Journal of Cleaner Production 270 (2020) 121833

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Operating within Planetary Boundaries without compromising well-being? A Data Envelopment Analysis approach

Michael Ehrenstein [a], Raúl Calvo-Serrano [b], Ángel Galán-Martín [b], Carlos Pozo [c], Patricia Zurano-Cervelló [d], Gonzalo Guillén-Gosálbez [b, *]

[a] Centre for Process Systems Engineering, Department of Chemical Engineering, Imperial College London, London, SW7 2AZ, UK
[b] Institute for Chemical and Bioengineering, Department of Chemistry and Applied Biosciences, ETH Zürich, Vladimir-Prelog-Weg 1, 8093, Zürich, Switzerland
[c] LEPAMAP Research Group, University of Girona, C/ Maria Aurèlia Capmany 61, 17003, Girona, Spain
[d] Departament d'Enginyeria Quimica, Universitat Rovira i Virgili, Av. Paisos Catalans 26, 43007, Tarragona, Spain

ARTICLE INFO

Article history:
Received 10 January 2020
Received in revised form
5 April 2020
Accepted 19 April 2020
Available online 11 May 2020

Handling editor. Zhifu Mi

Keywords:
Planetary boundaries
Environmental efficiency of well-being
Data Envelopment Analysis
Improvement targets

ABSTRACT

As humanity's impact on the environment continues to increase, it brings with it an increased risk of abrupt and irreversible changes at the global scale. The Planetary Boundaries (PBs) framework, introduced in 2009, identifies a safe operating space for several processes deemed critical to the continued stability of the Earth system. At a national level, countries face the challenge of limiting their environmental impact while enabling their inhabitants to lead happy lives. Different economies of various types and stages of development exhibit varying emissions and resource needs, yet they all exert pressure on the same Earth system processes. Considering this broad context, here we apply Data Envelopment Analysis to assess the efficiency of nations in "converting" their environmental impact into a happy populace, or, in other words, the environmental efficiency of well-being. We further calculate aspirational improvement targets for countries violating one or more PBs and identify trends within income categories as defined by the World Bank. We found that only around one third of the 151 countries analysed operate efficiently, with only 12 of them doing so within PBs. Following best practices, most countries could meet PBs while increasing their happiness level at the same time. Conversely, reductions in well-being would be required for most high-income countries to operate within PBs, though none by more than 18%. Overall, this work highlights both the differences and similarities between nations concerning how they provide well-being while providing high-level targets towards the global goal of conserving the Earth system without compromising our well-being.

1. Introduction

Over the previous century, humanity has pursued national and global development via the path of ever-increasing economic growth, while relying mainly on economic indicators such as the gross domestic product to guide future action (Costanza et al., 2014; Raworth, 2012). However, much of this growth to date has come at the steep cost of the depletion of the Earth's resources as well as excessive pollution. Notably, greenhouse gas levels in the atmosphere are steadily increasing, and have already resulted in an estimated average global temperature increase of 1 °C (IPCC, 2018). At the same time, mismanagement of waste threatens terrestrial and marine ecosystems around the world, with an estimated 4 to 12 million tons of plastic entering the oceans in 2010 alone (Geyer et al., 2017). Global water demand paints a similarly dire picture, with about 4 billion people experiencing water scarcity for at least one month every year (Mekonnen and Hoekstra, 2016), and the potential displacement of 24–700 million people in Africa alone by 2030 (Hameeteman, 2013).

Meanwhile, progress on social development needs to continue globally. Targets such as the eradication of hunger and poverty are essential to fulfil human rights and ensure a "good" life for all. A

* Corresponding author.
E-mail address: gonzalo.guillen.gosalbez@chem.ethz.ch (G. Guillén-Gosálbez).

https://doi.org/10.1016/j.jclepro.2020.121833

global agenda to move towards these goals is codified in the United Nations Sustainable Development Goals (SDGs) (UN General Assembly, 2015). Developed in 2015 by the UN General Assembly, these 17 goals set targets to be achieved by 2030, via collective action by all ratifying countries. Several of the SDGs relate to the satisfaction of basic human needs, such as ending extreme poverty, ending hunger and malnutrition, access to clean water and sanitation, and access to affordable and clean energy. Other goals relate to humanity's impact on the environment, e.g. responsible consumption and production, climate action, and sustainable use of terrestrial and marine resources.

Meeting the SDGs requires, therefore, mitigating the effects of anthropogenic activities on the planet while ensuring a certain level of living standards for all. Indeed, when talking about the assessment and adjustment of environmental impacts at the national and global scales, it is essential to consider how to meet basic human needs and desires, without compromising the stability of the natural system. Balancing these different factors at the national and global levels is challenging, and different countries sit at different positions in terms of environmental impact and well-being: many wealthy countries perform well in terms of social indicators like nutrition and access to sanitation, but these achievements are attained at the expense of poor environmental performance (O'Neill et al., 2018).

Understanding the link between environmental degradation and well-being is key to design better policies and set up realistic expectations on how to best satisfy our needs in an environmentally respectful manner. The concept of environmental efficiency of well-being, first introduced by Dietz et al. (2009), provides a conceptual framework to investigate the efficiency of generating human well-being from natural capital using a regression-based approach. After controlling for affluence and human capital, the authors found that stressing the environment does not improve human well-being directly, though it may do so indirectly via increased affluence. Knight and Rosa (2011) define an indicator for the environmental efficiency of well-being based on regression residuals, and investigated its relationship with a range of economic, social, and political indicators. A scientometric analysis of the scientific literature on sustainability and well-being was performed by Qasim (2017), mapping citation networks and analysing relevant indicators.

Previous work attempted to measure the environmental efficiency of well-being using single impact metrics, such as the ecological footprint (Knight and Rosa, 2011), which are unable to quantify environmental sustainability precisely. Furthermore, the focus has often been to study this efficiency ratio but without conducting an in-depth analysis of the best-practices exhibited by countries in transforming impacts into well-being. However, such analysis is essential to understand how to best attain certain levels of development in a sustainable manner. Finally, yet importantly, these works have quantified the environmental efficiency of well-being without addressing the issue of whether efficient countries are "truly" sustainable.

To enhance our understanding of the inherent trade-off between well-being and environmental impact, we carry out here a systematic analysis of the environmental efficiency of well-being in 151 countries. Our study employs the recently proposed concept of Planetary Boundaries (PBs), first introduced by Rockström et al. (2009) and updated in 2015 (Steffen et al., 2015), to quantify the environmental impact of countries precisely and evaluate whether they are environmentally sustainable. Furthermore, we apply Data Envelopment Analysis (DEA) to carry out an in-depth analysis of the tradeoffs between environmental impact and well-being. This technique allows classifying countries as efficient or inefficient, while defining improvement targets for the latter that could be in principle attained via implementation of best practices across nations. Altogether, our analysis addresses the question of how to maximise well-being in a sustainable way (within the ecological limits of the Earth), while considering the current level of technological development.

This article is structured as follows. We first define the scope of the analysis, followed by the description of the data sources and methods employed in this work. Next, the results of the analysis are presented, including a preliminary statistical investigation of the data. Lastly, these results are discussed, while conclusions drawn in the final section.

2. Scope of the analysis

We are given data on environmental footprints (i.e., performance in Earth system processes) and happiness (proxy of well-being) of a set of countries, the level of efficiency of which we wish to quantify. This efficiency is here understood as the ability to generate well-being at a certain environmental cost. No consensus exists on how to best assess well-being, though measures may be split into the categories hedonic (pleasure-seeking) and eudaimonic (flourishing), as discussed by Brand-Correa and Steinberger (2017). Herein, happiness will be used as a (hedonic) proxy for well-being, and, for the remainder of this work, "happiness" and "well-being" will be used interchangeably.

The goal of the analysis is twofold. First, to classify countries into efficient or inefficient, where the former attain the maximum level of well-being observed for a given environmental impact -or, equivalently, a minimum impact for a given well-being level. Therefore, a country is deemed efficient if there is no other country showing simultaneously lower impact and higher well-being. The second part of the analysis focuses on establishing improvement targets for the inefficient countries that, if attained, would make them efficient. More precisely, these targets can be defined as aspirational impact (or well-being) levels, which in practice should be attainable as they have been observed in other nations. In both analyses, we evaluate the environmental performance in terms of PBs to quantify absolute sustainability together with the efficiency of countries.

3. Methods

The data sources are next described before introducing the DEA method applied to study the tradeoffs between environmental impact and well-being. To carry out our analysis, we employ a recently proposed DEA formulation, which was adequately modified to consider ecological limits, i.e., PBs, in the assessment.

3.1. Data sources

3.1.1. Environmental assessment: Planetary Boundaries

PBs attempt to quantify a safe operating space for humanity at a global level, within which the prevailing stable conditions of the Holocene (the era of the past 12,000 years) are likely to be maintained. The PBs represent impact thresholds on critical Earth system processes which may be irreversibly changed by human action. So far, PBs for nine Earth system processes have been defined: Climate change, introduction of novel entities, stratospheric ozone depletion, atmospheric aerosol loading, ocean acidification, biogeochemical flows (nitrogen and phosphorous), freshwater use, land-system change, and biosphere integrity (functional and genetic diversity). Out of these boundaries, five are currently being transgressed (climate change, phosphorous and nitrogen flows, land-system change, and genetic diversity), which calls for urgent action to ensure sustainable development. Hence, by quantifying, monitoring and improving the impact on these critical PBs, humanity may be able to avoid triggering highly deleterious events that could hamper irreversibly our well-being.

Data on environmental footprints of nations were obtained from the recent work by O'Neill et al. (2018), who analysed the transgression of five PBs, two environmental footprint indicators, and the achievement of social thresholds in 151 countries, all above one million inhabitants. Specifically, the boundaries under consideration are CO_2 emissions, phosphorous and nitrogen flows, blue water consumption, land-use change (as measured by the eHANPP indicator), as well as ecological and material footprint indicators. Their values for each country were obtained from the Supplementary Data file of the above publication.

3.1.2. Assessment of human well-being

For the same 151 countries, happiness levels were sourced from the World Happiness Report (WHR) 2018 (Sachs et al., 2018), which is published annually by the United Nations Sustainable Development Solutions Network. The WHR provides the happiness level (value between 0 and 10) for 156 countries. These happiness levels are based on average values from the previous three years obtained from national average data from the Gallup World Poll, which considers responses to the Cantril life ladder. Here, respondents are asked to report their current happiness between the best (10), and worst (0) possible life for them individually. The life ladder values were obtained for each country as the most recent entry in the data file accompanying Chapter 2 of the WHR 2018. To ensure a meaningful analysis, data gaps were covered using the method described in Section 2 in the Supplementary Materials (SM) of the manuscript.

3.2. Data Envelopment Analysis

Here we employ DEA to analyse the environmental efficiency of well-being, which allows us to compare several indicators of environmental impact simultaneously. To this end, we study the countries' relative position with respect to the efficient frontier, which is composed of the best performing entities. This allows us to classify countries into efficient and inefficient, where the former show the lowest impact for a given well-being level or, equivalently, the maximum well-being for a given impact level. Furthermore, we calculate improvement targets for inefficient countries based on the best performing regions, and use them to provide insight into the overall room for improvement across nations.

DEA is a linear programming (LP) method used to assess the efficiency of a number of alternative decision-making units (DMUs) consuming multiple inputs to produce multiple outputs. It was first introduced in 1978 by Charnes et al., (1978) to assess the resource utilisation efficiency of DMUs in public programs. DEA allows for the consideration of several inputs (to be minimised) and outputs (to be maximised) at the same time.

Since its inception, DEA was applied to a variety of research areas, including management science and operations research. More recently, the method has gained traction in the field of environmental sustainability (Zhou et al., 2018), human development (Mariano et al., 2015), as well as chemical process design (Gonzalez-Garay and Guillen-Gosalbez, 2018; Rodríguez Vallejo et al., 2018). Notably, the combination of life cycle assessment

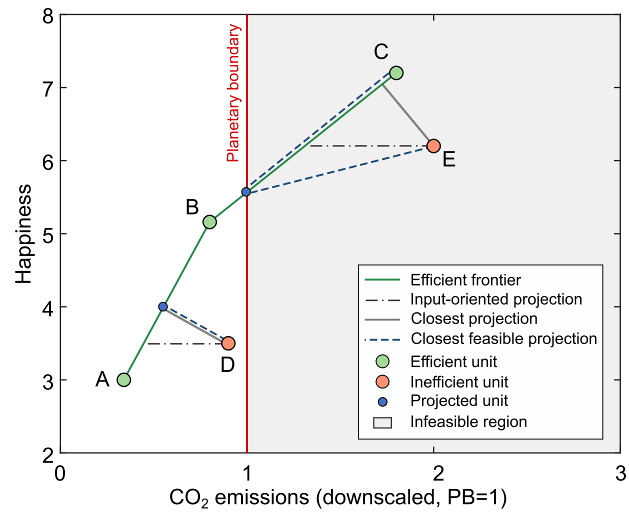

Fig. 1. Motivating example of DEA for a single input (CO_2 emissions) and output (happiness).

and DEA has found applications in the environmental assessment of a wide variety of systems such as food waste management (Cristóbal et al., 2016), electricity (Ewertowska et al., 2016), and agriculture (Khoshnevisan et al., 2015; Lozano et al., 2009).

We will assess here the environmental efficiency of countries by comparing them in terms of a range of inputs (measured for instance by CO_2 emissions or nitrogen flows, downscaled by PBs) and one output (happiness), shown for the single-input case in Fig. 1. A country is efficient if there is no other country that achieves a greater output for the same levels of inputs, or, conversely, if no other country requires lesser input for the same level of output.

The efficiency coefficient calculated for each DMU ranges from 0 to 1. Units with an efficiency of 1 are termed efficient and form the efficiency frontier in the input-output space. The remaining units (with efficiency $\in$ [0,1)) are deemed inefficient, and for these improvement targets can be established by projecting them onto the efficient frontier.

Different types of projections have been proposed in the literature. Output-oriented DEA models maximise outputs of inefficient units while keeping inputs constant; in contrast, input-oriented DEA minimises their inputs while keeping outputs constant. In our study, the former would maximise happiness for a given environmental footprint, while the latter would minimise environmental impacts for a given level of well-being. Note that these two modelling approaches only affect the way in which the efficiencies and improvement targets are computed, but not the classification of DMUs as either efficient or inefficient.

The above can be illustrated with a simple case entailing one input, CO_2 emissions, and one output, happiness, as shown in Fig. 1. Here, countries A-E represent DMUs, where A, B, and C are efficient, and form the efficient frontier ABC, also called the "best practice frontier". Countries D and E, on the other hand, are inefficient, as there are some units on the efficient frontier with both lower emissions and higher happiness levels simultaneously.

3.2.1. Determining the current level of efficiency: the slack-based measure

To assess the efficiency of a unit o among a set of DMUs j, and given a number of inputs x_i and outputs y_r, various DEA variants have been proposed over the years which may be categorised into radial methods (e.g. the original CCR model (Charnes et al., 1978)) and non-radial models (e.g. the slack-based measure (SBM)). We will employ here the input-oriented SBM model under variable returns to scale (VRS), introduced by Tone (2001), in order to avoid some of the shortcomings of radial models: they generally have lower discriminatory power compared to the SBM, and operate under the assumption that all inputs can be reduced proportionally to make an DMU efficient, which might be unrealistic (Chang et al., 2013). In its LP form, the SBM may be expressed as follows:

$$\begin{aligned}
\rho_I^* = \min_{\lambda, s^-, s^+} \quad & 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \\
\text{s.t.} \quad x_{io} &= \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \quad \forall \ i \\
y_{ro} &= \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \quad \forall \ r \\
\lambda_j, s_i^-, \ & s_r^+ \geq 0 \qquad \forall \ j, \ i, \ r
\end{aligned} \tag{M1}$$

Here, ρ_I^* is the input-oriented SBM-efficiency of DMU o, while λ_j represents the weight of DMU j, and input and output slacks are denoted by s_i^- and s_r^+, respectively. DMU o is SBM-input-efficient if $\rho_I^* = 1$, which in turn means that all input slacks s_i^- are zero (whereas output slacks may be nonzero). The efficiency of each DMU o is calculated by solving model M1 separately for said DMU.

The above model identifies efficient DMUs considering a given set of inputs and outputs, while ranking inefficient DMUs according to their efficiency score. However, given a large number of DMUs, it is expected that a considerable number will be deemed efficient (Iribarren et al., 2010). Therefore, further discrimination between efficient units is often desirable, and can be achieved by the implementation of a super-efficiency DEA model. A super-efficiency model assigns efficient units an efficiency score ≥ 1, thereby enabling the ranking of units formerly "identical" in DEA performance. Beyond the original SBM, Tone further introduced a slack-based measure of super-efficiency (Tone, 2002) which will be applied here to rank efficient units:

$$\begin{aligned}
\delta_I^* = \min_{\bar{x}, \bar{y}, \lambda} \quad & \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}_i}{x_{io}} \\
\text{s.t.} \quad \bar{x}_i &\geq \sum_{j=1,\, j\neq o}^{n} x_{ij}\lambda_j \qquad \forall \ i \\
\bar{y}_r &\leq \sum_{j=1,\, j\neq o}^{n} y_{rj}\lambda_j \quad \forall \ r \\
\sum_{j=1,\, j\neq o} & \lambda_j = 1 \\
\bar{x}_i \geq x_{io} \ \forall i, \ & \bar{y}_r = y_{ro} \ \forall \ r, \ \lambda_j \geq 0 \ \forall \ j
\end{aligned} \tag{M2}$$

Solving model M2 for each DMU o found efficient in model M1 yields the super-efficiency score δ_I^* (≥ 1).

3.2.2. *Quantifying the potential for improvement: improvement targets using an alternative MILP DEA model*

In addition to the calculation of the efficiency and super-efficiency of DMU o, DEA allows for the identification of improvement targets for inefficient units via projection onto the efficient frontier. There are standard models to compute these targets, yet as such they are unable to handle constraints on inputs and outputs. Hence, a customised formulation is next introduced to incorporate PBs in the assessment of countries. Referring to Fig. 1, unit E can be projected onto the efficiency frontier while keeping the happiness level constant. For the input-oriented model, this projection quantifies how much the inputs need to be reduced to reach an efficiency of 1. The target inputs and outputs of unit o are calculated from the inputs and outputs of some efficient units, the so called members of its peer group, alongside the optimal unit weights λ_j^*:

$$x_{io}^T = \sum_j x_{ij}\lambda_j^*, \quad \forall \quad i \tag{1}$$

$$y_{ro}^T = \sum_j y_{rj}\lambda_j^*, \quad \forall \quad r \tag{2}$$

The improved values for inputs x_{io}^T and outputs y_{ro}^T now represent the target coordinates of unit o.

We stress that, in the context of our analysis, the drawback of the standard DEA projection method is that it can lead to projected points that transgress PBs. More precisely, the pitfall of standard DEA models is that they could compute projected points that violate PBs. In Fig. 1, the input-oriented projection of E results in a target that still violates the downscaled PB for CO_2 emissions. Furthermore, regular projections in the VRS model do not target the closest point on the efficient frontier, thereby resulting in aspirational designs that may be quite far from the starting point, and which require more "effort" to reach the efficient status than necessary. This is again illustrated in the example in Fig. 1, where the closest projection of point D requires a smaller reduction in emissions, coupled with an increase in happiness.

Therefore, to overcome these limitations improvement targets are here determined with a customised DEA model based on the approach proposed by Aparicio et al. (2007). Their model performs a minimum-distance projection of inefficient units based on some distance metric. One advantage of this approach, compared to traditional alternatives, is that it allows defining bounds on inputs and outputs during the projection, thereby ensuring the feasibility of the projected points in terms of PBs. This method was already applied in a variety of areas, including healthcare (Aparicio et al., 2014), education (Ruiz et al., 2015), and chemical process design (Rodríguez-Vallejo et al., 2018).

We will here apply projections minimising the L2-distance, also known as Euclidian distance, representing the shortest distance between two points in the input-output space. This is illustrated in Fig. 1 by the projection of points D and E to the closest possible efficient points. Mathematically, the closest targets are calculated by first solving the standard DEA model introduced above to obtain the set of efficient units; in a subsequent step, the following variable returns to scale model (Aparicio et al., 2014) is solved:

$$\begin{aligned}
&\min \sum_r \left(\frac{s_{ro}^{+}}{y_{ro}}\right)^2 + \sum_i \left(\frac{s_{io}^{-}}{x_{io}}\right)^2 + \sum_r \left(\frac{s_{ro}^{+'}}{y_{ro}}\right)^2 + \sum_i \left(\frac{s_{io}^{-'}}{x_{io}}\right)^2 \\
&\text{s.t.} \quad \sum_{j\in E} \lambda_j x_{ij} = x_{io} - s_{io}^{-} + s_{io}^{-'}, \quad \forall\, i \\
&\sum_{j\in E} \lambda_j y_{rj} = y_{ro} + s_{ro}^{+} - s_{ro}^{+'}, \quad \forall\, r \\
&\sum_{j\in E} \lambda_j = 1 \\
&-\sum_i \nu_i x_{ij} + \sum_r \mu_r y_{rj} + \Psi + d_j = 0, \quad \forall\, j\in E \\
&\sum_{j\in E} \lambda_j x_{ij} \le UB_i, \quad \forall\, i \qquad \text{(M3)} \\
&\sum_{j\in E} \lambda_j \mathrm{y}_{\mathrm{rj}} \ge LB_{\mathrm{r}}, \quad \forall \mathrm{r} \\
&\nu_i \ge 1, \quad \forall\, i \\
&\mu_r \ge 1, \quad \forall\, r \\
&d_j \le M b_j, \quad \forall\, j\in E \\
&\lambda_j \le 1 - b_j, \quad \forall\, j\in E \\
&b_j \in \{0,1\}, \quad \forall\, j\in E \\
&\lambda_j, d_j, s_{ro}^{+}, s_{io}^{-}, s_{ro}^{+'}, s_{io}^{-'} \ge 0, \ \forall\, j,\ r,\ i
\end{aligned}$$

Model M3 differs from the VRS closest target model by Aparicio et al. in three ways. Firstly, the definition of upper and lower bounds (UB_i and LB_r, in the model) on inputs and outputs, respectively, allows the model to project units only onto regions of the efficient frontier satisfying certain bounds. In Fig. 1, the L2-projection of unit E would result in a target close to unit C. However, since this target lies outside the safe space defined by the PBs, the unit is instead projected onto the intersection of the efficient frontier and the PB. Secondly, two additional slack variables have been introduced, $s_{io}^{-'}$ and $s_{ro}^{+'}$, which allow the input and output values to "worsen" when an inefficient unit is projected onto the efficient frontier. This is again the case for unit E, whose closest feasible projection results in a reduction in happiness. Thirdly, while Aparicio et al. solve the closest target model for every inefficient unit, in our case model M3 will be solved for all units. This is justified by the definition of bounds UB_i and LB_r. More precisely, this will allow us to evaluate units that, while efficient, violate the aforementioned bounds (i.e., PBs) and, therefore, need to be projected within the safe space to ensure sustainable development. This is the case for unit C in Fig. 1, which is projected onto the intersection of the efficient frontier and the PB. Finally, we note that the targets obtained here are invariant to the units of measurement due to the division of the slacks by their respective inputs and outputs in the objective function.

3.2.3. Returns to scale

A further feature of DEA is the ability to classify efficient DMUs into three distinct regions according to the returns to scale (RTS) concept. In the "increasing returns to scale" (IRS) subregion, units can increase their outputs at a larger rate than their inputs (e.g., a certain increase in outputs can be attained with a relatively smaller increase in inputs). In the "constant returns to scale" (CRS) subregion, the input/output ratio is maintained constant, while units in the "decreasing returns to scale" (DRS) subregion can reduce their inputs at a relatively smaller decrease in their outputs. Note that this analysis is again carried out using an input-oriented approach. The RTS analysis is meaningful because it provides insight into how hard it is for countries (in environmental terms) to improve further their well-being at different well-being levels. Further details on this approach can be found in Section 1 of the SM.

4. Results

We discuss next the results of our study, presenting first a preliminary analysis of the data using elasticities, before describing the DEA results.

4.1. Regression and elasticity

Before applying DEA, we analyse the relationship between the inputs and the output, that is, the environmental footprint indicators and happiness levels, using linear regression and elasticities. Specifically, we apply the concept of elasticity, which provides the sensitivity of one variable to changes in another. This elasticity represents the proportional change of a dependent variable when varying an independent variable by one percent. Mathematically, this is based on the simple exponential model:

$$H = kI^b \tag{3}$$

where, for our purposes, H represents happiness, and I impacts. This can be transformed to yield:

$$log(H) = \log(k) + b\,\log(I) \tag{4}$$

where variable b represents the elasticity of happiness H with respect to impacts I, while $\log(k)$ is a constant. This means that for every percentage change in impact, there will be a change of b percent in happiness. The elasticity can take both positive and negative values, based on the relationship between the variables. If the absolute value of the elasticity is greater than or equal to 1, the relationship is said to be elastic, resulting in a larger change in H when varying I. Conversely, absolute elasticity values between 0 and 1 describe and inelastic relationship, where larger changes in driving force are needed to attain the same percentage variation in the output.

This approach has previously been applied to the analysis of environmental impacts by York et al. (2003), coining the term ecological elasticity. It was also applied to study burden-shifting in the context of designing energy systems (Algunaibet and Guillén-Gosálbez, 2019). Similarly, O'Neill et al. (2018) analysed the relationship between 7 biophysical and 11 social indicators using linear, linear-logarithmic, and saturation models.

We investigate the elasticity of happiness with regards to environmental footprint indicators by means of ordinary least squares (OLS) regression. This was first attempted via multiple linear regression. However, a high level of significance for the overall model, coupled with low significance of each individual estimator, suggested multi-collinearity in the data. This was confirmed by high values (>10 in several cases) of the variance inflation factors, as well as the correlation analysis provided in

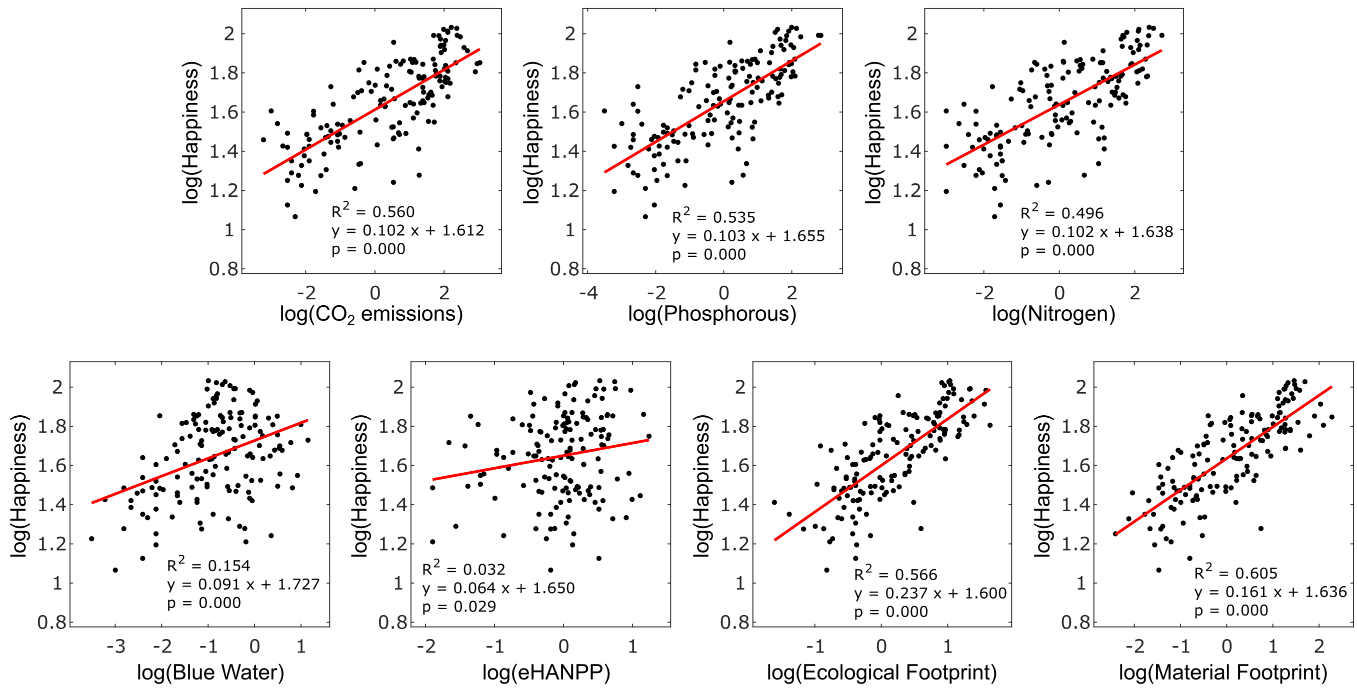

Fig. 2. Log-transformed data and best linear fit for environmental footprint indicators and happiness.

Section 3 and Fig. S1 in the SM. The regression analysis was hence conducted by regressing indicators against happiness individually.

Fig. 2 shows scatter plots of the log-transformed data, alongside the best linear fit obtained from the OLS regression. As seen, happiness shows a positive correlation with all indicators. In other words, a higher level of happiness in a nation is associated with larger impacts on the environment. This relationship is significant at $p < 0.05$ in all cases, with the lowest significance found in happiness vs. eHANPP. Fig. 2 further shows the best fit parameters for the regression, including the elasticities of happiness with regards to the individual indicators. These results show that happiness is inelastic with regards to all indicators, with elasticity values ranging from 0.064 (eHANPP) to 0.237 (Ecological Footprint). This suggests that at current technologic and societal levels, large increases in environmental impact may be required to increase further the happiness of a nation's populace. To put this into perspective, a 10% increase in happiness *ceteris paribus* would require an increase of 100% (or doubling) in CO_2 emissions based on an elasticity of 0.102. Note that these regression results should be taken with caution as they do not account for endogeneity, which appears when the explanatory variable is correlated with the error term (Wooldridge, 2016).

4.2. Data Envelopment Analysis

4.2.1. Efficiencies

We next apply DEA to assess the environmental efficiency of 151 countries. As already mentioned, happiness levels were used as the single output of the model, while seven per-capita environmental footprint indicators served as inputs: CO_2 emissions, nitrogen and phosphorous flows, blue water use, eHANPP, ecological footprint, and material footprint. The global distribution of efficiencies is shown in the map in Fig. 3, where countries meeting all PBs are outlined in magenta. As mentioned above, downscaled values of PB indicators were taken from the work of O'Neill et al. (2018).

Darker shades represent higher efficiencies, while regions in grey represent areas omitted in this analysis. Clusters of efficient countries can be seen in Central and East Asia, Africa, as well as Central and Northern Europe. Overall, 43 countries (28.5%) were found to be efficient. A histogram of these efficiencies is shown in Fig. 4 together with a breakdown in terms of income of the countries. It can be seen that efficiencies values can differ substantially across nations, with many countries operating at or above the efficient frontier, i.e. 43 with efficiencies above 100%, while 52 countries only achieve an efficiency below 40%. About 2/3 of countries show efficiencies below 70%, which highlights the large potential for improvement.

We refined our analysis by classifying countries into four groups, based on their national income per person as defined by the World Bank (Prydz and Wadhwa, 2019). Low-income countries are defined as having a gross national income (GNI) per capita of $995 or below; lower middle-income countries have a GNI per capita between $996 and $3,895; upper middle-income countries fall between $3,896 and $12,055; and high-income economies show values above $12,056. Based on 2017 income values, 30 countries are classified as low-income; 37 as lower middle-income; 39 as upper middle-income; and 45 as high income.

The largest proportion of efficient countries (efficiency $\geq$ 1.0) corresponds to the lower middle and low-income groups (65% of the countries with high efficiencies belong to these two groups), with high-income countries, making up most of the remainder of efficient countries (25%). Contrarily, few upper middle-income countries are found to be efficient. They make up the remaining 10% of the efficient countries, and are skewed strongly towards low efficiencies: more than three quarters of countries in this income category fall below a 50% efficiency level.

4.2.2. Improvement targets

Improvement targets for all countries were calculated using the closest target model M3 introduced earlier, applying the L2 distance and enforcing meeting PBs in the projections. Before projection, a total of only 20 countries (13%) satisfied all PBs. Out of these, 12 belonged to the low-income category, seven to the lower-middle income category, and only a single country from the upper

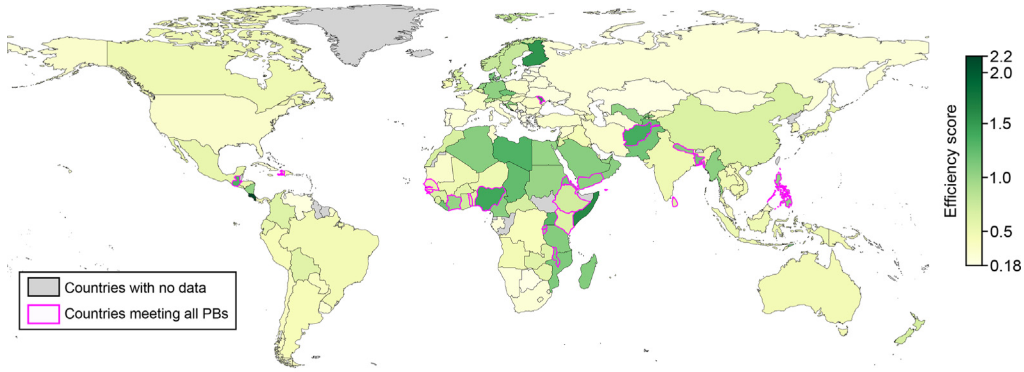

Fig. 3. DEA efficiency and super-efficiency of countries under investigation, alongside countries satisfying PBs in magenta. Countries without available data are depicted in grey.

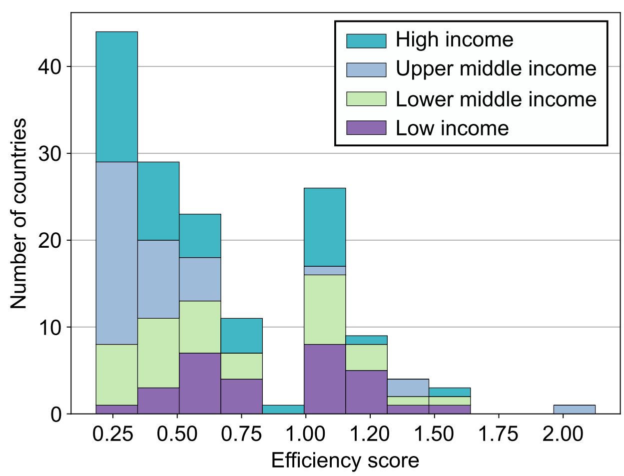

Fig. 4. Histogram of efficiencies obtained using DEA, with the breakdown by income category.

middle-income category. Currently, no high-income country in the dataset satisfies all PBs concurrently, which confirms that these countries are using excessive natural resources to meet their lifestyles.

We note that improvement targets are established through linear combinations of indicator values in a set of peer countries. The latter can be seen as following best practices and, consequently, inefficient countries should try to mimic their behaviour to the extent possible.

Fig. 5 ranks countries who act as peers at least five times and shows their happiness levels, with dark blue bars denoting that the country satisfies all PBs. Guatemala has the largest number of peers among all countries, both within PBs and outside. Combined with the fact that it has the highest happiness levels among countries satisfying PBs, this suggests that it follows best practices, which may be imitated if circumstances allow. Together with Costa Rica and Nicaragua, three out of the five countries with the most peers hail from Latin America. These results are consistent with previous findings that Latin American countries are environmentally efficient in generating well-being (Knight and Rosa, 2011). Pakistan, as the country with the second-most peer relationships, performs well in land use and the ecological and material footprints, while showing a high level of happiness relative to countries with a similar impact. Only two high-income countries act as peers to at least five others. Denmark is only surpassed in happiness by two other countries, and outperforms those in all environmental indicators, while Israel has low land use alongside a high level of

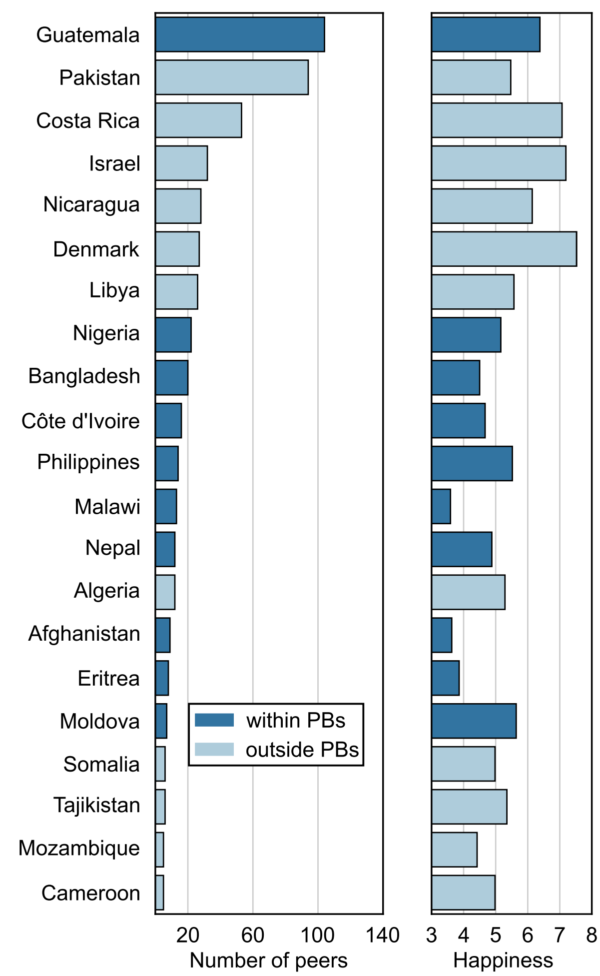

Fig. 5. Ranking of countries acting as peers more frequently, alongside happiness values.

happiness.

The average percentage change in each indicator value after the projection is shown as heatmap in Fig. 6. This includes projected units that were already efficient but failed to satisfy one or more PBs. As an example, Finland is currently efficient but operates outside the safe operating space dictated by the PBs. Positive values indicate an increase in the indicator value upon projection, while negative values represent a reduction. Hence a value of −50% would mean that a reduction by half of the current value is needed to

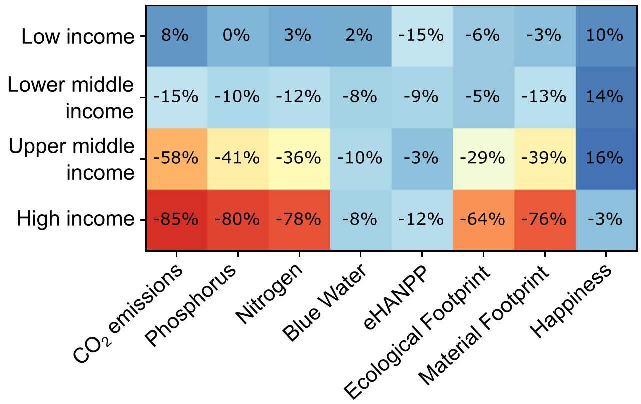

Fig. 6. Average improvement targets by income group.

become efficient and at the same time operate within PBs. The converse is true for happiness, where an increase of e.g. 10% may be needed to become efficient.

Targets for the indicators on CO_2, phosphorous and nitrogen emissions, as well as the ecological and material footprints, behave similarly across income groups, with the smallest reductions required for low-income countries, which increase as we move to higher incomes. Notably, there is a pronounced gap between lower middle and upper middle-income countries, most likely due to the transgression of PBs in the latter, which has strong implications on the projections. In the latter, reductions in impacts of 29% or even more would be necessary in all of the indicators, except for water consumption and eHANPP, to become efficient. This trend continues for high income-countries, which would require massive reductions (64% or more) of the same indicators (all except water and eHANPP) to satisfy PBs and become efficient.

Blue water represents an interesting case, where all but the low-income countries would require a similar reduction, on average. Overall, most of the countries satisfy the water PB (124 out of 151), although this analysis does not take into account regional and seasonal variations in water resource use or availability, and therefore does not capture water shortages found today in many areas (Mekonnen and Hoekstra, 2016).

Fig. 7 shows the histogram of improvement targets for happiness. As seen, when following best practices, the majority of countries could meet PBs while at the same time increasing their happiness. Conversely, 49 countries would require some reduction in happiness to meet PBs, most of them (29) within the high-

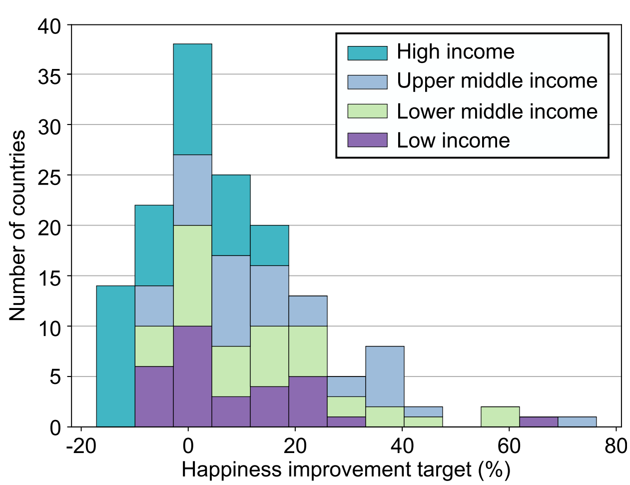

Fig. 7. Histogram of happiness improvement targets by income category.

income category. Remarkably, all countries could meet PBs without worsening their current happiness level by more than 18%.

4.2.3. Returns to scale

Aside from improvement targets, the RTS concept provides further insight into the environmental efficiency of well-being attained by countries. While improvement targets shed light on the changes required to make an inefficient unit efficient, RTS identifies whether, for a given country, the scale of inputs to outputs is more or less productive. As noted above, the most productive scale is CRS, where the ratio outputs to inputs is the highest observed. Fig. 8 shows the classification of countries according to their behaviour in terms of RTS.

Overall, only five countries (3%) were found to lie in the IRS subregion, 22 (15%) in the CRS subregion, and 124 (82%) in the DRS subregion. This already confirms that improving further the current levels of well-being may require increasing substantially current impact levels. Furthermore, it can be seen from the map that the decreasing returns to scale dominates in most continents but Africa. Increasing and constant returns to scale, on the other hand, occur mostly in sub-Saharan Africa, and parts of Central and Southern Asia.

Fig. 9 further breaks down the RTS by income category (LI - low income; LMI - lower middle income; UMI - upper middle income; HI - high income). In terms of income levels, it can be seen how the number of countries belonging to the DRS subregion increases with the income level. Notably, all but one high-income country (the Czech Republic) fall into this region. These results confirm that higher income countries are ensuring high levels of well-being at the expense of very high impacts. The opposite trend can be observed for constant returns to scale, where low-income countries represent the largest share among all the income groups. Among the five countries belonging to the IRS subregion, three are low-income, two belong to the lower and upper middle-income categories, respectively, while no high-income country is represented.

5. Conclusions

Reducing environmental impacts without compromising the populations' ability to lead happy lives is a key challenge in sustainable development. In this work, the PBs framework was combined with DEA to assess the environmental efficiency of well-being in 151 countries. We found that only one third of the countries are efficient, while most of them show low efficiency levels (two thirds of them with an efficiency below 70%). These results already suggest that it might be (theoretically) possible to reduce drastically the pressure exerted on the environment while maintaining or marginally decreasing current levels of well-being.

In terms of PBs, only 20 countries meet all of them concurrently, out of which 13 are fully efficient while seven are not. Hence, "environmentally efficient" should not be wrongly interpreted as "environmentally sustainable", as countries such as Croatia are efficient, yet they transgress some PBs. The maximum level of happiness among the countries that meet all the PBs simultaneously is 6.38 (4.88, 5.64 and 6.38 for those in the low, lower middle, and upper middle-income categories, respectively). Hence, empirical evidence show that it is possible to attain reasonable levels of happiness while operating within PBs.

A customised closest target DEA model was employed to quantify the potential to operate within PBs without compromising excessively our well-being. Here we found that low and lower middle-income countries would need small impact reductions to meet PBs, while upper middle and high income would need more drastic cuts (even above 80%, on average, in some cases). These reductions would have implications on the happiness level. Indeed,

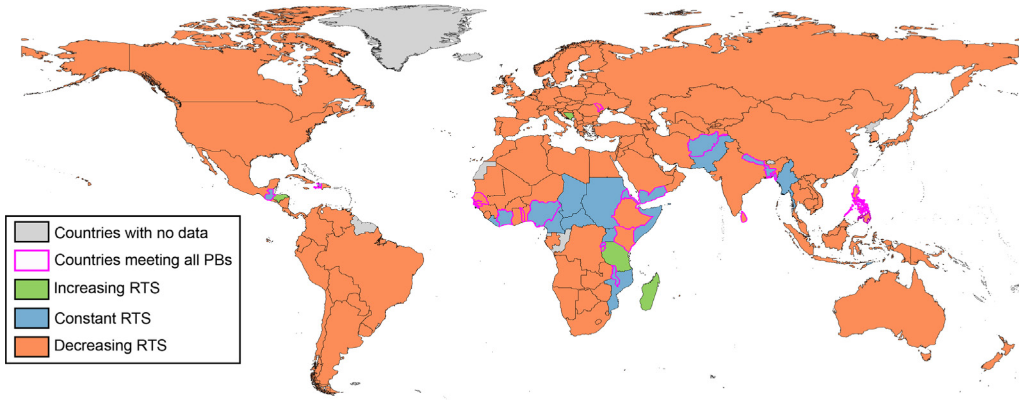

Fig. 8. Classification of countries based on their performance concerning RTS.

for most countries it would be theoretically possible to increase their happiness level while meeting PBs, yet for some others this might not be an option. Particularly, 64% of high-income countries would need to reduce their well-being to meet PBs, yet this reduction would not be that substantial (less than 18% in the worst case).

Note that DEA provides theoretical targets, yet it does not specify how to attain them in practice. Indeed, empirical evidence shows that, theoretically, it would be possible to operate within PBs while showing reasonable happiness levels. How to accomplish this goal effectively, however, may vary across countries and it remains unclear the extent to which the improvement targets are attainable in practice. Regardless of the approach followed, it seems evident that richer countries transgressing PBs will need to reduce their footprints. This will very likely require drastic changes in their production and consumption patterns combined with better technology and more effective mitigation strategies. The challenge, then, will be to reduce impacts without sacrificing well-being. Happiness correlates with income level, but also with other variables such as life expectancy and social support, among others (Sachs et al., 2018) (Figs. S2–S4 provided in Section 4 of the SM). Hence, a holistic approach towards well-being considering PBs and most likely implying a paradigm shift away from the maximization of gross domestic product as single objective should be pursued by countries.

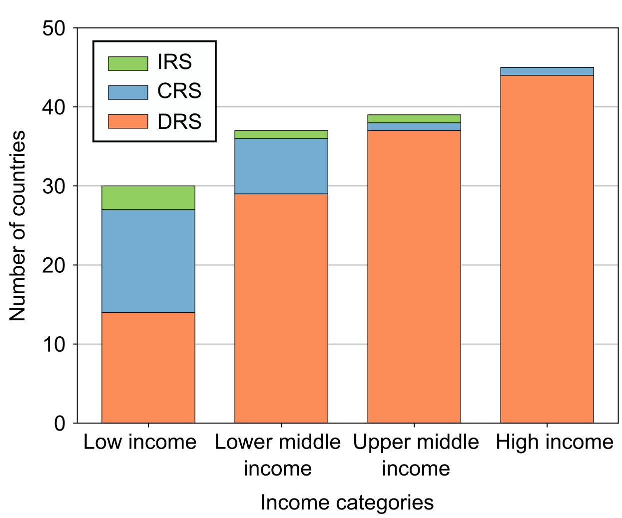

Fig. 9. RTS subregion distribution by income category.

Overall, our work aims to identify pathways to underpin sustainable development and operate within the Earth's capacity without compromising well-being. Even though the analyses presented herein simplify the complex relationship between economic performance, societal achievements, and environmental impact, we believe they serve to illustrate the scale at which happiness and environmental impacts are linked. While every country is unique, many similarities exist, so nations could draw inspiration from their peers when pursuing sustainable development within PBs.

Funding

This work was supported by the Commonwealth Scientific and Industrial Research Organisation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.jclepro.2020.121833.

References

Algunaibet, I.M., Guillén-Gosálbez, G., 2019. Life cycle burden-shifting in energy systems designed to minimize greenhouse gas emissions: novel analytical method and application to the United States. J. Clean. Prod. 229, 886–901. https://doi.org/10.1016/j.jclepro.2019.04.276.

Aparicio, J., Borras, F., Ortiz, L., Pastor, J.T., 2014. Benchmarking in Healthcare: an Approach Based on Closest Targets. https://doi.org/10.1007/978-3-662-43437-6_5.

Aparicio, J., Ruiz, J.L., Sirvent, I., 2007. Closest targets and minimum distance to the Pareto-efficient frontier in DEA. J. Prod. Anal. 28 (3), 209–218. https://doi.org/10.1007/s11123-007-0039-5.

Brand-Correa, L.I., Steinberger, J.K., 2017. A framework for decoupling human need satisfaction from energy use. Ecol. Econ. 141, 43–52.

Chang, Y.-T., Zhang, N., Danao, D., Zhang, N., 2013. Environmental efficiency analysis of transportation system in China: a non-radial DEA approach. Energy Pol. 58, 277–283. https://doi.org/10.1016/j.enpol.2013.03.011.

Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2 (6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.

Costanza, R., Kubiszewski, I., Giovannini, E., Lovins, H., McGlade, J., Pickett, K.E., et al., 2014. Development: time to leave GDP behind. Nature News 505 (7483), 283.

Cristóbal, J., Limleamthong, P., Manfredi, S., Guillén-Gosálbez, G., 2016. Methodology for combined use of data envelopment analysis and life cycle assessment applied to food waste management. J. Clean. Prod. 135, 158–168. https://

doi.org/10.1016/j.jclepro.2016.06.085.
Dietz, T., Rosa, E.A., York, R., 2009. Environmentally efficient well-being: rethinking sustainability as the relationship between human well-being and environmental impacts. Hum. Ecol. Rev. 114–123.
Ewertowska, A., Galán-Martín, A., Guillén-Gosálbez, G., Gavaldá, J., Jiménez, L., 2016. Assessment of the environmental efficiency of the electricity mix of the top European economies via data envelopment analysis. J. Clean. Prod. 116, 13–22.
Geyer, R., Jambeck, J.R., Law, K.L., 2017. Production, use, and fate of all plastics ever made. Science Advances 3 (7), e1700782.
Gonzalez-Garay, A., Guillen-Gosalbez, G., 2018. SUSCAPE: a framework for the optimal design of SUStainable ChemicAl ProcEsses incorporating data envelopment analysis. Chem. Eng. Res. Des. 137, 246–264.
Hameeteman, E., 2013. Future water (In)security: Facts, figures, and predictions. Proceedings of the Water Congress, Presented by Hilbren Buys, Bursa, Turkey 22–24.
IPCC, 2018. Summary for policymakers. In: Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R., et al. (Eds.), Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change. World Meteorological Organization.
Iribarren, D., Vázquez-Rowe, I., Moreira, M.T., Feijoo, G., 2010. Further potentials in the joint implementation of life cycle assessment and data envelopment analysis. Sci. Total Environ. 408 (22), 5265–5272. https://doi.org/10.1016/j.scitotenv.2010.07.078.
Khoshnevisan, B., Bolandnazar, E., Shamshirband, S., Shariati, H.M., Anuar, N.B., Kiah, M.L.M., 2015. Decreasing environmental impacts of cropping systems using life cycle assessment (LCA) and multi-objective genetic algorithm. J. Clean. Prod. 86, 67–77.
Knight, K.W., Rosa, E.A., 2011. The environmental efficiency of well-being: a cross-national analysis. Soc. Sci. Res. 40 (3), 931–949. https://doi.org/10.1016/j.ssresearch.2010.11.002.
Lozano, S., Iribarren, D., Moreira, M.T., Feijoo, G., 2009. The link between operational efficiency and environmental impacts: a joint application of life cycle assessment and data envelopment analysis. Sci. Total Environ. 407 (5), 1744–1754.
Mariano, E.B., Sobreiro, V.A., do Nascimento Rebelatto, D.A., 2015. Human development and data envelopment analysis: a structured literature review. Omega 54, 33–49.
Mekonnen, M.M., Hoekstra, A.Y., 2016. Four billion people facing severe water scarcity. Science Advances 2 (2), e1500323.
O'Neill, D.W., Fanning, A.L., Lamb, W.F., Steinberger, J.K., 2018. A good life for all within planetary boundaries. Nature Sustainability 1 (2), 88–95. https://doi.org/10.1038/s41893-018-0021-4.
Prydz, E.B., Wadhwa, D., 2019. Classifying countries by income. Retrieved October 10, 2019, from The World Bank website: https://datatopics.worldbank.org/world-development-indicators/stories/the-classification-of-countries-by-income.html.
Qasim, M., 2017. Sustainability and wellbeing: a scientometric and bibliometric review of the literature. J. Econ. Surv. 31 (4), 1035–1061.
Raworth, K., 2012. A safe and just space for humanity: can we live within the doughnut. Oxfam Policy and Practice: Climate Change and Resilience 8 (1), 1–26.
Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., et al., 2009. Planetary boundaries: exploring the safe operating space for humanity. Ecol. Soc. 14 (32) https://doi.org/10.1038/461472a.
Rodríguez Vallejo, D.F., Galán-Martín, Á., Guillén-Gosálbez, G., Chachuat, B., 2018. Data envelopment analysis approach to targeting in sustainable chemical process design: application to liquid fuels. AIChE J. https://doi.org/10.1002/aic.16480 aic.16480.
Ruiz, J.L., Segura, J.V., Sirvent, I., 2015. Benchmarking and target setting with expert preferences: an application to the evaluation of educational performance of Spanish universities. Eur. J. Oper. Res. 242 (2), 594–605.
Sachs, J.D., Layard, R., Helliwell, J.F., 2018. World Happiness Report 2018.
Steffen, W., Richardson, K., Rockström, J., Cornell, S.E., Fetzer, I., Bennett, E.M., et al., 2015. Planetary boundaries: guiding human development on a changing planet. Science 347 (6223). https://doi.org/10.1126/science.1259855.
Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Oper. Res. 130 (3), 498–509.
Tone, K., 2002. A slacks-based measure of super-efficiency in data envelopment analysis. Eur. J. Oper. Res. 143 (1), 32–41. https://doi.org/10.1016/S0377-2217(01)00324-1.
UN General Assembly, 2015. Transforming Our World: the 2030 Agenda for Sustainable Development. United Nations.
Wooldridge, J.M., 2016. Introductory Econometrics: A Modern Approach. Nelson Education.
York, R., Rosa, E.A., Dietz, T., 2003. STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. Ecol. Econ. 46 (3), 351–365. https://doi.org/10.1016/S0921-8009(03)00188-5.
Zhou, H., Yang, Y., Chen, Y., Zhu, J., 2018. Data envelopment analysis application in sustainability: the origins, development and future directions. Eur. J. Oper. Res. 264 (1), 1–16. https://doi.org/10.1016/j.ejor.2017.06.023.