International Ecological Footprint Inequality: A methodological review and some results.

Jordi Teixidó-Figueras * +
Juan Antonio Duro *

* Departament d'Economia and CREIP, Universitat Rovira i Virgili, Av. de la Universitat, 1, Postal adress: 43204. Reus, Spain.

+ Corresponding author. Email: jordijosep.teixido@urv.cat. Phone: (+34) 977 75 9884

Abstract Scarcities of environmental services are no longer merely a remote hypothesis. Consequently, analysis of their inequalities between nations becomes of paramount importance for the achievement of sustainability. This paper aims, on the one hand, at revising methodological aspects of the inequality measurement of certain environmental data and, on the other, at extending the scarce empirical evidence relating to the international distribution of Ecological Footprint (EF). Most of the techniques currently important in the literature are revised and then tested on EF data with interesting results. We consider the underlying properties of different inequality indices. Those indices which fit best with environmental inequality measurements are CV_2 and GE(2) because of their neutrality property. Subgroup and Source decompositions are also discussed from a methodological perspective. Empirically, this paper contributes to the environmental inequality measurement of EF: this inequality has been quite stable. Subgroup decomposition by using exogenous country groups (World Bank classification) conclude that between group inequality explains almost the totality of international EF-inequality. Source decomposition warns of the dangers of confining CO_2 emissions reduction to crop-based energies because of the implications for basic needs satisfaction.

Keywords Ecological Footprint · International environmetal distribution ·

Inequality measurement · Inequality decomposition

1. Introduction

According to Martinez-Alier and O'Connor (1999), Ecological distribution refers to the social, spatial and temporal inequalities in the human use of environmental resources and services. A typical example is the depletion of natural resources. This paper deals with the empirical measurement of such ecological distribution in terms of natural resource consumption as measured by the Ecological Footprint framework.

Since the scarcity of natural resources is now tangible, distributional issues are brought to the top of the agenda. Business-as-usual scenarios are not feasible neither in a physical nor social sense. Standard economics has attempted to solve current distributional conflicts via growth (a rising tide lifts all boats), and so the main concern has been to do with efficient allocation issues. Nevertheless, since ecological economics puts the *scale* goal on the table (Daly, 1992), fair ecological distribution becomes, not only a necessary condition, but also an ethical issue, for the achievement of sustainability. Interestingly, the core concern of sustainable development is that of working towards guaranteeing the rights and interests of future generations. However, such an approach cannot ignore today's deprived people while trying to prevent deprivation in the future - this would be outrageous (Anand and Sen, 2000). In fact, poor people, in the same way as happens with future generations, do not have any way of expressing their preferences in a market that measures them in monetary units (Padilla, 2002). What ethical system can justify a concern about the well-being of those yet to be born, while not caring for the well-being of those alive today? (Daly and Farley, 2004). In this regard, degrowth proposals might solve distributional problem between generations, but also it might, at the same time, make distributional concerns within generations more pressing (Aubauer, 2006)

Since allocation of resources is determined neither by ethical nor by ecological criteria, but by the dominance of market mechanisms (Røpke, 2001), distributional analysis of responsibilities for the depletion of ecological functions comes to the fore as an important tool for policy makers. Such responsibilities may not be equally distributed among countries, hence, neither are the commitments. The success of any international agreement depends highly on the perception of equitability by the parties (Duro and Padilla, 2006; Heil and Wodon, 2000; Padilla and Serrano, 2006). Greater responsibilities should involve greater efforts toward global sustainability[1]. From Rio 1992 to Durban 2011, passing through Kyoto 1995, distributional issues have unquestionably determined the international agreements reached. Consequently, an in-depth understanding of ecological inequalities may be critical in achieving greater consensus.

[1] As stated in the Principles of UNFCCC (Article 3): "The Parties should protect the climate system for the benefit of present and future generations of humankind, on the basis of equity and in accordance with their common but differentiated responsibilities and respective capabilities. Accordingly, the developed country Parties should take the lead in combating climate change and the adverse effects thereof."

As a result, papers focussed on the distribution analysis of ecological variables are becoming of greater interest in environmental economics: it is noticeable that empirical applications have risen significantly in recent years (Alcantara and Duro, 2004; Aldy, 2006; Criado and Grether, 2010; Dongjing et al. 2010; Duro and Padilla, 2006; Duro and Padilla, 2008; Duro et al., 2010; Duro and Padilla, 2011; Cantore, 2011; Ezcurra, 2007; Heil and Wodon, 1997, 2000; List, 1999; Brooks and Sethi, 1997; Miketa and Mulder, 2005; Nguyen Van, 2005; Padilla and Serrano, 2006; Steinberger et al., 2010; Strazicich and List, 2003; White, 2007; Wu and Xu, 2010). Additionally, as consequence of this literature proliferation, a burgeoning methodology discussion is growing around the adaptation of well-known income inequality tools to environmental issues (Maguire and Sheriff, 2011; Duro, 2012a).

This paper's aim is thus twofold: firstly, we summarize and order the empirical application of inequality approaches to environmental economics. In so doing, we revise the methodologies applied and propose the use of decompositions which are typically applied in the main literature devoted to income distribution. We consider the primary aspects which should be taken into account when these methodologies are applied to ecological issues; such translations are not always direct. Secondly, we analyse empirically the international inequality in Ecological Footprint (EF), since it is a more comprehensive indicator than CO_2 emissions (on which analyses of this sort usually focus) and since there is less empirical evidence for its distribution. Additionally, EF is a reliable proxy for critical natural capital, which makes its distributional analysis of deep interest.

To the best of our knowledge, the existing evidence on international EF inequality is limited to White (2007), using 2003 data, to Dongjing et al.(2010), with five waves covering from 1996 to 2005 and to Duro and Teixidó-Figueras (2013), with data from 1980 to 2007[2]. Both White (2007) and Dongjing et al. (2010) used the Gini index to calculate inequality and White (2007) decomposed it by using different additive sources. In contrast, Duro and Teixidó-Figueras (2013) used Generalized Entropy indices and decomposed inequality by multiplicative factors using data from 1980 to 2007. In the present paper a wider set of inequality indices has been used at the same time as a review of the underlying properties of the ecological distribution framework. Additionally we perform and discuss the inequality decomposition by additive sources and by subgroups of countries for a longer period (1961 to 2007) than previous attempts, which allows for the disentanglement of some interesting stylised facts.

This empirical analysis consists of capturing, in the first place, the main trends in EF inequality over 47 years. Next, an additive decomposition is performed in order to distinguish between the underlying blocks of the observed inequality (Shorrocks, 1980, 1984).

[2] Wu and Xu (2010) analysed the EF distribution for the Chinese region of Heihe River Basin

The paper is organized as follows: Section 2 defines the meaning and significance of Ecological Footprint as an indicator of natural resource consumption. Section 3 revises the inequality approach methodology when the analysis is applied to environmental issues. Section 4 shows the empirical application of such methodologies by measuring EF inequality and its decompositions. Finally, Section 5 concludes the paper.

2. The Ecological Footprint indicator

A commonplace in ecological economics is the incommensurability problem which deals with the fact that is only possible to compare in nature once there is a common denominator available[3]. The EF, introduced by (Rees, 1992) and developed by (Wackernagel and Rees, 1996), proposes as common denominator a global bio-productive hectare, where each such hectare has the average biological productivity of the whole earth. So then, the question becomes how many global hectares a given population uses to maintain its consumption patterns; the answer is the EF[4]. The EF accounts for the biosphere regenerative capacity *occupied* by human activities via resource consumption (including household consumption as well as collective consumption such as schools, roads, fire brigades, etc.) and waste assimilation (Ewing et al., 2010a, b).

The EF framework has been widely used as an indicator of Sustainability as it is compared with a country's bio-capacity. This approach has given rise to a considerable debate, resulting in several criticisms of the measure (Fiala, 2008; Van den Bergh and Verbruggen, 1999). Different (un)sustainability indicators are available, such as EF, Material Flow Accounts (MFA), human appropriation of Net Primary Production (HANPP), etc., each providing different critical information in an attempt to assess the complex concept of sustainability. Thus, sustainability assessment should accept its complexity and incommensurability and might best be carried out by multi-criteria decision making (Martinez-Alier and Roca, 2001; Martinez-Alier et al., 1998). Nonetheless, such debates are beyond the scope of this paper since EF is merely used as a proxy of resource consumption measurement. Indeed, any aggregate indicator (for example, measures of aggregate economic output) will have both strengths and weaknesses, and this also applies to EF.

---

[3] Money has been used to do so; however money is not a particularly objective instrument for evaluating what something is worth, especially for natural capital. See (Martinez-Alier and Roca, 2001; Røpke, 2001).

[4] The basic equation necessary to develop an intuitive understanding of how EF is calculated is: Yield= Tonnes per year/Area – this may be rearranged as Area= Tonnes per year/Yield (Wackernagel et al., 2004). In order to obtain a consumption based indicator of EF, it is necessary to add the EF of imports (EF_I) and subtract the EF of exports (EF_E). In this way, we obtain the EF of consumption (EF_C): $EF_C = EF_P + EF_I - EF_E$

EF accounts are made up of six types of land use[5]: cropland, grazing land and fishing ground (to supply the food and clothes consumed), forest land (for timber and the fuel wood needed), energy land (accounting for the uptake of carbon emissions i.e. the carbon footprint)[6], and finally, built-up land (accounting for land covered by human infrastructure).

$$EF_i = \sum_k EF_{ki} \tag{1}$$

where *k* = Cropland, grazing land, fishing ground, forest land, carbon land, built-up land, and subindex *i* indicates the country. Therefore, expression (1) in per capita terms would be:

$$e_i = \frac{EF_i}{P_i} = \frac{\sum_{k=1}^{K} EF_{ki}}{P_i} = \sum_{k=1}^{K} e_{ki} \tag{2}$$

Figure 1 shows the world EF per capita evolution throughout the period in terms of its sources. Notice the shift from cropland-based societies to carbon-based societies during the period analysed.

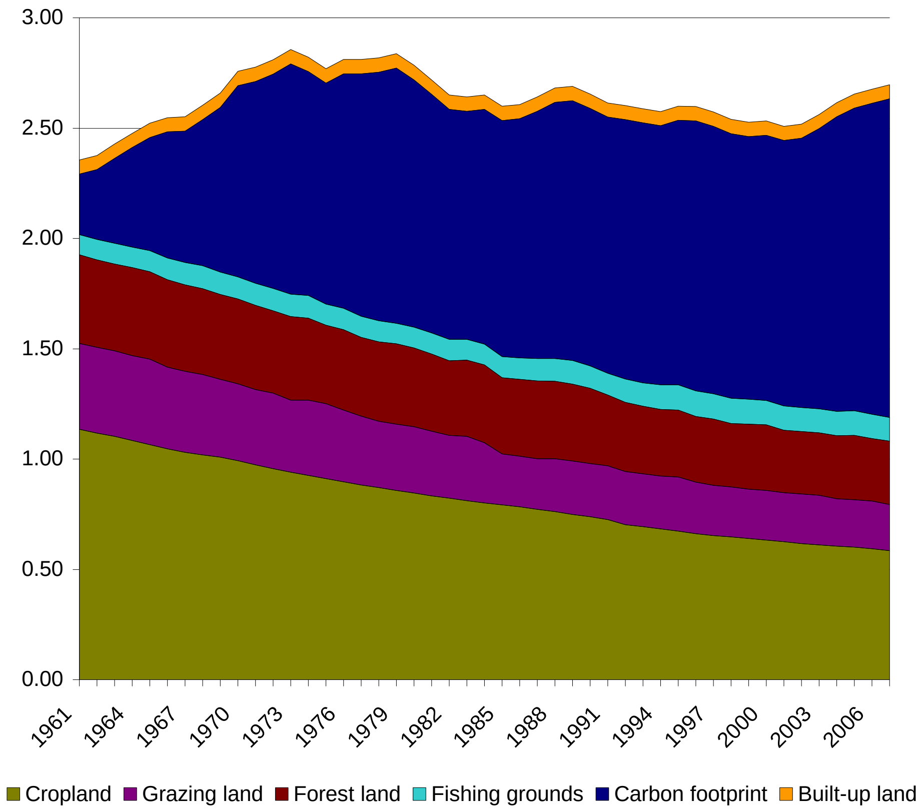
Because of its construction, EF encapsulates in its definition unequal relations between countries and generations. Hence, its distributional analysis allows us to capture an additional dimension when applied to ecological distribution.

Data on Ecological Footprint have been taken from Global Footprint Network, 2010 and they cover 119 countries over the period 1961 to 2007. The sample amounts to 90% of the world population, 91% of the 2007-GDP and 82% of the World Ecological Footprint. The results presented must be read correctly: EF per capita is the EF of the whole country, divided by the country's population: our focus is on analysing the international inequality of resource consumption in a macro-political way. Consequently, we use per capita EF values of each country so that we deliberately ignore the EF inequality within each country

[5] For the underlying assumptions see (Ewing et al., 2010b).

[6] EF measures land appropriation by consumed products; some of them appropriate land directly (paper, food, housing, etc), while the use of fossil energy included in all products (carbon footprint) is appropriated by a fictive and indirect use of land. The idea is to calculate how great an area would be needed to replace the use of fossils or to soak up their emissions. In fact, a sustainable economy would not drain natural capital, but continuously would produce the energy which is used (Røpke, 2001).

Figure 1. World Ecological Footprint per capita 1961- 2007



Source: Present authors from Global Footprint Network data

3. Inequality and the environment: some basic methodological aspects.

The development of distributional analysis methods in economics has been tackled in the context of Social Welfare Theory (Atkinson, 1970; Theil, 1979; Cowell, 1980, 2011; Shorrocks, 1980), which has traditionally focused on the measurement of income inequality and its direct implication for social welfare. Here, however, the direct implications of such inequalities will be on Sustainable Development.

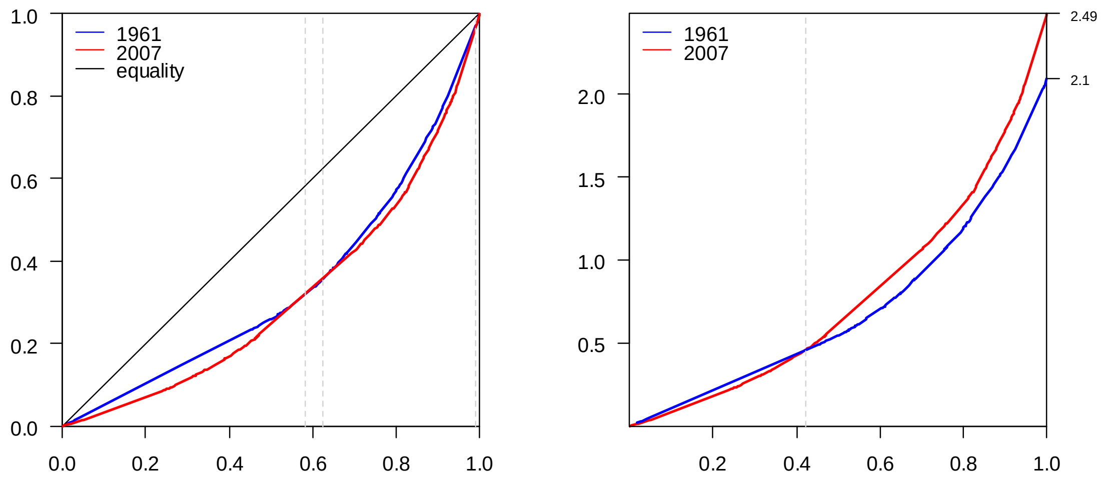
Figure 2 (left) shows Lorenz curves[7] for EF distributions of 1961 and 2007. Since both curves intersect, Lorenz criterion does not allow an unambiguous comparison about which year exhibits a more equitable situation. Yet, even if 1961 had Lorenz-dominated 2007, Lorenz curves ignore the average level of EF (or exposure levels of contamination). Therefore, it may be undesirable to conclude that the 1961 situation is preferable to that of 2007 just because of there being more equity (Maguire and Sheriff, 2011). In order to take into account the

[7] Groot (2010) and Padilla and Serrano (2006) used Lorenz Curves for the case of the analysis of international distribution of CO_2 emissions. Steinberger et al (2010) used them for Material Flow indicators while White (2007) used for the EF of one year.

distribution averages of both years compared, figure 2-right illustrates the Generalized Lorenz Curve (GLC). However, intersections do not permit an unambiguous comparison for either of them. Besides, greater mean income is desirable, although greater EF mean is not, since that involves more environmental impact (scale goal). Hence, focussing on the lower part of the distribution (first and second quintiles), 2007 exhibits a more desirable situation. In contrast, in the higher parts of the distribution the more desirable situation is that of the 1961 distribution. In this regard, using GLC complements significantly the information contained in typical Lorenz Curves, however, given the intersections, any of these tools allow to state which distribution exhibits a more desirable situation unless we focus on particular quantiles of the distribution.

Which year exhibits a more desirable situation depends on which part of the distribution is considered more relevant - this necessarily involves value judgements (Atkinson, 1970; Cowell, 2011; Shorrocks and Foster, 1987). Here, inequality indices show their true worth by ranking distributions unambiguously, based on the imposition of specific value judgements. Indeed, one of this paper's aims is actually to argue that such unavoidable value judgements should be explicit and in line with the problem being analysed, rather than there being an arbitrary selection of index.

Figure 2: Second Order stochastic dominance between 1961 and 2007 using Lorenz Curves and Generalized Lorenz Curves (GLC).



Note: The Lorenz Curves intersect at 0.581, 0.635, and 0.99. GLC intersect at 0.423.
Source: present authors from Global Footprint Network data.

3.2 Inequality measurement: Indices

The literature on the measurement of inequality has identified three basic properties which any inequality index should satisfy: scale independence, the population principle and the Pigou-Dalton Principle of transfers[8]. Most of the more common inequality indices do satisfy such basic properties. Consequently, empirical analyses on ecological inequalities usually employ the inequality indices commonly used in the income literature; the Gini index *G* (Heil and Wodon, 1997; Heil and Wodon, 2000; Wu and Xu, 2010; Steinberger et al., 2010), the Generalized Entropy indices *GE* (Alcantara and Duro, 2004; Duro and Padilla, 2006; Duro et al., 2010) or the Atkinson index *A* (White, 2007; Hedenus and Azar, 2005). In addition, it is also useful that the decomposability axiom be satisfied in order to disentangle the main contributions to the Total inequality (see Section 4). Authors take advantage of the properties of such indices in order to unambiguously analyse inequalities in environmental impact indicators.

Table 1. Summary of inequality indices considered and their characteristics

Index	Formula	Basic axioms	Decomposability	Transfer-Sensitivity
Variance	$\sigma_{\omega}^{2} = p_i \sum_{i=1} (e_i - \mu)^2$	No	Yes	Neutral
Gini	$G = \frac{1}{2\mu} \sum_i \sum_j p_i p_j \left\| e_i - e_j \right\|$	Yes	No	On the distribution mode
Squared Coefficient of variation	$CV_{\omega}^{2} = \frac{\sigma_{\omega}^{2}}{\mu^2}$	Yes	Yes	Neutral.
Atkinson index	$A(\varepsilon) = 1 - \left[\sum_i p_i \left(\frac{e_i}{\mu} \right)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}, \varepsilon \neq 1$ $A(\varepsilon) = 1 - \exp\left[\sum_i p_i \log\left(\frac{e_i}{\mu} \right) \right], \varepsilon = 1$	Yes	No	Bottom of distribution (ε>0). DT axiom
Generalized Entropy index (Theil *β=0*)	$GE(0) = \sum_i p_i \log\left(\frac{\mu}{e_i} \right)$	Yes	Yes	Bottom of distribution. DT axiom
Generalized Entropy index (Theil *β=1*)	$GE(1) = \sum_i p_i \left(\frac{e_i}{\mu} \right) \log\left(\frac{e_i}{\mu} \right)$	Yes	Yes	Bottom of distribution. DT axiom
Generalized Entropy index (*β=2*)	$GE(2) = \frac{1}{2} \sum_i p_i \left[\left(\frac{e_i}{\mu} \right)^2 - 1 \right]$	Yes	Yes	Neutral

Notes: p_i is the population share of country *i*, e_i is the EF per capita, or the per capita value of any variable of interest; μ is the mean of such a variable and ε is the inequality aversion parameter for Atkinson indices.

Source: Present Authors.

[8] Three basic properties (Goerlich, 1998): scale-independence: the inequality measure remains unaltered by changes of the same proportion in all the observations. Population independence: the inequality index remains unchanged with replications of the population. 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.

Nonetheless, these indices were built axiomatically based on several assumptions which fit well for the measurement of income inequality, but which do not necessarily fit so well for ecological variables. In line with this, it is worth considering a remarkable property which usually is present in many inequality indices: the Diminishing Transfer Principle (DT) (Kolm, 1976). In the income framework, the society will value more "positively" a concrete increase of income for a poor individual than for a rich one[9] (i.e. inequality index will decrease more when there is a fixed transfer to a relatively poor individual than when the same transfer is made to a relatively richer person). This rationale does not make such sense when, for example, that transfer is in terms of pollution! Hence, the particular sensitivity of the different indices to the location where distributive changes take place must be taken into account when environmental outcomes are being analysed.

The Gini Index, though not explicitly defined, has more sensitivity to transfers occurring close to the distribution mode. In contrast, because of the Diminishing Transfers principle, *GE* indices (when $\beta<2$), and Atkinson indices (as long as $\varepsilon>0$) have more sensitivity to the low ranks of the distribution. This means that changes that have occurred within those countries exhibiting a low *e*, will have more weight in the inequality measurement than the same changes occurring in other parts of the distribution. On the other hand, CV^2 and *GE(2)*, as they have neutral sensitivity[10], will not favour any particular part of the distribution. This distributive neutrality is assessed as a shortcoming in most of income distribution studies, however neutral measures become appealing choices when there is no obligation to favour any particular part of the distribution (Duro 2012a). Consider an EF distribution and a progressive transfer between two low EF countries: say the lowest EF country increases its EF by 5% while the relatively higher EF country, reduces by -5%). Then consider the same situation with the same progressive transfer but in a higher part of the EF distribution, between two high EF countries. Ceteris paribus, indices that satisfy the DT principle, will register a higher reduction in EF inequality in the first situation than in the second, while neutral indices will register exactly the same inequality reduction. The Gini index would register a higher reduction in inequality when that transfer occurred in the distributional mode. These features determine the differences among inequality indices that are measuring the same distribution. Therefore, as Duro (2012a) proposes, it would be recommendable to compare the patterns suggested by a wide range of indices in order to make the analysis more robust. However, in tracking environmental inequality evolution, it is suggested that it would be appealing to also use neutral indices as a reference point since they weight distribution movements equally. When such tracking is on

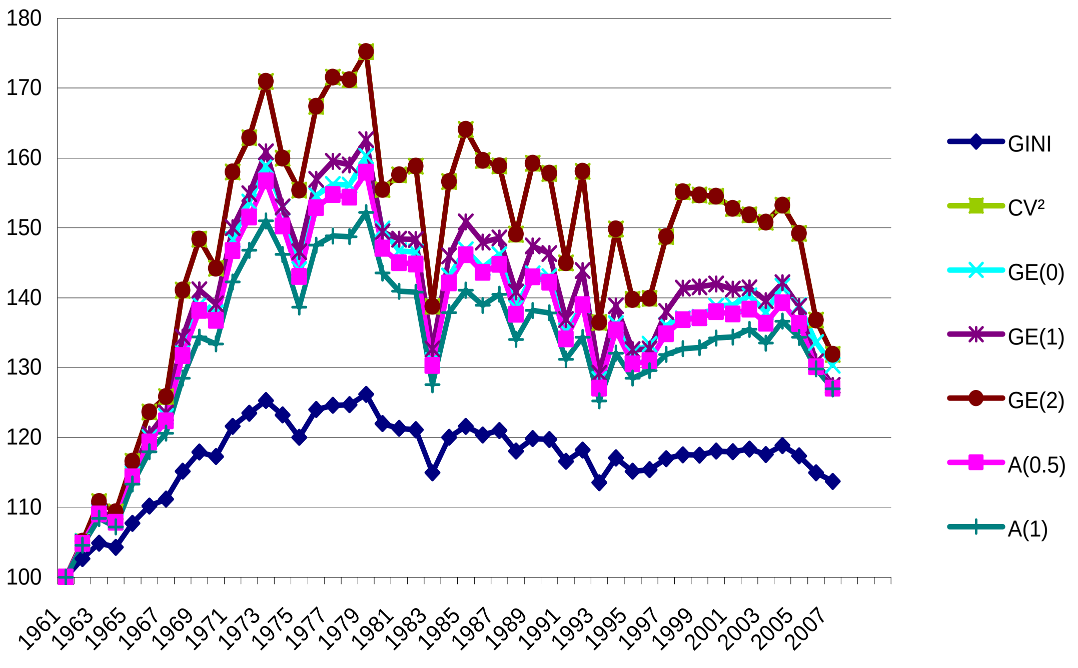
[9] The reason will be found in the concavity of the implicit Social Welfare Function

[10] The *GE(2)* and CV^2 are cardinally equivalent; which means that not only will they rank distributional inequality identically (ordinal equivalence) but also the percentage change from ion inequality between the ranked distribution is the same. Indeed $GE(2) = 1/2\,CV^2$

income issues instead of environmental issues, then the researcher needs to cope with an implicit welfare function (which in Atkinson indices is explicit) and as a result they give more importance to transfers occurring within those more deprived. In environmental distributions, however, it is more sensible not to do so

Figure 3 shows the evolution of inequality in the course of the period analysed according to different well known indices. Despite all them sharing a similar pattern, it is remarkable that the significant differences in growth rates observed depend on the index used. Moreover, a detailed observation of Figure 3 will show that, in some periods, the indices even indicate different signs for the inequality trend: in the period 1980-82 neutral indices (CV^2-*GE(2)*) show a clear increase in observed inequality whereas *GE(0)*, *GE(1)* and Gini show a slim decrease. In contrast, during the periods 1986-87 and 1998-2000, a reduction in inequality is shown by neutral indices whereas the Gini, GE(0), GE(1) and Atkinson indices indicate an increase in the observed inequality.

Figure 3. Inequality trends in EF according to the main inequality indices (1961 – 2007)



Note: 1961=100 for all indices (see appendix A3 for the inequality indices' values)

Source: Present authors from data of Global Footprint Network

As a result, the inequality trend in EF displays a quite stable pattern of global growth in the long term when we consider the whole period (from 1961 to 2007). At the same time, the World EF per capita increased from 2.36 global hectares to 2.70 (Figure 1). Hence, the world not only increased its ecological impact but also it became more unequal in the considered period. Nonetheless, it is worth noting some particular episodes throughout the period: during the first twenty years (1961-1981), there was a significant increase in EF inequality at the same time that World EF registered the most significant increase of the whole period, mainly driven by the Carbon Footprint component. Once the 80s had passed, the inequality shows a tendency towards a slight decrease, this being more noticeable from 2003 onwards. Indeed, from 2003 to 2007 a new increase in global EF is observed, though this time accompanied by a decrease in EF inequality. The heavy industrialization of super-populated China in the last decades has had an equalizing effect on the EF distribution[11], India has behaved similarly. However, the EF inequality observed can hide different underlying trends, as will be shown by decomposition techniques[12].

4. Additive Decomposition analyses

Additive decomposition analysis turns to be a very useful in measuring and understanding the level, causes and development of observed inequalities. 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 the main origin of total inequality. However, a necessary condition for doing this is the satisfaction of an extra property: decomposability (Bourguignon, 1979; Cowell, 2000; 2011). This property implies that there should be a coherent relationship between the whole inequality observed and its constituent parts. i.e. if inequality in a component or subgroup increases then this implies, ceteris paribus, that inequality overall goes up (Shorrocks, 1984). Such a property additionally restricts the available inequality indices to a concrete family: Generalized Entropy indices or some cardinally-equivalent transformation. There are two classic ways of additively decomposing the global inequality: subgroup decomposition and source decomposition.

4.1 Subgroup decomposition

This consists in determining the contribution to the total inequality of each of the different mutually exclusive subgroups in the population. Here, the inequality can be expressed as the sum of the inequality *between* groups and the weighted inequality *within* those groups. The

[11] The same analysis as shown in Figure 3 has been performed, excluding China from the sample. These results show an uninterrupted increase in the EF inequality. This is consistent with Duro and Padilla (2006), where the reducing trend in CO_2 emissions inequality was found to be less evident without China and India in the sample.

[12] The analyses of EF inequality consist in measuring differences in per capita EF weighted by relative population. Following Duro (2013) we have decomposed the inequality changes in terms of changes in the per capita EF vector (with relative population weights held constant) and in terms of changes in the vector of relative population (holding per capita EF constant). Our results, available on request, showed that in the periods where there is a significant change of EF inequality, such evolution was always mainly driven by changes in the per capita EF vector rather than in changes in the world population structure. Therefore, international EF inequality has been a matter of differences in the ‘size’ of the people rather than changes in the number of people in countries.

between component is the inequality which would exist if each member of the group had the average EF of that group. On the hand, the *within* component consists of the inequality which would be observed if the inequality between groups did not exist, so that the *within* inequality is the existing inequality in each group weighted by the population or pollution share. It takes the form

$$I(e) = \sum_{g}^{G} \omega_g I(e)_g + I(e)_0 \tag{3}$$

where $\omega_g = \omega_g(p_g, e_g)$, *g=1,G,* are the weights for each *within* inequality, p_g and e_g being the relative population and the relative EF, respectively. Translating that expression to GE indices, we obtain (Shorrocks, 1980, 1984):

$$GE(\beta) = \sum_{g}^{G} \omega_g GE_g(\beta) + GE_0(\beta) \tag{4}$$

where $\omega_g = p_g^{1-\beta} y_g^{\beta}$. So, only for $\beta = 1$ or $\beta = 0$ (Theil indices) may the weights be read as population proportions ($\beta = 0$) or EF proportions ($\beta = 1$). The case for $\beta \neq 0, 1$ leads to a problem of interpretation since the weights are a non-linear combination of population and pollution shares, and those weights do not add to one. Furthermore, given that the decomposition for $\beta=1$ corresponds to weighting observations by relative EF instead of by relative population, it is important to keep in mind that conceptually, the *between* inequality as defined above would involve transfers among observations, which could also lead to interpretation problems. For that reason, the Theil measure with $\beta = 0$ (*GE(0)*) is the most unambiguous solution (see Goerlich, 1998; Shorrocks, 1980)

Subgroup decomposition has been performed using exogenous groups of countries such as those defined by the World Bank[13]. Figure 4 illustrates this decomposition using three GE indices. The main result is that the bulk of the inequality during the analysed period is largely explained by the *between* inequality component (between 83%-88% according to *GE(0)*). Therefore, it could be said that the inequality in EF would be drastically reduced if differences among groups were eliminated, or equivalently, that if the inequality *within* groups were null, there would be no significant reduction in global inequality. Such an empirical finding has important policy implications in terms of achieving international agreements. In the light of these results, the probability of achieving broader and deeper consensus would increase if, instead of holding

[13] World Bank groups are: East-Asia and Pacific, Europe and Central Asia, South Asia, Industrial countries, Latin America and the Caribbean, Middle East and North Africa, and Sub-Saharan Africa. See appendix A2

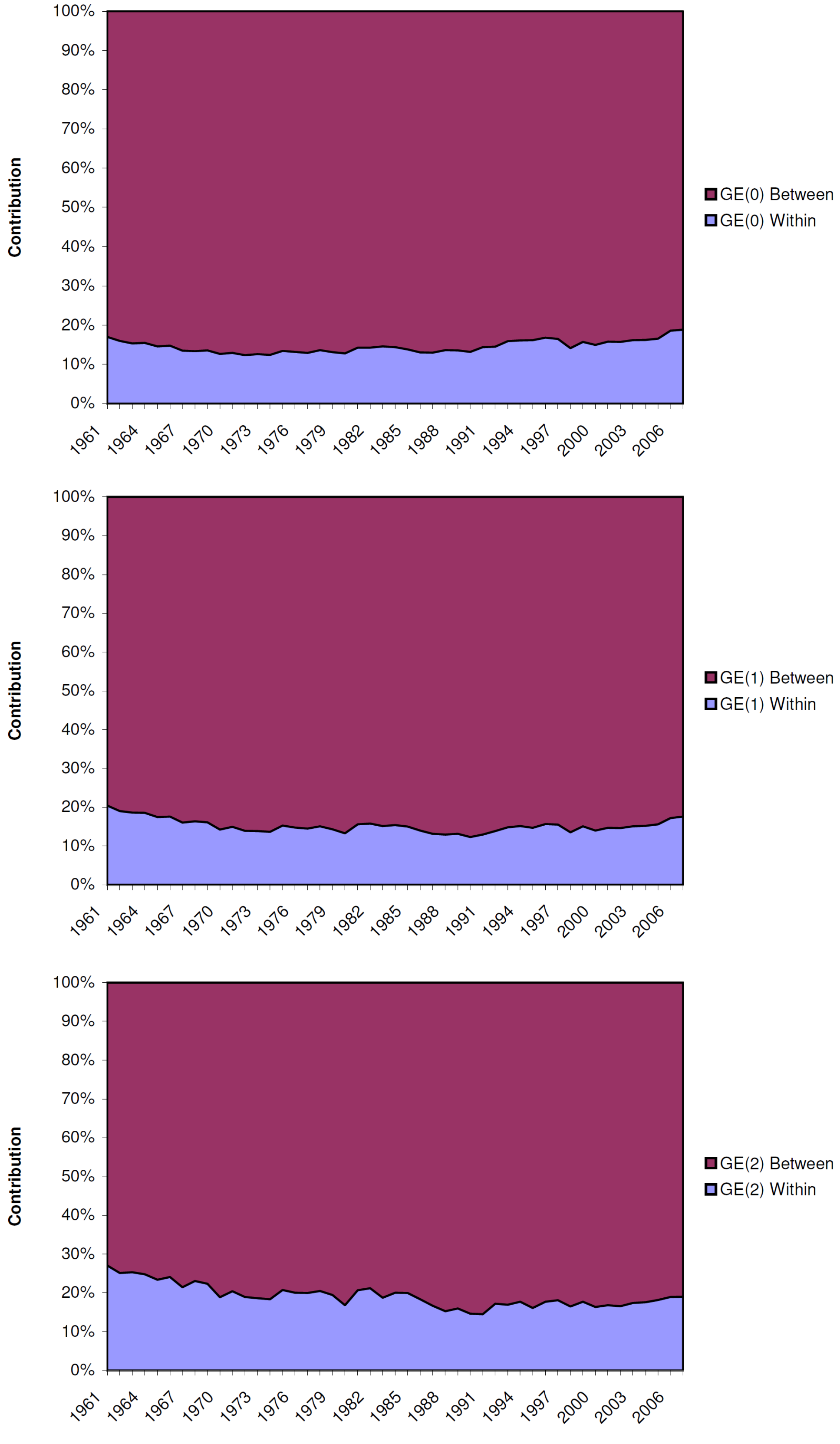
international meetings where all countries participate, the framework were in regional terms such as those defined by World Bank groups (assuming there are no other political issues on the table within these regions). This is because inequality within these groups is not so marked.

Duro and Teixidó-Figueras (2013) used *GE(0)* to decompose EF inequality according to the regional classification of the International Energy Agency[14]. Despite the differences in the groups used, those authors achieved similar results as those discussed here. Contrastingly, in other studies where different indicators were used, the pattern observed in the between-component (and inversely in the within-component) usually shows drastic decreasing for either CO_2 emissions (Duro and Padilla 2006; Padilla and Serrano 2006) or energy intensities (Alcantara and Duro 2004). Therefore, according to these results (supported by previous evidence), the EF asymmetries have been conspicuously and persistently determined by the world region to which the country belongs.

From a methodological perspective, it must be noted that *GE(2)* is the inequality index which, because of its neutrality property, is in best accord with this paper's aim. However, we have also shown that the best choice for decomposing such an inequality by subgroups is *GE(0)*. As a result, our analysis leads us to believe that, insofar as environmental inequalities are being measured, the three indices used in this analysis should be considered for their particularities, while paying attention to the minutiae of each index when interpreting results. Nevertheless, as far as our empirical results are concerned, the three subgroup decompositions performed by EF are robust in the sense that all of them point to the same conclusion of an EF inequality being significantly driven by the differences between regional groups of the World Bank.

[14] Wu and Xu (2010) performed a subgroup decomposition of the EF of the Heihe River Basin of Northwestern China. Their results point out that EF inequality in that region was mainly derived from the inter-regional inequality between urban and rural areas

Figure 4. Subgroup decomposition of EF inequality according to regional classification of the World Bank by *GE(0)*, *GE(1)* and *GE(2)*.



Source: Present Authors from Global Footprint Network data

4.2 The source decomposition

Source decomposition aims to quantify how much EF inequality can be attributed to different EF components – this may have deep policy implications for the achievement of equity. However, the contribution of a component to the whole inequality can adopt different forms (see Shorrocks, 1982; 1988). It can be stated that the contribution of component *k* to the overall inequality is three-fold, consisting of: the component's inequality, the component's share in whole EF, and the correlation between components.

It may be instructive to begin by considering the inequality of each EF component. Indeed, that may be regarded as a component's contribution to overall EF inequality[15]. Figure 5 shows the *GE(2)* for each EF component. The Fishing, Forest, and Built footprints show stable trends, with a relatively high inequality for Fishing. On the other hand, the Cropland footprint exhibits a quite stable low inequality trend (a slight reduction); such a low inequality in the Cropland footprint could be indicative of the special status of some biomass consumption from cropland (food and fibre for human consumption), this being necessary for the most basic subsistence (Steinberger et al., 2010). In contrast, the Grazing footprint inequality, despite also registering a reduction in the course of the period, always remains the most unequal distribution as compared to the remaining EF components. The explanation of such a high inequality may be found in the meat-intensive diets of industrialized countries (White, 2000). Finally, the Carbon footprint inequality displays a significant reduction during the period - this is consistent with the findings of Padilla and Serrano (2006), Ezcurra (2007) and Heil and Wodon (1997, 2000) who analyse CO_2 emissions inequality[16].

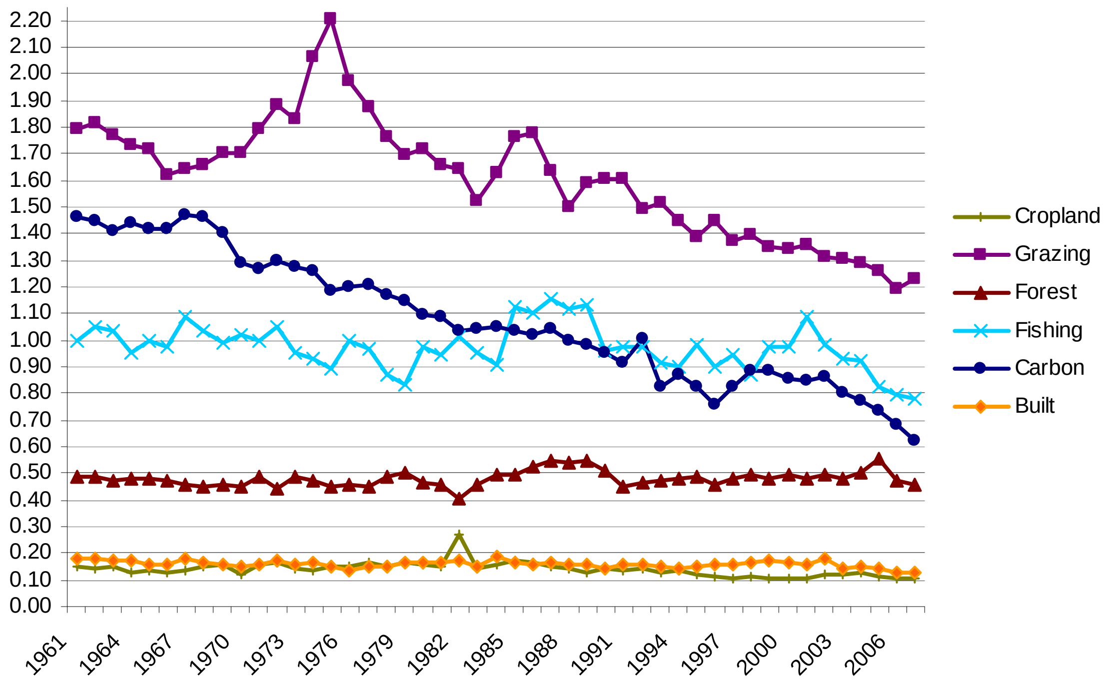
In 1961, the most unequal distributions of footprint were for grazing, followed by carbon and then by fishing. However, by the end of 2007, the ranking shows grazing as still the being the most unequal, but now followed by fishing rather than carbon, which becomes the third most

[15] It is a common practice in the empirical literature to use each component's inequality as a contribution to the overall inequality (see Shorrocks 1988). Actually, Steinberger et al. (2010) analysed international inequality in Domestic Material Consumption and the inequality of its components (biomass DMC, construction minerals DMC, ores/industrial minerals DMC and fossil fuels DMC). Dongjing et al. (2010) analysed international inequality of Ecological Footprint and also the inequality of two aggregated subcomponents: Renewable Resources Footprint and Energy Footprint.

[16] Steineberger et al. (2010) estimated the Gini index of Domestic Material Consumption (DMC) and of its different components (biomass, construction minerals, fossil fuels, ores/industrial minerals) for the year 2000. Despite both indicators sharing raw data, the results obtained are not comparable, since the indicators deal with different research questions and so are constructed differently. EF focuses mainly on biomass consumption. Nevertheless, it is interesting to observe some relatively similar results: the Gini coefficient for total DMC is 0.35 and the Gini coefficient in the same year of EF is 0.39; the Gini coefficient for fossil fuels DMC is 0.58 while the Gini coefficient for Carbon Footprint for our data is 0.576. Additionally, if the Cropland, forest, grazing, and fishing footprints are added together in order to construct a "pure biomass footprint", the resulting Gini coefficient for 2000 would be 0.300, very close to the 0.29 Gini for Biomass Material Consumption of the Steinberger et al. paper. Therefore, our analysis is in line with that of Steinberger et al. 2010, while adding new which are compatible. Our calculations are available on request.

unequal distribution. Hence, the most unequal distributions, and thus the main contributors to EF inequality, according to this relatively simplistic interpretation, are diet-related issues followed by a decreasing energy-related issue.

Figure 5. Inequality of EF components 1961-2007 according to *GE(2)*



Source: Present Authors from Global Footprint Network data

The component's inequality does not take into account the weight of each component in the EF, so, despite providing critical information, this approach does not distinguish the relative importance of having a high inequality in a component which accounts for 99% share of EF versus having a high inequality in the component which accounts for 1% share of EF. Hence, the second issue which must be considered in accounting for component's k contribution is its weight (importance) in the EF. Along these lines, any contribution to inequality consists of a weighted inequality index of each component.

By definition, EF can be broken down into the sum of its components (cropland, grazing land, fishing ground, forest land, carbon land, built-up land). Recall expressions (1) and (2)

The idea behind the weighted source decomposition is thus to break down overall EF inequality into the part for which each EF component is responsible. Therefore, the source decomposition will have the form

$$I(e)=\sum_{k=1}^{K} S_k =\sum_{k=1}^{K}\lambda_k I(e_k)=\sum_{k=1}^{K}\frac{\mu_k}{\mu} I(e_k) \tag{5}$$

where S_k is the absolute contribution of component e_k to the overall EF inequality which is a function of the component's inequality $I(e_k)$ and its weight (or importance) λ_k in the EF, μ_k and μ being the k^{th} component's mean and EF's mean respectively. If we normalize it by the inequality index, the relative contribution will be obtained, i.e.

$$s_k =\frac{S_k}{I(e)},\quad \sum_{\mathbf{k}}^{\mathbf{K}} s_k =1 \tag{6}$$

As the Gini index is the most popular inequality index, its natural decomposition is widely applied to such an index, first proposed by Fei et al. 1978, and performed by White (2007) for the EF sources. However, the natural decomposition of the Gini index has several technical problems, whose description will allow us to deal with the third issue of source decomposition; the role of correlations among sources.

The correlations involve interaction effects among sources and so their distribution might be affected by those interactions; for instance, having a higher carbon footprint (due to the higher energy demands of colder countries) might require a higher demand for wool and so of grazing footprint. Accordingly, the inequality contribution of, say, a grazing footprint would be a combination of its weighted direct effects on the overall EF-inequality and its weighted indirect effects, i.e. the correlations with other sources. Thus, those indirect effects must be allocated to the different contributions. As a result, the contribution of a source to an overall inequality is not only about its inequality and its weight, but also the correlations among the sources, which is the last piece of the source contribution jigsaw.

Thus, the natural decomposition of the Gini index consists of performing expression (5) with the Gini formula. However, if we did that with the EF data we would find that the sum of the weighted Ginis of the sources is greater than the Gini of the EF[17]. Since the Gini index depends on ranking the observations, to solve this shortcoming, Fei, et al. (1978) proposed ranking the distribution of sources (e_k) according to the ranking of the aggregate variable (e), and then calculating the Gini indices of the sources; these ranked source Ginis are known as Pseudo-Ginis in specialised literature. As a result, expression (5) becomes consistent. This natural decomposition has at least two shortcomings: the first is that by ranking component k according to the aggregate variable, it makes the contribution of component k independent of its own

[17] This is given for the mathematical theorem of Triangle Inequality $|a+b|\le|a|+|b|$ in the Gini decomposition. See Goerlich (1998), Shorrocks (1982); Cowell (2000)

distribution and dependent instead on the aggregate variable distribution (here e). Second, and related to the previous point, the correlations among the k components are allocated in an implicit and quite arbitrary way (by ranking e_k according to e). As a result, the source decomposition of the Gini index turns out to be a less interesting exercise. In fact, without further restriction on the decomposition rule, the results obtained are non-unique, since they depend on an arbitrary way of allocating the interaction effects. The same occurs with other natural decomposition rules such as those of the family of the Generalized Entropy indices (Theil indices) (see Bourguignon, 1979; Cowell 2000; 2011; Shorrocks, 1982).

In contrast, the natural decomposition of the variance (which is equivalent to the natural decomposition of CV^2), shows clearly what the interaction effects are and consequently allows an explicit and non-arbitrary allocation of them:

$$Var_{\omega}(e) = Var_{\omega}(\sum_{k=1}^{K} e_k) = \sum_{k=1}^{K} \lambda_k Var_{\omega}(e_k) + \sum_{k}^{K}\sum_{j\neq k}^{K} \lambda_k \operatorname{cov}_{\omega}(e_k, e_j) \tag{7}$$

where the contribution of source k is a combination of a weighted factor's dispersion (first term) plus its weighted indirect effects (second term, which is null when the sources are uncorrelated). Such a particularity of this type of decomposition rule allows the researcher to allocate the interaction of S_k inequality contributors in a non-arbitrary and explicit way. Therefore, independently of the inequality index used to measure and track inequality (G, $A(\varepsilon)$, $GE(\beta)$, CV^2, etc), when such inequality needs to be decomposed in terms of its additive sources, since any source decomposition rules base their results on the allocation of correlations, the specialized literature suggests doing it by the natural decomposition of the variance (or of its equivalent CV^2). This is allocating the term of the covariances $\operatorname{cov}(e_k, e_j)$ to the inequality contributions S_k. According to Shorrocks (1982), in the absence of further information, it appears that a sensible rule is to allocate to each contribution of source k, half of all its indirect effects. This is half of the term $\operatorname{cov}_{\omega}(e_k, e_j)$. In doing so, we obtain the "natural decomposition of CV^2" proposed by the same author:

$$S_k^{*}(CV^2) = \lambda_k \frac{\operatorname{var}_{\omega}(e_k) + \sum_{j\neq k} \operatorname{cov}_{\omega}(e_k, e_j)}{\mu^2} = \lambda_k \frac{\sum_{j} \operatorname{cov}_{\omega}(e_k, e_j)}{\mu^2} = \lambda_k \frac{\operatorname{cov}_{\omega}(e_k, e)}{\mu^2} \tag{8}$$

Shorrocks (1982) proves that, under some very plausible axioms[18], the natural decomposition of the variance or its equivalent, the CV^2, is the only unambiguous decomposition method

[18] The conditions are: a) the inequality index and the sources are continuous and symmetric. b) The contributions do not depend on the aggregation level. c) The contributions of the factors sum the global inequality. d) The contribution of source k is zero if factor k is evenly distributed. e) With two only factors, where one of them is a permutation of the other, the contributions must be equal.

independent of the index used to measure the whole inequality. This result is very opportune in environmental analyses, since CV^2 benefits from the neutrality property defended in this article as an appealing property for analyzing ecological inequality.

Besides, the results obtained by the natural decomposition of the CV^2, coincide with those provided by the Shapley Value Decomposition which allows for the interpretation of the contributions of source *k* not only as "its direct effect plus one half of all its interaction terms", but also as the expected marginal contribution to inequality of the source *k*.

The Shapley Value Decomposition technique implies considering the impact on global inequality of eliminating the inequality in each EF component (i.e. change the real distribution of component *k* for μ_k in all observations). Since there is no natural order for equalising each *k* component, Shapley decomposes the averages of all these impacts over all possible sequences of component's *k* inequality elimination (Sastre and Trannoy, 2002). So, the Shapley contribution will be $S_k^{ShD} = I(Se) - I(Se - \{e_K\} + \mu_k)$ where *Se* is a Subset of EF`s components $(Se \subseteq e, k \in Se)$. It takes the form:

$$S_k^{SD}(K,I) = \sum_{\substack{S \subseteq K \\ j \in S}} \frac{(k-se)!(se-1)!}{k!} \left[I(Se) - I(Se - \{e_k\} + \mu_k) \right] \tag{9}$$

The main advantages of using the Shapley methods are that consistent and unambiguous decompositions can be performed using any inequality index, provided the method is sensitive to the index chosen (in contrast to the natural decomposition rule described). One major shortcoming, however, is that the contributions obtained are not independent from the level of disaggregation. The resulting contribution is defined as the expected marginal contribution of the factor *k* (when such an expectation is made over all possible sequences of factor *k*'s inequality elimination).

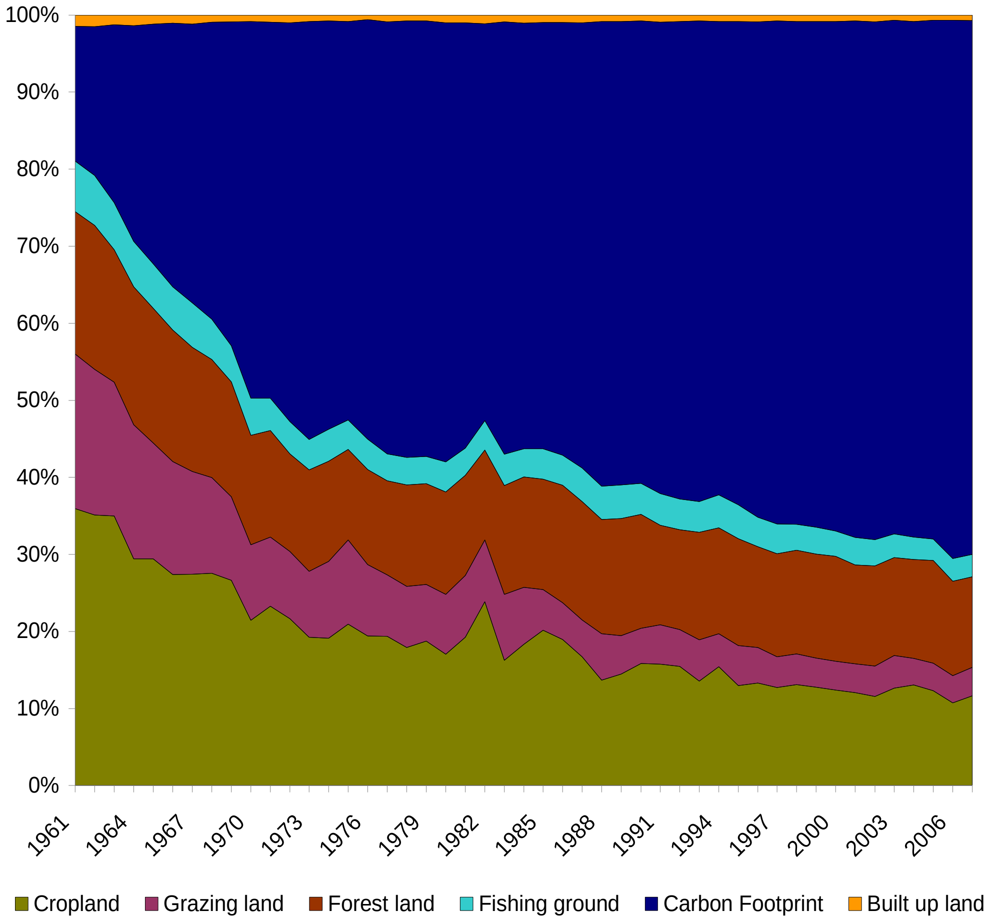
Thus Figure 6 (appendix A4) shows the changes in contribution of EF components during the period, as estimated by the natural CV^2 decomposition. In the first place, the result shows a clearly growing trend of Carbon footprint contribution to EF inequality, until this becomes the main contributor to the overall inequality. Focusing on 2003, the results obtained coincide with those obtained by White (2007) who decomposed the Gini index for that year. In 2003, our results also show a predominance of the inequality contribution of Carbon footprint (our results were 66.52% while White's were 65.6)[19]. However, because of the methodology employed by White (2007), those contributions cannot be interpreted as transparently as those obtained here

[19] The differences between the source contributions estimated by White (2007) (W) and those obtained here (T-D) in 2003 are rather small: Carbon: W (65.6%), T-D (66.5%); Forest: W (11.2%), T-D (12.7%); Built: W (3.2%), T-D (0.7%). Food (Grazing+ Cropland+ Fishing): W (20.1%), T-D (19.9%).

because of the ambiguity in the allocation of correlations. In contrast, the inequality contributions estimated here might be interpreted as the direct effect of the source distribution plus half of all its interaction effects, or equivalently, the expected marginal contribution of source k to overall inequality. Fortunately, the empirical results are quite similar on this occasion[20].

If we consider the long term trend (which has not yet been evidenced empirically) it is worth noting the significant growth of the Carbon footprint's contribution to the EF Inequality (from 18% to 69%). In contrast, the Cropland footprint which was originally the main contributor to inequality has reduced its contribution drastically (from 36% to 11%). Grazing and Fishing footprints also follow a shrinking inequality contribution trend (from 20% to 4% in the former and a smaller reduction in the latter, from 7% to 3%).

Figure 6: Relative contributions of EF components estimated by Natural decomposition of CV^2 (1961-2007)



Note: The contributions can be read according to a Shorrocks (1982) or Shapley value decomposition.
Source: Present Authors from Global Footprint Network

[20] Araar (2006) discusses, among other issues, the decomposition of the Gini index and gives a clue as to why its decomposition can be close to the Shorrocks solution; this is the low-ranking effect.

It is interesting to notice that the contributions of a component to the overall EF inequality differ from that component's inequality indices as shown in Figure 5. It has been shown that all these inequalities decreased in the course of the period, however, some contributions, have not decreased in the same proportion, the Carbon Footprint contribution has even increased significantly. When the Carbon footprint exhibited the highest inequality (in 1961), its contribution according the Shorrocks rule was 17%, whereas it had become 69% by 2007 when its inequality reached the lowest level in the period. The reason must be sought in the Carbon footprint's share of the whole EF, which passed from representing 11% to representing 53% of the EF (see figure 1). Similarly, high inequalities in the Grazing and Fishing footprints are compensated by representing a low share of the overall EF. The Cropland footprint, in contrast, exhibited low and reducing levels of inequality. However, its contribution to overall inequality has not reduced in the same proportion because, in spite of a reducing EF share (from 47% in 1961 to 21% in 2007), it still is the second largest EF share. Indeed, the low inequality along with an important EF share of the cropland footprint stems from the strong link Cropland has with the basic needs of humanity.

These results point towards profound policy implications: climate change negotiations are now mainly focused on the carbon emissions of different countries. However, the fact is these negotiations are one dimensionally based, which can be counterproductive; for instance, as EF source decomposition points out, converting cropland to bio-fuel land in order to reduce CO_2 emissions[21] will, at the same time, lead unavoidably to an increase in the cropland footprint share. Thus the low inequality of cropland footprint would be seriously compromised and this, in turn, could have serious implications, not only for international agreements, but also in terms of social unrest in many countries due to the strong link between cropland and basic human needs. In this way, complementing international CO_2 emissions-based negotiations with other ecological indicators (such as EF or other physical indicators) is of extreme importance, since only then can some future errors be avoided. Furthermore, the fact that some indicators were production based (as they are currently) and others were consumption based (as is EF) might allow us to deal with sustainability and equity in a more comprehensive way. Actually, the use of multiple indicators in multilateral agreements points to an extension of the idea of multi-criteria analyses of sustainability assessment (Martinez-Alier et al. 1998). The political feasibility of this issue might be driven by the same spirit of the ongoing "Beyond GDP" initiative in the European Union, by which other indices than GDP are proposed to measure progress and welfare. In this context, and as White (2007) also suggests, it could be claimed that policies aimed at reducing the carbon footprint (reduction in energy use) of countries will lead, not only to a more sustainable scale, but also to a more equitable distribution of EF. However,

[21] Assuming that land use change does not increase CO_2 emissions.

in order to achieve this, other environmental and social dimensions need to be taken into account.

6. Conclusions

This paper has focussed on the analysis of international inequality in natural capital consumption, as measured by the Ecological Footprint framework. Our aim in doing so has been twofold: on the one hand, we revise the methodologies on inequality measurement when they are applied to environmental issues rather than to income. On the other hand, we extend the empirical evidence relating to the international distribution of Ecological Footprint (EF) by using a longer EF time series than in previous attempts. The result is the application and discussion of a wide range of inequality methods for international EF distribution from 1961 to 2007.

Although there exist different types of inequality indices, and several of them are widely used in ecological inequality measurement, we have demonstrated that some typical properties of those indices do not fit well when environmental issues, rather than income, are being analysed. For instance, Atkinson's and some Generalized Entropy indices weight the low parts of the distribution more heavily because of their Diminishing Transfers Principle property. Gini coefficient instead weights the distribution mode more heavily. Neither of these behaviours is justified in environmental inequalities. In this sense, the neutrality character (all parts of distribution being treated equally) of *GE(2)* or CV^2 has been discussed as a desirable property to being satisfied (jointly with those basic properties). As a result, neutral indices show a quite stable inequality trend in the course of the period in spite of a significant increase in the first decade and a lower reduction in the last years of the period.

Additionally we have performed the subgroup decomposition by using exogenous country groups (World Bank classification). Estimations performed by different indices robustly conclude that *between* group inequality explains almost the totality of international EF-inequality (83-87%). This result leads to two important conclusions: firstly, there is a heavy international division in natural resource consumption patterns defined by World Bank classification groups, indicating highly homogenous consumption patterns within those groups. The time persistence of this result points towards the EF per capita having been historically determined by the world region to which the country belongs. Secondly, since the *within* inequality in per capita EF is so relatively low, reaching international environmental agreements (as far as they were based on EF) may be more fruitful for global environment protection if these were to be held on a regional basis (such as those defined by World Bank) instead of World agreements.

Regarding source decomposition, we have noted the only non-ambiguous way of decomposing inequality by sources is the natural decomposition of CV^2, which allows, besides, interpreting contributions in marginal terms. The empirical results point out that, although all EF component inequality has reduced, the contribution to total EF inequality has not necessarily followed the same movement. This is due to changes in components proportions in total EF. For instance, Carbon Footprint's inequality has reduced; nevertheless, its contribution to inequality has increased because of its increasing share of the total EF. In contrast, Grazing and Fishing footprints (related to the diets of industrialized countries) exhibit relatively high levels of international inequality, however, they contribute modestly to overall EF inequality because of its low share of the total EF. The Cropland Footprint contribution to EF inequality has reduced significantly as a result of both having historically low inequality (basic subsistence highly depends on cropland consumption) and having decreased its EF share in the course of the period. This analysis provide important clues for international environmental policies: reducing per capita carbon footprint of countries will lead, not only to a more sustainable scale, but also to a fairer distribution of EF, enabling greater possibilities for international environmental agreements. Nevertheless, if that goal is implemented by converting typical cropland utilities in commercial energy (bio-fuels), this policy will necessarily impact on Cropland Footprint equality and probably its share of total EF will also increase. As a result, the subsistence function of cropland will be seriously threatened. Hence, multi-criteria assessment should be extended to environmental negotiations.

Environmental inequality measurement has been widely analysed in recent years because of its important implications in terms of universal ethics and environmental policy. Such literature, however, has focussed mainly on narrower environmental indicators such as CO_2 emissions and hardly at all on more multifaceted indicators such EF. Additionally, the methods applied to measure inequality are not always correctly adjusted to suit an environmental economics framework. Therefore, the results and discussions presented here may be of interest to researchers and policy makers concerned with a Fair Sustainability framework.

Acknowledgments: The authors thank two anonymous reviewers for their helpful comments and suggestions. Financial support from the project ECO2010-18158 is gratefully acknowledged.

References

Alcantara, V., and 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.

Anand, S., and Sen, A. (2000). Human development and economic sustainability. *World Development, 28*(12), 2029-2049.

Araar, A. (2006). *On the decomposition of the gini coefficient: An exact approach, with an illustration using Cameroonian data* CIRPEE.

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory, 2*(3), 244-263.

Aubauer, H. P. (2006). A just and efficient reduction of resource throughput to optimum. *Ecological Economics, 58*(3), 637-649.

Brooks, N., and Sethi, R. (1997). The distribution of pollution: Community characteristics and exposure to air toxics. *Journal of Environmental Economics and Management, 32*(2), 233-250.

Bourguignon, F. (1979). Decomposable income inequality measures. *Econometrica, 47*(4), pp. 901-920.

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

Cowell, F. (1980). On the structure of additive inequality measures. *Review of Economic Studies, 47*(3), 521-531.

Cowell, F. (2000). Chapter 2 measurement of inequality. *Handbook of income distribution.* Edited by A. B. Atkinson and F. Bourguignon (pp. 87-166) Elsevier.

Cowell, F. (2011). *Measuring inequality.* Oxford University Press. New York

Criado, C. O., and Grether, J. (2010). *Convergence in per capita CO_2 emissions: A robust distributional approach.* CEPE Center for Energy Policy and Economics, ETH Zürich.

Daly, H. E. (1992). Allocation, distribution, and scale: Towards an economics that is efficient, just, and sustainable. *Ecological Economics, 6*(3), 185-193.

Daly, H. E., and Farley, J. (Eds.). (2004). *Ecological economics: Principles and applications* (2nd edition ed.) Island Press.

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.

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

Duro, J.A. 2013, "Weighting vectors and international inequality changes in environmental indicators: An analysis of CO_2 per capita emissions and Kaya factors", *Energy Economics,* vol. 39, no. 0, pp. 122-127.

Duro, J.A. and 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., Alcántara, V., and Padilla, E. (2010). International inequality in energy intensity levels and the role of production composition and energy efficiency: An analysis of OECD countries. *Ecological Economics, In Press, Corrected Proof*

Duro, J. A., and 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., and Padilla, E. (2008). Analysis of the international distribution of per capita CO_2 emissions using the polarization concept. *Energy Policy, 36*(1), 456-466.

Duro, J. A., and Padilla, E. (2011). Inequality across countries in energy intensities: An analysis of the role of energy transformation and final energy consumption. *Energy Economics, 33*(3), 474-479.

Ewing, B., Moore, D., Goldfinger, S., Oursler, A., Reed, A., and Wackernagel, M. (2010a). *The ecological footprint atlas 2010.* Oakland: Global Footprint Network.:

Ewing, B., Reed, A., Galli, A., Kitzes, J., and Wackernagel, M. (2010b). *Calculation methodology for the national footprint accounts, 2010 edition.* Oakland: Global Footprint Network.

Ezcurra, R. (2007). Is there cross-country convergence in carbon dioxide emissions? *Energy Policy, 35*(2), 1363-1372.

Fei, J. C. H., Rainis, G., and Kuo, S. W. Y. (1978). Growth and the family distribution of income by factor components. *The Quarterly Journal of Economics, 92*(1), 17-53.

Fiala, N. (2008). Measuring sustainability: Why the ecological footprint is bad economics and bad environmental science. *Ecological Economics, 67*(4), 519-525.

Global Footprint Network. *Global footprint network, 2010 edition.* Retrieved April, 2011, from www.footprintnetwork.org

Goerlich, F. J. (1998). Desigualdad, Diversidad y Convergencia:(algunos) instrumentos de medida. Mimeo. Instituto Valenciano de Investigaciones económicas.

Groot, L. 2010, "Carbon Lorenz curves", *Resource and Energy Economics,* vol. 32, no. 1, pp. 45-64.

Hedenus, F., and Azar, C. (2005). Estimates of trends in global income and resource inequalities. *Ecological Economics, 55*(3), 351-364.

Heil, M. T., and Wodon, Q. T. (1997). Inequality in CO_2 emissions between poor and rich countries. *The Journal of Environment and Development, 6*(4), 426-452.

Heil, M. T., and Wodon, Q. T. (2000). Future inequality in CO_2 emissions and the impact of abatement proposals. *Environmental and Resource Economics, 17*(2), 163-181.

Kolm, S. (1976). Unequal inequalities. II. *Journal of Economic Theory, 13*(1), 82-111.

List, J. (1999). Have air pollutant emissions converged among U.S. regions? evidence from unit root tests. *Southern Economic Journal, 66*(1), 144-155.

Maguire, K., and Sheriff, G. (2011). Comparing distributions of environmental outcomes for regulatory environmental justice analysis. *International Journal of Environmental Research and Public Health, 8*(5), 1707-1726.

Martinez-Alier, J., Munda, G. and O'Neill, J. 1998, "Weak comparability of values as a foundation for ecological economics", *Ecological Economics,* vol. 26, no. 3, pp. 277-286.

Martinez-Alier, J., and O'Connor, M. (1999). Distributional issues: An overview. In J. C. J. M. van den Bergh (Ed.), *Handbook of environmental and resource economics* (pp. 380-392). Northampton, Massachusetts, USA: Edward Elgar Publishing Limited.

Martinez-Alier, J., and Roca, J. (Eds.). (2001). *Economía ecológica y política ambiental*. Mexico, D.F.: Fondo de Cultura económica.

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.

Padilla, E. (2002). Intergenerational equity and sustainability. *Ecological Economics, 41*(1), 69-83

Padilla, E., and Serrano, A. (2006). Inequality in CO_2 emissions across countries and its relationship with income inequality: A distributive approach. *Energy Policy, 34*(14), 1762-1772.

Rees, W. E. (1992). Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environment and Urbanization, 4*(2), 121-130.

Røpke, I. (Ed.). (2001). *Human ecology in the new millenium. Ecological unequal exchange, chapter 4*

Sastre, M., and Trannoy, A. (2002). *Shapley inequality decomposition by factor components: Some methodological issues* Springer Wien.

Shorrocks, A. F. (1980). The class of additively decomposable inequality measures. *Econometrica, 48*(3), pp. 613-625.

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

Shorrocks, A. F. (1984). Inequality decomposition by population subgroups. *Econometrica, 52*(6), pp. 1369-1385.

Shorrocks, A. F. (1988). Aggregation issues in inequality measures. *Measurement in economics*, Physica-Verlag. Ed. W. Eichlorn.

Shorrocks, A. F., and Foster, J. E. (1987). Transfer sensitive inequality measures. *The Review of Economic Studies, 54*(3), pp. 485-497.

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.

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

Theil, H. (1979). The measurement of inequality by components of income. *Economics Letters, 2*(2), 197-199.

Van den Bergh, J., and Verbruggen, H. (1999). Spatial sustainability, trade and indicators: An evaluation of the 'ecological footprint'. *Ecological Economics, 29*(1), 61-72.

Wackernagel, M., and Rees, W. (Eds.). (1996). *Our ecological footprint. reducing human impact on the earth.* New Society Press.

Wackernagel, M., Monfreda, C., Schulz, N. B., Erb, K., Haberl, H., and Krausmann, F. (2004). Calculating national and global ecological footprint time series: Resolving conceptual challenges. *Land use Policy, 21*(3), 271-278.

White, T. (2000). Diet and the distribution of environmental impact. *Ecological Economics, 34*(1), 145-153.

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

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.

Appendix

A1. World Ecological Footprint per capita

Year	Cropland		Grazing land		Forest		Fishing ground		Carbon F.		Built land		EF
1961	1.13	(48.16%)	0.39	(16.54%)	0.40	(17.04%)	0.09	(3.89%)	0.27	(11.63%)	0.06	(2.75%)	2.36
1962	1.12	(47.00%)	0.39	(16.38%)	0.40	(16.70%)	0.09	(3.92%)	0.32	(13.28%)	0.06	(2.72%)	2.38
1963	1.10	(45.41%)	0.39	(16.00%)	0.39	(16.17%)	0.09	(3.87%)	0.39	(15.88%)	0.06	(2.67%)	2.43
1964	1.08	(43.79%)	0.38	(15.53%)	0.40	(16.13%)	0.09	(3.72%)	0.45	(18.22%)	0.06	(2.62%)	2.48
1965	1.07	(42.26%)	0.39	(15.34%)	0.40	(15.71%)	0.10	(3.79%)	0.51	(20.32%)	0.06	(2.57%)	2.52
1966	1.05	(41.09%)	0.37	(14.51%)	0.40	(15.52%)	0.10	(3.89%)	0.57	(22.44%)	0.06	(2.55%)	2.55
1967	1.03	(40.36%)	0.37	(14.41%)	0.39	(15.38%)	0.10	(3.97%)	0.60	(23.34%)	0.06	(2.55%)	2.55
1968	1.02	(39.13%)	0.36	(14.01%)	0.39	(14.91%)	0.10	(4.01%)	0.66	(25.44%)	0.07	(2.50%)	2.60
1969	1.01	(37.96%)	0.35	(13.26%)	0.38	(14.46%)	0.10	(3.80%)	0.75	(28.08%)	0.07	(2.45%)	2.66
1970	0.99	(35.99%)	0.35	(12.61%)	0.38	(13.95%)	0.10	(3.65%)	0.87	(31.43%)	0.07	(2.36%)	2.76
1971	0.97	(35.07%)	0.34	(12.29%)	0.38	(13.75%)	0.10	(3.60%)	0.91	(32.95%)	0.07	(2.35%)	2.78
1972	0.96	(34.04%)	0.34	(12.16%)	0.37	(13.31%)	0.10	(3.60%)	0.97	(34.56%)	0.07	(2.32%)	2.81
1973	0.94	(32.92%)	0.33	(11.44%)	0.38	(13.28%)	0.10	(3.56%)	1.04	(36.51%)	0.07	(2.28%)	2.86
1974	0.93	(32.84%)	0.34	(12.07%)	0.37	(13.17%)	0.10	(3.62%)	1.02	(35.99%)	0.07	(2.31%)	2.82
1975	0.91	(32.91%)	0.34	(12.26%)	0.36	(12.86%)	0.10	(3.47%)	1.00	(36.14%)	0.07	(2.36%)	2.77
1976	0.90	(31.89%)	0.33	(11.59%)	0.36	(12.94%)	0.10	(3.47%)	1.06	(37.78%)	0.07	(2.32%)	2.81
1977	0.88	(31.38%)	0.31	(11.10%)	0.36	(12.73%)	0.10	(3.39%)	1.10	(39.08%)	0.07	(2.32%)	2.81
1978	0.87	(30.89%)	0.30	(10.67%)	0.36	(12.76%)	0.10	(3.41%)	1.13	(39.95%)	0.07	(2.32%)	2.82
1979	0.86	(30.24%)	0.30	(10.60%)	0.36	(12.80%)	0.09	(3.32%)	1.16	(40.74%)	0.07	(2.30%)	2.84
1980	0.85	(30.41%)	0.30	(10.75%)	0.36	(12.86%)	0.09	(3.35%)	1.12	(40.27%)	0.07	(2.36%)	2.78
1981	0.83	(30.64%)	0.29	(10.81%)	0.35	(12.83%)	0.10	(3.53%)	1.08	(39.78%)	0.07	(2.41%)	2.72
1982	0.82	(31.04%)	0.29	(10.76%)	0.34	(12.76%)	0.10	(3.63%)	1.04	(39.34%)	0.07	(2.48%)	2.65
1983	0.81	(30.73%)	0.29	(11.04%)	0.35	(13.08%)	0.09	(3.56%)	1.03	(39.11%)	0.07	(2.47%)	2.64
1984	0.80	(30.23%)	0.27	(10.32%)	0.35	(13.28%)	0.09	(3.58%)	1.06	(40.12%)	0.07	(2.46%)	2.65
1985	0.79	(30.51%)	0.23	(8.83%)	0.35	(13.34%)	0.09	(3.65%)	1.07	(41.16%)	0.07	(2.50%)	2.60
1986	0.78	(30.08%)	0.23	(8.75%)	0.35	(13.40%)	0.10	(3.72%)	1.08	(41.55%)	0.07	(2.50%)	2.61
1987	0.77	(29.24%)	0.23	(8.70%)	0.35	(13.36%)	0.10	(3.82%)	1.12	(42.43%)	0.07	(2.46%)	2.64
1988	0.76	(28.39%)	0.24	(8.97%)	0.35	(13.07%)	0.10	(3.84%)	1.16	(43.30%)	0.07	(2.43%)	2.68
1989	0.75	(27.87%)	0.24	(8.97%)	0.35	(12.99%)	0.11	(3.96%)	1.18	(43.79%)	0.07	(2.42%)	2.69
1990	0.74	(27.82%)	0.24	(9.06%)	0.34	(12.88%)	0.10	(3.79%)	1.17	(43.99%)	0.07	(2.45%)	2.65
1991	0.73	(27.75%)	0.24	(9.34%)	0.32	(12.28%)	0.10	(3.75%)	1.16	(44.39%)	0.07	(2.49%)	2.61
1992	0.70	(27.02%)	0.24	(9.24%)	0.31	(12.03%)	0.11	(4.10%)	1.18	(45.15%)	0.06	(2.46%)	2.60
1993	0.69	(26.82%)	0.24	(9.24%)	0.31	(11.82%)	0.11	(4.12%)	1.18	(45.52%)	0.06	(2.48%)	2.59
1994	0.68	(26.57%)	0.24	(9.28%)	0.30	(11.73%)	0.11	(4.32%)	1.17	(45.61%)	0.06	(2.49%)	2.57
1995	0.67	(25.93%)	0.24	(9.41%)	0.30	(11.68%)	0.11	(4.41%)	1.20	(46.10%)	0.06	(2.47%)	2.60
1996	0.66	(25.46%)	0.23	(9.04%)	0.30	(11.45%)	0.12	(4.45%)	1.22	(47.12%)	0.06	(2.47%)	2.60
1997	0.65	(25.41%)	0.23	(8.83%)	0.30	(11.65%)	0.11	(4.47%)	1.21	(47.14%)	0.06	(2.50%)	2.57
1998	0.65	(25.50%)	0.23	(8.88%)	0.29	(11.36%)	0.11	(4.48%)	1.20	(47.24%)	0.06	(2.53%)	2.54
1999	0.64	(25.32%)	0.22	(8.87%)	0.29	(11.65%)	0.11	(4.51%)	1.19	(47.11%)	0.06	(2.54%)	2.53
2000	0.63	(24.97%)	0.22	(8.88%)	0.30	(11.76%)	0.11	(4.34%)	1.20	(47.51%)	0.06	(2.54%)	2.53
2001	0.63	(24.95%)	0.22	(8.86%)	0.28	(11.30%)	0.11	(4.39%)	1.20	(47.95%)	0.06	(2.56%)	2.51
2002	0.62	(24.46%)	0.23	(8.97%)	0.28	(11.24%)	0.11	(4.31%)	1.22	(48.46%)	0.06	(2.55%)	2.52
2003	0.61	(23.83%)	0.22	(8.77%)	0.28	(11.08%)	0.11	(4.25%)	1.27	(49.56%)	0.06	(2.50%)	2.56
2004	0.61	(23.16%)	0.21	(8.18%)	0.29	(10.96%)	0.11	(4.22%)	1.33	(51.03%)	0.06	(2.45%)	2.62
2005	0.60	(22.62%)	0.22	(8.12%)	0.29	(10.97%)	0.11	(4.18%)	1.37	(51.69%)	0.06	(2.41%)	2.66
2006	0.59	(22.17%)	0.22	(8.07%)	0.28	(10.61%)	0.11	(4.12%)	1.41	(52.63%)	0.06	(2.39%)	2.68
2007	0.59	(21.69%)	0.21	(7.75%)	0.29	(10.61%)	0.11	(4.03%)	1.44	(53.54%)	0.06	(2.37%)	2.70

Source: Present Authors from Global Footprint Network

A2. Countries sampled and World Bank regional groups.

East Asia and Pacific: Cambodia; China; Indonesia; Korea, DPR; Korea, Rep; Lao PDR; Malaysia; Myanmar; Papua New Guinea; Philippines; Singapore; Thailand; Timor-Leste; Vietnam.

Europe and Central Asia: Albania; Bulgaria; Hungary; Poland; Romania; Turkey.

Industrial: Australia; Austria; Belgium; Canada; Denmark; Finland; France; Germany; Greece; Ireland; Italy; Japan; Luxembourg; Netherlands; New Zealand; Norway; Portugal; Spain; Sweden; Switzerland; United Kingdom; United States of America.

Latin America and Caribbean: Argentina; Bolivia; Brazil; Chile; Colombia; Costa Rica; Cuba; Dominican Republic; Ecuador; El Salvador; Guatemala; Haiti; Honduras; Jamaica; Mexico; Nicaragua; Panama; Paraguay; Peru; Trinidad and Tobago; Uruguay; Venezuela Bolivarian Rep.
Middle East and North Africa: Algeria; Egypt; Iran; Iraq; Israel; Jordan; Kuwait; Lebanon; Libyan AJ; Morocco; Oman; Qatar; Saudi Arabia; Syrian AR; Tunisia; Yemen.
South Asia: Afghanistan; India; Nepal; Pakistan; Sri Lanka.
Sub-Saharan Africa: Angola; Benin; Burkina Faso; Burundi; Cameroon; Central African R; Chad; Congo; Congo, DR; Côte d'Ivoire; Gabon; Gambia; Ghana; Guinea; Guinea-Bissau; Kenya; Liberia; Madagascar; Mali; Mauritania; Mauritius; Mozambique; Namibia; Niger; Nigeria; Rwanda; Senegal; Sierra Leone; Somalia; South Africa; Sudan; Togo; Uganda; Zimbabwe.

A3. Inequality indices of EF per capita

year	GINI	T(0)	T(1)	T(2)	CV^2	A(0.5)	A(1)
1961	0.331863	0.179226	0.189064	0.221799	0.443598	0.088832	0.164083
1962	0.340601	0.18826	0.198431	0.233125	0.46625	0.093128	0.171601
1963	0.348073	0.195861	0.207045	0.245799	0.491598	0.096857	0.177873
1964	0.346067	0.193413	0.204768	0.242528	0.485056	0.095781	0.175858
1965	0.357436	0.205764	0.217594	0.258574	0.517148	0.101607	0.185975
1966	0.365708	0.215069	0.227701	0.274284	0.548568	0.105995	0.193514
1967	0.368823	0.220491	0.233514	0.279064	0.558128	0.108694	0.197875
1968	0.382148	0.236772	0.254051	0.312909	0.625818	0.117006	0.210828
1969	0.391247	0.249119	0.266751	0.329111	0.658222	0.122718	0.220513
1970	0.389138	0.247006	0.262932	0.319889	0.639778	0.121455	0.218864
1971	0.403557	0.265816	0.283596	0.350375	0.70075	0.130326	0.23342
1972	0.40974	0.275489	0.292825	0.361321	0.722642	0.134602	0.240799
1973	0.415801	0.284671	0.304146	0.379181	0.758362	0.139184	0.247738
1974	0.408946	0.27418	0.289289	0.354787	0.709574	0.133488	0.239805
1975	0.398244	0.258086	0.277122	0.344603	0.689206	0.127065	0.227471
1976	0.411443	0.277105	0.29676	0.371164	0.742328	0.135767	0.242025
1977	0.413506	0.279962	0.30151	0.380464	0.760928	0.137442	0.244187
1978	0.413749	0.279761	0.300625	0.37962	0.75924	0.137135	0.244035
1979	0.418671	0.28729	0.307383	0.388589	0.777178	0.140282	0.249706
1980	0.404805	0.268524	0.28246	0.344797	0.689594	0.130622	0.235493
1981	0.402587	0.262972	0.280508	0.349538	0.699076	0.128809	0.231237
1982	0.401942	0.262577	0.280454	0.352258	0.704516	0.128627	0.230933
1983	0.381493	0.23479	0.250775	0.30778	0.61556	0.115723	0.209263
1984	0.398198	0.256443	0.275983	0.347329	0.694658	0.12624	0.226201
1985	0.403467	0.26323	0.285199	0.363881	0.727762	0.129786	0.231435
1986	0.399454	0.258645	0.279678	0.354078	0.708156	0.127559	0.227903
1987	0.401498	0.261941	0.280809	0.352391	0.704782	0.128578	0.230443
1988	0.391679	0.24834	0.266193	0.330683	0.661366	0.122253	0.219905
1989	0.39766	0.257045	0.278703	0.353083	0.706166	0.126997	0.226666
1990	0.397332	0.256368	0.276652	0.349914	0.699828	0.126318	0.226143
1991	0.386913	0.242348	0.258756	0.321538	0.643076	0.11912	0.215217
1992	0.392158	0.248985	0.271967	0.350584	0.701168	0.123491	0.220409
1993	0.376785	0.229976	0.244149	0.302631	0.605262	0.112856	0.205447
1994	0.38846	0.244235	0.262502	0.332241	0.664482	0.120241	0.216696
1995	0.382126	0.23678	0.250645	0.309904	0.619808	0.115911	0.210835
1996	0.382961	0.238944	0.250801	0.310256	0.620512	0.11633	0.212541
1997	0.388101	0.243835	0.260967	0.329826	0.659652	0.119759	0.216383
1998	0.389878	0.245512	0.267234	0.344002	0.688004	0.12154	0.217696
1999	0.389766	0.245884	0.267659	0.343098	0.686196	0.121786	0.217987
2000	0.391711	0.248794	0.268371	0.342659	0.685318	0.122543	0.22026
2001	0.391375	0.249028	0.266981	0.338792	0.677584	0.12228	0.220442
2002	0.39272	0.251387	0.267341	0.336766	0.673532	0.122897	0.222279
2003	0.390124	0.247222	0.263856	0.334474	0.668948	0.121108	0.219033
2004	0.394409	0.253854	0.26877	0.339853	0.679706	0.123678	0.224195
2005	0.389538	0.248936	0.262337	0.330875	0.66175	0.121054	0.22037
2006	0.381548	0.239448	0.247386	0.303389	0.606778	0.115576	0.212938
2007	0.377429	0.233587	0.240921	0.292457	0.584914	0.112849	0.208311

Source: Present Authors from Global Footprint Network

A4. Natural decomposition of the EF per capita

Year	Fishing	Cropland	Grazing	Forest	Carbon	Built	Total
1961	0.0654	0.3593	0.2007	0.1853	0.1751	0.0146	1
1962	0.0646	0.3513	0.1890	0.1871	0.1934	0.0150	1
1963	0.0610	0.3494	0.1733	0.1717	0.2308	0.0124	1
1964	0.0591	0.2949	0.1739	0.1790	0.2807	0.0137	1
1965	0.0576	0.2946	0.1501	0.1751	0.3114	0.0116	1
1966	0.0558	0.2737	0.1468	0.1703	0.3425	0.0102	1
1967	0.0576	0.2744	0.1333	0.1613	0.3620	0.0118	1
1968	0.0526	0.2759	0.1243	0.1532	0.3856	0.0091	1
1969	0.0469	0.2665	0.1086	0.1490	0.4209	0.0085	1
1970	0.0481	0.2146	0.0980	0.1418	0.4892	0.0084	1
1971	0.0418	0.2325	0.0899	0.1382	0.4881	0.0090	1
1972	0.0416	0.2165	0.0872	0.1269	0.5176	0.0099	1
1973	0.0393	0.1922	0.0860	0.1316	0.5424	0.0083	1
1974	0.0413	0.1916	0.0999	0.1302	0.5310	0.0080	1
1975	0.0383	0.2103	0.1091	0.1179	0.5184	0.0083	1
1976	0.0395	0.1937	0.0929	0.1235	0.5437	0.0061	1
1977	0.0350	0.1936	0.0802	0.1221	0.5614	0.0086	1
1978	0.0354	0.1792	0.0796	0.1313	0.5663	0.0078	1
1979	0.0350	0.1874	0.0736	0.1312	0.5655	0.0076	1
1980	0.0390	0.1709	0.0779	0.1328	0.5710	0.0099	1
1981	0.0351	0.1926	0.0804	0.1302	0.5529	0.0100	1
1982	0.0380	0.2385	0.0799	0.1169	0.5150	0.0115	1
1983	0.0404	0.1624	0.0854	0.1407	0.5602	0.0085	1
1984	0.0363	0.1831	0.0738	0.1433	0.5517	0.0105	1
1985	0.0393	0.2015	0.0525	0.1429	0.5523	0.0096	1
1986	0.0393	0.1899	0.0475	0.1526	0.5620	0.0096	1
1987	0.0439	0.1673	0.0478	0.1539	0.5789	0.0098	1
1988	0.0428	0.1368	0.0603	0.1488	0.6038	0.0084	1
1989	0.0440	0.1446	0.0500	0.1517	0.6011	0.0084	1
1990	0.0403	0.1584	0.0454	0.1481	0.5998	0.0080	1
1991	0.0410	0.1571	0.0513	0.1287	0.6108	0.0089	1
1992	0.0399	0.1546	0.0478	0.1297	0.6197	0.0084	1
1993	0.0401	0.1355	0.0534	0.1392	0.6230	0.0077	1
1994	0.0422	0.1540	0.0427	0.1377	0.6139	0.0083	1
1995	0.0441	0.1296	0.0520	0.1385	0.6267	0.0081	1
1996	0.0382	0.1332	0.0462	0.1307	0.6432	0.0087	1
1997	0.0388	0.1273	0.0400	0.1337	0.6530	0.0078	1
1998	0.0334	0.1311	0.0398	0.1347	0.6529	0.0084	1
1999	0.0350	0.1276	0.0379	0.1354	0.6570	0.0085	1
2000	0.0326	0.1241	0.0373	0.1364	0.6610	0.0085	1
2001	0.0352	0.1204	0.0375	0.1284	0.6698	0.0077	1
2002	0.0339	0.1154	0.0398	0.1305	0.6735	0.0086	1
2003	0.0308	0.1262	0.0424	0.1269	0.6652	0.0069	1
2004	0.0291	0.1305	0.0345	0.1284	0.6691	0.0082	1
2005	0.0276	0.1233	0.0352	0.1332	0.6725	0.0069	1
2006	0.0294	0.1074	0.0353	0.1227	0.6986	0.0071	1
2007	0.0292	0.1163	0.0370	0.1172	0.6923	0.0073	1

Source: Present Authors from Global Footprint Network