, 676–698

White, T. J. 2007. Sharing resources: The global distribution of the ecological footprint. Ecological Economics 64(2), 402-410.

Wiebe, C., Bruckner, M., Giljum, S., Lutz, C., Polzin, C., 2012. Carbon and materials embodied in the international trade of emerging economies: A multi-regional input-output assessment of trends between 1995 and 2005. Journal of Industrial Ecology 16, 636-646.

Wiedmann, T. O., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J. and Kanemoto, K. 2015. The material footprint of nations. Proceedings of the National Academy of Sciences 112(20), 6271-6276.

Wu, C., and Xu, Z. 2010. Spatial distribution of the environmental resource consumption in the heihe river basin of northwestern china. Regional Environmental Change 10(1), 55-63.

York, R., Rosa, E. A., and Dietz, T. 2003a. STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. Ecological Economics 46(3), 351-365.

York, R., Rosa, E.A. and Dietz, T. 2003b, Footprints on the Earth: The Environmental Consequences of Modernity, American Sociological Review 68(2), 279-300.

Yu, Y., Feng, K., Hubacek, K., 2013. Tele-connecting local consumption to global land use. Global Environmental Change 23, 1178-1186.

Zagheni, E. 2011, The Leverage of Demographic Dynamics on Carbon Dioxide Emissions: Does Age Structure Matter?, Demography 48(1), 371-399.

Supplementary Information.

Annexes:

A1. Correlation Matrix for drivers

	GDP per capita	% Pop. ages 15-64	Population density	Urban pop/total Pop	NPP_{pot}	Daily min. temperature
GDP per capita	1.000					
% Pop. ages 15-64	0.335	1.000				
Population density	-0.101	-0.072	1.000			
Urban pop/total Pop	0.635	0.397	-0.402	1.000		
NPP_{pot} per capita	0.099	-0.033	-0.391	0.377	1.000	
Daily min. temperature	-0.299	-0.648	0.317	-0.293	-0.058	1.000

A2. Inequality indices for drivers

	Gini	Rkg	T0	Rkg	T1	Rkg	T2	Rkg
GDP per capita	0.749	1	1.330	1	1.152	1	1.804	1
NPP_{pot} per capita	0.659	2	0.869	2	0.862	2	1.620	3
Population density	0.503	3	0.562	3	0.544	3	1.627	2
Daily min. temperature	0.450	4	0.522	4	0.303	4	0.327	4
Urban pop/total Pop	0.250	5	0.103	5	0.100	5	0.102	5
% Pop. ages 15-64	0.046	6	0.004	6	0.004	6	0.004	6

A3. Regression results for CO2 emissions with Carbon Dioxide Information Analysis Center (CDIAC) dataset included

	(6)	(7)	(8)
VARIABLES	CO_2 Territ. (CDIAC)	CO_2 Territ. (G.Peters)	CO_2 Consum based (G.Peters)
Income	0.023***	0.028***	0.038***
	(0.006)	(0.006)	(0.005)
Active Population	0.121***	0.117***	0.090***
	(0.012)	(0.014)	(0.012)
Pop. density	-0.0004	-0.0004	-0.0002
	(0.0003)	(0.0003)	(0.0003)

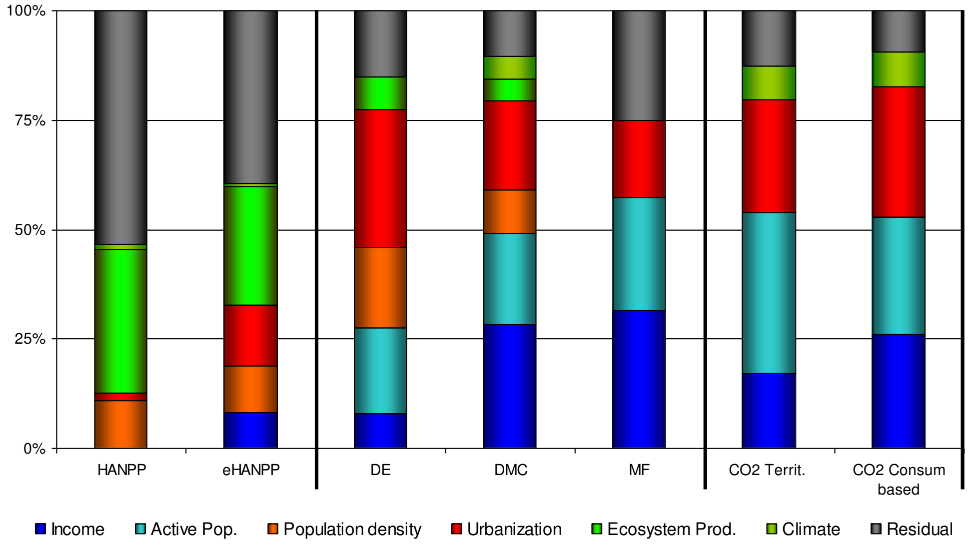
Urbanization	0.025***	0.019***	0.021***
	(0.003)	(0.004)	(0.003)
Ecosystem Productivity	-0.007***	-0.003	-0.004
	(0.003)	(0.003)	(0.003)
Climate	-0.018**	-0.016**	-0.017**
	(0.007)	(0.008)	(0.007)
Constant	-7.897***	-21.243***	-19.716***
	(0.762)	(0.930)	(0.785)
R-squared	0.843	0.874	0.906
Mean VIF	1.93	2.04	2.04
Observations	150	86	86

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A4. Regression-based decomposition. Contributions (%) CO2 emissions distribution with CDIAC dataset included

		(6)	(7)	(8)
	Distributional contributors	CO_2 Territ. (CDIAC)	CO_2 Territ. (G.Peters)	CO_2 Consump. (G.Peters)
ECO	Income	**10.71**	**16.92**	**26.27**
	Active Population	**38.08**	**36.22**	**26.68**
DEM	Population density	-	-	-
	Urbanization rate	**27.92**	**25.41**	**29.88**
GEO	Ecosystem Productivity	-0.75	-	-
	Climate	7.03	7.57	8.11
	Residual	*15.69*	*12.57*	*9.43*
	Total	100	100	100
	Inequality – GINI	0.569	0.546	0.579

A5. Graph Environmental inequality decomposition by drivers' contributions



A6. Inequality measurement and traditional decomposition

The development of distributional analysis in economics has been traditionally tackled in the context of social justice theories through the analysis and evaluation of income distribution and related features of economic inequality. Inequality indices are a widely used tool to compare the dispersion a distribution exhibits, and allow for consistent comparisons among different distributions. To do so, however, some basic axioms are indispensable: anonymity, population principle, scale independence, and Pigou-Dalton principle of transfers (see Cowell 2011):

1-Anonymity. This assumption states that all permutations of individual labels are regarded as distributionally equivalent. $(x_1, x_2, x_3 \ldots x_n) \sim (x_2, x_1, x_3 \ldots x_n)$.

2-Population principle: the inequality index remains unchanged with replications of the population. $(x_1, x_2, x_3 \ldots x_n) \sim (x_1, x_1, x_2, x_2, x_3, x_3 \ldots x_n, x_n) \sim \ldots$

3-Scale independence (homotheticity): the inequality measure remains unaltered by changes of the same proportion in all the observations. This means that the measured inequality of the slices of the cake should not depend on the size of the cake. $(x_1, x_2, x_3 \ldots x_n) \sim (\lambda x_1, \lambda x_2, \lambda x_3 \ldots \lambda x_n)$.4-Pigou-Dalton Principle of transfers: any transfer from an observation (country) with a high level of a variable to an observation (country) at a lower level (which does not invert the relative rankings) should reduce the value of the inequality index. Consider an arbitrary distribution $x_{A:=} (x_1, \ldots, x_i, \ldots, x_j, \ldots x_n)$ and a number such that $0 < \delta < x_i \leq x_j$; then being $x_B := (x_1, \ldots, x_i - \delta, \ldots, x_j + \delta, \ldots x_n)$, the latter is set as more unequal than the former. This axiom is probably the most essential one, insofar as the inequality approach is concerned.

One fourth additional desirable axiom for any inequality index is the decomposability, which allows to account for the underlying structure of the observed inequality. Decomposing an index consists of determining which part of the total inequality observed is attributable to each of its components. Such information might be critical for policy making, since it could indicate where the source of the total inequality lies. In our context, we will use a STIRPAT model (York et al 2003) to determine the driver's (table 2) contribution to the different environmental indicators, and then apply Regression-Based Decomposition (Fields, 2003). Specifically, our STIRPAT will consist in using the different environmental indicators described (table 1) as dependent variables and drivers (table 2) as independent variables: environmental indicator = f(economic factors, demographic factors, geographic factors).

Shorrocks (1982, 1983) demonstrated that independently of the inequality index used to measure a distribution's dispersion, decomposing its inequality in terms of its additive contributors could be done through the decomposition of the variance

$$\mathrm{var}_{\omega}(Y) = \mathrm{var}_{\omega}\left(\sum_{k=1}^{K} y_k\right) = \sum_{k=1}^{K} \lambda_k \, \mathrm{var}_{\omega}(y_k) + \sum_{k}^{K} \sum_{j \neq k}^{K} \lambda_k \, \mathrm{cov}_{\omega}(y_k, y_j) \qquad (1)$$

where Y is the variable of interest, k stands for the additive sources, ω for the analytical weight and λ the source's relative share within the y. The first term accounts for the direct contribution of source k whereas the second term accounts for the correlation among sources. Shorrocks argued that the only unambiguous way of allocating such indirect contributions of sources (correlations), in absence of further information, was by the use the natural decomposition of the variance which consisted in attributing to each source half of the covariances in which such source is involved (in other natural decompositions such as those interaction effects are arbitrarily allocated to contributors). This results in that, independently of the inequality index used, the contribution of source k can be expressed:

$$\mathrm{var}_{\omega}(y_k) = \mathrm{var}_{\omega}(y_k) + \sum_{j \neq k} \mathrm{cov}_{\omega}(y_k, y_j) = \sum_{j} \mathrm{cov}_{\omega}(y_k, y_j) = \mathrm{cov}_{\omega}(y_k, Y) \quad (2)$$

which divided by the $\mathrm{var}_{\omega}(Y)$ yields the proportion of the total variance explained by source k. The rule of natural decomposition of the variance benefits from persuasive axioms. According to Shorrocks (1982) the natural decomposition of the variance is the only non-ambiguous decomposition of inequality by sources independently of the inequality measure used. The main reason is that correlation among components is allocated in an explicit and rational way without violating the basic axioms of inequality measurement (1- the inequality index and the sources are continuous and symmetric. 2- The contributions do not depend on the aggregation level. 3- The contributions of the factors add up to the global inequality. 4- The contribution of source k is zero if factor k is evenly distributed. 5- With only two factors, where one of them is a permutation of the other, the contributions must be equal.).

Following Fields (2003) we will use this result to be used in a regression instead of a sum of components. Typical application of this Regression-Based decomposition is in economic inequality; so that it can be shown whether income inequality is driven by race, sex, education access, etc. (access to education is usually the one that more contributes to income inequality). In our case, we can disentangle to what extent international distribution of environmental indicators considered is linked to its anthropogenic drivers.

A7. Inequality indices:

Index	Formula	Transfer-Sensitivity
Gini	$G = \frac{1}{2\mu} \sum_i \sum_j p_i p_j \lvert y_i - y_j \rvert$	On the distribution mode
Theil index (Generalized Entropy β=0)	$T(0) = \sum_i p_i \ln\left(\frac{\mu}{y_i}\right)$	Bottom of distribution.
Theil index (Generalized Entropy β=1)	$T(1) = \sum_i p_i \left(\frac{y_i}{\mu}\right) \ln\left(\frac{y_i}{\mu}\right)$	Bottom of distribution.
Theil index (β=2)	$T(2) = \frac{1}{2} \sum_i p_i \left[\left(\frac{y_i}{\mu}\right)^2 - 1\right]$	Neutral

Variance of Logarithms	$\mathrm{var}(\ln y) = p_i \sum_{i=1} \left[\ln\left(\frac{y_i}{\mu^*} \right) \right]^2$	Bottom of distribution.

Notes: p_i is the population share of country i, y_i is the environmental indicator per capita, or the per capita value of any variable of interest; μ is the mean of such a variable and μ* is the mean of the logartim of y

Source: Teixidó-Figueras and Duro (2015a)

Table A7. Decomposition according to Expression (5).

Env. Ind.	Drivers	Coeff.	$sd(X_k)$	$corr(X_k, lnY)$	$sd(Y)$	$s_k(lnY)$
HANPP	GDP per capita	-	-	-	-	-
	% Pop. ages 15-64	-	-	-	-	-
	Population density	-0.001	173.269	-0.418	0.817	**10.80%**
	Urban pop/total Pop	-	-	-	-	-
	NPP_{pot} per capita	0.021	20.177	0.629	0.817	**32.50%**
	Daily min. temp.	0.021	8.680	0.040	0.817	**0.90%**
eHANPP	GDP per capita	0.015	10.122	0.369	0.665	**8.20%**
	% Pop. ages 15-64	-	-	-	-	-
	Population density	-0.001	173.269	-0.440	0.665	**10.70%**
	Urban pop/total Pop	0.008	21.011	0.574	0.665	**13.70%**
	NPP_{pot} per capita	0.014	20.177	0.624	0.665	**27.10%**
	Daily min. temp.	0.023	8.680	0.030	0.665	**0.90%**
DE	GDP per capita	0.008	10.122	0.555	0.621	**7.60%**
	% Pop. ages 15-64	0.038	5.274	0.585	0.621	**19.00%**
	Population density	-0.001	173.269	-0.583	0.621	**17.90%**
	Urban pop/total Pop	0.011	21.011	0.803	0.621	**30.40%**
	NPP_{pot} per capita	0.005	20.154	0.435	0.621	**7.20%**
	Daily min. temp.	-	-	-	-	-
DMC	GDP per capita	0.025	10.100	0.726	0.639	**28.30%**
	% Pop. ages 15-64	0.040	5.297	0.638	0.639	**21.00%**
	Population density	-0.001	173.262	-0.463	0.639	**9.80%**
	Urban pop/total Pop	0.008	20.993	0.800	0.639	**20.50%**
	NPP_{pot} per capita	0.004	20.154	0.353	0.639	**4.90%**
	Daily min. temp.	-0.007	8.682	-0.576	0.639	**5.40%**
MF	GDP per capita	0.038	10.124	0.721	0.906	**30.30%**
	% Pop. ages 15-64	0.066	5.273	0.651	0.906	**24.90%**
	Population density	-	-	-	-	-
	Urban pop/total Pop	0.011	21.013	0.697	0.906	**17.10%**
	NPP_{pot} per capita	-	-	-	-	-
	Daily min. temp.	-	-	-	-	-
CO2 WB	GDP per capita	0.023	10.101	0.615	1.319	**10.70%**
	% Pop. ages 15-64	0.121	5.297	0.783	1.319	**38.00%**
	Population density	-	-	-	-	-
	Urban pop/total Pop	0.025	20.963	0.711	1.319	**27.90%**
	NPP_{pot} per capita	-0.007	20.163	0.073	1.319	**-0.80%**
	Daily min. temp.	-0.018	8.682	-0.610	1.319	**7.00%**
CO2 GP	GDP per capita	0.029	10.478	0.663	1.170	**16.90%**
	% Pop. ages 15-64	0.117	4.672	0.775	1.170	**36.20%**
	Population density	-	-	-	-	-
	Urban pop/total Pop	0.019	21.004	0.735	1.170	**25.50%**
	NPP_{pot} per capita	-	-	-	-	-
	Daily min. temp.	-0.016	8.744	-0.638	1.170	**7.60%**
CO2 consump	GDP per capita	0.038	10.478	0.750	1.139	**26.30%**
	% Pop. ages 15-64	0.090	4.672	0.723	1.139	**26.70%**
	Population density	-	-	-	-	-
	Urban pop/total Pop	0.021	21.004	0.779	1.139	**29.90%**
	NPP_{pot} per capita	-	-	-	-	-
	Daily min. temp.	-0.017	8.744	-0.610	1.139	**8.10%**