Empirical Ecological distribution: international inequality of Ecological Footprint

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Abstract

The responsibility in depleting ecological functions until getting into ecological crisis might not be equally distributed among countries. Such inequality is measured by distributional analysis of the Ecological Footprint (EF) by widely known income inequality tools. Nonetheless, firstly is necessary to discuss several methodological aspects in order to acclimatize typically income tools to environmental issues. Next, empirical analysis is performed: firstly, it has been measured the inequality using different available index and suggesting GE(2) as the most appropriate. Secondly, subgroup and source decomposition has been performed by implementing different techniques available. The EF-inequality observed is quite stable, however, the decomposition of such inequality shows, on the one hand, a heavy *between* inequality component explaining the bulk of overall inequality when exogenous groups are used (such as World Bank classification groups). Source decomposition, on the other hand, illustrates the building blocks of the observed inequality. Carbon footprint is one of the main contributors to EF-inequality due to weighting issues rather than its own inequality, which actually decreases along the period. Grazing and Fishing footprint, corresponding to industrialized countries typical diet, are the more unequal components although they are lower contributors to overall EF-inequality.

1 Introduction

Ecological distribution refers to the social, spatial and temporal asymmetries or inequalities in the use by humans of environmental resources and services (whether trades or not), for example, in the depletion of natural resources (Martinez-alier and O'connor, 1999). This paper deals with ecological distribution measurement.

Recently, the issues focused on distribution analysis of ecological variables are taking greater interest in ecological economics: analysis on issues of ecological convergence between countries, or equivalently, the evolution of inequalities between countries in terms of pollution, consumption of materials or energy efficiency, etc. (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; Ezcurra, 2007; Heil and Wodon, 1997; Heil and Wodon, 2000; List, 1999; Heil and Wodon, 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). Nevertheless, the most important feature that makes this topic coming up is the global warming.

The aggravation of ecological crisis, i.e. collapse of the three highly correlated ecological functions: resource supply, waste assimilation and environmental services such as life support, brings distributional issues to the top of the agenda. Standard economics has been solving distributional conflicts via growth, focusing thus in efficient allocation issues. Nonetheless, since ecological economics puts *scale* goal on the table (Daly, 1992), just ecological distribution becomes both necessary and ethical condition for sustainability achievement. Provided that earth and its resources are finite (scale goal), stopping infinite economy-scale growth will solve the distributional problem with future generations, although at expense of worsening the distributional problem within present generations. Actually, the most popular definition of sustainability claims for *meeting the needs of the present without compromising the ability of future generations to meet their own needs* (Brundtland Report). So it is not a fact of the well-being of people yet to born but also of the well-being of people alive today (Aubauer, 2006) (Daly and Farley, 2004). The deeper the ecological crisis gets, the more important becomes an equal distribution of ecological functions use since resource scarcity is no longer seen as a remote threat (Steinberger et al., 2010)

The responsibility in depleting ecological functions until getting into ecological crisis might not be equally distributed among countries. This inequality is of great relevance for designing of global policies since the success of any international agreement highly depends 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. From Rio 1992 to Durban 2011 passing through Kyoto 1995, distributional issues have unquestionably determined the success of those Conventions. Distributional analyses emerge as an important tool to policy makers.

This paper contributes to this framework by analysing the inequality in natural capital consumption by countries as defined by the Ecological Footprint framework. So, it will be analysed the inequality trends of national Ecological Footprint by the application of widely used methods of income and wealth inequality. Such methodology allows identifying the main contributors of inequality observed by decomposition techniques. Additionally, the paper contributes to some methodological discussions when these tools are applied to environmental issues.

The paper is organized as follows: section 2 defines the meaning and significance of Ecological Footprint as indicator resource consumption. Section 3 discusses methods used in this sort of analysis. Section 4 shows the empirical results and section 5 concludes.

2 The Ecological Footprint indicator

One common place in ecological economics is the incommensurability problem which deals with the fact that is not possible to compare in nature provided that there is not a common denominator available[1]. The EF, introduced by (Rees, 1992) and developed by (M. Wackernagel and Rees, 1996), proposes as common denominator a global bioproductive hectare, where each global hectare (gh) holds the average biological productivity of the whole earth. So then, the question is how many Global hectares a given population uses to maintain its consumption patterns.

The Ecological Footprint (EF) measures the consumption of renewable natural resources by human economies. It accounts for the area of productive land and water required by ecosystems to produce the resources that the population consumes and assimilate the wastes that the population produces in a given year, wherever on Earth the land and water is located. Specifically, it measures the regenerative capacity of the biosphere *occupied* by human activities (see Ewing et al., 2010a,b; Kitzes and Wackernagel, 2009; Kitzes et al., 2009; Monfreda et al., 2004; Rees, 2000; Wackernagel and Rees, 1996; Wackernagel et al., 2004)[2]. Consequently, it has become a popular indicator which aims to measure the amount of "critical natural capital" (Ekins, 2003; Victor, 1991) provided that it accounts for one of the key aspects of natural capital: earth's ability to provide conditions conducive for life. Since both renewal

[1] Money has been used to do so, however money is not a particularly objective instrument to evaluate what something worth, much less for natural capital. See (Martinez-alier & Roca, 2001; Røpke, 2001). Actually, Joan Robinson made the same criticism about capital ((Victor, 1991))

[2] The concept stems from human ecology in the process of defining a suitable way of translating carrying capacity concept to human species (Rees, 2000)

and absorption depend on the health and integrity of ecosystems, regenerative capacity is a reliable proxy for the life supporting capacity of natural capital. Therefore, in order to track human demand on those ecological services, the EF accounts how much of the biosphere regenerative capacity is used by the human economy (Monfreda et al., 2004).

Since the EF appears as a popular tool for measuring sustainability there has been a huge debate around it, yielding several criticisms (Fiala, 2008; Van den Bergh and Verbruggen, 1999) which encourage further improvements on the measurement (Bicknell et al., 1998; Ewing et al., 2010a; Ewing et al, 2010b; Kitzes and Wackernagel, 2009; Kitzes et al., 2009; Monfreda et al., 2004). Nonetheless, those debates should be beyond of the analysis presented in this paper as long as the most of the criticism focus on EF as sustainability indicator, and we just deal with resource consumption measurement. On the other hand, there is a growing consensus in the field that none perfect indicator for sustainability does exist, even it's no desirable. Different available indicators, such as EF, Material Flow Accounts (MFA), human appropriation of Net Primary Production (HANPP), etc, provide different information. So the assessment of sustainability should be done accepting its complexity and incommensurability by multi-criteria decision making (Kitzes et al., 2009; Martinez-alier and Roca, 2001).

Any aggregate indicator will have both strengths and weaknesses (as for example, measures of aggregate economic output). Therefore, the EF is an aggregate indicator of natural resource consumption, whose strength and weakness have been object of extensive academic literature, what actually makes the EF a good aggregate indicator because it benefits from the scrutiny of its properties and its limitations are well-known (Caviglia-Harris et al. 2009; Kitzes and Wackernagel, 2009; White, 2007).

The EF analyses have been performed at different scales; products, individuals, firms, regions, countries or the whole world. The country level Footprint assessment has been developed for many nations under different methods (Aubauer, 2011; Bicknell et al., 1998; Ferng, 2001; Monfreda et al., 2004; Van Vuuren and Smeets, 2000; Wackernagel and Rees, 1996; Wiedmann et al., 2006), however the most widely used methodology for national footprint accounting is Global Footprint Network's standards (Global Footprint Network, 2010), where the accounts are based on a variety of international and national data sources, including databases from United Nation Food and Agricultural Organization, the United nations Statistics division and the International Energy Agency (FAOSTAT, UN Comtrade, IEA) and is overseen by Global Footrpint Network's National Accounts Review Committee, with research contributions solicited from the global community of footprint researchers (Global Footprint Network, 2010 ; Kitzes et al., 2009). Different analyses have been performed using country EF to test different hypothesis such as Environmental Kuznets curve or IPAT/STRIPAT model (Bagliani et al., 2008; Caviglia-Harris et al., 2009; Dietz et al. 2007; York et al., 2003).

Additionally, EF has been adopted by a growing number of government authorities, agencies, and policy makers as a measure of ecological performance. Remarkable examples are those international applications such as the European Environment Agency (EEA, 2010) and the European Parliament and the European Comission (Best et al., 2008), who considers the EF a useful tool to measure environmental performance of the EU, or the United Nations Development Programme who considers EF to capture the environmental dimension of human development (UNDP, 2010).

2.1 Calculation of EF

It is assumed that the majority of resources people consume and wastes they generate can be quantified, tracked and measured in terms of biologically productive area necessary to maintain flows (Ewing et al., 2010b). Specifically, the EF accounts for six types of land: cropland, grazing land and fishing ground to supply food and clothes consumed, forest land for timber and fuel wood needed, energy land that account for the uptake of carbon emissions yielded (carbon footprint)[3], and finally, there is the built-up land that account for land covered by human infrastructure: so

$EF = \sum_k C_k$ where k = Cropland, grazing land, fishing ground, forest land, carbon land, built-up land.

The basic equation necessary to figure out how the EF is calculated is the next: yield= tonnes per year/Area, what could be rearranged to Area= tonnes per year/yield. So the calculation consists in dividing the quantity of resources consumed in a particular year by that year's global yield. The area is then multiplied by the year's equivalence factor (EQF) of the type of bioproductive area occupied in order to translate the specific land area into world average biologically productive area. So then, the resulting Footprint is expressed in global hectares (Wackernagel et al., 2004).

$$EF_P = \frac{T_i}{Y_{W_i}} \cdot EQF_i$$

[3] 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 its emissions. Actually, a sustainable economy would not drain natural capital, but all the time must produce the energy that is used (Røpke, 2001).

Where T_i is the annual amount of product *i* harvested or waste emitted, Y_w is the world-average yield for the production of each product *i* , given by all the annual tonnes of product *i* produced globally, divided by all areas un the world on which this product is grown; EQF_i is the *equivalence* factor for the production of each product *i* (Ewing et al., 2010; Galli et al., 2007).

In other words, the consumption is converted in terms of area needed, so that each type of land is standardized to the world average productivity. Therefore a cropland hectare of Zambia in 2007 is equivalent to 0.2 world average hectare of cropland, while a forest land of Germany is 4.1 times the world forest average hectare. Once the average hectares of each land use type per country is obtained, it is necessary to translate all those kind of lands into a single earth average bioproductive land (*EQF*), only then all those components can be added up to the global Ecological Footprint of each country.

In order to obtain a consumption based indicator of the EF it is necessary adding the EF of imports (EF_I) and subtracting the EF of exports (EF_E). In this way, we will obtain the EF of consumption (EF_C):

$$EF_C = EF_P + EF_I - EF_E$$

The Ecological Footprint of consumption for a given country measures the biocapacity demanded by the final consumption of all the residents of the country. This includes their household consumption as well as their collective consumption, such as schools, roads, fire brigades, etc., which serve the household, but may not be directly paid for by the households (Ewing et al., 2010b).

2.3. Distributional analysis to EF

In 2007 the human demand of the world was of 17.9 billion of global hectares despite the fact that only were accounted 11.8 global hectares available. How is this possible? In the EF framework, this result must be interpreted as an ecological overshoot i.e. it is being consumed more biosphere regenerative capacity than actually exists and therefore, future's generation regenerative capacity is being depleted. On the other hand, if we consider a country-scale frame, there may be situations in which the country's EF is larger than its national territory (measured in global hectares), and also situations where the contrary is true; countries with smaller EF than its national territory. Hence, there is clear distributional content in what EF index captures (Martinez-alier, 2002). A country can be appropriating of "unused" current biocapacity of other countries or, as long there is overshot, the appropriation could be on future generation's biocapacity. After all, allocation of resources is determined by neither ethical nor ecological criteria, but by the dominance of market mechanisms (Røpke, 2001). Thus, EF crystallizes in its own definition unequal relations between countries and generations. So its distributional analysis allows us to capture an additional dimension when the object is ecological distribution.

To our best knowledge, international distributional analysis on the EF has been performed by three previous works: (White, 2007) for a 2003 sample, where the Gini index is calculated and decomposed by additive factors, using EF components, and the Atkinson's family index to decompose by multiplicative factors. (Dongjing et al., 2010) also calculates the Gini coefficient joinly with the Lorenz asymmetries for years 1996, 1999, 2001, 2003, and 2006. Finally, (Wu and Xu, 2010) analysed the inequality of the EF in a Northwestern region of China[4], calculating the Gini index and a subgroup decomposition for the Theil index.

3 Distribution and environment: methodology

The development of distributional analyses methods in economics have been tackled in the context of Social Welfare Theory ((F. Cowell, 2011; Theil, 1979)). It focuses on the measurement of income inequality and its direct implication for social welfare. Therefore, methodology applied to analyse the environmental distribution issues may be borrowed from that income inequality literature. Nonetheless, it is worth to take into account that not always there is an automatic application of those techniques, used to deal with "goods" as income, when the variable of interest is actually a "bad" as pollution is.

The inequality approach application on ecological economics is being applied increasingly in last years. The authors have performed different well-known inequality measures such as the Gini index (Heil and Wodon, 1997; Heil and Wodon, 1997; Heil and Wodon, 2000; Wu and Xu, 2010), Theil family index (Alcantara and Duro, 2004; Duro and Padilla, 2006; Duro et al., 2010) or Atkinson index (White, 2007; Hedenus and Azar, 2005). These authors take advantage of the properties of such indices in order to analyse unambiguously the inequality on environmental impact indicators, which in turn have been mainly on CO_2 emissions or energy intensities.

3.1 Methodological framework

In the roots of inequality analysis we will find that the key is the comparison between two states in order to decide which one is better off in terms, for instance, of welfare. Ranking different distributions become a useful way in doing so. The Lorenz criterion (second-order distributional dominance)[5] is surely the most popular issue to making such ranking, which consists in comparing the Lorenz Curves among the different distributions: consider two different distributions, *A* and *B*. As long as the whole Lorenz curves of state *A* lies inside Lorenz curve of

[4] Heihe River Basin

[5] The first order dominance criteria are based on the quantiles of the distribution that are yielded by the (generalized) inverse of the distribution function (Pen's Parade) (Cowell, 2011). It is less restrictive than second order Dominance though, and implications to environmental applications are similar than described for GLC.

state *B*, it is possible support that state *A* is a more evenly-spread distribution. However, it is very common to find out that the curves intersect between them, what makes ambiguous the ranking (see figure 1, top). In such a case, (Shorrocks, 1983) proposed the Generalized Lorenz Curve (GLC), which allows to solve some of the intersections cases by multiplying the original Lorenz curve by its mean. This implies that, as long as the mean of distribution *A* is higher than the mean of distribution *B*, *A* will always dominate *B*. The convexity of the curve reports how much unequal is the distribution (such as the Lorenz Curve) while the height is defined by the mean. So, the greater the mean and the more concave the curve, the more Welfare holds the state. Unfortunately, Shorrocks solution of GLC is not always working out. Yet it could yield intersections between the GLC, even when the means are different (see figure 1, bottom). Besides, it could be reasonable to rescale the Lorenz curve by the mean when either wealth or income is concerned (greater income mean means more wealth to share, so more welfare), but not any more when the variable of interest is a sort of pollutant or an "unsustainability" indicator such as EF: it had not sense to suggest that the distribution with greater EF mean is more desirable. Actually, in our case: the lower the mean, the more sustainable the situation. So, focusing on figure 1 (bottom), we can observe that 2007 EF mean is higher than 1961 EF mean. Thus, we could state that the situation become worse in this sense. On the other hand, if we focus on convexity of the curves we will see there is an intersection between them leading to a situation where the low parts of the distributions (low polluters) is more even-spread than high parts of the distribution. Which year has more inequality? Is in this point where inequality indexes exhibit their utility to rank distributions unambiguously, however, value judgements plays its particular roll.

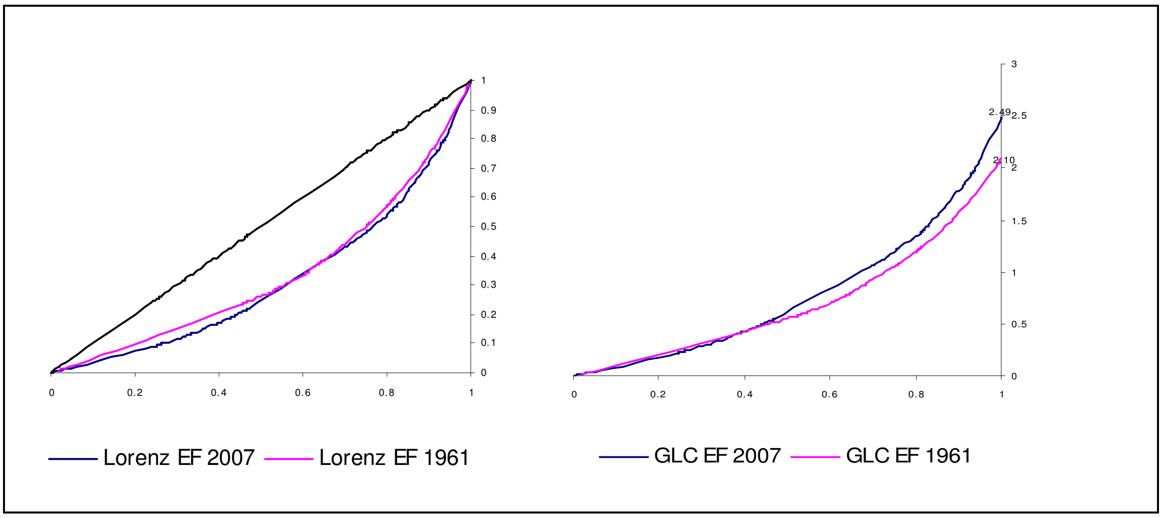

Figure 1. The Lorenz Curves are intersecting in 0.581, 0.635, and 0.99. GLC are intersecting in the percentile 0.423.

According to Cowell (2011) a simple definition of what an inequality index could be roughly summarized by a scalar numerical representation of intertemporal differences in income (or others) within a given population. So, inequality indexes allow comparisons between distributions. However, such comparisons are sensitive to the index chosen as will be seen.

The axiomatic approach consists in determining the criteria that we want to be satisfied by inequality measures in order to build the index that could better fit to our analysis. Nonetheless, there are at least three basic properties that reasonably must be satisfied by any inequality index (Goerlich, 1998): scale-independence, population independence and Pigou-Dalton principle of transfers[6].

Different Inequality indexes will lead unavoidably to weight differently the different parts of distribution, or what is equivalent the transfers will be weighted differently depending on which part of the distribution are them occurring. This is caused by the inevitable value judgements when inequality is being measured (Atkinson, 1970; Cowell, 2011; Shorrocks and Foster, 1987). The society will value more "positively" an increase of income for poor than for rich individuals[7]. Such behaviour is known in the literature as Diminishing Transfer Principle (Kolm, 1976). In contrast, such rationale would not make such sense when the transfer is a greater amount of pollution: would a "progressive" transfer of pollution between low pollutant countries be weighted heavier than the same transfer between high pollutant countries? Probably would not (Duro, 2012).

The most of the indices commonly used do satisfy the described basic properties: Gini, Generalized Entropy family indexes (for which Theil index or Mean logarithmic deviation are special cases), Atkinson family indexes, coefficient of variation and its square among others. However, only some of them do not satisfy the diminishing transfer principle. Among these, it is worth knowing that the Gini Index has more sensitivity to the transfer occurred closed mean. On the other hand, those indexes that weight more the top of the distribution neither are suited to the environmental analysis. Therefore, as (Duro, 2012) proposes, neutral measures become more attractive when there is no obligation to favour any particular part of the distribution.

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[6] 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 (that does not invert the relative rankings) should reduce the value of the inequality index.

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

Table 1. Summary of inequality indexes considered			
index	Formula	Basic axioms	Transfer-Sensivity
Gini	$G=\frac{1}{2\mu}\sum_i\sum_j p_i p_j \left\| y_i - y_j \right\|$	Yes except the decomposability axiom	on the mean
CV²	$CV_\omega^2=\frac{\sigma^2{}_\omega}{\mu^2}$	Yes, but difficult interpretation on subgroup decomposition	Neutral. . A certain transfer is weighted identically independently of where it is held in the distribution
T(0)- MLD	$T(0)=\sum_i p_i \log\left(\frac{\mu}{y_i}\right)$	Yes	very bottom of distribution
T(1)	$T(1)=\sum_i p_i\left(\frac{y_i}{\mu}\right)\log\left(\frac{y_i}{\mu}\right)$	Yes	bottom of distribution
T(2)	$T(2)=\frac{1}{2}\sum_i p_i\left[\left(\frac{y_i}{\mu}\right)^2-1\right]$	Yes, but difficult interpretation on subgroup decomposition	Neutral

3.2 Additive decomposition

Decomposition methodology turns to be really useful in the ongoing interest in measuring and understanding the level, causes and development of inequality. Decomposing an index consists in determining which part of total inequality observed is attributable to each of its components. A necessary condition for doing so is the satisfaction of the fourth axiom; decomposability, what in turn limits the available inequality indexes to a concrete family of such indexes: the Generalized Entropy indexes or some ordinally-equivalent transformation. This leads to two basic ways of decomposing global inequality additively: subgroup decomposition, source decomposition[8].

Subgroup decomposition consists in finding out which is the contribution to whole inequality of the different subgroups of the population, which are mutually excludable. Hence, inequality can be expressed as the sum of inequality *between* groups and weighted inequality *within* those groups. The *between* component is the inequality that would exist if each member of the group has the mean "income" of that group, that is to say that each country of the group has the mean EF per capita. On the hand, the *within* component consists in the inequality that would be observed if inequality between groups would not exist, so that the *within* inequality is the

[8] It is worth knowing that these decompositions can be performed using different techniques available in the literature; each of them with different advantages and drawbacks. These are the analytical decomposition (Bourguignon, 1979; F. A. Cowell, 1980; A. F. Shorrocks, 1980; A. F. Shorrocks, 1982) or the shapely value decomposition (Sastre & Trannoy, 2002; A. F. Shorrocks, 1999). Also must be considered the Regression Based decomposition which is becoming popular as a useful tool of decomposing Inequality, however it could be read as a fourth way of decomposing rather than a methodological tool because it decomposes inequality by explanatory factors defined as is common in regressions, so that it requires more and different data. See (F. A. Cowell & Fiorio, 2009; Fields, 2003; Morduch & Sicular, 2002). A wide review on inequality decompositions could be found on (Heshmati, 2004)

existing inequality in each group weighted by population or pollution (income). It takes the form

$$I = \sum_{g}^{G} \omega_g I_g + I_0$$

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

$$T(\beta) = \sum_{g}^{G} \omega_g T_g(\beta) + T_0(\beta)$$

where $\omega_g = p_g^{1-\beta} y_g^{\beta}$. So that only for $\beta = 1$ or $\beta = 0$ the weights can read as proportions of population ($\beta = 0$) or EF ($\beta = 1$). The case for $\beta \neq 0,1$ leads to a problem of interpretation since the weights are a mixture of population and pollution, and those weights do not add one. Furthermore, since the decomposition for $\beta = 1$ correspond to weight observations by relative pollution (or income) instead of relative population, it is important to keep in mind that conceptually, the *between* inequality as defined above involve transfers among observations. Therefore, the low inequality aversion $\beta = 0$ is the most unambiguous solution (see Goerlich, 1998; Shorrocks, 1980)

The source decomposition aims to quantify how much EF inequality can be attributed to the inequality of the EF components

$$EF_i = \sum_{k=1}^{K} C_{ki}$$

where C_{ki} are the components described in the EF (Cropland, grazing land, fishing ground, forest land, carbon land, built-up land). Nonetheless, as can be foreseen, it will be correlation between those components, informing about the existence of interaction effects between them. Those interaction effects must be taken into account when interpreting the results obtained. Otherwise, the policy implications could be biased. In other words, is of paramount importance to distinguish between direct contribution to global inequality and indirect contribution, what actually is the contribution of some other component. An easy way to see this is by using the decomposition of the variance:

$$Var_\omega(EF) = Var_\omega\left(\sum_{k=1}^{K} C_k\right) = \sum_{k=1}^{K} Var_\omega(C_k) + \sum_{k} \sum_{j \neq k} Cov_\omega(C_k, C_j)$$

If the components are independent, the second term of the expression, the $Cov_{\omega}(C_k, C_j)$, would be zero. However this is not the case and so, it is necessary to distribute those interactions effects when assigning the different contributions to inequality. Some decompositions, such the decomposition of Gini Index proposed by (Fei et al., 1978) consists in weighting the pseudo-Gini index[9] in order to construct a consistent decomposition. Nonetheless, the indirect effects are being assigned implicitly and usually also arbitrarily. It was proved by Shorrocks (1982) that most of the common indexes can be decomposed in a way that factor contributions can coincide with the decomposition of any other index. Therefore, it makes sense to assign existing interaction effects in an explicit reasonable way. The interpretation of source decomposition actually gives us some clues of how to do it.

The literature considers four different ways for interpreting the contribution to inequality, what actually can be read as four ways of assigning interaction terms. These different interpretations can lead to different contributions to inequality:

a) The contribution equals the inequality of each source: $S_k = I(C_k)$.

b) The contribution of each factor equals the variation observed in Inequality when that factor is removed: $S_k = I(EF) + I(EF - C_k)$.

c) The contribution of a factor is equal to the inequality observed when all the remaining factors are evenly distributed: $S_k = I(C_k + \mu - \mu_k)$. There are not interaction effects. Is the "pure" contribution to global inequality.

d) The contribution of a factor equals the variation observed in global inequality when that factor is evenly distributed: $S_k = I(EF) - I(EF - C_k + \mu_k)$. All the interaction effects involving *k* are allocated to that factor.

Shorrocks (1982) proves that under some very plausible assumptions[10] the natural decomposition of the variance or what is equivalent, the natural decomposition of the square of the Coefficient of Variation (CV^2), is the only decomposition method independently of the index used. Such decomposition allows connecting a rational and explicit way of assigning interaction terms with two of the interpretation described; the interactions effects of each factor are allocated by the mean of interpretations *c* and *d*. Otherwise, interaction terms will be assigned arbitrarily (Shorrocks, 1982).

[9] Also known as concentration indexes. This is to rank the distribution of the different components according to the ranking performed by the aggregate factor. White (2007) used this methodology in decomposing EF

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

$$S_k^c(CV^2) = CV_\omega(C_k + \mu - \mu_k)^2 = \frac{Var_\omega(C_k)}{\mu^2}$$

$$S_k^d(CV^2) = CV_\omega(EF)^2 - CV_\omega(EF - C_k + \mu_k)^2 = \frac{Var_\omega(C_k) + 2\sum_{j \neq k} Cov_\omega(C_j, C_k)}{\mu^2}$$

$$S_k(CV^2) = \frac{1}{2}(S_k^c + S_k^d) = \frac{Cov_\omega(C_k, EF)}{\mu^2}$$

In other words, the contribution of each factor is its dispersion plus the half of its interaction effects (1/2 of covariance term). Then, according to Shorrocks (1982) the percent contribution of factor k would be uniquely defined by the natural decomposition of the variance (or CV2) independently of the index used to measure overall inequality:

$$s_k(CV^2) = \frac{S_k(CV^2)}{CV^2(EF)}$$

On balance, the main advantage of Shorrocks decomposition is the non arbitrariness in assigning interaction terms jointly with the interpretation issue. Nonetheless, the literature has criticized that method because its independence of inequality index used, what actually is not a problem in this paper because we have already defended the properties of CV^2 as the more desirable ones given our framework. Nevertheless, it could be alleged that the interpretation of half of the interaction terms for each k factor is not so intuitive for the most of the cases (Shorrocks, 1999). One solution is the Shapley value decomposition, which has its origins in game theory (Shapley, 1953) and can be understood as a generalization of the Shorrocks natural decomposition method (Rodriguez-Hernadez, 2004) [11]. The Shapley decomposition is sensitive to the index used and contributions can be interpreted in marginal way.

The Shapley value is an allocation method that assigns the gains of a coalition of players among its members as a function of what they contribute to the coalition taking into account all possible orders in which the player joins the coalition. In the inequality decomposition context, this technique implies considering the impact on global inequality of eliminating each EF component (by removing it directly or by equalizing its distribution by substituting k source by its mean). So the marginal contribution of factor $k(SEF \subseteq EF, k \in SEF)$ to EF inequality would be

$S_k(SEF, I) = I(SEF) - I(SEF - \{C_K\})$ where SEF is a Subset of EF components.

[11] The Shapley value decomposition also takes into account all existing factors in the estimation of inequality contribution, it is symmetric and consistent, but in contrast to Shorrocks (1982), the Shapley value decomposition is sensitive to the index used. For deeper details see (Araar, 2006; Rodriguez-Hernadez, 2004; Sastre and Trannoy, 2002; Shorrocks, 1999)

But, since there is no natural order of eliminating them, Shapley decomposition averages all these impacts over all possible sequences of elimination (Sastre and Trannoy, 2002). So, the Shapley contribution will be:

$$S_k(K,I) = \sum_{\substack{S \subseteq K \\ j \in S}} \frac{(k-sef)!(sef-1)!}{k!}\left[I(SEF) - I(SEF - \{C_k\})\right]$$

where *SEF* is a subset of the *K* components of *EF*, and C_k is the component removed. Nonetheless, the way in which that component is removed will lead to two different decompositions by Shapley value. This decomposition can be performed in two different ways, which differ in the treatment of components not included in the considered subset. In the first, defined as Zero Shapley Decomposition, the components not included in *SEF* are removed. In the second, known as Equalized Shapley decomposition, what is removed is the inequality of those components no included in *SEF*.

So the result are expected marginal contributions of the factors when such an expectation is made over all possible sequences of elimination, and therefore the contributions to inequality can be interpreted in the same marginal way. Therefore, Zero Shapley decomposition could be matched with a sophisticated version of interpretation *b* described above since factor k is completely removed, while equalized Shapley decomposition, which instead of removing factor k, it removes its inequality will lead to a sophistication of interpretation *d*. In respect to the later, Shorrocks (1999) proves that the equalized Shapley decomposition yields the natural decomposition of the CV^2 when CV^2 is used to measure inequality[12].

The square of the coefficient of variation (CV^2) is one of the indexes satisfying the desirable basic axioms as well as its cardinally equivalent, *GE(2)* [13]. Hence, both are neutral indexes (they do not give more importance to ant particular part of the distribution). Furthermore, CV^2 is consistent with source decomposition methods. For these reasons, despite providing some other widely used indexes such as Gini coefficient, neutral indexes will be used as a reference to our empirical analysis. On the other hand, attending the rationale discussed in the subgroup decomposition, the two measures of Theil (*GE(0)* and *GE(1)*) will be also used.

[12] If the variance is used to measure inequality both Zero Shapley Decomposition and Equalized Shapley Decomposition yields the natural decomposition of the variance (or CV2). If CV2 is used, it only holds for Equalized Decomposition.

[13] $GE(2) = \frac{1}{2}CV^2$ (Goerlich, 1998)

4 Empirical results

Data on Ecological Footprint have been taken from (Global Footprint Network, 2010) and it covers 119 countries from 1961 to 2007. The sample amounts 90% of world population, 91% of 2007-GDP and 82% of the World Ecological Footprint. The presented results must be read in a proper way: the EF per capita is the EF of the whole country divided by the country's population; no more, no less. It is not pretended to assume that every person within a country has the same EF. In contrast, our focus is on analysing the inequality of resource consumption in a macro political way.

Table 2 shows the evolution of Inequality along the period analysed. Although the stability observed in the long term pattern, it can be remarked some particular episodes: in the first twenty years of the analysed period there was a significant increase in the EF inequality. Passed the decade of the 80s the inequality shows a tendency toward a slim decrease, which is more remarkable from 2003. The heavy industrialization of super populated China in the last decades has had an equalizing effect in the EF distribution[14]. Also India has a similar performance. Nonetheless, underlying such stability in the inequality trend can hide different trends as will be shown by decomposition techniques.

[Table 2]

Additionally, figure 2 compares that evolution using different inequality indexes. It is remarkable the significant differences in growth rates observed depending on the index used. Firstly, Gini index is quite more stable than other indexes proposed. The main reason of such behaviour must be found in the distribution mode preference of Gini index. *GE(0)* favour the low part of the distribution, as *GE(1)*, while *GE(2)* and CV^2 are neutral indexes since do not favour any particular part of the distribution [15]. A detailed observation of figure 2 will illustrate that even in some episodes the indexes indicate different signs in inequality trend: in the period 1980-82 neutral indexes (CV^2-*T(2)*) show a clear increase in inequality observed while other Theil measures (*T(0)* and *T(1)*) and Gini shows a slim decrease in the same period. On contrast, in periods 1986-87 and 1998-00, a reduction of inequality takes place according to neutral indexes while Gini and Theils indexes indicates an increase of inequality observed.

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[14] It has been performed the same analysis as showed in table 2 excluding from China from the sample. The results show a non-stop increase in the EF inequality. Consistent with Duro and Padilla (2006), where the reducing trend in CO2 emissions inequality found becomes less pressing without China and India in the sample.

[15] The coincidence in rates is due to cardinality equivalence.

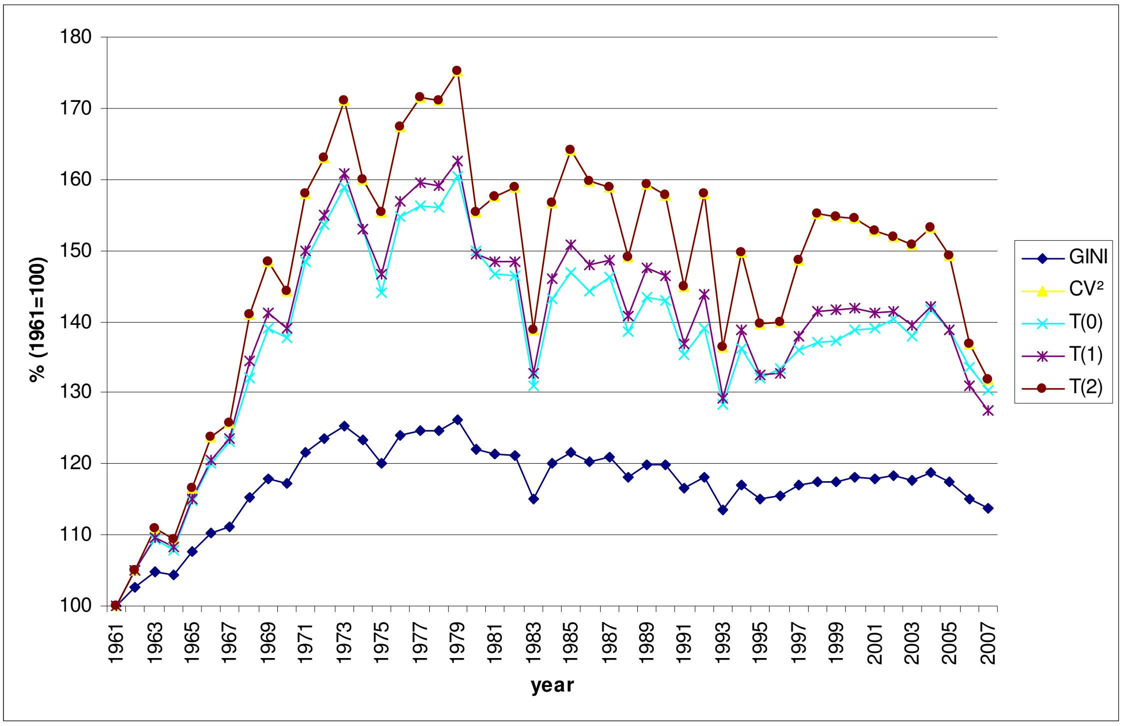

Figure 2. Inequality trends in EF (1961=100 for all indexes)

Hence, from a methodological point of view, the index chosen to measure inequality is not free of discussion. The inequality observed will depend on the index chosen to measure it. In other words, it is a fact of value judgement: whether those value judgements are acceptable or not, will depend on the problem analysed, which in turn will lead to different policy implications (as discussed above and in Duro (2012)).

Decomposition analysis illustrate in more detail the building blocks of the inequality observed. Despite the relatively stable evolution of EF inequality (especially from 1980s), there are some none so stable trends underlying such behaviour. Subgroup decomposition has been performed using exogenous groups such as those defined by World Bank (table 3). A first interesting result is that the bulk of inequality along the analysed period has been explained by the *between* inequality component (between 83%-88% according to *T(0)*). Therefore, it could be said that the inequality in EF would be drastically reduced if differences among groups were eliminated, or what is equivalent, if the inequality *within* groups were null there would not be a significant reduction in global inequality. Hence, EF inequality is well explained by these exogenous groups of World Bank classification.

Nonetheless, it is also worthwhile analysing the very evolution of this *between* (*within*) differences. Observing in more detail the subgroup decomposition of *T(0)* (table 3, left), we will see that the between group component performs an inverted U-shape along the period: in 1961 it accounted for the 83% of the EF inequality. This *between* factor grows until 88% in 1972 and stays around 86-87% until the beginnings of the 90s, when it shrank until contributing in 81% of the overall inequality in 2007. On the other hand, also in the table 3 (middle and right) there are the same subgroup decomposition for both *T(1)* the neutral index *GE(2)*. The *Between* component of *T(1)* shows a similar tendency as described for *T(0)*, although it exhibits some differences which may be explained on one hand for different sensibility to distribution parts and the other hand for different weights on countries. T(1), as described above, correspond to weight contributions by EF while T(0) do it by population. On contrast, GE(2) can not be interpreted in this line, however, it is a neutral index. The *Between* component of the later shows a more drastic increase in its contribution to overall EF inequality: from 73% in 1961 to 86% to 1991, after which there is a slim reduction until 81% of 2007. Despite the differences in the groups used in other studies that use different indicators, the pattern observed in the between component (and inversely in the within) usually shows drastic decreasing for either CO_2 emissions (Duro and Padilla 2006; Padilla and Serrano 2006) or energy intensities (Alcantara and Duro 2004).

[Table 3]

Secondly, the inequality has been decomposed according to EF components. Firstly, the contribution of each source could be interpreted as the inequality of each component (interpretation *a*) as showed in table 4, where we can observe the inequality of each component. Fishing, Forest, and Built footprints present a stable evolution in its inequality, with a relatively high inequality in fishing ground inequality. Cropland footprint, on the other hand, exhibits a quite stable trend with a slight reduction along the period and a relatively low inequality levels. The later could be indicative of the special status of biomass from cropland, necessary for the most basic subsistence (Steinberger et al., 2010). On contrast, Grazing footprint inequality, despite registering also a reduction along the period, always remains as the more unequal distribution compared with remaining ecological footprint components. The explanation of such high inequality must be found in the intensive-meat diets of industrialized countries (White, 2000). Finally, Carbon footprint inequality presents a significant reduction along the period, which is consistent with those findings of Padilla and Serrano (2006), Ezcurra (2007), Heil and Wodon (1997) and Heil and Wodon (2000) who analyse CO_2 emissions inequality.

It is also remarkable that in the beginning of the period, in 1961, the ranking of EF components according to its inequality were grazing footprint as the more unequal, followed by carbon footprint and then by fishing footprint. Nonetheless, at the end of the period in 2007, the ranking turns to grazing footprint as the more unequal, but followed by fishing footprint instead of carbon footprint, which passes to the third more unequal distribution. Hence, the most unequal distributions are diet related issues followed by a decreasing energy related issue distribution.

[Table 4]

In this same line, Steineberger et al. (2010) estimated Gini index to Domestic Material Consumption (DMC) and its different components (biomass, construction minerals, fossil fuels, ores/industrial minerals) for year 2000. Despite both indicators share raw data, the results obtained are not comparable since the indicators deals with different research questions and so are constructed differently. EF focuses mainly on biomass consumption. Nonetheless, it is interesting to observe some relatively closed results: the Gini coefficient for total DMC is 0.35 and the Gini coefficient for same year of EF is 0.39, Gini coefficient for fossil fuels DMC is 0.58 while the Gini coefficient for carbon footprint for our data is 0.58[16]. Additionally, if the Cropland, forest, grazing, and fishing footprint are added together in order to construct a "biomass" footprint, the resulting Gini coefficient for 2003 would be 0.30[17], so closed to 0.29 of Steinberger et al. paper. Therefore, our analysis is in line with that of Steinberger et al. 2010, adding new details in the same direction.

The inequality analyses of each component, despite contributing with relevant information it is not consistent with total EF inequality analysed. For this reason it is pertinent to perform the natural decomposition according to Shorrocks (1982), where the interpretation of the contribution to overall inequality observed is the average of *c* and *d* methods described in section 3.2. In the first place, the result (in table 5) shows a clearly growing trend of Carbon footprint contribution to EF inequality until becoming the main contributor to overall inequality. This result is consistent with White (2007) who constructed the natural decomposition of the Gini index for year 2003. Nonetheless, such decomposition does not explicit the allocation of interaction effects. Moreover, what was not yet evidenced empirically was this significant growth of that heavy percentage in the last four decades. The cropland and grazing footprint inequality were in the first years of the sample the main contributors to global inequality in EF (56% of total Inequality in 1961), while at the end of the period, carbon footprint inequality becomes the main contributor (73% of total inequality in 2007). Such evolution is not a fact of growing inequality in carbon footprint: as seen above, the carbon footprint inequality decreases along the analysed period. On contrary, it is a fact of growing carbon footprint levels due to the

[16] Gini 2003 for Carbon footprint is 0.575558
[17] Gini 2003 for biomass footprint constructed is 0.300186

advent of high-carbon economy. Hence, the growing contribution of carbon Footprint in overall EF inequality is mainly attributable to a weighting issue of several countries.

On balance, the evolution in EF inequality is quite stable, however the inequality observed for some of its components is far from stable. Besides, their contribution to overall EF inequality hides diverging inequality trends of EF-components: the increasing trend in the contribution of carbon footprint in EF inequality underlies a decreasing inequality trend in that specific component. The contribution to EF-inequality of grazing land footprint is quite low compared to the high inequality it exhibits.

[Figure 3 and figure 4]

Additionally, the Equalized Shapley decomposition has been performed for *GE(2)* (figure 4). Although it does not change the empirical result described using Shorrocks rule decomposition (Shorrocks 1999), this decomposition method allows a cleaner interpretation of them as expected marginal contributions to overall inequality. The rationale behind such methodology would correspond to interpretation *d* described in section 3.2.

Table 7. Zero Shapley Decomposition of *GE(2)*

Year	Fishing	Cropland	Grazing	Forest	carbon	Built	Total
1961	49%	-156%	150%	-28%	120%	-36%	100%
1975	26%	-94%	116%	-16%	92%	-23%	100%
1985	39%	-72%	76%	-5%	82%	-20%	100%
1995	40%	-75%	69%	5%	78%	-17%	100%
2007	30%	-60%	69%	9%	66%	-15%	100%

Table 7 shows what would correspond to the sophisticated version of Shorrocks interpretation *b* for several years of the sample. Since it is decomposed by Shapley method, table 7 show the expected marginal effects of each factor to overall EF inequality when that factor is removed in all possible sequences (Zero Shapley decomposition method). As can be observed, in the beginning of the analysed period, there is a high contribution of grazing and carbon footprints to EF inequality followed by Fishing footprint: closed to results obtained in table 4 (interpretation *a*). At the same time, the more equal distributions exhibit negative contributions[18] to overall EF inequality. Such contributions, however change significantly along the period until a situation were the less contributing factor in 2007 is Cropland, which despite its growing trend, contributes negatively to EF inequality (if Cropland footprint does not exists, the EF inequality would be 60% more unequal; so it have an equalizing effect in EF distribution). On the other

[18] The Equalized Shapley decomposition allocates null contribution when a factor is perfectly even distributed. On contrast, the Zero Shapley decomposition considers that an even distributed component contributes negatively to the overall inequality. See Sastre and Trannoy (2002) for technical issues.

hand, according to this method, grazing land footprint has the most positive contribution to EF inequality (if grazing land footprint does not exist, the EF inequality would be 69% more equally distributed; so it increases 69% EF inequality).

In summary, provided that there is no consensus in the literature in how to quantify a source contribution to overall inequality, it has been performed the four existing interpretations using different available methodologies. In doing so, the analysis on source contribution to inequality provides much more relevant information in order to disentangle the building blocks of observed EF inequality. Table 8 summarizes such building blocks according methods used. As can be observed, many do not coincide; even some of them show opposite findings because of different interpretations about what a contribution to inequality means.

Table 8. Summary of results obtained for different existing methods to assess contribution to overall inequality

Contribution to overall inequality as…	fishing	cropland	grazing	forest	carbon	built
Inequality of each component	High	Low and decreasing	High. Despite decreasing still high	moderate and quite stable along the period	High in the begining and moderate at the end of the sample	Low and decreased
Natural Shorrocks rule	Low (6.5%) to lower (2.9%)	High contribution which decrease to low contribution	Low (20%) to lower (3.7%)	Low (18%) to lower (11.7%)	from low (17.5%) to high (69.2%)	Insignificant (from 1.5% to 0.7%)
Expected marginal contribution (Equalized Shapley)	Low (6.5%) to lower (2.9%)	High contribution which decrease to low contribution	Low (20%) to lower (3.7%)	Low (18%) to lower (11.7%)	from low (17.5%) to high (69.2%)	Insignificant (from 1.5% to 0.7%)
Expected marginal contribution (Zero Shapley)	High. Despite decreasing still high	negative. Much more negative in the beginning	High. Despite decreasing still high	Negative but increased until getting a low positve contribution	High. Despite decreasing still high.	Negative. Much more negative in the beginning

5 Conclusions

This paper has focused on the analysis of the distribution of the renewable natural resource consumption as measured by Ecological Footprint framework. The aim in doing so has been threefold: on principals, on methods and on empirical results.

On principals, we highlight the importance of measuring ecological distribution in the framework of sustainable development. Sustainable development is not only a fact of scale but also of distribution and allocation (Daly 1992; Luks and Stewen, 1999). Otherwise, the sustainability would be understood as an unjust and inefficient concept. Consequently, it is of paramount importance to take into account how the pie is being shared. On the other hand, heterogeneity among countries must be taken into account in the global achievement of political consensus. Greater inequality in resource consumption leads to greater inequality in the responsibilities in the ecological crisis, what actually requires greater inequality in the commitments supported by countries. So the analysis presented give important clues of better achievement of International Environmental Agreements. In line with this, more effective policies can be implemented the distribution of ecological impacts are better known and spatially localized.

Secondly, on methods, we make our contribution in filling the yet existent gap in the ecological economics literature when it deals with application of inequality economics tools to environmental indicators. Some implicit axioms in some common used inequality index could not fit properly when environmental issues instead of income are being analysed, as weighting heavily the low polluter countries than the high ones. In this sense, the neutrality character of *GE(2)* has been discussed as a desirable property for being satisfied among other basic axioms. Additionally, we have dealt with inequality additive decomposition methodology. On the one hand, it has been performed a subgroup decomposition, what has no yet done for national EF accounts. On the other hand, it has been discussed the source decomposition methodologies by putting special emphasis in the way in which interaction effects are assigned among components. The only existing evidence on decomposition by sources of EF (White, 2007) was made by assigning interaction effects in a implicit and arbitrary way. Additionally, it has been taken into account all possible existing interpretations of source contribution to overall inequality. In doing so, Shapely value decomposition techniques have been used in order to take advantage of its particularities.

Finally, our empirical results also expand those existing in the international EF distribution. Firstly, we provide longer data allowing observe inequality trends in the sample period. The inequality of EF has been quite stable in the last decades, partly because of the performance of China, whose behaviour has prevented EF-inequality from increasing. The subgroup decomposition of such inequality by exogenous of World Bank groups of countries has showed the *between* groups inequality explains the bulk of international EF-inequality (83-87%).Hence 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. Finally, the source decomposition has allowed disentangling various underlying phenomena on the apparent stability of overall EF inequality: the increasing contribution of carbon footprint to the EF inequality is mainly due to a weighting issue rather than an increase on carbon footprint inequality, which actually decreases. The contribution of grazing and fishing footprints exhibit high levels of international inequality despite contributing modestly to overall EF-inequality. Such footprints are linked with relatively high fish and meat intensive diets of industrialized countries. In contrast, cropland footprint, remains as one of the more even distributed components of the EF. Actually, it has an equalizing effect on overall EF-inequality.

The main reason is probably the fact that basic subsistence highly depends on cropland consumption. Besides, the contribution of cropland footprint to overall EF-inequality registers a significant decrease along the period. Such reduction is given once more because of the weighting issues: low EF countries usually has crop-dominant footprint while high EF countries are carbon-Footprint dominant (Ewing et al.,2010).

Further research is needed to disentangle deeply what is behind the apparent stability of EF inequality. In this sense, multiplicative decomposition (Duro and Padilla, 2006) can give further details underlying in the observed distribution. Additionally, intra-distribution group generation and intra-distribution dynamics should be considered to fulfil a comprehensive distributional analysis by using polarization methods (Duclos, Esteban, and Ray, 2004; Duro and Padilla, 2008) and mobility approaches respectively (Fields and Ok, 1996). Both methodologies widely developed and applied in the income literature but seldom did it in environmental issues.

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Appendix

Table 2. Inequality indexes of EF per capita.

year	GINI	T(0)	T(1)	T(2)	CV²
1961	0.331863	0.179226	0.189064	0.221799	0.443598
1962	0.340601	0.18826	0.198431	0.233125	0.46625
1963	0.348073	0.195861	0.207045	0.245799	0.491598
1964	0.346067	0.193413	0.204768	0.242528	0.485056
1965	0.357436	0.205764	0.217594	0.258574	0.517148
1966	0.365708	0.215069	0.227701	0.274284	0.548568
1967	0.368823	0.220491	0.233514	0.279064	0.558128
1968	0.382148	0.236772	0.254051	0.312909	0.625818
1969	0.391247	0.249119	0.266751	0.329111	0.658222
1970	0.389138	0.247006	0.262932	0.319889	0.639778
1971	0.403557	0.265816	0.283596	0.350375	0.70075
1972	0.40974	0.275489	0.292825	0.361321	0.722642
1973	0.415801	0.284671	0.304146	0.379181	0.758362
1974	0.408946	0.27418	0.289289	0.354787	0.709574
1975	0.398244	0.258086	0.277122	0.344603	0.689206
1976	0.411443	0.277105	0.29676	0.371164	0.742328
1977	0.413506	0.279962	0.30151	0.380464	0.760928
1978	0.413749	0.279761	0.300625	0.37962	0.75924
1979	0.418671	0.28729	0.307383	0.388589	0.777178
1980	0.404805	0.268524	0.28246	0.344797	0.689594
1981	0.402587	0.262972	0.280508	0.349538	0.699076
1982	0.401942	0.262577	0.280454	0.352258	0.704516
1983	0.381493	0.23479	0.250775	0.30778	0.61556
1984	0.398198	0.256443	0.275983	0.347329	0.694658
1985	0.403467	0.26323	0.285199	0.363881	0.727762
1986	0.399454	0.258645	0.279678	0.354078	0.708156
1987	0.401498	0.261941	0.280809	0.352391	0.704782
1988	0.391679	0.24834	0.266193	0.330683	0.661366
1989	0.39766	0.257045	0.278703	0.353083	0.706166
1990	0.397332	0.256368	0.276652	0.349914	0.699828
1991	0.386913	0.242348	0.258756	0.321538	0.643076
1992	0.392158	0.248985	0.271967	0.350584	0.701168
1993	0.376785	0.229976	0.244149	0.302631	0.605262
1994	0.38846	0.244235	0.262502	0.332241	0.664482
1995	0.382126	0.23678	0.250645	0.309904	0.619808
1996	0.382961	0.238944	0.250801	0.310256	0.620512
1997	0.388101	0.243835	0.260967	0.329826	0.659652
1998	0.389878	0.245512	0.267234	0.344002	0.688004
1999	0.389766	0.245884	0.267659	0.343098	0.686196
2000	0.391711	0.248794	0.268371	0.342659	0.685318
2001	0.391375	0.249028	0.266981	0.338792	0.677584
2002	0.39272	0.251387	0.267341	0.336766	0.673532
2003	0.390124	0.247222	0.263856	0.334474	0.668948
2004	0.394409	0.253854	0.26877	0.339853	0.679706
2005	0.389538	0.248936	0.262337	0.330875	0.66175
2006	0.381548	0.239448	0.247386	0.303389	0.606778
2007	0.377429	0.233587	0.240921	0.292457	0.584914

Table 3.decomposition by countries subgroups using World Bank geographical groups.T(0), T(1) and GE(2).

	Between I. T(0)					Between I. T(1)					Between I. T(2)				
year	Within I.	**%**	Between I.	%	T(0)	Within I.	**%**	Between I.	%	T(1)	Within I.	**%**	Between I.	%	T(2)
1961	0.0305	17%	0.1487	83%	0.1792	0.0386	20%	0.1505	80%	0.1891	0.0599	27%	0.1619	73%	0.2218
1962	0.0301	16%	0.1581	84%	0.1883	0.0377	19%	0.1607	81%	0.1984	0.0586	25%	0.1746	75%	0.2331
1963	0.0300	15%	0.1659	85%	0.1959	0.0386	19%	0.1685	81%	0.2070	0.0622	25%	0.1836	75%	0.2458
1964	0.0299	15%	0.1635	85%	0.1934	0.0380	19%	0.1668	81%	0.2048	0.0602	25%	0.1824	75%	0.2425
1965	0.0301	15%	0.1757	85%	0.2058	0.0380	17%	0.1796	83%	0.2176	0.0605	23%	0.1981	77%	0.2586
1966	0.0318	15%	0.1833	85%	0.2151	0.0401	18%	0.1876	82%	0.2277	0.0660	24%	0.2082	76%	0.2743
1967	0.0298	14%	0.1907	86%	0.2205	0.0374	16%	0.1961	84%	0.2335	0.0599	21%	0.2192	79%	0.2791
1968	0.0316	13%	0.2051	87%	0.2368	0.0416	16%	0.2125	84%	0.2541	0.0721	23%	0.2408	77%	0.3129
1969	0.0338	14%	0.2153	86%	0.2491	0.0430	16%	0.2238	84%	0.2668	0.0735	22%	0.2557	78%	0.3291
1970	0.0312	13%	0.2158	87%	0.2470	0.0374	14%	0.2256	86%	0.2629	0.0604	19%	0.2595	81%	0.3199
1971	0.0344	13%	0.2314	87%	0.2658	0.0423	15%	0.2413	85%	0.2836	0.0715	20%	0.2789	80%	0.3504
1972	0.0340	12%	0.2415	88%	0.2755	0.0408	14%	0.2520	86%	0.2928	0.0684	19%	0.2929	81%	0.3613
1973	0.0358	13%	0.2489	87%	0.2847	0.0421	14%	0.2621	86%	0.3041	0.0707	19%	0.3085	81%	0.3792
1974	0.0341	12%	0.2401	88%	0.2742	0.0395	14%	0.2498	86%	0.2893	0.0650	18%	0.2898	82%	0.3548
1975	0.0346	13%	0.2234	87%	0.2581	0.0422	15%	0.2349	85%	0.2771	0.0715	21%	0.2731	79%	0.3446
1976	0.0366	13%	0.2405	87%	0.2771	0.0437	15%	0.2531	85%	0.2968	0.0743	20%	0.2969	80%	0.3712
1977	0.0361	13%	0.2438	87%	0.2800	0.0438	15%	0.2577	85%	0.3015	0.0761	20%	0.3044	80%	0.3805
1978	0.0381	14%	0.2417	86%	0.2798	0.0453	15%	0.2553	85%	0.3006	0.0776	20%	0.3020	80%	0.3796
1979	0.0376	13%	0.2497	87%	0.2873	0.0440	14%	0.2634	86%	0.3074	0.0756	19%	0.3130	81%	0.3886
1980	0.0343	13%	0.2342	87%	0.2685	0.0374	13%	0.2450	87%	0.2825	0.0580	17%	0.2868	83%	0.3448
1981	0.0374	14%	0.2255	86%	0.2630	0.0437	16%	0.2368	84%	0.2805	0.0722	21%	0.2773	79%	0.3495
1982	0.0374	14%	0.2252	86%	0.2626	0.0442	16%	0.2363	84%	0.2805	0.0747	21%	0.2775	79%	0.3523
1983	0.0342	15%	0.2006	85%	0.2348	0.0379	15%	0.2129	85%	0.2508	0.0577	19%	0.2500	81%	0.3078
1984	0.0369	14%	0.2195	86%	0.2564	0.0424	15%	0.2336	85%	0.2760	0.0695	20%	0.2779	80%	0.3473
1985	0.0363	14%	0.2269	86%	0.2632	0.0427	15%	0.2425	85%	0.2852	0.0727	20%	0.2912	80%	0.3639
1986	0.0338	13%	0.2248	87%	0.2586	0.0390	14%	0.2406	86%	0.2797	0.0650	18%	0.2891	82%	0.3541
1987	0.0340	13%	0.2280	87%	0.2619	0.0370	13%	0.2439	87%	0.2808	0.0587	17%	0.2936	83%	0.3524
1988	0.0338	14%	0.2146	86%	0.2483	0.0345	13%	0.2317	87%	0.2662	0.0506	15%	0.2801	85%	0.3307
1989	0.0349	14%	0.2221	86%	0.2570	0.0366	13%	0.2422	87%	0.2787	0.0563	16%	0.2967	84%	0.3531
1990	0.0338	13%	0.2225	87%	0.2564	0.0340	12%	0.2427	88%	0.2767	0.0511	15%	0.2988	85%	0.3499
1991	0.0348	14%	0.2075	86%	0.2423	0.0334	13%	0.2253	87%	0.2588	0.0466	14%	0.2750	86%	0.3215
1992	0.0362	15%	0.2128	85%	0.2490	0.0377	14%	0.2342	86%	0.2720	0.0603	17%	0.2902	83%	0.3506
1993	0.0366	16%	0.1934	84%	0.2300	0.0361	15%	0.2080	85%	0.2441	0.0512	17%	0.2514	83%	0.3026
1994	0.0394	16%	0.2048	84%	0.2442	0.0398	15%	0.2227	85%	0.2625	0.0589	18%	0.2733	82%	0.3322
1995	0.0382	16%	0.1986	84%	0.2368	0.0368	15%	0.2139	85%	0.2506	0.0499	16%	0.2600	84%	0.3099
1996	0.0402	17%	0.1988	83%	0.2389	0.0392	16%	0.2116	84%	0.2508	0.0550	18%	0.2552	82%	0.3103
1997	0.0402	16%	0.2036	84%	0.2438	0.0406	16%	0.2204	84%	0.2610	0.0597	18%	0.2702	82%	0.3298
1998	0.0347	14%	0.2108	86%	0.2455	0.0361	13%	0.2312	87%	0.2672	0.0568	17%	0.2872	83%	0.3440
1999	0.0387	16%	0.2072	84%	0.2459	0.0403	15%	0.2273	85%	0.2677	0.0608	18%	0.2823	82%	0.3431
2000	0.0372	15%	0.2116	85%	0.2488	0.0375	14%	0.2308	86%	0.2684	0.0560	16%	0.2866	84%	0.3427
2001	0.0393	16%	0.2097	84%	0.2490	0.0392	15%	0.2278	85%	0.2670	0.0569	17%	0.2819	83%	0.3388
2002	0.0396	16%	0.2118	84%	0.2514	0.0391	15%	0.2282	85%	0.2673	0.0558	17%	0.2810	83%	0.3368
2003	0.0399	16%	0.2073	84%	0.2472	0.0398	15%	0.2241	85%	0.2639	0.0582	17%	0.2763	83%	0.3345
2004	0.0412	16%	0.2126	84%	0.2539	0.0409	15%	0.2279	85%	0.2688	0.0598	18%	0.2801	82%	0.3399
2005	0.0412	17%	0.2077	83%	0.2489	0.0409	16%	0.2214	84%	0.2623	0.0600	18%	0.2709	82%	0.3309
2006	0.0446	19%	0.1949	81%	0.2394	0.0425	17%	0.2049	83%	0.2474	0.0573	19%	0.2460	81%	0.3034
2007	0.0440	19%	0.1896	81%	0.2336	0.0423	18%	0.1986	82%	0.2409	0.0555	19%	0.2369	81%	0.2925

Table 4. GE(2) for per capita EF components

Year	Fishing	Cropland	Grazing	Forest	carbon	Built
1961	0.9997	0.1465	1.7905	0.4863	1.4592	0.1803
1962	1.0482	0.1455	1.8151	0.4861	1.4503	0.1813
1963	1.0365	0.1517	1.7664	0.4707	1.4120	0.1691
1964	0.9558	0.1271	1.7351	0.4788	1.4383	0.1732
1965	1.0003	0.1332	1.7172	0.4824	1.4194	0.1608
1966	0.9738	0.1281	1.6214	0.4694	1.4166	0.1555
1967	1.0892	0.1361	1.6404	0.4541	1.4707	0.1793
1968	1.0377	0.1484	1.6601	0.4513	1.4596	0.1638
1969	0.9912	0.1555	1.7041	0.4561	1.4028	0.1569
1970	1.0205	0.1230	1.7050	0.4530	1.2936	0.1519
1971	1.0003	0.1577	1.7919	0.4884	1.2702	0.1591
1972	1.0469	0.1620	1.8830	0.4456	1.2940	0.1688
1973	0.9507	0.1424	1.8276	0.4891	1.2770	0.1591
1974	0.9328	0.1347	2.0625	0.4710	1.2573	0.1614
1975	0.8952	0.1477	2.2071	0.4490	1.1857	0.1502
1976	1.0011	0.1535	1.9760	0.4545	1.2014	0.1323
1977	0.9650	0.1664	1.8776	0.4511	1.2101	0.1537
1978	0.8711	0.1532	1.7607	0.4892	1.1715	0.1519
1979	0.8311	0.1640	1.6985	0.5048	1.1442	0.1633
1980	0.9751	0.1607	1.7188	0.4645	1.0931	0.1663
1981	0.9443	0.1528	1.6555	0.4549	1.0860	0.1650
1982	1.0136	0.2665	1.6433	0.4050	1.0384	0.1744
1983	0.9520	0.1437	1.5238	0.4589	1.0392	0.1536
1984	0.9053	0.1563	1.6245	0.4975	1.0521	0.1844
1985	1.1217	0.1746	1.7650	0.4983	1.0373	0.1635
1986	1.1034	0.1613	1.7775	0.5277	1.0233	0.1567
1987	1.1545	0.1490	1.6340	0.5483	1.0416	0.1616
1988	1.1171	0.1434	1.4993	0.5433	0.9940	0.1582
1989	1.1301	0.1309	1.5891	0.5482	0.9808	0.1574
1990	0.9568	0.1404	1.6072	0.5124	0.9509	0.1388
1991	0.9772	0.1369	1.6033	0.4501	0.9130	0.1603
1992	0.9724	0.1391	1.4900	0.4625	1.0062	0.1547
1993	0.9185	0.1245	1.5145	0.4706	0.8252	0.1482
1994	0.8977	0.1372	1.4504	0.4802	0.8704	0.1434
1995	0.9848	0.1233	1.3874	0.4910	0.8231	0.1537
1996	0.9024	0.1136	1.4505	0.4583	0.7598	0.1565
1997	0.9457	0.1038	1.3730	0.4763	0.8239	0.1576
1998	0.8736	0.1096	1.3955	0.4966	0.8851	0.1624
1999	0.9780	0.1075	1.3522	0.4823	0.8832	0.1708
2000	0.9780	0.1061	1.3414	0.4958	0.8561	0.1664
2001	1.0859	0.1063	1.3608	0.4773	0.8445	0.1574
2002	0.9842	0.1165	1.3106	0.4970	0.8656	0.1813
2003	0.9323	0.1204	1.3039	0.4815	0.8050	0.1405
2004	0.9191	0.1265	1.2927	0.5010	0.7752	0.1529
2005	0.8226	0.1161	1.2583	0.5585	0.7321	0.1405
2006	0.7943	0.1040	1.1924	0.4729	0.6824	0.1302
2007	0.7820	0.1060	1.2286	0.4592	0.6199	0.1296

Table 5. Natural decomposition of the Ecological Footprint per capita

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

Table 6. Shapley value decomposition by sources of Ecological Footprint

Year	Fishing	Cropland	Grazing	Forest	Carbon	Built
1961	0.0654	0.3591	0.2007	0.1851	0.1750	0.0147
1962	0.0646	0.3512	0.1889	0.1869	0.1934	0.0151
1963	0.0611	0.3500	0.1736	0.1717	0.2311	0.0125
1964	0.0589	0.2943	0.1739	0.1788	0.2803	0.0137
1965	0.0576	0.2942	0.1502	0.1752	0.3112	0.0116
1966	0.0557	0.2740	0.1468	0.1704	0.3428	0.0102
1967	0.0577	0.2743	0.1332	0.1612	0.3619	0.0118
1968	0.0525	0.2758	0.1240	0.1531	0.3856	0.0091
1969	0.0469	0.2664	0.1085	0.1488	0.4208	0.0085
1970	0.0480	0.2146	0.0980	0.1417	0.4892	0.0084
1971	0.0419	0.2325	0.0899	0.1382	0.4884	0.0090
1972	0.0416	0.2166	0.0874	0.1269	0.5175	0.0099
1973	0.0393	0.1922	0.0860	0.1317	0.5424	0.0083
1974	0.0412	0.1912	0.0998	0.1300	0.5298	0.0080
1975	0.0382	0.2098	0.1089	0.1178	0.5171	0.0083
1976	0.0394	0.1937	0.0929	0.1235	0.5442	0.0062
1977	0.0350	0.1934	0.0800	0.1221	0.5609	0.0086
1978	0.0354	0.1793	0.0795	0.1314	0.5667	0.0078
1979	0.0350	0.1874	0.0736	0.1312	0.5653	0.0076
1980	0.0389	0.1706	0.0777	0.1327	0.5702	0.0099
1981	0.0351	0.1923	0.0803	0.1302	0.5521	0.0100
1982	0.0380	0.2386	0.0798	0.1169	0.5152	0.0114
1983	0.0405	0.1628	0.0855	0.1410	0.5617	0.0086
1984	0.0363	0.1833	0.0740	0.1434	0.5524	0.0105
1985	0.0394	0.2019	0.0526	0.1431	0.5534	0.0097
1986	0.0393	0.1896	0.0476	0.1525	0.5615	0.0096
1987	0.0439	0.1669	0.0477	0.1537	0.5780	0.0098
1988	0.0428	0.1366	0.0602	0.1487	0.6032	0.0084
1989	0.0441	0.1447	0.0500	0.1517	0.6011	0.0084
1990	0.0402	0.1584	0.0453	0.1481	0.6000	0.0080
1991	0.0410	0.1575	0.0513	0.1290	0.6122	0.0089
1992	0.0399	0.1546	0.0478	0.1297	0.6196	0.0084
1993	0.0401	0.1355	0.0533	0.1394	0.6240	0.0077
1994	0.0423	0.1542	0.0426	0.1378	0.6148	0.0083
1995	0.0442	0.1298	0.0520	0.1387	0.6272	0.0081
1996	0.0381	0.1332	0.0463	0.1307	0.6430	0.0087
1997	0.0388	0.1273	0.0401	0.1336	0.6525	0.0078
1998	0.0334	0.1310	0.0398	0.1347	0.6528	0.0084
1999	0.0350	0.1275	0.0379	0.1353	0.6559	0.0085
2000	0.0326	0.1242	0.0373	0.1365	0.6610	0.0085
2001	0.0352	0.1205	0.0376	0.1285	0.6704	0.0077
2002	0.0338	0.1152	0.0399	0.1303	0.6722	0.0086
2003	0.0309	0.1264	0.0426	0.1271	0.6660	0.0069
2004	0.0291	0.1304	0.0347	0.1285	0.6692	0.0082
2005	0.0276	0.1234	0.0353	0.1331	0.6737	0.0069
2006	0.0295	0.1072	0.0354	0.1224	0.6985	0.0070
2007	0.0292	0.1163	0.0372	0.1171	0.6929	0.0073

Figure 3: Natural decomposition of the variance (Shorrocks 1982).

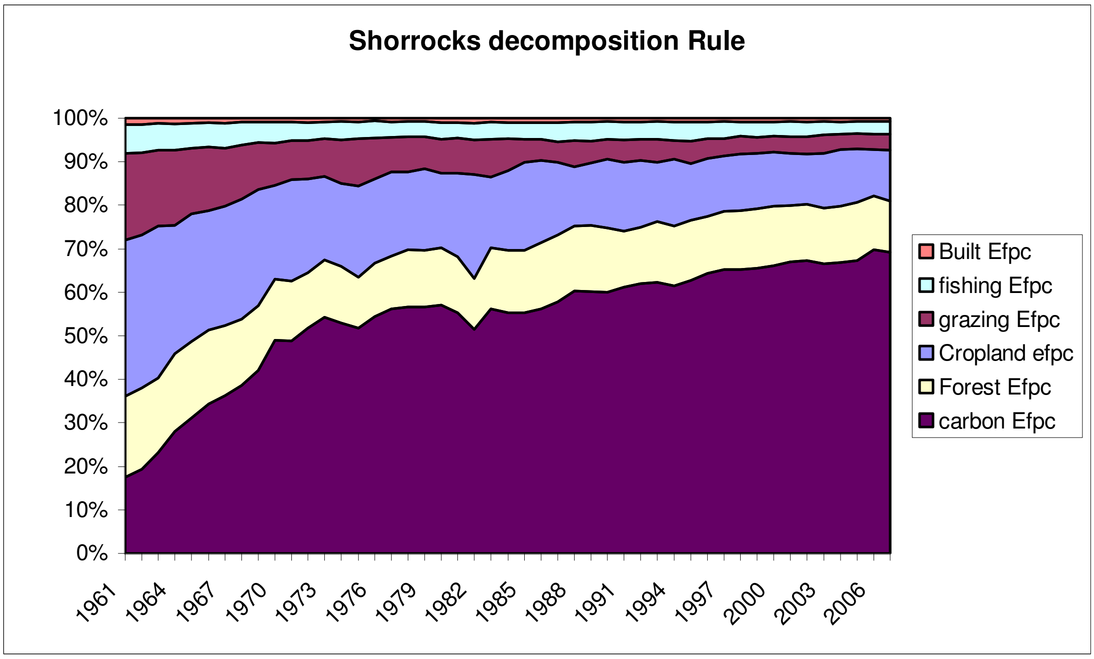

Figure 4: Shapley value decomposition of GE(2) (Shorrocks 1982).